Cheaper Is Not Better:
On the Superior Performance of High-Fee Mutual Funds

Jinfei Sheng Mikhail Simutin Terry Zhang*

November 2017

Abstract

The well-established negative relation between expense ratios and future net-of-fees performance of actively managed equity mutual funds guides portfolio decisions of institutional and retail investors. We show that this relation is an artifact of the failure to adjust performance for exposure to the profitability and investment factors. High-fee funds exhibit a strong preference for stocks with low operating profitability and high investment rates, characteristics recently found to associate with low expected returns. We show that after controlling for exposures to profitability and investment factors, high-fee funds significantly outperform low-fee funds before expenses, and perform equally well net of fees. Our results have important implications for asset allocation decisions and support the theoretical prediction that skilled managers extract rents by charging high fees.

JEL Classification: G23, G11, J24
Keywords: Mutual fund performance, fee-performance relation, factor models, valuation cost

*We thank Vikas Agarwal, Jan Bena, Janis Berzins (discussant), Jonathan Berk, Oliver Boguth, Murray Carlson, Stephen Dimmock (discussant), Richard Evans, Jack Favilukis, Adlai Fisher, Lorenzo Garlappi, Ron Giammarino, Will Gornall, Leonard Kostovetsky (discussant), Kai Li, Juhani Linnainmaa, Russell Lundholm, Elena Pikulina, Elena Simintzi, Juan Sotes-Paladino (discussant), Yuehua Tang, and seminar and conference participants at 2017 Finance Down Under Conference, 2017 China International Conference in Finance, 2017 European Finance Association Conference, 2017 Northern Finance Association Conference, and UBC for helpful comments. We also thank Lu Zhang for sharing with us data about q-factors. Jinfei Sheng and Terry Zhang are at Sauder School of Business, University of British Columbia. 2053 Main Mall, Vancouver, BC, V6T 1Z2, Canada. Mikhail Simutin is at Rotman School of Business, University of Toronto. 105 St. George Street, Toronto ON, M5S 3E6, Canada. Emails: jinfei.sheng@sauder.ubc.ca; mikhail.simutin@rotman.utoronto.ca; terry.zhang@sauder.ubc.ca.

1. Introduction

At the end of 2016, domestic U.S. equity mutual funds were responsible for managing over $6.4 trillion in assets. These funds continue to be the primary investment vehicle for households, with over ninety million people in the U.S. holding their shares. The average fund charges over 1% in fees, and each year investors spend tens of billions of dollars on fund expenses, which supposedly compensate managers for their ability to generate value.

Economic principles and theoretical arguments suggest that fees of a fund should be commensurate with the value it creates for investors. Skilled managers should generate better before-fee performance but capture all rents by charging higher expenses, leading to a flat relation between fund expenses and net-of-fees performance (Berk and Green, 2004). In stark contrast with the theory, empirical studies fail to find a positive relation between fund expense ratios and before-fee performance. The literature concludes that net of expenses, investors in high-fee funds earn significantly worse factor-adjusted returns than do investors in low-fee funds.[1]

The seemingly poor factor-adjusted performance of high-fee funds has shaped asset allocation decisions of both retail and institutional investors. For example, in his best-selling book aimed at individual investors, Malkiel (2016) writes, "The best-performing actively managed funds have moderate expense ratios… I suggest that investors never buy actively managed funds with expense ratios above 50 basis points." More sophisticated investors also avoid high-fee funds. For instance, in a study of asset flows of defined contribution pension plans, Sialm, Starks, and Zhang (2015, p. 832) show that "plan sponsors and participants invest more in funds with lower expense ratios."

[1] See, for example, Jensen (1968), Malkiel (1995), Gruber (1996), Wermers (2000), Gil-Bazo and Ruiz-Verdú (2009), Fama and French (2010).

In addition to offering these billion-dollar practical implications, the inverse relation between fees and performance raises important and unanswered questions. Specifically, how should the literature square this relation with the theory? And why do high-fee funds continue to exist if their managers extract more economic rents than the value they add? In this paper we offer an explanation, which reconciles theory with empirics, and calls for revisiting the oft-offered practical advice to prefer low-fee funds over high-fee counterparts.

In our first set of analyses, we establish that funds with different expense ratios invest in fundamentally different stocks. In particular, relative to firms held by funds in the lowest fee decile, firms held by funds in the top fee decile grow their assets at a faster rate (19% vs 12% annually) and have lower gross profit ratios (28% vs 34%). Importantly, these firms are precisely the types that conventional factor models misprice: firms with high asset growth and low profitability have significantly negative three- and four-factor alphas (Cooper, Gulen, and Schill, 2008; Novy-Marx, 2013). As a result of high-fee funds tilting their portfolios to such stocks, analyses based on conventional models lead to the premature conclusion of poor performance of these funds and the practical guidance to avoid investing in them. We re-examine the fee-performance relation through the lens of a recently proposed Fama-French (2015) five-factor model, which is designed to capture differences in average returns of stocks with different profitability and investment patterns and is hence well-suited to study factor-adjusted performance of funds with different fees.

In striking contrast with the conclusions of the prior literature, we find that high-fee funds generate significantly better factor-adjusted gross-of-expenses performance than do low-fee funds. Results of panel regressions of funds' five-factor alphas on expense ratios suggest that funds that charge 1% higher fee deliver 1% more alpha. We show that after deducting expenses, high-fee funds do not underperform low-fee funds. In other words, the seemingly poor performance of these funds documented in prior literature is but an artifact of the failure to adjust performance for the exposure to priced factors. Importantly, our results strongly support the predictions of Berk and Green (2004) that high-fee mutual funds generate higher alpha before fees, and that fees are unrelated to net-of-expenses performance because skilled managers extract rents by charging higher fees.

To better understand why high-fee funds invest more in high-investment low-profitability stocks, we consider two hypotheses. Under the *naïve investor hypothesis*, we conjecture that these companies appeal to unsophisticated investors who are also less price-sensitive, which allows high-fee funds to charge higher expenses. We find this is not the case: high-fee funds with more or less sophisticated investors exhibit similar propensities to invest in high-investment low-profitability stocks.

Alternatively, under the *valuation cost hypothesis*, we conjecture that high-fee funds tilt their portfolios to high-investment low-profitability companies because estimating their intrinsic value is more difficult. Funds that choose to specialize in investing hard-to-value companies must spend more resources on valuation per unit of capital, for example by hiring more talented managers, which justifies the higher fees on a percentage basis. Because companies that are difficult-to-value are more likely to be the ones with fast growth rate and low profit, traditional factor models, being unable to correctly price low profit and high investment companies, will produce biased performance evaluation for high-fee funds. To test this hypothesis, we first use various measures to classify companies into easy-to-value and hard-to-value groups and closely examine the sub-sample of funds that invest more in hard-to-value companies. We find that our results on the relation between fund fees and five-factor alphas are more pronounced among these funds. In particular, the failure of fees to relate to the four-factor alphas is more striking, and high-fee funds display even stronger tilt towards low profit and high growth companies in this sub-sample.

The mutual fund literature has long been puzzled by the fact that high-fee funds can survive market competition from low-fee funds (e.g., Gruber, 1996). If investors do not account for differences in profitability and asset growth rates of stocks held by high- and low-fee funds, they may erroneously conclude that high-fee funds lack skill, withdraw assets, and ultimately contribute to fund termination. We do not find support for this conjecture: we show that the five-factor alpha is a better predictor of a fund's survival than the four-factor alpha. The advantage of the five-factor model over the four-factor model in predicting a fund's survival is more pronounced among funds with more institutional clients and funds that invest heavily in high-growth companies. This evidence suggests that some investors, particularly more sophisticated ones, recognize the value that high-fee funds deliver.

Our results contribute to the large literature on mutual fund performance.[2] An important long-standing debate in this research is whether fund managers deliver performance that justifies the fees they charge (e.g., Daniel et al., 1997; Carhart, 1997; Berk and Green, 2004; Fama and French, 2010; Berk and van Binsbergen, 2015). Our key contribution is to show that – consistent with the theory of Berk and Green (2004) – skilled managers indeed extract rents by charging high fees.

We also extend the growing literature that investigates how anomalies associated with investment and profitability rates impact mutual funds. Several recent papers advance this research by addressing questions distinct from ours. For example, Busse et al. (2016) argue that mutual fund performance measures should control for portfolio characteristics, such as investment and profitability. Jordan and Riley (2015) find that idiosyncratic volatility can predict mutual fund performance measured with three- and four-factor models, but cannot predict five-factor alpha. Jordan and Riley (2016) find that five-factor mutual fund alphas

[2] The literature has grown tremendously since Jensen (1968). See Ferson (2010), Musto (2011), and Wermers (2011) for recent comprehensive reviews.

exhibit more persistence than alphas from other models, highlighting the apparent superiority of the five-factor model over its predecessors. Our paper adds to this strand of literature by documenting the implications of exposures to the investment and profitability factors for the fee-performance relation, which is one of the central questions in the mutual fund literature.

The rest of the paper is organized as follows. Section 2 describes the data and the sample. Section 3 presents our main finding on fee-performance relation. Section 4 analyzes portfolio holdings of high-fee mutual funds. Section 5 explores the reasons behind the high-fee funds' preference for certain types of stocks. Section 6 provides robustness tests. Section 7 concludes.

