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

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In contrast with theoretical predictions, high-fee active equity funds generate worse net-of-expenses performance. We show that this fee-performance puzzle is driven by the preference of high-fee funds for stocks with low operating profitability and high investment rates, characteristics associated with low expected returns. After controlling for exposures to profitability and investment factors, we find high-fee funds significantly outperform low-fee funds before expenses and achieve similarly poor net-of-fees performance. In resolving the fee-performance puzzle, our findings provide support to the theoretical prediction that net alphas are unrelated to fees and challenge the common advice to prefer low-fee funds over high-fee counterparts. (*JEL* G23, G11, J24)

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Fees charged by actively managed mutual funds directly reduce returns to investors while generating profits for fund companies. These fees are large and vary substantially across funds. For example, in the United States in 2019, they amounted to tens of billions of dollars and ranged from 0.5% per year for the "cheapest" decile of funds to 2% for the most "expensive" decile. Given this magnitude and

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heterogeneity, an ongoing debate among academics, investment managers, and legal practitioners has centered on understanding the economics of fees.

Economic intuition and theoretical arguments suggest that the fee a fund charges should be commensurate with the value it creates for investors. Skilled managers should generate better before-fee performance but capture all the surplus by charging higher expenses, leading to a flat relation between fund expenses and net-of-fees performance.[1] In stark contrast with theory, empirical studies do not 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.[2]

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."

In addition to offering these billion-dollar practical implications, the inverse link between fees and net performance raises important unanswered questions. Specifically, how should the literature square this link with the theory, which predicts a flat relation? And, why do high-fee funds continue to exist if their managers extract more economic surplus than the value they add (Christoffersen and Musto 2002; Elton, Gruber, and Busse 2004; Huang, Wei, and Yan 2007)? In this paper we provide answers, which reconcile theory with empirics and call for revisiting the oft-offered advice to prefer low-fee funds over high-fee counterparts.

In our first set of analyses, we establish that actively managed equity mutual funds with different expense ratios invest in fundamentally different stocks. We find that relative to funds in the lowest fee decile, funds in the high-fee group hold firms that grow their assets 50% faster and generate 18% lower gross profit margins. Importantly, these firms are precisely the types that conventional factor models misprice: companies 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 the relatively poor performance of these funds and the practical guidance to avoid investing in them.

1 Several types of fees, including management fees and 12b-1 fees, compose the overall expense ratio of a fund. For ease of exposition, except where we specifically analyze the components of the overall expense ratio, we use the terms "expenses" and "fees" interchangeably.

2 See, for example, Jensen (1968), Malkiel (1995), Gruber (1996), Wermers (2000), Gil-Bazo and Ruiz-Verdú (2009), Fama and French (2010), and Cooper, Halling, and Yang (2021).

Given that funds with different fees invest in stocks with different investment and profitability characteristics, it is crucial to account for these differences when studying the fee-performance relation. In our second set of tests, we therefore reexamine this relation through the lens of recently proposed models designed to capture differences in average returns of stocks with different profitability and investment patterns (e.g., Fama and French 2015; Hou, Xue, and Zhang 2015). In 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. In particular, the results of panel regressions of funds' Fama-French (2015) five-factor gross-of-fees alphas on expense ratios suggest that alphas increase close to one-for-one with fees. We show that after deducting expenses, high-fee funds do not underperform low-fee funds. In other words, the seemingly poor relative performance of high-fee funds documented in prior literature is an artifact of the failure to adjust performance for the exposure to priced factors. Importantly, these results are consistent with the theoretical predictions of Berk and Green (2004) that high-fee mutual funds generate higher alphas before fees, and that fees are unrelated to net-of-expenses performance because skilled managers extract the surplus by charging higher fees. When we consider adding index funds into the sample, we find similar results. In fact, during our sample period, average fees of index funds and the lowest decile of active funds are similar (0.58% vs. 0.57% per year), as are their five-factor alphas (−0.61% vs. −0.62%). These results are also consistent with the predictions of Berk and Green (2004), whose model suggests similar future net-of-fee performance for active and index funds.

To better understand why the funds' propensity to invest in low-profitability high-investment stocks is associated with higher fees, in our final set of analyses 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 funds to charge higher expenses. We do not find support for this hypothesis. For example, the sophistication of the funds' investor base, proxied by the share of assets in institutional or broker-sold share classes, is unrelated to the propensity of high-fee funds to tilt to high-investment low-profitability stocks or to stocks with lottery-type payoffs that may appeal to naïve investors.

Alternatively, under the *valuation cost hypothesis*, we conjecture that fees of funds that tilt their portfolios to high-investment low-profitability companies are high because analyzing the intrinsic value of these stocks is more difficult. Funds that specialize in investing in hard-to-value companies must spend more resources on valuation per unit of capital, 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 rates and low profits, using traditional factor models that do not correctly price such companies leads to biased inferences in evaluating the performance of high-fee funds.

We find several pieces of evidence that are consistent with the valuation cost hypothesis. The results of our textual analysis of the "Principal Investment

Strategies" section of fund prospectuses reveal that high-fee funds focus more on research and fundamental valuation when describing their investment approaches. More pointedly, we find that high-fee funds invest significantly more in companies with high proxies for valuation difficulty: those that have high idiosyncratic volatility, low asset tangibility, and high forecast dispersion from sell-side analysts. When we decompose a fund's expense ratio into the distribution cost and the asset management cost, we find that the relation between a fund's expense ratio and proxies of the valuation cost of its underlying companies is entirely driven by the component of the expense ratio that reflects the asset management costs, that is, management fees and expenses, rather than the distribution costs, such as 12b-1 fees. In addition, we show that the positive relation between expenses and before-fee performance is particularly pronounced among funds that tilt their portfolios to hard-to-value companies. This result suggests that returns to active research are greatest when focusing on those companies. In other words, in line with the valuation cost hypothesis, funds investing in hard-to-value companies compensate their managers more richly by charging higher management fees. At the same time, these managers produce more alpha.

Our findings bring new insights to the long-standing debate on the value of active asset management.[3] An important question in this literature 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). Prior research has established that while the average mutual fund underperforms its benchmark after fees, growing evidence suggests that some managers appear to be skilled (e.g., Cremers and Petajisto 2009; Amihud and Goyenko 2013; Doshi, Elkamhi, and Simutin 2015). We contribute to this research by showing that once priced characteristics of their portfolios are taken into account, high-fee funds generate positive factor-adjusted returns before fees, consistent with managers of these funds being skilled.[4]

More broadly, our results suggest that multifactor models that control for exposures to profitability and investment factors, such as the Fama-French (2015) five-factor model, are preferable to conventionally used models, such as the capital asset pricing model (CAPM), when measuring fund performance.[5] Given the strong relation between a fund's fees and its exposures to the priced profitability and investment factors that we uncover, our results suggest that failing to account for loadings on these two factors can significantly affect inferences about fund

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

[4] To be clear, our results do not endorse investing in high-fee funds. While these funds achieve positive before-fee alphas, their managers extract surplus through fees, and the average net-of-expenses factor-adjusted performance is as negative as it is for low-fee funds.