2. Data

We obtain mutual fund data by linking the CRSP Survivor-Bias-Free U.S. Mutual Fund Database with the Thomson Reuters Mutual Fund Holdings Database using the MFLINKS table (Wermers, 2000). Following the literature, we apply several filters to form our sample (e.g., Kacperczyk, Sialm, and Zheng, 2008). We remove passive index funds by searching through fund name, index fund indicator, and Lipper objective name. We then restrict our sample to the U.S. domestic equity funds based on the CRSP style code. We eliminate funds that hold less than 70% or more than 130% of their assets in equity. We also require a fund to have at least 10 stock holdings and at least $15 million in asset in real 2014 terms, which is approximately $5 million in 1980. In order to estimate the performance for each fund, we require at least five years of return history. Our final sample contains 2,463 funds and spans the period from 1980 to 2014. [3]

If a fund has multiple share classes, we aggregate information of the different classes. Fund-level returns and expense ratios are the class size-weighted averages. If size information

[3] The results remains similar if we require at least three years of return history, leaving us with 2,821 unique funds (See Section 6).

is missing, we take the return and expense ratio of the oldest share class. Fund size is the aggregate of all share classes. We define fund age as the age of its oldest share class.

To proxy for investor sophistication, we use fund distribution channel and whether it is a retail or institutional fund. Following Sun (2014), we classify a share class as broker-sold (as opposed to directly sold), if its 12b-1 fee is higher than 25 basis points or if it charges a front- or back-end load fees. Fee data are obtained from the CRSP database. We classify a fund as broker-sold if more than 75% of its assets are held in broker-sold share classes. We label a share class as institutional if its name contains words beginning with "inst", or if it is of class Y or I. We label a fund as an institutional fund if more than half of its assets are in the institutional share classes. Finally, we identify funds that belong to the same fund family and calculate fund family size as the sum of total assets of affiliated funds. Panel A of Table 1 reports fund-level summary statistics. The average fund is 13.7 years old, charges a 1.23% fee, and turns over its assets 1.02 times each year.

Our analysis of mutual fund holding requires stock-level data, which we obtain from the CRSP and COMPUSTAT files, restricting the sample to common stocks (share code 10 and 11). For each stock, we measure characteristics such as CAPM beta, market capitalization, book-to-market ratio, and momentum. We also construct investment- and profitability-related variables such as asset growth, equity issuance, operating profitability, and stock age. To gauge whether a company is difficult to value, we use proxies such as asset tangibility, idiosyncratic volatility and readability of their financial statement. The appendix provides details on variable definitions. We winsorize firm-level variables at top and bottom 0.5%. We take natural logarithms of growth rates and market capitalization. To study investment strategies of different funds, we take position-weighted averages of characteristics of stocks they hold at the end of each year. Panel B of Table 1 shows summary statistics of portfolio characteristics.

3. Stock characteristics in holdings of high-fee funds

Our goal in this section is to explore whether there are systematic differences between high-fee and low-fee mutual funds in terms of their portfolio holdings. We first compute the average characteristics of stock holdings of funds with different expense ratios. In addition to stock characteristics related with traditional risk factors, such as book-to-market, size, and momentum, we investigate asset growth rate, operating profitability, sales growth rate, equity issuance rate, and stock age. For every fund, we take position-weighted averages across all stocks in its portfolio to calculate average characteristics of stockholdings. We then run the following panel regression:

$$Avg\ char_{j,t} = b_0 + b_1 Expense\ ratio_{j,t-1} + \boldsymbol{c}' Controls_{jt-1} + \epsilon_{j,t-1} \quad (1)$$

where $Avg\ char_{j,t}$ is one of the measures of stock characteristics for fund j in year t; $fee_{j,t-1}$ is the fund j's expense ratio in year $t-1$; $Controls_{j,t-1}$ are fund level control variables, including fund turnover ratio and the natural logarithm of fund size, age, and fund family size. Since our focus is on the cross-sectional comparison between high-fee and low-fee funds, we also include year fixed effects to control for time series trends in the mutual fund industry. We cluster standard errors at the fund level and scale all variables by their standard deviations annually to better facilitate the interpretation of the magnitude of coefficients.

The main focus of this test is on b_1, the coefficient on expense ratio. For example, for asset growth rate, positive b_1 indicates high-fee funds prefer companies with high asset growth rate. Table 2 presents our findings. To our surprise, the coefficients on expense ratio are significant in all eight characteristics that we consider. With respect to traditional risk related characteristics in columns (1)-(3), high-fee funds invest more in low B/M stocks, small stocks, and high momentum stocks. In addition, high-fee funds also invest more in high asset growth, high sales growth, and stocks with more equity issuance as shown in columns (4)-(6). Columns

(7) and (8) shows that high-fee funds invest more in young stocks and stocks with low profitability. This tables suggests that funds charging different fees have systematically different investment preferences. Broadly speaking, high-fee funds prefer companies that are relatively young, have better growth opportunities, and are in a stage of rapid expansion. Table 8 in the robustness section shows that even after controlling for contemporaneous risk related characteristics, such as CAPM beta, size, book-to-market, and momentum, the propensity of high-fee to invest in high growth low profit companies is still statistically significant. Table 8 will also show that this relationship is not driven by value-weighting stock characteristics. Using equal weighting, we have similar results.

In terms of the economic significance, we observe the absolute magnitude of the coefficient in columns (4)-(8) are often greater than the coefficients in columns (1)-(3). To better gauge the economic magnitude of tilt by high-fee funds, we plot the actual level of asset growth rate and operating profitability against fund fee deciles in Figure 1. The plot shows the average value of a fund's portfolio characteristics at each decile of expense ratio. The benefit of this plot is that it does not impose a linear structure between fee and stock characteristics, which better demonstrates the reliability of fee as an indicator of tilt towards certain characteristics. As the plot shows, stock characteristics change nearly monotonically with fees. The average asset growth rate of companies invested by funds in the bottom decile is about 12% a year, while in the highest decile is about 19%. The 7% difference between top and bottom deciles is half of the average asset growth rate of all companies. For the operating profitability measure, companies held by bottom decile funds on average earn 6 percentage points more than companies held by top decile funds.

Strikingly, funds charging different fees systematically invest in different stocks. One may be concerned this result is only driven by a specific sample period. The landscape of the mutual fund industry and academic understanding of the determinants of asset returns have both changed significantly since the 1990s. It is possible that the preference of high-fee funds for different types of stocks has changes over time. To test this conjecture, we run regression Equation (1) for each year and plot the coefficient on fee over time.

Figure 2 shows the cross-sectional regression coefficients of many characteristics on fee for each year from 1980 to 2014. The coefficients are more volatile during the 1980s and early 1990s, potentially because of the smaller number of observations. The coefficients are consistently positive for asset growth rate and negative for profitability since 1995. Overall, Figure 2 confirms that high-fee funds' investment preference is persistently different from that of low-fee funds over time.

Two questions arise from our findings in Table 2. How would their different investment preferences affect the performance evaluation of high-fee funds vs. low-fee funds? Why do high-fee funds prefer to invest in certain types of companies than others? Section 4 will address the first question regarding performance evaluation and section 5 will explore reasons behind the investment preference of high-fee funds. For the ease of exposition in the following sections, we will focus on two main characteristics, namely asset growth rate and operating profitability, as these two characteristics have been shown to capture many dimensions of firm characteristics relevant in asset pricing (Fama and French, 2015; Hou, Xue, and Zhang, 2015).

4. Mutual fund fee-performance relation

The investment preference of high-fee mutual funds has important implications to fundamental questions in mutual fund literature. In this section, we revisit one of the central questions in the mutual fund literature: the relation between fund fee and future performance. While economic principles suggest that funds with higher fees should deliver better before-fee performance (e.g., Berk and Green, 2004), the literature finds that high- and low-fee funds deliver similar results before expenses are deducted. After expenses, high-fee funds have been shown to perform considerably worse (Gil-Bazo and Ruiz-Verdú, 2009; Fama and French, 2010).

Motivated by recent developments in the empirical asset pricing literature (Fama and French, 2015), we measure performance using not only the commonly considered models but also the five-factor model. For each performance model and each month *t*, we regress a fund's *j* monthly return in the previous five years on factors to obtain loadings $\boldsymbol{\beta}_{jt}^{Model}$ for that month. We use the CAPM as well as the three-, four-, and five-factor models for our main results. We use additional models and specifications in the robustness section. We compute monthly alphas are as

$$\alpha_{jt}^{Model} = r_{jt}^{e} - \boldsymbol{\beta}_{jt}^{Model\prime}\boldsymbol{r}_{\boldsymbol{t}}^{\boldsymbol{Factor}},$$

where r_{jt}^{e} is fund *j*'s excess return before fee or after fee, and $\boldsymbol{r}_{\boldsymbol{t}}^{\boldsymbol{Factor}}$ is a vector of realized factor returns in each model.

We measure a fund's gross monthly alpha using its gross return, which is net return plus the monthly fee. Panel C of Table 1 reports summary statistics of monthly alphas based on different types of the benchmark models.

4.1 Empirical evidence

Figure 3 summarizes future performance of funds grouped into deciles on the basis of fees. Panel A plots before-fee alphas from different models. The results from the CAPM, three- and four-factor models confirm the findings of the prior literature: gross fund performance is unrelated to fees. By contrast, alphas from the five-factor model display a very different pattern: they increase significantly with fees. The difference in the five-factor alpha of the top and bottom deciles is economically large at 0.9% per year and statistically significant (*t*=4.0).

Panel B shows that irrespective for the model, actively managed mutual funds with both high and low expense ratios achieve poor net-of-fees factor-adjusted performance. In addition, consistent with the previously established results, net-of-expenses fund performance as measured by the CAPM, three-, and four-factor models, deteriorates with fees. Strikingly, this negative relation is absent when we use five-factor alphas. The difference in five-factor performance of funds with high and low expense ratios is economically small and statistically indistinguishable from zero. Taken together, the evidence in Figure 1 provides the missing support of the prediction of Berk and Green (2004) that skilled managers extract rents by charging higher fees, and consequently actively managed funds deliver similar net-of fees performance.