[5] Addressing questions distinct from ours, several recent papers study how exposures to the investment and profitability factors affect mutual fund performance. For example, Jordan and Riley (2015) show 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 exhibit more persistence than alphas from other models.

performance. In this sense, our paper parallels the work by Bessembinder and Zhang (2013) and Bessembinder, Cooper, and Zhang (2019) who find that abnormal stock returns following a number of corporate events documented in prior literature are an artifact of the failure to control for priced stock characteristics.

Our paper also contributes to the ongoing discussion on the capital allocation within the mutual fund industry. Clifford et al. (2013), Barber, Huang, and Odean (2016), Berk and van Binsbergen (2016), and Ben-David et al. (2022) show that investors do not account for funds' exposures to all risk factors when evaluating fund performance. Building on this work, Song (2020) points outs that if investors confound the effects of funds' exposures to priced risk factors with managerial skill, they may allocate too little capital to skilled managers, leading these managers to perform better in the future. In our context, investors who do not account for funds' exposures to profitability and investment factors would avoid high-fee funds, surmising that they are riskier than they are. To investors who do take these exposures into account, high-fee funds would appear to have low capital relative to managerial skill. In equilibrium, these investors would allocate capital to these funds until funds' net alphas are unrelated to fees, consistent with our empirical findings. While our empirical results are consistent with this equilibrium, exploring the optimality of capital flows in the mutual fund industry or their impact on market efficiency is outside the scope of our paper.[6]

Should investors account for exposures to the profitability and investment factors when measuring fund performance? To the extent that these are priced factors, as recent literature argues,[7] we argue that the answer to this question is yes. Failing to do so would cause risk and risk-adjusted returns to be mismeasured. Barber, Huang, and Odean (2016) make an even stronger statement, arguing that "investors should consider all factor-related returns – priced and *unpriced* – when assessing the skill of a manager" (p. 2606). This intuition suggests that investors in high-fee funds are not worse off: they take on less profitability and investment risk and so earn lower expected returns, but not lower alpha.

Practically, our findings imply that the oft-given and commonly followed advice to prefer low-fee funds over those with high fees deserves rethinking. If investment and profitability are priced factors, as a growing literature suggests (e.g., Ball et al. 2015; Hou, Xue, and Zhang 2015; Asness, Frazzini, and Pedersen 2019), this advice is akin to a recommendation to choose small value funds over large growth funds because CAPM alphas of the former group can be expected to be higher. Instead, investors should recognize that high-fee funds invest in fundamentally different stocks, with lower exposures to priced factors and, consequently, with lower expected returns.

6 For example, greater allocation of capital to funds that specialize in investing in fast-growing, low-profitability firms may improve the cost of financing and pricing efficiency of these firms (cf. Bhamra and Uppal 2019). We leave this area of research for future work.

7 See Novy-Marx (2013), Fama and French (2015), Hou, Xue, and Zhang (2015), and Hou et al. (2021).

1. 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). Specifically, as our focus is on understanding the fee-performance puzzle documented within active funds (e.g., Gil-Baso and Verdú 2009; Fama and French 2010), we remove passive funds by examining fund names and index fund indicators, verifying in Section 5 that our results remain robust to retaining them in the sample.[8] We show that our and reconsider these funds in robustness tests of Section 5. We then exclude mutual funds that are not U.S. domestic equity funds based on the CRSP style code, Thomson Reuters style code, and Lipper objective name. We eliminate mixed funds or highly levered funds, which hold less than 70% or more than 130% of their assets in equity. For the analysis of holdings, we require a fund to have at least 10 stock holdings. We remove extremely small funds, that is, those with less than $20 million in asset in real 2017 terms, which is approximately $6 million in 1980. To estimate factor-adjusted performance for each fund, we require at least 5 years of return history. Our final sample contains 2,925 funds and spans the period from 1980 to 2017.

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. Following the literature, we winsorize expense ratios at the 99th percentile to remove extreme outliers. Fund size is the aggregate of all share classes. We define fund age as the age of its oldest share class. To proxy for the sophistication of a fund's investors, we use information about the fund's distribution channel and information on its investor base. Following Sun (2021), 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 front- or back-end load fees. We define a fund's broker share as the fraction of assets in broker-sold share classes. We label a share class as institutional if its name contains words beginning with "inst," if it is of class Y or I, or if its institutional flag is Y in CRSP. We measure a fund's institutional share as the fraction of its assets in institutional share classes. We use Lipper class code to control for the style of a fund. Finally, we identify funds that are in the same fund family based on their management company name and calculate fund family size as the sum of total assets of its affiliated funds. Panel A of Table 1 reports fund-level summary statistics.

Our analysis of mutual fund holdings requires stock-level data, which we obtain from the CRSP, COMPUSTAT, and IBES files, restricting the sample to common stocks (share code 10 and 11). For each stock, we measure characteristics such as the CAPM beta, market capitalization, book-to-market ratio, and momentum. We

[8] Other reasons we exclude index funds are the potential investor segmentation across the active and passive space (Gruber 1996; French 2008; and Sun 2021) and a small number of index funds during a large part of our sample period.

Table 1
Summary statistics for fund and portfolio characteristics

A. Fund characteristics

	Mean	Median	SD	p5	p25	p75	p95
Expense ratio	1.22%	1.17%	0.43%	0.59%	0.94%	1.46%	2.00%
Fund size (million)	1,308	237.1	5,038	22.1	73.643	853.9	5,071
Fund age, years	12.3	9.9	9.9	1.3	4.8	17.3	32.3
Family size (million)	34,171	4,864	90,313	55.7	744.779	21,776	223,098
Turnover ratio	84%	63%	80%	11%	33%	107%	229%
Broker-sold share	47%	37%	44%	0%	0%	100%	100%
Institutional share	30%	5%	39%	0%	0%	65%	100%
12b-1 fee	0.17%	0.05%	0.22%	0.00%	0.00%	0.27%	0.66%