The sort-based results in Figure 1 are informative, but to evaluate the fee-performance relation more formally, we run the following panel regression:

$$\alpha_{jt}^{Model} = d_0 + d_1 Expense\ ratio_{jt-1} + \boldsymbol{h}' Control_{jt-1} + F_t + \varepsilon_{jt-1}, \qquad (2)$$

where $Expense\ ratio_{jt-1}$ is the fund j's expense ratio in month $t-1$, and $Control_{jt-1}$ is a vector of month $t-1$ controls, including the turnover ratio, the logarithm of fund size, fund age, and the size of fund family. We include month fixed effects and cluster standard errors by month.

Panel A of Table 4 reports the results of regression equation (2) with before-fee alphas. Regressions (1)-(3) show funds that charge higher fees do not provide better performance as measured by conventional factor models. However, in specification (4), which controls for fund exposure to the investment and profitability factors, the coefficient on the *Expense ratio* is significantly positive, suggesting high-fee funds deliver better performance. Regression (5), where we use the difference between five- and four-factor alphas as the dependent variable, shows that the coefficient on the *Expense ratio* remains positive and thus suggests that controlling for the investment and profitability factors is behind our new result.

Panel B of Table 4 repeats the analysis using after-fee alphas. Consistent with prior literature, regressions (1)-(3) show that the coefficients on *Expense ratio* are large and negative, suggesting that performance – measures using conventional models – declines with fees. Crucially, and consistent with the theoretical arguments that skilled managers extract rents by charging higher fees (Berk and Green, 2004), specification (4) shows that the coefficient on *Expense ratio* is statistically insignificant from zero. In other words, expenses are not related to future after-fee performance when investment and profitability factors are controlled for.

4.2 Sub-sample analysis of fee-performance relationship

We next investigate whether the positive relation between the expense ratio and the improvement in performance due to the use of the five-factor model is driven by a particular group of funds or applies to all funds broadly. To this end, we separate funds into two groups based on each of their size, age, family size, turnover ratio, institutional indicator, or broker sold indicator. Specifically, for each of the first four characteristics, we define a dummy variable equal to one if the variable is greater than the sample median in each year. We then regress the five-factor alpha on the expense ratio, a characteristic dummy, and an interaction term of the dummy variable and expense ratio, controlling for other fund attributes. If the positive relation is concentrated in certain types of funds, we should expect the coefficients on the interaction term to be significant.

Table 4 reports the results of this test with before-fee alpha.[4] Across all columns, irrespective of the particular fund type used to define the dummy variable, the coefficients on *Expense ratio* remain statistically and economically significant. The performance of high-fee

[4] Results obtained using after-fee alphas are similar and are omitted for brevity.

funds as measured by the five-factor alpha thus appears consistent across different types of funds. The coefficients on the interaction terms are all insignificant. Therefore, the improvement in performance evaluation for high-fee funds is not driven by any particular type of fund.

Why does the performance of high-fee funds improve after controlling for investment and profitability factors? The reason is that the stocks high fee funds invest most have high asset growth rate and low profitability. Thus, high-fee funds should have low risk loadings on the investment and profitability risk factor. Table 5 reports this result in a formal test. Columns (1) and (2) show the coefficients on Expense ratio are negative and significant after controlling for fund characteristics and contemporaneous loadings on the other risk factors, such as the market, size, and value factors. This finding suggests that high-fee funds tend to load less on the investment and profitability factors. The realized risk premium of the investment factor and the profitability factor are 0.34% and 0.37% per month in the 1985 to 2014 period. Based on the magnitude of the coefficients in columns (1) and (2), a 1 percentage point increase in fee would reduce the required rate of return by 0.85 percentage point (i.e. $0.97\times0.34+1.41\times0.37=0.85$) in the five-factor model compared with the three-factor model. This difference in risk loadings explains why high-fee funds appear to have poor performance in the traditional models. Table 9 in the robustness section will show that the positive relationship between expense ratio and performance is robust to other factor models, such as the Hou, Xue, and Zhang four-factor model and the Fama-French five-factor model augmented with the momentum factor.

5. Explanations

Our findings in previous sections show that after controlling for investment and profitability factors, high-fee funds do not underperform low-fee funds before deducting expenses and perform equally well net of fees. We show that these results are in contrast with prior literature because high-fee funds overweight firms with high investment and low profitability, characteristics that commonly used models do not control for. In this section, we evaluate two hypotheses to understand why mutual fund expense ratios relate systematically to these characteristics.

5.1 Naïve investor hypothesis

The behavioral finance literature has postulated that naïve investors overinvest in fast-growing companies due to cognitive biases. For example, Lakonishok, Shleifer, and Vishny (1994) and La Porta et al. (1997) argue that unsophisticated investors over-extrapolate high growth rate of a company into its future, causing it to be overpriced. Extrapolation is often erroneous, since data suggest the high growth rate does not persist for a long period of time. In a related study, Frazzini and Lamont (2008) document a dumb money effect in retail investor flows. They find retail investors display positive sentiment towards growth stocks and allocate more capital to funds that hold more such stocks.

Motivated by this literature, we propose the *naïve investor hypothesis*, which conjectures that fast-growing companies are more appealing to naïve investors, who are also less likely to be price sensitive about mutual fund fees. These companies can be expected to have a high rate of asset growth, low profitability, and high equity issuance to finance the growth. If such companies attract unsophisticated investors, we would expect that some fund managers invest more in high growth stocks to attract more unsophisticated investors. Since unsophisticated investors tend to be less price sensitive, the fund manager can charge higher fees than what is justified by the performance.[5]

[5] Indeed, the literature has explored how fund managers set fees strategically to exploit investors who are less sensitive to price. Christoffersen and Musto (2002) find that retail money funds tend to increase fees after a large amount of outflow. The propose that outflows are an indication of performance-sensitive investors leaving the

To test the *naïve investor hypothesis*, we split our sample of funds into two groups by their level of investor sophistication. Under the naïve investor hypothesis, we expect that among funds with less sophisticated investors, high fee funds would tilt more towards high growth and low profit companies. We use four variables to proxy for investor sophistication: fund size, past fund performance, and indicator variables for broker-sold and institutional funds (Del Guercio and Reuter, 2014; Sun, 2014). We expect investor sophistication to be greater among bigger funds, better-performing funds, those not sold through brokers, and institutional funds. For each of fund performance and fund size, we define a dummy variable equal to one if the fund characteristic is greater than the sample median in each year. Section 2 describes how we create institution fund dummy and broker-sold fund dummy variables. We re-run regression Equation (1) after adding the dummy variable and the fee-dummy interaction term.

Table 6 summarizes regression results for each of the investor sophistication proxy in four separate panels. For the naïve investor hypothesis to be the dominant driver of high-fee funds' investment choice, we would expect to see that sophisticated high-fee funds have weaker titl towards these growth characteristics. This means that the coefficient on the interaction terms should be of the opposite sign to that on the expense ratio when using past fund performance, fund size, and institutional fund indicator as sophistication proxies. When using the broker-sold fund indicator, the coefficients on the interaction term and the expense ratio should be of the same sign.

In contrast to the predictions of the hypothesis, we find that the coefficients on the interaction term are typically statistically indistinguishable from zero. When they are statistically significant, they are of the sign opposite to that predicted by the hypothesis. In other words, in those cases as investor sophistication increases, the association between

fund, which also signals a decrease in the average price sensitivity among investors remaining in the fund, causing the managers to subsequently raise price.

expense ratio and growth-related characteristics strengthens. Overall, the results summarized in Table 6 suggest that the *naïve investor hypothesis* does not explain the link between expense ratios and portfolio stock characteristics of mutual funds.

5.2 Valuation cost hypothesis

We now hypothesize that high-growth and low-profitability stocks are likely to be hard to value. Their valuation involves considerably more uncertainty and demands more time and effort from fund managers per unit of capital. The high valuation cost, in turn, necessitates higher fees on a percentage basis. In other words, funds charge high fees because they invest in difficult-to-value stocks characterized by high growth and low profitability. We label this alternative explanation the *valuation cost hypothesis*.

Empirical evidence suggests that the four-factor model fails to capture low average returns of stocks with high asset growth rate or low profitability, even for a randomly chosen portfolio of such type of stocks, the four-factor alpha is negative. Hence, the performance evaluation of high fee funds, who overweight these companies, will be negatively biased by the traditional factor models.

To test the validity of the valuation cost hypothesis, we perform sub-sample analysis on the group of funds that invest more in hard-to-value companies. We use three measures to identify whether a company is hard-to-value. The first measure we use is idiosyncratic volatility, as determining the value of a firm with higher idiosyncratic volatility is likely to be challenging (e.g., Kumar, 2009). Our second measure is based on the textual analysis of a company's annual reports. Following Loughran and McDonald (2011), we construct an uncertainty index by counting the uncertainty words such as "almost" and "appears"', and dividing it by the total number of words in each annual report.[6] The index is higher if the annual

[6] The word list is available from Bill McDonald's website: http://www3.nd.edu/~mcdonald/.

report contains more uncertain words. We deem a company as opaque if its uncertainty index is high. The last measure we consider is tangibility: valuing a firm whose intangible assets represent a large portion of its asset base can be difficult (e.g., Baker and Wurgler, 2006). Finally, we aggregate each company-level measure of valuation cost to the fund level using portfolio weights of a fund.

We create dummy variables to indicate if a fund's valuation cost measure is above the median of the sample in each year. Table 7 shows our main results with the fee interacted with the valuation cost dummy. From Table 7, we can see that our main results are strengthened when high-fee funds specialize in the segment of the market that is more difficult to understand. Columns (1) and (2) show that high-fee funds tilt more towards high asset growth, equity issuance, and low profit companies, especially, when these funds invest in hard-to-value companies. The interaction terms are all almost always significant and are in line with the predictions of the valuation cost hypothesis. Column (3) shows that the bias of the four-factor model against high-fee funds is more pronounced when they hold companies that are difficult to value. Overall, this analysis supports the predictions of the *valuation cost hypothesis*.