B. Stock characteristics

	Mean	Median	SD	p5	p25	p75	p95
Stock age, years	12.39	8.08	13.53	0.58	3.17	16.67	40.00
CAPM beta	1.07	0.99	0.72	0.07	0.57	1.46	2.40
Market cap (million)	1,787	120	11,125	4	27	582	5,961
Book-to-market ratio	0.78	0.60	0.71	0.11	0.33	1.00	2.10
Momentum	10.0%	4.3%	52.7%	−62.7%	−19.9%	28.8%	103.2%
Asset growth rate	12.6%	6.8%	36.6%	−33.2%	−2.9%	20.4%	81.5%
Operating profitability	9.3%	18.1%	52.6%	−70.6%	4.0%	29.9%	56.4%
Equity issuance rate	6.2%	0.5%	20.3%	−8.4%	0.0%	4.6%	43.3%
Idiosyncratic volatility	3.5%	2.7%	2.8%	0.9%	1.7%	4.4%	9.2%
Tangibility	26%	18%	25%	1%	5%	40%	79%
Analyst dispersion	0.37%	0.11%	0.89%	0.00%	0.05%	0.30%	1.52%
Max return	8.8%	5.6%	12.8%	1.4%	3.3%	10.0%	25.0%

C. Correlations of fund-level portfolio characteristics

	Beta	*B/M*	*Size*	*Momentum*	*Asset growth*	*Equity issuance*	*Profitability*
B/M	−30%						
Size	−39%	−17%					
Momentum	26%	−42%	−14%				
Asset growth	49%	−59%	−30%	49%			
Equity issuance	44%	−17%	−42%	37%	61%		
Profitability	−22%	−36%	48%	6%	−8%	−34%	
Stock age	−61%	25%	76%	−34%	−64%	−53%	34%

This table reports the summary statistics for fund characteristics (panel A), stock characteristics (panel B), and the correlation of fund portfolio characteristics (panel C). Fund size and fund family size are measured in nominal terms in millions of dollars. Broker-sold share is the percentage of a fund's assets in share classes sold through brokers. Institutional share is the percentage of a fund's assets in share classes sold to institutional investors. Panel C displays the correlation matrix of the characteristics of portfolio holdings of mutual funds, which are computed as the position-weighted averages across stocks held by a fund. Correlations are reported as time-series averages of cross-sectional correlations. Detailed definitions are in the appendix. The sample period is 1980 to 2017.

also compute investment- and profitability-related characteristics, such as asset growth, equity issuance, operating profitability, and stock age. To gauge whether a company is difficult to value, we construct proxies, such as asset tangibility, idiosyncratic volatility, and analyst forecast dispersion. To measure whether a stock offers lottery-type payoffs, we use the measure of Bali, Cakici, and Whitelaw (2011), the maximum daily return over the past 1 month ("MAX").

The appendix provides details on variable definitions. We winsorize firm-level variables at the top and bottom 1%. We take natural logarithms of growth rates and market capitalizations. Panel B of Table 1 shows summary statistics of these stock characteristics. To study portfolio-level attributes of the funds, we take position-weighted averages of characteristics of stocks they hold at the beginning of each year. Panel C of Table 1 shows the pairwise correlations of these average characteristics at the fund portfolio level. As expected, many of the characteristics are strongly correlated. For example, the average correlation for asset growth and equity issuance is 61%.

2. Mutual Fund Fees and Portfolio Characteristics

In this section we uncover systematic differences in the characteristics of stock holdings of funds with different expense ratios. In addition to the commonly considered characteristics, such as size, book-to-market ratio, and momentum, we investigate asset growth rate, operating profitability, equity issuance rate, and stock age. For every fund at the first observation of each year, we take position-weighted averages across all stocks in its portfolio. We then run the following panel regression:

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

where $Avg\ \ char_{j,t}$ is one of the above-mentioned stock characteristics for fund j in year t, $Expense\ \ ratio_{j,t-1}$ is the fund's expense ratio in year $t-1$, and $Controls_{j,t-1}$ include the natural logarithm of fund size, fund age (in months), and the size of other affiliated funds in the same family. We include year-times-style fixed effects, double-cluster standard errors by time and fund, and scale all variables by their standard deviations annually to facilitate the interpretation of the magnitudes of the coefficients.

Table 2 shows that funds with different expenses invest in systematically different stocks. The coefficients for the expense ratio are significant for all characteristics we study. Specifically, regressions (1)–(4), which focus on the commonly considered characteristics, show that high-fee funds tilt their portfolios to high-beta, low book-to-market, small stocks with high momentum. Specifications (5) and (6) show that high-fee funds also invest more in stocks with high asset growth rates and high equity issuance rates. Finally, regressions (7) and (8) shows that high-fee funds invest more in young stocks and stocks with low profitability. Overall, the results of this analysis suggest that funds charging different fees have fundamentally different investment preferences. Broadly speaking, high-fee funds prefer younger firms in a stage of rapid expansion that have not yet achieved high profitability. Note that we include style-year fixed effects, suggesting that the results are not driven by differences in styles (e.g., small-cap growth vs. large-cap value).

The absolute magnitudes of the coefficients in regressions (5)–(8) are often greater than those in specifications (1)–(4), indicating that growth- and

Table 2
Fund fees and characteristics of stock holdings

	(1) *Beta*	(2) *B/M*	(3) *Size*	(4) *Momentum*	(5) *Asset growth*	(6) *Equity Issuance*	(7) *Profitability*	(8) *Stock age*
Expense ratio$_{t-1}$	0.13***	−0.03**	−0.07***	0.03*	0.11***	0.13***	−0.12***	−0.13***
	(7.49)	(−2.54)	(−8.86)	(1.93)	(10.21)	(10.84)	(−8.32)	(−11.82)
log(Fund size$_{t-1}$)	0.03*	0.03*	0.03***	−0.06***	−0.00	0.02*	−0.04***	−0.03*
	(1.82)	(1.70)	(4.10)	(−3.97)	(−0.25)	(1.82)	(−2.94)	(−1.87)
log(fund age$_{t-1}$)	−0.01	−0.04***	0.00	0.02*	0.02	−0.01	0.01	−0.00
	(−0.62)	(−2.99)	(0.40)	(1.72)	(1.60)	(−0.85)	(0.98)	(−0.36)
log(fund family size$_{t-1}$)	0.04**	−0.01	0.01	0.04**	0.04***	0.06***	−0.04***	−0.03**
	(2.63)	(−1.03)	(1.38)	(2.56)	(3.88)	(5.01)	(−2.79)	(−2.52)
Observations	38,505	38,510	38,511	38,510	38,511	38,510	38,510	38,511
Adj. R^2	.752	.498	.872	.737	.433	.448	.554	.597
Style × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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 1 year. Characteristics of stockholdings are position-weighted averages across all stocks in a fund's portfolio. Regressions include style-year fixed effects, where style is defined based on Lipper class codes. All variables are scaled by their standard deviations to facilitate comparison. Standard errors are clustered at both fund and year levels. The sample period is from 1980 to 2017.
*$p < .1$; **$p < .05$; ***$p < .01$.

profitability-related characteristics are economically more important in capturing portfolio differences among funds charging different fees. To better gauge the economic magnitude of tilts by high-fee funds, we plot average asset growth rates, equity issuance rates, operating profitability, and stock age against fund fee deciles in Figure 1. The benefit of this plot is that it does not impose a linear structure between fees and stock characteristics. The figure shows that stock characteristics change strikingly and monotonically with fees. For example, the average asset growth rate of companies held by funds in the bottom decile is less than 12% a year, while in the highest decile it reaches 18%. This difference of over 6% represents half of the average asset growth rate of all companies. The plot also reveals that companies held by the funds in the bottom fee decile on average achieve operating profitability that is 6 percentage points higher than do companies held by funds in the top decile.[9] For comparison, we also show the average characteristics of index funds by the diamond in Figure 1. The stock characteristics of index funds are more similar to those of low-fee funds than high-fee funds.

To evaluate the time series dynamics of the preference of high-fee funds for low-profitability high-growth firms, we run regression (1) annually and plot the time series of the coefficients for the expense ratio in Figure 2. While the coefficients are somewhat more volatile during the early part of the sample, potentially because of the smaller number of funds, the plot shows that the differences in portfolio

[9] While these characteristics are correlated with each other (see Table 1), in untabulated results we find that all four characteristics are statistically significant when included jointly as regressors to explain the expense ratio.

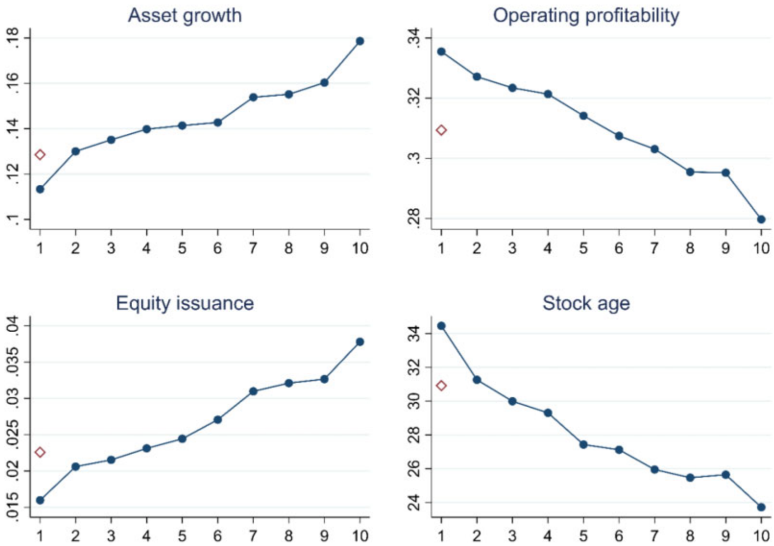

Figure 1
Characteristics of stock portfolios of funds charging different fees
This figure plots average characteristics of stocks held by actively managed equity mutual funds grouped into deciles on the basis of the expense ratio (groups 1 to 10) and index funds (marked by a diamond). For each fund, we calculate its stock characteristics as the position-weighted averages across companies held by the fund. The characteristics are defined in detail in the appendix. The sample period is 1980–2017.

characteristics of funds with different fees have been remarkably persistent over time.

3. Mutual Fund Fee-Performance Relation

The persistent preference of high-fee funds for fast-growing, low-profitability stocks has important implications for the relation between expenses and performance of mutual funds. To the extent that these stock characteristics are associated with lower expected returns, as recent literature has shown (e.g., Fama and French 2015; Hou, Xue, and Zhang 2015), failure to account for these characteristics can lead to erroneous conclusions on the relation between fees and fund performance. Such failure would be analogous to using the CAPM to evaluate the performance of a large-cap growth fund: without explicitly accounting for loadings on size and value factors, the performance of this fund would appear poor on average. In our context, accounting for exposures to asset growth and profitability factors of funds with different fees is necessary to get a clearer picture of the relation between expenses and performance of mutual funds.

To control for exposures to asset growth and profitability factors, we use the five-factor model of Fama and French (2015) in our main analysis here and verify robustness to using other models that include investment and profitability factors in Section 5. To contrast our results with those of prior literature, we also use the

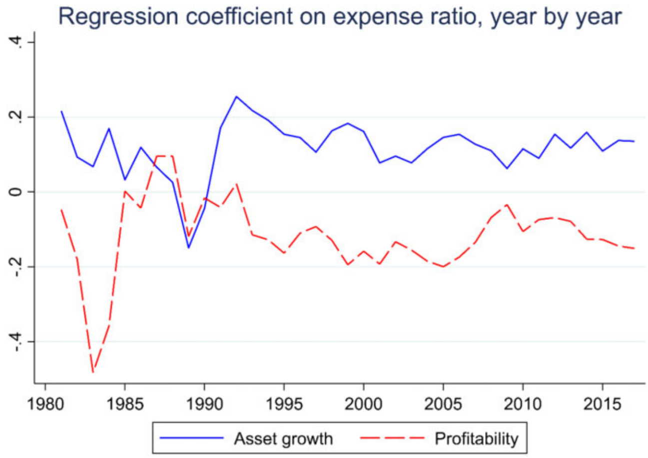

Figure 2
Fund fees and time series dynamics of fund portfolio characteristics
This figure plots the time series of coefficients for the *Expense ratio* variable from an annual cross-sectional regression:

$$Average\ chracteristic_{j,t} = b_0 + b_1 Expense\ ratio_{j,t-1} + \boldsymbol{b}^{'} Controls_{j,t-1} + \epsilon_{j,t},$$

where $Average\ characteristic_{j,t}$ is the position-weighted average of either the asset growth rate or the operating profitability for fund *j*'s stock portfolio in year *t*; $Expense\ ratio_{j,t-1}$ is the fund *j*'s expense ratio in year $t-1$; and $Controls_{j,t-1}$ are fund-level control variables, including the natural logarithm of fund age, fund size, fund family size and style fixed effects. Detailed variable definitions are provided in the appendix. All variables are scaled by their standard deviation and demeaned in each year. The sample period is 1980 to 2017.

commonly considered models, such as the CAPM, as well as three- and four-factor models (Fama and French 1993; Carhart 1997). For each model and in each month *t*, we regress a fund's monthly return in the 5 years leading up to month *t* on factors to obtain loadings $\boldsymbol{\beta}_{jt}^{Model}$. We compute monthly alphas as

$$\alpha_{jt}^{Model} = r_{jt}^{e} - \boldsymbol{\beta}_{jt}^{Model'} \boldsymbol{r}_{t}^{Factor},$$

where r_{jt}^{e} is fund *j*'s excess return before fee or after fee, and $\boldsymbol{r}_{t}^{Factor}$ is a vector of realized factor returns. We measure a fund's gross monthly alpha using its gross return, which is the net return plus the annual expense ratio divided by 12.