6. Robustness and additional results

6.1 Robustness

To evaluate robustness of our results, in this section we conduct several tests modifying various aspects of our empirical methods. In Table 8, we evaluate robustness of the propensity of high-fee funds to hold high-growth low-profitability stocks. In Panel A, we address a potential concern that this result may be driven by the omission of other stock characteristics as controls. In regressions of portfolio characteristics on expense ratios and other variables, we therefore add averages of CAPM beta, market capitalization, momentum, and B/M ratio of the stockholdings as regressors. Our results remain similar to those in the base-case analysis summarized in Table 2.

We calculate average characteristics of a fund's stock portfolio as position-weighted averages across all stocks in the fund's portfolio. This approach correctly captures the total tilt of the fund to a particular stock attribute. Nonetheless, it can also be instructive to consider the characteristics of the average stock in the portfolio. In other words, we are interested in whether the characteristics of the average stock the manager holds systematically relate to fund fees. To this end, we regress characteristics of stockholdings computed as equal-weighted averages across all stocks in a fund's portfolio on expense ratios and other variables. Panel B of Table 8 shows the coefficients on the expense ratio remain statistically and economically similar to those in Table 2.

We then consider a shorter three-year rolling window to calculate factor loadings of the funds. Panel A of Table 9 shows that our results remain consistent with those in the base case that uses a five-year window. Specifically, we show that after controlling for exposures to profitability and investment factors, high-fee funds significantly outperform low-fee funds before deducting expenses, and perform equally well net of fees. In Table 9, we also add the Fama-French Five-Factor model augmented with the momentum factor (FFC6) and the Hou-Xue-Zhang Four Factor model as additional robustness test.

In our second set of robustness tests, we address the concern that our results may be impacted by the lower data quality and the small number of mutual funds in 1980s and early 1990s. We hence analyze the fee-performance relation using the post-1995 subsample. Panel B of Table 9 shows that our results remain statistically and economically similar to those in the full-sample analysis.

6.2 Fund survival

The mutual fund literature has been puzzled with the fact that high-fee funds can survive market competition from low-fee funds for such a long time. Our results resolve this puzzle by showing that the perceived underperformance is just an artifact of the imperfection of the four-factor benchmark model. If this model misjudges the value of high-fee funds because they invest in companies that have high asset growth and low profitability, do investors in the real world take growth factors into account by paying less attention to the four-factor alpha? If investors do consider growth factors, funds that invest in high growth stocks can survive in the long run if they beat a benchmark that adjust for growth factors. To test this idea, we examine whether investors care about four- or five-factor alpha for different types of funds.

Table 10 presents the results of this test. To compare investors' attention towards the two performance measures, we use the difference in the five- and four-factor alphas as explanatory variable to predict if a fund will survive in the next year. Column (1) shows that on average, the difference in the two alphas relates positively and significantly to a fund's survival, suggesting that investors appear to pay more attention to the five-factor alpha. We then further partition the sample into four subsamples: institutional funds investing in low asset growth companies, institutional funds investing in high asset growth companies, retail funds investing in low asset growth companies, and retail funds investing in high asset growth companies. Columns (2)-(5) reports results for these four types of funds and show that the coefficient on the difference in alpha is always positive, more positive for institutional funds or funds invest heavily in high asset growth stocks. The coefficient on the difference in alpha is almost all significant, except for retail funds that invest in low growth companies. This evidence suggests that the five-factor alpha matters for a fund's survival, especially if it is an institutional fund or invests heavily in high asset growth stocks.

7. Conclusion

Previous literature uncovers a robust inverse relation between fees charged by actively managed mutual funds and future after-fee fund performance. Before deducting expenses, high-fee funds have been found to perform just as well as do low-fee funds. Theoretically, this result is puzzling as it suggests that managers of high-fee funds extract more rents than the value they add. Empirically, the apparent negative relation between expenses and net-of-fees performance has helped to guide allocations of billions of dollars of retail and institutional investors, who shun high-fee funds. The relation is also puzzling as it calls into question the continued existence of high-fee funds.

This paper resolves the puzzle by showing that factor models used to establish the prior fee-performance results are inadequate to control for differences in performance of funds with different fees. High-fee funds exhibit a strong preference for stocks with high investment rates and low profitability, characteristics that have been recently shown to associate with low expected returns. The commonly used three- and four-factor models produce large negative alphas for these types of stocks, leading to a premature conclusion that high-fee funds underperform net of expenses.

We evaluate the fee-performance relation using the recently proposed five-factor model that controls for exposures to the investment and profitability factors. The results we obtain stand in stark contrast with those in the prior literature. We find that high-fee funds significantly outperform low-fee funds before deducting expenses, and do equally well net of fees. Our findings support the theoretical prediction that skilled managers extract rents by charging high fees, and call into question the widely offered advice to avoid high-fee funds.

References

Agarwal, V., Jiang, W., Tang, Y. and Yang, B., 2013, Uncovering hedge fund skill from the portfolio holdings they hide, *Journal of Finance* 68(2), 739-783.

Ang, A., Hodrick, R.J., Xing, Y. and Zhang, X., 2006. The cross-section of volatility and expected returns. *Journal of Finance*, *61*(1), 259-299.

Baker, M. and Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. *Journal of Finance*, *61*(4), 1645-1680.

Berk J, and Green R. 2004, Mutual fund flows and performance in rational markets. *Journal of Political Economics* 12(6), 1269–1295.

Berk, J.B. and Van Binsbergen, J.H., 2015, Measuring skill in the mutual fund industry. *Journal of Financial Economics* 118(1), 1-20.

Busse, J.A., Jiang, L. and Tang, Y., 2016, Double adjusted mutual fund performance, Working paper, *Available at SSRN 2516792*.

Brav, A., Geczy, C. and Gompers, P.A., 2000, Is the abnormal return following equity issuances anomalous?, *Journal of Financial Economics 56*(2), 209-249.

Carhart, M.M., 1997, On persistence in mutual fund performance, *Journal of Finance 52*(1), 57-82.

Christoffersen, S.E. and Musto, D.K., 2002, Demand curves and the pricing of money management. *Review of Financial Studies 15*(5), 1499-1524.

Cooper, M.J., Gulen, H. and Schill, M.J., 2008, Asset growth and the cross-section of stock returns, *Journal of Finance 63*(4), 1609-1651.

Daniel, K., Grinblatt, M., Titman, S. and Wermers, R., 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance 52*(3), 1035-1058.

Daniel, K. and Titman, S., 2006, Market reactions to tangible and intangible information, *Journal of Finance 61*(4), 1605-1643.

Edelen, R.M., Ince, O.S. and Kadlec, G.B., 2016, Institutional investors and stock return anomalies, *Journal of Financial Economics* 119(3), 472-488.

Fama, E.F. and French, K.R., 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics 33*(1), 3-56.

Fama, E.F. and French, K.R., 2008, Dissecting anomalies, *Journal of Finance 63*(4), 1653-1678.

Fama, E.F. and French, K.R., 2010, Luck versus skill in the cross-section of mutual fund returns, *Journal of Finance 65*(5), 1915-1947.

Fama, E.F. and French, K.R., 2015, A five-factor asset pricing model, *Journal of Financial Economics 16*(1), 1-22.

Ferson, W.E., 2010, Investment performance evaluation, *Annual Review of Financial Economics 2*(1), 207-234.

Frazzini, A. and Lamont, O.A., 2008, Dumb money: Mutual fund flows and the cross-section of stock returns, *Journal of Financial Economics 88*(2), 299-322.

French, K.R., 2008, Presidential address: The cost of active investing, *Journal of Finance 63*(4), 1537-1573.

Hou, K., Xue, C. and Zhang, L., 2015. Digesting anomalies: An investment approach. *The Review of Financial Studies*, *28*(3), pp.650-705.

Gil-Bazo, J. and Ruiz-Verdú, P, 2009, The relation between price and performance in the mutual fund industry, *Journal of Finance 64*(5), 2153-2183.

Gruber, M.J., 1996. Another puzzle: The growth in actively managed mutual funds. *Journal of Finance*, 51(3), 783-810.

Guercio, D.D. and Reuter, J., 2014, Mutual fund performance and the incentive to generate alpha, *Journal of Finance 69*(4), 1673-1704.

Jordan, B.D. and Riley, T.B., 2015, Volatility and mutual fund manager skill. *Journal of Financial Economics 118*(2), 289-298.

Jordan, B.D. and Riley, T.B., 2016, Skill and Persistence in Mutual Fund Returns: Evidence from a Six-Factor Model, Working paper, *Available at SSRN 2717091*.

Jensen, M.C., 1968, The performance of mutual funds in the period 1945–1964, *Journal of Finance 23*(2), 389-416.

Kacperczyk, M., van Nieuwerburgh S., Veldkamp L., 2014, Time-Varying Fund Manager Skill, *Journal of Finance* 69, 1455-1484.

Kacperczyk, M., Sialm, C. and Zheng, L., 2008, Unobserved actions of mutual funds, *Review of Financial Studies 21*(6), 2379-2416.

Kumar, A., 2009. Hard-to-value stocks, behavioral biases, and informed trading. *Journal of Financial and Quantitative Analysis*, *44*(06), 1375-1401.

La Porta, R., Lakonishok, J., Shleifer, A. and Vishny, R., 1997, Good news for value stocks: Further evidence on market efficiency, *Journal of Finance 52*(2), 859-874.

Lakonishok, J., Shleifer, A. and Vishny, R.W., 1994, Contrarian investment, extrapolation, and risk. *Journal of Finance 49*(5), 1541-1578.

Lewellen, J., 2011, Institutional investors and the limits of arbitrage, *Journal of Financial Economics 102*(1), 62-80.

Lewellen, J. and Nagel, S., 2006. The conditional CAPM does not explain asset-pricing anomalies. *Journal of Financial Economics*, *82*(2), 289-314.