3.1 Empirical evidence

Figure 3 summarizes future performance of funds grouped into deciles on the basis of fees disclosed in the most recent fiscal year-end. Panel A plots before-fee alphas from different models. The results from the CAPM, as well as 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.

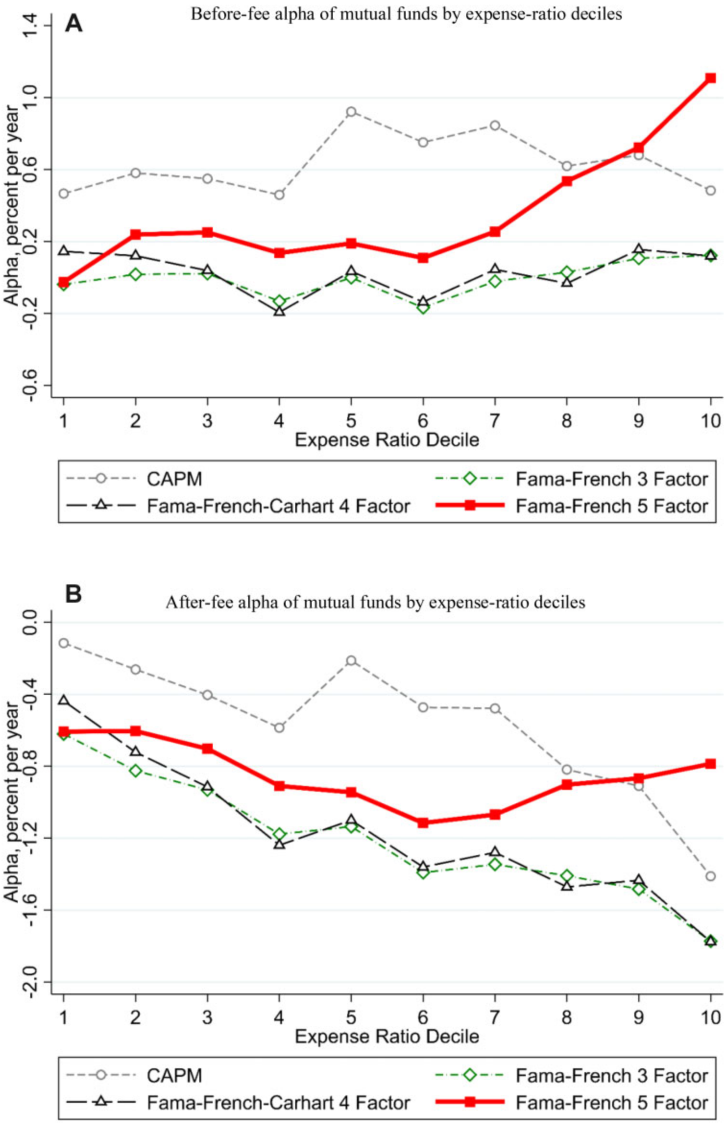

Figure 3
Mutual fund fee-performance relation
This figure plots alphas, in percent per year, of funds grouped into deciles on the basis of expense ratios reported in the most recent fiscal year. Alphas are measured using four models: the CAPM, the Fama-French three-factor, the Fama-French-Carhart four-factor, 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 benchmark return, calculated as the sum of the products of factor returns in *t* and factor loadings estimated from rolling regressions on 5 years of monthly data. 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 1980–2017.

Panel B shows that regardless of the model, actively managed mutual funds with both high and low expense ratios achieve poor average net-of-fees factor-adjusted performance. Consistent with the results of prior literature, 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 the five-factor model. The difference in the five-factor alphas of funds with high and low expense ratios is economically small and statistically indistinguishable from zero. In fact, comparing net five-factor alphas for each of the 45 pairs of deciles, we find that none of the differences is significant at the 5% level. Overall, the evidence from the five-factor model in Figure 3 is consistent with the prediction of Berk and Green (2004) that skilled managers extract rents by charging higher fees, and consequently funds with different fees deliver similar net-of-fees performance.

The sort-based results in Figure 3 are informative, but to evaluate the fee-performance relation more formally, we run the following panel regression:

$$\alpha_{jt}^{Model} = d_0 + d_1 Expense\ \ ratio_{jt-1} + \boldsymbol{h}' Control_{jt-1} + FE_{j,t} + \varepsilon_{jt}, \qquad (2)$$

where $Expense\ \ ratio_{jt-1}$ is the fund j's expense ratio measured at the most recent fiscal year-end, and $Control_{jt-1}$ is a vector controls measured at the same time as fees, including the logarithm of fund size, fund age (in months), and the total size of other affiliated funds in the family.[10] We include month times style fixed effects and cluster standard errors by month.

Panel A of Table 3 reports the results of the panel regression (2) with before-fee alphas. The first three specifications show that funds charging higher fees do not deliver better performance as measured by alphas from conventional factor models. However, in specification (4), which controls for fund exposures to the investment and profitability factors, the coefficient for the *Expense ratio* is significantly positive, suggesting that high-fee funds deliver better performance. The size of the coefficient indicates that funds with 1% higher fees deliver 0.87% higher alphas.

Panel B of Table 3 repeats the analysis using after-fee alphas. Consistent with prior literature, regressions (1)–(3) show that the coefficients for the *Expense ratio* are large and negative, suggesting that net performance, as measured 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 for the *Expense ratio* is statistically indistinguishable from zero. In other words, expenses are not related to future after-fee performance when investment and profitability factors are controlled for.

Why does the performance of high-fee funds improve after controlling for investment and profitability factors? The reason is that high-fee funds tilt their

[10] We choose fund size, age, and fund family size as our key control variables because they are salient characteristics available to investors when selecting mutual funds and because these variables can potentially explain a fund's risk or return. These variables are often used in the literature (e.g., Khorana, Servaes, and Tufano 2009; Gil-Bazo and Ruiz-Verdú 2009; Cremers et al. 2016). The results are robust to including additional controls, such as turnover ratio and broker share, as we will show in Section 5.3.

Table 3
Mutual fund fee-performance relation

	(1) α_t^{CAPM}	(2) α_t^{FF3}	(3) α_t^{FFC4}	(4) α_t^{FF5}
A. Before-fee alpha				
Expense ratio$_{t-1}$	−0.47	0.04	−0.14	0.87***
	(−1.14)	(0.13)	(−0.47)	(3.38)
log(Fund size$_{t-1}$)	−0.16***	−0.05	−0.09*	0.06
	(−2.86)	(−1.09)	(−1.66)	(1.02)
log(Fund age$_{t-1}$)	0.14	0.03	0.05	−0.05
	(1.46)	(0.35)	(0.54)	(−0.56)
log(Fund family size$_{t-1}$)	0.06**	0.06**	0.05*	0.07***
	(2.20)	(2.40)	(1.90)	(2.66)
Observations	367,904	367,904	367,904	367,904
Adj. R^2	.343	.170	.171	.172
Style × Month FE	Yes	Yes	Yes	Yes
B. After-fee alpha				
Expense ratio$_{t-1}$	−1.41***	−0.90***	−1.08***	−0.07
	(−3.44)	(−3.10)	(−3.56)	(−0.27)
log(Fund size$_{t-1}$)	−0.16***	−0.05	−0.09	0.06
	(−2.80)	(−1.02)	(−1.59)	(1.08)
log(Fund age$_{t-1}$)	0.14	0.03	0.05	−0.06
	(1.41)	(0.30)	(0.49)	(−0.61)
log(Fund family size$_{t-1}$)	0.06**	0.06**	0.05*	0.08***
	(2.22)	(2.43)	(1.93)	(2.69)
Observations	367,904	367,904	367,904	367,904
Adj. R^2	.343	.170	.171	.172
Style × Month FEs	Yes	Yes	Yes	Yes

This table presents the results of panel regressions of fund alphas on expense ratios, both in percent per month, and control variables. 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 5-year rolling window regression. In panel A (B), alpha is computed using before-fee (after-fee) returns. Control variables include the logarithm of fund size, fund age (in months), and fund family size, measured from the most recent fiscal year and scaled by 10 to facilitate exposition. All regressions include style-month fixed effects, where style is defined based on Lipper class code. Standard errors are clustered at both fund and month levels. The sample period is 1980 to 2017.
*$p < .1$; **$p < .05$; ***$p < .01$.

portfolios toward firms with high asset growth rates and low profitability, characteristics associated with lower expected returns. In other words, loadings of high-fee funds on the investment and profitability risk factors, both of which carry positive factor premiums, are low. Table 4 establishes the relation between fund expenses and factor loadings in a formal test. Regressions (1) and (2) show that the *Expense ratio* is negatively and significantly related to funds' loadings on the asset growth and profitability factors. Specifications (3) and (4) show that this result is robust to additionally controlling for loadings on the other factors, such as the market, size, and value. The realized premiums of the investment and profitability factors are 0.25% and 0.36% per month during our sample period. Based on the coefficients in columns 1 and 2, a 1-percentage-point increase in a fund's fee corresponds to a decline in its five-factor adjusted return by 0.75 percentage points (0.87 × 0.25% + 1.49 × 0.36%). These results suggest that in analyses of the mutual fund fee-performance relation, it is critical to account for the fact that funds with different expenses have dramatically different loadings on the asset growth

Table 4
Fund fees and loadings on the investment and profitability factors

	(1) FF5 CMA factor loading	(2) FF5 RMW factor loading	(3) FF5 CMA factor loading	(4) FF5 RMW factor loading
Expense ratio$_{t-1}$	−0.87***	−1.49***	−0.74***	−1.22***
	(−4.84)	(−10.29)	(−4.38)	(−10.31)
log(Fund size$_{t-1}$*)*	−0.07*	−0.05	−0.08*	−0.04*
	(−1.79)	(−1.52)	(−2.02)	(−1.71)
log(Fund age$_{t-1}$*)*	−0.12	−0.00	−0.10	0.00
	(−1.50)	(−0.06)	(−1.31)	(0.09)
log(Fund family size$_{t-1}$*)*	0.01	−0.07***	0.01	−0.05***
	(0.57)	(−5.20)	(0.47)	(−3.85)
FF5 market factor loading$_t$			−0.22**	0.03
			(−2.51)	(0.53)
FF5 HML factor loading$_t$			−0.16***	0.28***
			(−2.90)	(9.48)
FF5 SMB factor loading$_t$			−0.30***	−0.06**
			(−6.11)	(−2.06)
Observations	29,362	29,362	29,362	29,362
Adj. R^2	.187	.179	.247	.259
Year × Style FEs	Yes	Yes	Yes	Yes

This table reports the results of panel regressions of funds' investment (CMA) or profitability (RMW) factors loadings at the beginning of each year on annual expense ratios and other fund characteristics. To obtain the loadings, we regress a fund's monthly before-fee return in the previous 5 years on Fama-French five-factor portfolios and use the coefficients as risk loadings. Control variables include the logarithm of fund size, fund age (in months), and fund family size, measured from the most recent fiscal year, as well as contemporaneous loadings on market, size, and value factors. All regressions include style-year fixed effects, where style is defined based on Lipper class code. Standard errors are clustered at both fund and month levels. The sample period is 1980 to 2017.
**p* < .1; ***p* < .05; ****p* < .01.

and profitability factors. Relying on conventional models, which fail to do this, can lead to a premature conclusion that high-fee funds have poor performance.

3.2 The fee-performance relation conditional on fund characteristics

Next, we investigate whether the relation between expense ratios and the performance holds across different subsamples of funds. To this end, we separate funds into two groups based on each of their size, age, family size, turnover ratio, institutional ownership share, or broker-sold share. Specifically, for each of these fund-level characteristics, we create two subsamples depending on whether a fund's characteristic is above or below the sample median in each month. We then regress five-factor alphas on the expense ratios and other fund attributes within each subsample.