Loughran, T. and McDonald, B., 2011, When is a liability not a liability? textual analysis, dictionaries, and 10-ks. *Journal of Finance* 66, 35–65.

Malkiel, B.G., 1995. Returns from investing in equity mutual funds 1971 to 1991. *Journal of Finance*, 50(2), 549-572.

Malkiel, B.G., 2013, Asset management fees and the growth of finance, *Journal of Economic Perspectives 27*(2), 97-108.

Malkiel, B.G., 2016. *A random walk down Wall Street: the time-tested strategy for successful investing*. WW Norton & Company.

Musto, D.K., 2011, The economics of mutual funds, *Annual Review of Financial Economics 3*(1), 159-172.

Novy-Marx, R., 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics 108*(1), 1-28.

Pedersen, H. L., 2015, *Efficiently inefficient: how smart money invests & market prices are determined*, Princeton University Press.

Petajisto, A., 2011, The index premium and its hidden cost for index funds, *Journal of Empirical Finance 18*(2), 271-288.

Sialm, C., Starks, L.T. and Zhang, H., 2015. Defined contribution pension plans: Sticky or discerning money?. *Journal of Finance*, *70*(2), 805-838.

Sun, Y., 2014, The effect of index fund competition on money management fees, Working paper, *Available at SSRN 2432361*.

Wermers, R., 2000, Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses, *Journal of Finance*, *55*(4), 1655-1703.

Wermers, R., 2011, Performance measurement of mutual funds, hedge funds, and institutional accounts, *Annual Review of Financial Economics 3*(1), 537-574.

Appendix: Variable definition

Variable	Definition
CAPM beta	Following Lewellen and Nagel (2006), we measure a stock's daily CAPM beta as the sum of the slope coefficients from a regression of the stock excess return in day *t* on the market excess returns in *t*, *t-1*, and average market excess return during *t-4* through *t-2*. We estimate the betas annually using one calendar year of data.
Market capitalization	The natural logarithm of stock i's market capitalization, measured in the end of December of each year.
B/M ratio	The ratio of stock i's book equity at the end of its fiscal year to its December end market capitalization. We adjust market capitalization for any share issuance between the fiscal and calendar year end. Following Fama and French (2008), book equity is common equity plus deferred taxes (if available). If common equity is not available, we replace it with total asset minus liability minus preferred equity (if available). The formula for B/M ratio is $B/M_{it} = \frac{BE_{it}}{ME_{it}}$.
Momentum	The cumulative return of a stock from January to November of each year.
Asset growth	The asset growth rate of company i in year t is defined as the natural logarithm of the ratio of its total asset in year t to total asset in year $t-1$. Total asset is measured as of the fiscal year end: $AG_{i,t} = \ln \frac{Asset_{i,t}}{Asset_{i,t-1}}$.
Equity issuance	Equity issuance: equity issuance for company i in year t is defined as the natural logarithm of the ratio of number of shares outstanding in year t to the number of shares outstanding in year $t-1$. Number of shares outstanding is measured as of December of each year. We adjust for stock splits between two year ends. The formula is $EI_{i,t} = \ln \frac{Adjusted\ Shares\ Outstanding_{i,t}}{Adjusted\ Shares\ Outstanding_{i,t-1}}$.
Operating profitability	For company i year t, we measure its operating profitability following Fama and French (2015). Specifically, profitability is measured as of the end of fiscal year as revenue minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense, all divided by the book equity. The formula is $OP_{i,t}^{stock} = \frac{(REV-COGS-SG\&A-INT\ EXP)_{i,t}}{Book\ Equity_{i,t}}$.
Stock age	Number of years a stock is publicly listed
Sales growth	The sales growth rate of company i in year t is defined as the natural logarithm of the ratio of its total sales in year t to total sales in year $t-1$.
Uncertain words	Loughran and MacDonald (2011) firm level uncertainty index.
Tangibility	For company i in year t, its tangibility is measured as the ratio of the amount of property, plant and equipment to its total asset.
Idiosyncratic volatility	For company i in year t, $IVOL$ is measured as the standard deviation of the residual of daily Fama-French three-factor regression as in Ang et al. (2006).

Figure 1: Characteristics of stock portfolios of funds charging different fees

This figure plots average characteristics of stock portfolios of funds grouped into deciles on the basis of fees. For each fund, we calculate its stock characteristics as the position-weighted averages across companies held by the fund. The characteristics, defined in detail in the Appendix, are the asset growth rate and operating profitability. The sample period is 1980-2014.

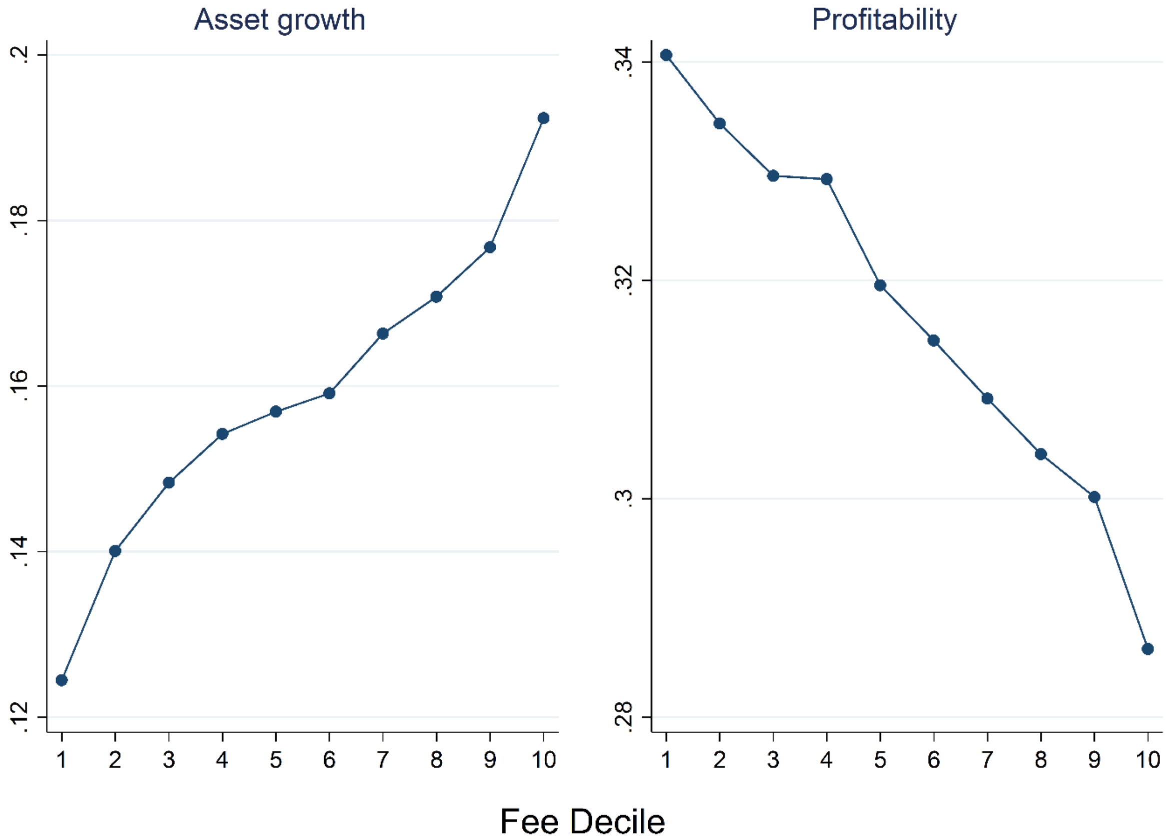

Figure 2: Fund fees and time series dynamics of fund portfolio characteristics

This figure presents the time series dynamics of the relation between fund fees and portfolio characteristics. For each characteristic, we plot the time series of coefficients on the *fee* variable from annual cross-sectional regressions

$$Average\ characteristic_{j,t} = b_0 + b_1 fee_{j,t-1} + \boldsymbol{b}'Controls_{jt-1} + \epsilon_{j,t-1},$$

where $Average\ characteristic_{j,t}$ is one of the thee measures of stock characteristics (asset growth rate and operating profitability) for fund j in year t; $fee_{j,t-1}$ is the fund j's expense ratio in year $t-1$; $Controls_{j,t-1}$ are fund level control variables, including turnover ratio, fund age, and the natural logarithm of fund size and family size. For each fund, we calculate its stock characteristics as the position-weighted averages across companies held by the fund. Detailed variable definitions are provided in the Appendix. All variables are scaled by their standard deviation in each year.