Table 5 reports the results of this test with before-fee five-factor alphas. It shows that the coefficients for the *Expense ratio* remain statistically positive and economically large in most subsamples. The fee-performance relation is particularly pronounced among younger funds, funds offered by smaller families, and those more directly sold to investors. The coefficients for the *Expense ratio* among those funds exceed one, suggesting that the performance benefit enjoyed by investors in these funds exceeds the additional fee. The fees that managers of such funds appear to

Table 5
Fee-performance relation conditional on fund characteristics
A. Conditioning on fund size, fund age, or fund family size

	(1) Fund size	(2)	(3) Fund age	(4)	(5) Family size	(6)
	≤ median	> median	≤ median	> median	≤ median	> median
Expense ratio$_{t-1}$	1.00***	0.65*	1.24***	0.36	1.14***	0.70**
	(3.51)	(1.83)	(4.44)	(1.07)	(3.39)	(2.50)
Observations	183,916	183,764	185,227	182,344	183,918	183,653
Adj. R^2	.164	.188	.178	.166	.171	.178
Month × Style FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

B. Conditioning on turnover ratio, institutional share, or broker share

	(1) Turnover ratio	(2)	(3) Institutional share	(4)	(5) Broker share	(6)
	≤median	> median	≤ median	> median	≤ median	> median
Expense ratio $_{t-1}$	0.62**	0.93***	0.97***	0.82**	1.36***	0.53
	(2.28)	(2.97)	(2.99)	(2.45)	(3.50)	(1.57)
Observations	179,194	176,805	153,079	149,078	182,988	170,609
Adj. R^2	.154	.211	.142	.232	.192	.165
Month × Style FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

This table presents results of regressions of the monthly before-fee Fama-French five-factor alpha on the fund's monthly expense ratio for subsamples of funds with different characteristics. Control variables (omitted for brevity) include the logarithm of fund size, fund age (in months), and fund family size. All independent variables are measured as of the most recent fiscal year-end of the fund. Regressions include style-month fixed effects and cluster standard errors by fund and month. In panel A, subsamples are selected based on whether a mutual fund's size, age and family size are above or below the sample median in each month. In panel B, subsamples are selected based on whether a mutual fund's turnover ratio, institutional ownership share, and broker-sold share are above or below the sample median in each month.
*$p < .1$; **$p < .05$; ***$p < .01$.

extract are thus smaller than the value they add, leaving some positive surplus to investors. The higher coefficients could arise for several reasons, for example, because of search cost or reputation concerns. Theoretically, as predicted by Garleanu and Pedersen (2018), investors should be compensated by higher alpha for their search efforts. Younger funds and funds offered by smaller families can be less well-known, and investors in these funds may need to incur greater search costs, particularly when purchasing them directly, rather than through a broker. Alternatively, Chevalier and Ellison (1997) have shown that the response of flow to performance is more sensitive for younger and smaller funds. Therefore, skilled managers of these funds might be willing to charge a lower fee to build a better track record, sharing some of the surplus with their investors.

4. Mechanisms

In the previous sections, we established that mutual funds charging different fees invest in different types of stocks. This difference in investment style has significant implications to the performance evaluation of these funds. In this section, we investigate why mutual fund expense ratios relate systematically to the propensity to invest in firms with certain asset growth and profitability profiles. We explore two potential explanations.

4.1 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 overextrapolate high growth rate of a company into the future, causing it to be overpriced. In a more related study, Frazzini and Lamont (2008) document a dumb money effect in retail investor flows. They find retail investors display positive sentiment toward growth stocks and allocate more capital to funds that hold more such stocks. Also, Solomon, Soltes, and Sosyura (2014) find that mutual funds receive more fund flow if they hold companies that have high return and are covered by the media.

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 sensitive to fund fees. These companies can be expected to have a high rate of asset growth and low profitability. If such companies attract unsophisticated investors, we would expect that some fund managers invest more in high-growth and low-profitability stocks to attract more unsophisticated investors. Since unsophisticated investors tend to be less price sensitive, the fund manager might be able to charge higher fees than what is justified by the performance.[11]

To test the *naïve investor hypothesis*, we construct two measures of a fund's investor sophistication. Institutional investors are widely recognized as more sophisticated than retail investors, and so our first proxy is the fraction of a fund's assets in the institutional share classes. The second proxy is broker share, defined as the fraction of a fund's assets sold through broker channels rather than directly to investors. Funds sold through brokers charge investors higher sales loads, which do not contribute to the management of the fund. Prior literature has shown that investors who purchase mutual funds through brokers are less performance-sensitive than investors who purchase mutual funds directly. In addition, brokers' incentives are more aligned with fund families (Del Guercio and Reuter 2014). Therefore, higher broker share of a fund corresponds to lower sophistication of its investors. We rerun regression (1) of average portfolio characteristics on the expense ratio, either investor sophistication proxy, and their interaction.

[11] Prior literature has explored how fund managers set fees strategically to exploit investors who are less sensitive to price. For example, Christoffersen and Musto (2002) find that retail money funds tend to increase fees after a large amount of outflow. They propose that outflows are an indication of performance-sensitive investors leaving the fund, which also signals a decrease in the average price sensitivity among investors remaining in the fund, causing the managers to subsequently raise fees.

Under the naïve investor hypothesis, we expect to see that high-fee funds with more sophisticated investors have weaker tilts toward stock characteristics that appeal to naïve investors. This implies that the coefficient for the interaction term of the expense ratio and institutional share should be of the opposite sign to that on the expense ratio. With broker share as the proxy of the lack of investor sophistication, the coefficients for the interaction term should have the same sign as the coefficient for the expense. In addition to the four stock characteristics from Figure 1, we also use the maximum daily return of a stock in the prior month. This characteristic, proposed by Bali, Cakici, and Whitelaw (2011), is motivated by the finding that retail investors prefer stocks with lottery-type payoffs.

We summarize the results of our tests in Table 6. In panel A, four of the five coefficients for the interaction term between the expense ratio and the institutional share are insignificant. Only in column 3, the coefficient is significant, suggesting that institutional investors reduce the propensity of high-fee funds to invest in low profit companies. In panel B, the coefficients for the interaction term between the expense ratio and the broker share all have the opposite sign as the coefficient for the expense ratio, which is inconsistent with the naïve investor hypothesis. Collectively, these results do not offer robust support for the naïve investor hypothesis: among funds with more sophisticated investors, the association between expense ratio and growth-related characteristics is the same, if not stronger. Additionally, the previously discussed results from Table 5 show that the positive relationship between fees and gross five-factor alphas is, if anything, stronger among funds with more sophisticated investors (such as those with low broker share). Overall, these results are inconsistent with the naïve investor hypothesis driving the relation between funds' expense ratios and portfolio tilts toward stocks with different asset growth or profitability.

4.2 Valuation cost hypothesis

Next, we consider the hypothesis that mutual fund expense ratios are commensurate with the amount of effort fund managers spend on valuing companies. Under this hypothesis, mutual funds investing in high-growth low-profitability firms charge high fees because it is considerably more difficult to value these companies, requiring more effort from fund managers per unit of capital. The high valuation cost, in turn, necessitates higher fees on a percentage basis. Another element of this hypothesis is that the potential reward for conducting costly research is also high for companies that are difficult to value. We label this alternative explanation the *valuation cost hypothesis*. Under this hypothesis, we expect to observe that high-fee funds invest more in companies that are more difficult to value and that investing in difficult-to-value companies generates higher alphas for funds that charge higher fees.