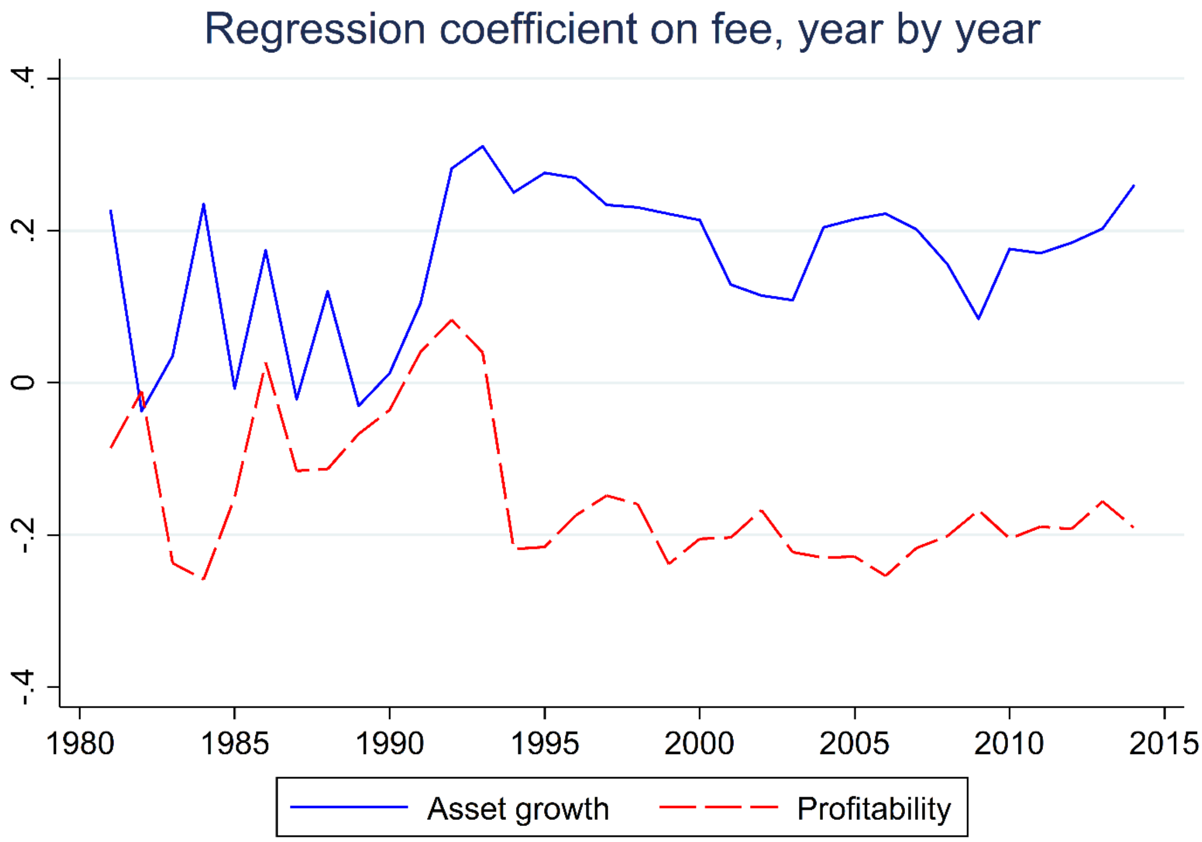

Figure 3: Mutual fund fee-performance relationship

This figure plots future alphas, in percent per year, of funds grouped into deciles on the basis of fees. We measure alpha with four benchmark models: the CAPM, the Fama-French three-factor, the Fama-French-Carhart four-factor, and the Fama-French five-factor. A fund's alpha in month *t* is the difference between the fund's excess return in month *t* and its expected return, calculated as the sum of the products of factor returns in *t* and factor loadings estimated from rolling regressions on five years of monthly data ending in *t-1*. Panel A plots the average before-fee alphas against the fee decile, and Panel B shows the corresponding plot for after-fee alphas. The sample period is 1980-2014.

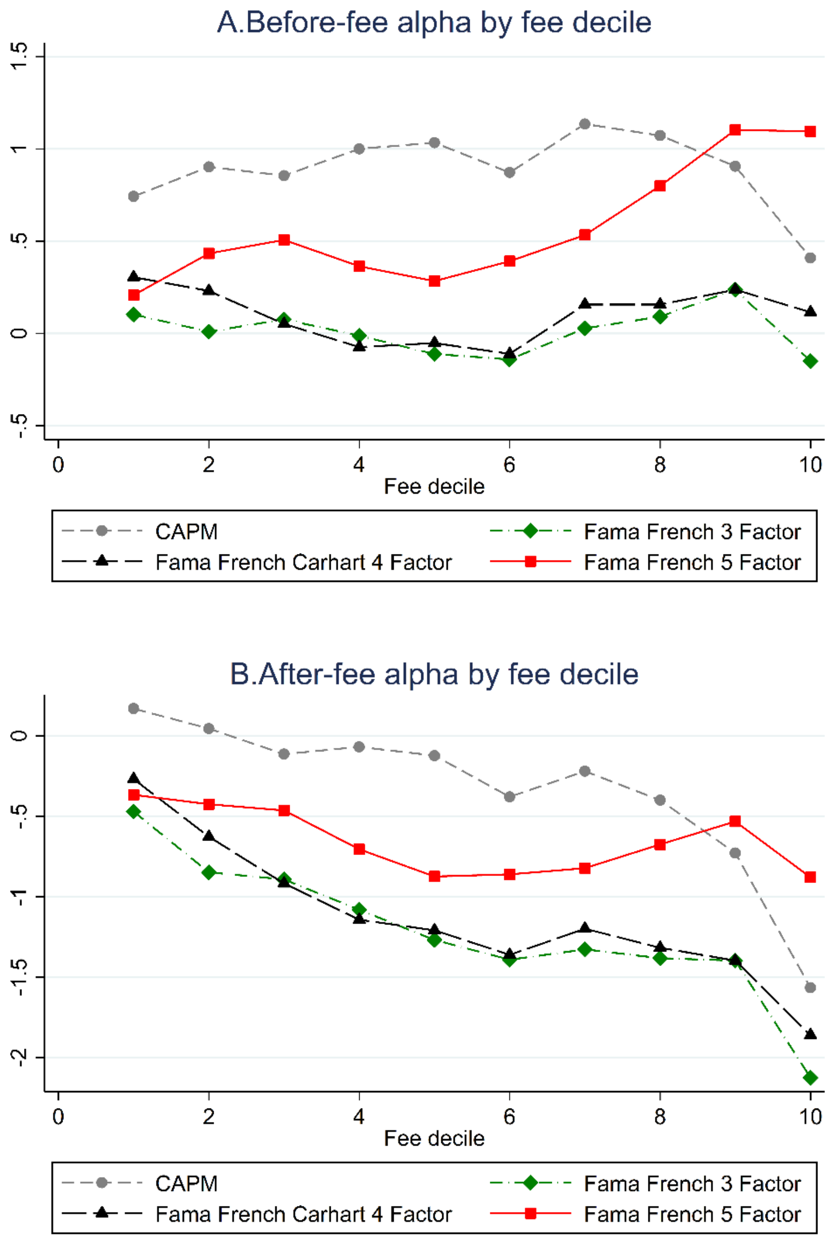

Table 1: Summary statistics for fund and portfolio characteristics

This table reports the average statistics for fund characteristics (Panel A), average stock characteristics of fund portfolios (Panel B) and performance measures (Panel C). For each fund-year observation, we calculate its average stock portfolio characteristics as the position-weighted average across companies held by the fund. Alphas are computed using the CAPM, the Fama-French three-factor model (FF3), the Fama-French-Carhart four-factor model (FFC4), the Fama-French five-factor model (FF5), the five-factor plus momentum model (FFC6), and Hou-Xue-Zhang four-factor model (HXZ4). We calculate monthly alpha using factor loadings estimated from a five-year rolling window regression. Detailed definitions are in the Appendix. The sample period is from 1980 to 2014.

	Mean	Median	SD	Min	p25	p75	Max
Panel A. Fund characteristics							
Expense ratio (%)	1.23	1.20	0.43	0.18	0.96	1.48	2.75
Fund age	13.74	10.75	10.63	0.17	5.92	18.08	54.75
Log(Fund size)	5.65	5.53	1.64	1.91	4.41	6.77	12.22
Turnover ratio	1.14	0.70	1.37	0.00	0.37	1.27	11.02
Log(Fund family size)	7.57	8.25	3.33	0.00	6.10	9.86	13.18
Panel B. Avg. stock characteristics in each fund							
CAPM beta	1.10	1.07	0.28	-0.24	0.96	1.22	3.66
Log(Market cap)	8.77	9.06	1.39	3.48	7.59	10.02	10.83
B/M ratio	0.44	0.42	0.18	0.04	0.31	0.54	1.72
Momentum	0.23	0.19	0.28	-0.59	0.07	0.35	3.38
Asset growth rate	0.16	0.13	0.13	-0.34	0.09	0.20	1.94
Share growth rate	0.03	0.02	0.04	-0.08	0.01	0.05	0.47
Operating profitability	0.32	0.33	0.09	-1.91	0.27	0.38	1.00
Stock age	27.17	26.74	11.54	1.36	17.71	36.41	72.62
Sales growth rate	0.03	0.02	0.04	-0.08	0.01	0.05	0.47
Idiosyncratic volatility	0.02	0.02	0.01	0.01	0.01	0.02	0.07
Tangibility	0.25	0.24	0.08	0.01	0.20	0.28	0.81
Financial uncertainty	0.01	0.01	0.00	0.01	0.01	0.02	0.02
Panel C. Monthly alphas before fee (%)							
Gross CAPM alpha	0.08	0.03	2.46	-32.34	-1.03	1.11	44.21
Gross FF3 alpha	0.00	-0.01	2.02	-31.22	-0.92	0.89	44.97
Gross FFC4 alpha	0.01	-0.01	2.02	-30.57	-0.90	0.88	42.94
Gross FF5 alpha	0.04	0.02	2.05	-31.82	-0.89	0.93	45.66
Gross HXZ4 alpha	0.05	0.01	2.02	-31.09	-0.87	0.91	43.85
Gross FFC6 alpha	0.04	0.04	2.16	-29.62	-0.93	1.00	46.39

Table 2: Fund fees and characteristics of stock holdings

This table reports the results of panel regressions of the characteristics of a fund's stockholdings (shown in the column heading) on the fund's attributes lagged by one year. Characteristics of stockholdings are position-weighted averages across all stocks in a fund's portfolio. All variables are scaled by their cross-sectional standard deviations in each year. Regressions include year fixed effects. Standard errors are clustered at the fund level. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

VARIABLES	(1) B/M ratio	(2) Log market cap	(3) Momentum	(4) Asset growth	(5) Equity issuance	(6) Sales growth	(7) Profitability	(8) Stock age
Expense ratio$_{t-1}$	-0.04**	-0.18***	0.07***	0.17***	0.19***	0.18***	-0.19***	-0.26***
	(-2.24)	(-9.25)	(5.50)	(10.88)	(12.52)	(11.37)	(-11.30)	(-13.40)
Log(Fund size)$_{t-1}$	-0.01	0.04**	-0.04**	0.03*	0.04***	0.03*	-0.02	-0.04*
	(-0.34)	(2.11)	(-2.54)	(1.68)	(2.91)	(1.93)	(-0.96)	(-1.95)
Fund age$_{t-1}$	-0.08***	0.13***	-0.01	-0.00	-0.05***	-0.01	0.07***	0.10***
	(-4.54)	(7.10)	(-0.78)	(-0.16)	(-3.30)	(-0.55)	(4.78)	(4.57)
Turnover ratio$_{t-1}$	-0.12***	-0.01	0.28***	0.20***	0.19***	0.20***	-0.05***	-0.12***
	(-6.98)	(-0.78)	(15.57)	(12.02)	(13.09)	(12.26)	(-3.17)	(-6.28)
Log(Fund family size)$_{t-1}$	-0.03	0.01	0.04***	0.05***	0.08***	0.05***	-0.04**	-0.04**
	(-1.61)	(0.55)	(2.93)	(3.14)	(5.64)	(3.06)	(-2.41)	(-2.31)
Observations	29,591	29,591	29,591	29,591	29,591	29,591	29,591	29,591
Adj. R^2	0.187	0.240	0.698	0.169	0.302	0.415	0.398	0.141
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Mutual fund fee-performance relation: Panel regressions

This table presents the results of panel regressions of fund alphas on lagged expense ratios, both in percent per month, and other fund characteristics. Alphas are computed using the CAPM, the Fama-French three-factor model (FF3), the Fama-French-Carhart four-factor model (FFC4), and the Fama-French five-factor model (FF5). Alphas are calculated using factor loadings estimated from a five-year rolling window regression. In Panel A (B), alpha is computed using before-fee (after-fee) returns. In specification (5), the dependent variables are the difference between the Fama-French five-factor alpha and the Fama-French-Carhart four-factor alpha. All regressions include month fixed effects and cluster standard errors by month. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Before-fee alpha

	(1) α_t^{CAPM}	(2) α_t^{FF3}	(3) α_t^{FF4}	(4) α_t^{FF5}	(5) α_t^{FF5}-α_t^{FFC4}
Expense ratio$_{t-1}$	-0.19	0.22	-0.01	1.03***	1.04***
	(-0.30)	(0.63)	(-0.03)	(3.21)	(3.60)
Log fund size$_{t-1}$	-0.02**	-0.00	-0.01	0.01	0.02**
	(-2.39)	(-0.63)	(-1.48)	(0.96)	(2.55)
Fund age$_{t-1}$	-0.00	-0.00	-0.00	-0.00	-0.00
	(-0.79)	(-0.03)	(-0.32)	(-0.76)	(-1.03)
Turnover ratio$_{t-1}$	-0.02	-0.02*	-0.03***	-0.00	0.03**
	(-1.49)	(-1.82)	(-2.73)	(-0.21)	(1.98)
Log fund family size$_{t-1}$	0.01***	0.01***	0.01***	0.01***	0.00**
	(3.00)	(3.41)	(2.68)	(4.36)	(2.34)
Observations	263,925	263,925	263,925	263,925	263,925
Adj. R^2	0.100	0.081	0.092	0.079	0.072
Month FE	Yes	Yes	Yes	Yes	Yes

Table 3 (continued)

Panel B. After-fee alpha

	(1) α_t^{CAPM}	(2) α_t^{FF3}	(3) α_t^{FF4}	(4) α_t^{FF5}	(5) α_t^{FF5}-α_t^{FFC4}
Expense ratio$_{t-1}$	-1.21*	-0.79**	-1.03***	0.01	1.04***
	(-1.89)	(-2.25)	(-2.86)	(0.03)	(3.60)
Log fund size$_{t-1}$	-0.02**	-0.00	-0.01	0.01	0.02**
	(-2.39)	(-0.62)	(-1.47)	(0.97)	(2.55)
Fund age$_{t-1}$	-0.00	-0.00	-0.00	-0.00	-0.00
	(-0.83)	(-0.11)	(-0.39)	(-0.82)	(-1.02)
Turnover ratio$_{t-1}$	-0.02	-0.02*	-0.03***	-0.00	0.03**
	(-1.50)	(-1.82)	(-2.74)	(-0.21)	(1.98)
Log fund family size$_{t-1}$	0.01***	0.01***	0.01***	0.01***	0.00**
	(3.02)	(3.43)	(2.71)	(4.39)	(2.34)
Observations	263,925	263,925	263,925	263,925	263,925
Adj. R^2	0.100	0.081	0.092	0.079	0.072
Month FE	Yes	Yes	Yes	Yes	Yes

Table 4: Fee-performance relation and fund characteristics

This table presents results of regressions of the gross Fama-French Five-Factor alpha on the lagged expense ratio and its interactions with fund characteristic dummies. For each of fund size, age, family size, and turnover ratio, the characteristic dummy is set to one if the characteristic value is above the cross-sectional median, and to zero otherwise. Regressions include month fixed effects and cluster standard errors by month. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES			α_t^{FF5}			
Expense ratio $_{t-1}$	1.08***	1.32***	1.21***	0.81***	0.93***	0.99**
	(3.23)	(3.90)	(3.30)	(2.81)	(2.76)	(2.12)
Fund size$_{t-1}$	0.01					
	(0.21)					
Expense ratio$_{t-1}$ × Fund size$_{t-1}$	-0.10					
	(-0.25)					
Fund age$_{t-1}$		0.06				
		(1.49)				
Expense ratio$_{t-1}$ × Fund age$_{t-1}$		-0.44				
		(-1.18)				
Fund family size$_{t-1}$			0.00			
			(0.00)			
Expense ratio$_{t-1}$ × Fund family size$_{t-1}$			-0.31			
			(-1.01)			
Turnover ratio$_{t-1}$				-0.01		
				(-0.21)		
Expense ratio$_{t-1}$×Turnover ratio$_{t-1}$				0.41		
				(1.23)		
Institutional fund dummy$_{t-1}$					-0.05	
					(-1.10)	
Expense ratio$_{t-1}$×Insititutional fund dummy$_{t-1}$					0.32	
					(0.73)	
Broker sold fund dummy$_{t-1}$						0.05
						(1.16)
Expense ratio$_{t-1}$×Broker sold fund dummy$_{t-1}$						-0.22
						(-0.58)
Observations	263,925	263,925	263,925	263,925	263,925	263,925
Adj. R^2	0.079	0.079	0.079	0.080	0.079	0.079
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Fund fees and loadings on the investment and profitability factors

This table reports the results of panel regressions of funds' investment or profitability factors loadings on expense ratios and other fund characteristics. To obtain the loadings, in each month, we regress a fund's monthly before-fee return in the previous five years on Fama-French five-factor portfolios and use the coefficients as risk loadings for that month. Control variables include log fund size, fund age, log fund family size, and turnover ratio are lagged by one month, as well as contemporaneous loadings on market, size, and value factors. Regressions include month fixed effects. Standard errors are clustered at the fund level. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1) Investment factor loading	(2) Profitability factor loading
Expense ratio$_{t-1}$	-0.97***	-1.41***
	(-6.18)	(-10.38)
Log fund size$_{t-1}$	-0.02***	-0.00
	(-4.92)	(-1.09)
Fund age$_{t-1}$	-0.00	0.00
	(-0.91)	(0.07)
Turnover ratio$_{t-1}$	-0.02***	-0.01***
	(-5.16)	(-5.68)
Log fund family size$_{t-1}$	-0.00	-0.01***
	(-0.50)	(-5.95)
FF5 market factor loading$_t$	-0.04	0.03
	(-1.31)	(0.96)
FF5 HML factor loading$_t$	-0.05**	0.21***
	(-2.12)	(10.72)
FF5 SMB factor loading$_t$	-0.13***	-0.02
	(-11.39)	(-1.55)
Observations	263,925	263,925
Adj. R^2	0.118	0.144
Month FE	Yes	Yes

Table 6: Fund fees and characteristics of stock holdings: Investor sophistication

This table reports the results of panel regressions of the characteristics of a fund's stockholdings (shown in column heading) on the fund's attributes lagged one year. Characteristics of stockholdings are position-weighted averages across all stocks in a fund's portfolio. For each characteristic of a fund's stockholdings, regressions are run separately for four proxies of sophistication of investors in a fund: lagged net five-factor alpha, broker-sold fund indicator, institutional fund indicator, and fund family size. Alpha and fund size are dummy variables set to one if their value is above the cross-sectional median, and to zero otherwise. All regressions include lagged fund-level variables controls: log family size, age, and turnover. All variables except dummy variables are scaled by their standard deviation in each year. Regressions include year fixed effects and cluster standard errors at the fund level. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1) Asset growth$_t$	(2) Profitability$_t$
Panel A: Past performance		
Expense ratio$_{t-1}$	0.181***	-0.186***
	(8.15)	(-8.17)
Net five-factor alpha$_{t-1}$	0.018***	-0.003
	(4.52)	(-0.53)
Expense ratio$_{t-1}$×Net five-factor alpha$_{t-1}$	0.001	-0.002
	(0.40)	(-0.96)
Panel B: Fund size		
Expense ratio$_{t-1}$	0.14***	-0.19***
	(7.56)	(-9.08)
Fund size$_{t-1}$	-0.19**	-0.10
	(-2.50)	(-1.17)
Expense ratio$_{t-1}$ × Fund size$_{t-1}$	0.07***	0.01
	(2.94)	(0.32)
Panel C: Broker-sold fund		
Expense ratio$_{t-1}$	0.20***	-0.24***
	(9.47)	(-10.04)
Broker-sold fund dummy$_{t-1}$	0.02	-0.20**
	(0.22)	(-2.24)
Expense ratio$_{t-1}$×Broker-sold fund dummy$_{t-1}$	-0.03	0.08***
	(-0.94)	(2.67)
Panel D: Institutional fund		
Expense ratio$_{t-1}$	0.18***	-0.18***
	(10.60)	(-10.04)
Institutional fund dummy$_{t-1}$	0.00	0.24**
	(0.04)	(2.36)
Expense ratio$_{t-1}$×Insititutional fund dummy$_{t-1}$	0.06	-0.12***
	(1.39)	(-2.84)
Fund level controls & Year FE	Yes	Yes

Table 7: Fund fees and characteristics of stock holdings: Valuation cost

Columns (1) and (2) of this table present the relation between expense ratio and fund portfolio characteristics, such as high asset growth and low profitability. In Column (3) the dependent variable is the difference between the five-factor alpha and the four-factor alpha. Panel A, B, and C, respectively, use idiosyncratic volatility, uncertainty word, and tangibility dummy variables to interact with the expense ratio. A dummy variable is one if a fund is above the median of the relevant measure among all funds at the time, and zero otherwise. All independent variables are lagged by one year. Standard errors are clustered at the fund level. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

VARIABLES	(1) Asset growth	(2) Profitability	(3) α_t^{FF5}-α_t^{FFC4}
Panel A: Idiosyncratic volatility			
Expense ratio $_{t-1}$	0.060***	-0.043***	0.437***
	(4.97)	(-3.18)	(2.96)
IVol dummy	0.654***	-0.646***	0.078**
	(10.05)	(-8.58)	(2.34)
Expense ratio$_{t-1}$×IVol dummy	0.046**	-0.087***	0.396*
	(2.16)	(-3.42)	(1.80)
Panel B: Uncertain words			
Expense ratio $_{t-1}$	0.045***	-0.112***	0.495***
	(3.86)	(-6.28)	(2.73)
Uncertainty dummy$_{t-1}$	0.548***	-0.272***	0.079*
	(9.56)	(-3.75)	(1.72)
Expense ratio$_{t-1}$×Uncertainty dummy$_{t-1}$	0.109***	-0.078***	0.501**
	(5.45)	(-3.06)	(1.98)
Panel C: Tangibility			
Expense ratio $_{t-1}$	0.128***	-0.202***	0.945***
	(6.12)	(-9.10)	(3.25)
Tangibility dummy$_{t-1}$	-0.652***	0.047	-0.103***
	(-10.29)	(0.62)	(-2.63)
Expense ratio$_{t-1}$×Tangibility dummy$_{t-1}$	-0.037*	0.072***	-0.391*
	(-1.69)	(2.72)	(-1.72)
Fund level control & Time FE	Yes	Yes	Yes

Table 8: Fund fees and characteristics of stock holdings: Robustness

This table reports the results of panel regressions of the characteristics of a fund's stockholdings (shown in column heading) on the fund's attributes lagged fund expense ratio. Additional control variables include log of fund size, fund age, turnover ratio, and log of fund family size, all measured at the same time as the expense ratio. All variables are scaled by their cross-sectional standard deviations in each year. Panel A evaluates robustness to adding contemporaneous company characteristics as regressors. As in the base-case analysis, characteristics of stockholdings are position-weighted averages across all stocks in a fund's portfolio. In Panel B, characteristics of stockholdings are equal-weighted averages across all stocks in a fund's portfolio. Regressions include year fixed effects. Standard errors are clustered at the fund level. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Asset growth	Equity issuance	Sales growth	Profitability	Stock age
Panel A. Controlling for other characteristics					
Expense ratio$_{t-1}$	0.06***	0.07***	0.06***	-0.07***	-0.06***
	(6.90)	(6.56)	(7.45)	(-5.89)	(-7.37)
Avg. CAPM beta$_t$	0.60***	1.09***	0.69***	-1.19***	-0.82***
	(17.23)	(27.20)	(17.70)	(-29.91)	(-32.48)
Avg. market cap$_t$	-0.30***	-0.32***	-0.31***	0.39***	0.77***
	(-31.49)	(-26.19)	(-33.31)	(32.20)	(86.95)
Avg. momentum$_t$	0.17***	0.20***	0.18***	0.04***	-0.03***
	(16.34)	(19.71)	(17.97)	(3.22)	(-4.42)
Avg. B/M ratio$_t$	-0.53***	-0.05***	-0.51***	-0.20***	0.32***
	(-43.66)	(-3.76)	(-42.14)	(-12.60)	(26.74)
Observations	29,591	29,591	29,591	29,591	29,591
Adj. R^2	0.584	0.533	0.714	0.624	0.766
Panel B. Equal weight stock characteristics within a fund					
Expense ratio$_{t-1}$	0.19***	0.20***	0.19***	-0.18***	-0.23***
	(11.35)	(12.87)	(11.52)	(-10.45)	(-12.40)
Observations	29,591	29,591	29,591	29,591	29,591
Adj. R^2	0.181	0.306	0.432	0.310	0.164
Fund level controls and year FE	Yes	Yes	Yes	Yes	Yes

Table 9: Robustness of the mutual fund fee-performance relation: Robustness

This table presents the results of panel regressions of fund alphas on lagged expense ratios, both in percent per month, and other fund characteristics. Alphas are computed using the CAPM, the Fama-French three-factor model (FF3), the Fama-French-Carhart four-factor model (FFC4), the Fama-French five-factor model (FF5), the Fama-French five-factor augmented with momentum model (FFC6), and the Hou-Xue-Zhang four-factor model (HXZ4). In Panel A, alphas are calculated using factor loadings estimated from a three-year (as opposed to five-year) rolling window regression. In Panel B, the results are based on the 1995-2014 sample. All regressions include month fixed effects and cluster standard errors by month. Control variables include log of fund size, fund age, turnover ratio, and log of fund family size, all measured at the same time as the expense ratio. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Before fee alpha						After fee alpha					
VARIABLES	α_t^{CAPM}	α_t^{FF3}	α_t^{FFC4}	α_t^{FF5}	α_t^{FFC6}	α_t^{HXZ4}	α_t^{CAPM}	α_t^{FF3}	α_t^{FFC4}	α_t^{FF5}	α_t^{FFC6}	α_t^{HXZ4}
Panel A. Three-year rolling window												
Expense ratio$_{t-1}$	-0.19	0.30	-0.02	0.97***	0.62*	0.87*	-1.20*	-0.71**	-1.03***	-0.04	-0.39	-0.14
	(-0.27)	(0.86)	(-0.05)	(2.84)	(1.91)	(1.79)	(-1.75)	(-2.02)	(-2.86)	(-0.12)	(-1.21)	(-0.29)
Observations	327,107	327,107	327,107	327,107	327,107	327,107	327,107	327,107	327,107	327,107	327,107	327,107
Adj. R^2	0.098	0.073	0.079	0.074	0.083	0.057	0.098	0.073	0.079	0.074	0.083	0.057
Panel B. Using the 1995-2014 sample												
Expense ratio$_{t-1}$	-0.17	0.16	-0.06	1.01***	0.68**	0.83*	-1.19*	-0.86**	-1.08***	-0.01	-0.34	-0.19
	(-0.25)	(0.42)	(-0.17)	(3.03)	(2.07)	(1.74)	(-1.77)	(-2.34)	(-2.87)	(-0.02)	(-1.04)	(-0.39)
Observations	250,201	250,201	250,201	250,201	250,201	250,201	250,201	250,201	250,201	250,201	250,201	250,201
Adj. R^2	0.097	0.081	0.092	0.080	0.091	0.062	0.097	0.081	0.093	0.079	0.091	0.062
Controls & Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Five-factor performance and fund survival

This table reports the results of panel regressions of fund survival dummy in year *t* on fund performance in *t* and *t-1* and control variables measured at the end of year *t-1*. For each fund-year observation, if it is the fund's last year in the sample, then we set the survival dummy to 0; otherwise, we set the survival dummy to 100. Fund performance is measured as the difference between the Fama-French five-factor and the Fama-French-Carhart four-factor alpha. A fund's alpha is the difference between the fund's excess return and its expected return, calculated as the sum of the products of factor returns and factor loadings estimated from rolling regressions on five years of lagged monthly data. The results are shown for the full sample and subsamples of institutional and retail funds with above- or below median asset growth rates. Regressions include year fixed effects. Standard errors are clustered by year. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	Full sample	Institutional funds		Retail funds	
		Low Growth	High Growth	Low Growth	High Growth
$\alpha_t^{FF5-FFC4}$	1.16***	1.65*	2.34**	0.22	1.38**
	(3.32)	(2.05)	(2.69)	(0.82)	(2.58)
$\alpha_{t-1}^{FF5-FFC4}$	0.61***	0.16	1.17*	0.27	0.73**
	(2.81)	(0.21)	(1.80)	(0.95)	(2.49)
Expense ratio_{t-1}	0.13	1.97**	2.00*	-0.28	-0.30
	(0.39)	(2.29)	(1.81)	(-0.77)	(-0.57)
Log fund size_{t-1}	2.48***	4.86***	4.23***	1.76***	2.49***
	(9.60)	(3.56)	(3.94)	(6.51)	(5.54)
Fund age_{t-1}	-0.23	-0.92	1.15*	-0.26	-0.24
	(-1.10)	(-1.30)	(1.78)	(-0.76)	(-0.99)
Turnover ratio_{t-1}	-9.47***	-16.14***	-16.10***	-8.47***	-8.81***
	(-10.81)	(-7.97)	(-10.15)	(-7.75)	(-9.39)
Log fund family size_{t-1}	-0.46***	-0.24	-1.15*	-0.25	-0.66
	(-3.02)	(-0.20)	(-1.86)	(-1.11)	(-1.69)
Observations	18,544	1,367	1,392	7,472	7,427
Adj. R^2	0.178	0.294	0.343	0.160	0.160
Year FE	Yes	Yes	Yes	Yes	Yes