To test the valuation cost hypothesis, we use three measures to identify whether a company is hard to value. Our first measure is idiosyncratic volatility (Ang et al. 2006), which has been linked to valuation difficulty (e.g., Kumar 2009). The

Table 6
Fund fees and characteristics of stock holdings: Role of investor sophistication

A. Institution share

	(1) *Asset growth*	(2) *Equity issuance*	(3) *Profitability*	(4) *Stock age*	(5) *MAX*
Expense ratio$_{t-1}$	0.12***	0.12***	−0.11***	−0.13***	0.10***
	(9.58)	(8.04)	(−6.00)	(−9.56)	(5.62)
Institution share$_{t-1}$	0.02*	0.00	0.02	−0.01	−0.02
	(1.88)	(0.03)	(1.56)	(−1.03)	(−1.36)
Expense ratio$_{t-1}$× Institution share$_{t-1}$	0.01	−0.02	0.03**	−0.01	−0.02
	(0.77)	(−1.58)	(2.38)	(−1.12)	(−1.35)
log(Fund size$_{t-1}$)	−0.01	0.02	−0.05**	−0.03*	0.03
	(−0.33)	(1.72)	(−2.79)	(−1.90)	(1.25)
log(Fund age$_{t-1}$)	0.02	−0.01	0.01	0.01	−0.06***
	(1.64)	(−0.46)	(1.07)	(0.58)	(−4.16)
log(Fund family size$_{t-1}$)	0.03***	0.05***	−0.04**	−0.03*	0.02
	(3.02)	(3.35)	(−2.79)	(−2.02)	(1.42)
Observations	29,412	29,411	29,411	29,412	29,412
Adj. R^2	.434	.435	.441	.600	.481
Year × Style FEs	Yes	Yes	Yes	Yes	Yes

B. Broker share

	(1) *Asset growth*	(2) *Equity issuance*	(3) *Profitability*	(4) *Stock age*	(5) *MAX*
Expense ratio$_{t-1}$	0.13***	0.13***	−0.13***	−0.15***	0.13***
	(10.66)	(8.75)	(−6.91)	(−11.29)	(7.73)
Broker share$_{t-1}$	−0.03**	−0.01	0.01	0.04***	−0.03***
	(−2.50)	(−0.61)	(0.51)	(3.06)	(−2.84)
Expense ratio$_{t-1}$× Broker share$_{t-1}$	−0.03***	−0.02*	0.03**	0.02**	−0.01
	(−3.09)	(−2.01)	(2.13)	(2.28)	(−1.00)
log(Fund size$_{t-1}$)	0.00	0.03**	−0.04**	−0.03**	0.03
	(0.31)	(2.40)	(−2.67)	(−2.45)	(1.56)
log(Fund age$_{t-1}$)	0.02	−0.01	0.01	−0.01	−0.04***
	(1.57)	(−0.59)	(0.71)	(−0.54)	(−2.96)
log(Fund family size$_{t-1}$)	0.04***	0.05***	−0.04***	−0.03**	0.03
	(3.94)	(4.50)	(−3.07)	(−2.59)	(1.66)
Observations	36,247	36,246	36,246	36,247	36,247
Adj. R^2	.443	.455	.525	.614	.498
Year × Style FEs	Yes	Yes	Yes	Yes	Yes

This table reports the results of panel regressions of the characteristics of a fund's stockholdings (shown in column headings) on the fund's expense ratio, a proxy of investor sophistication, their interaction and control variables. All independent variables are measured for the most recent fiscal year. Characteristics of stockholdings are position-weighted averages across all stocks in a fund's portfolio. In panel A, the proxy for investor sophistication is institutional share, which measures the fraction of a fund's assets from institutional share classes. In panel B, the proxy for investor sophistication is broker share, which measures the fraction of a fund's assets from share classes that are sold through brokers. All independent variables are scaled by the cross-sectional standard deviation. All regressions include style-year fixed effects, where style is defined based on Lipper class code. Standard errors are clustered at both fund and year levels. The characteristics are defined in detail in the appendix. The sample period is 1980 to 2017.
*$p < .1$; **$p < .05$; ***$p < .01$.

second 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). Our last measure is analyst forecast dispersion from the IBES database: stocks on whose value professional analysts disagree more are plausibly harder to

Table 7
Fund fees and characteristics of stock holdings: Role of equity valuation cost

A. Expense ratios and valuation costs

	(1) *Idiosyncratic volatility*	(2) *Asset tangibility*	(3) *Analyst dispersion*
Expense ratio$_{t-1}$	0.14***	−0.08***	0.05***
	(12.36)	(−4.50)	(3.56)
log(Fund size$_{t-1}$)	0.01	−0.03	0.03**
	(0.82)	(−1.31)	(2.21)
log(Fund age$_{t-1}$)	−0.01	0.01	−0.03***
	(−1.26)	(0.30)	(−3.14)
log(Family size$_{t-1}$)	0.02	0.03	0.00
	(1.60)	(1.35)	(0.27)
Observations	37,721	37,721	37,445
Adj. R^2	.613	.133	.303
Year × Style FEs	Yes	Yes	Yes

B. Asset management fees and valuation costs

	(1) *Idiosyncratic volatility*	(2) *Asset tangibility*	(3) *Analyst dispersion*
Expenses excluding 12b-1 fee$_{t-1}$	0.18***	−0.12***	0.03**
	(12.48)	(−6.46)	(2.22)
12b-1 fee$_{t-1}$	−0.00	0.02	0.02
	(−0.19)	(0.98)	(1.63)
log(Fund size$_{t-1}$)	0.04***	−0.06**	0.02
	(2.82)	(−2.44)	(1.68)
log(Fund age$_{t-1}$)	−0.02	0.01	−0.03**
	(−1.30)	(0.70)	(−2.64)
log(Family size$_{t-1}$)	0.04***	0.01	0.00
	(3.17)	(0.45)	(0.17)
Observations	35,506	35,506	35,502
Adj. R^2	.618	.105	.307
Year × Style FEs	Yes	Yes	Yes

This table reports the results of panel regressions of the characteristics of a fund's stockholdings (shown in the column headings) on the fund's attributes measured for the most recent fiscal 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. All regressions include style-year fixed effects, where style is defined based on Lipper class code. Standard errors are clustered at both fund and year levels. The sample period is 1980 to 2017.
*$p < .1$; **$p < .05$; ***$p < .01$.

value. We aggregate each company-level measure of valuation cost to the fund level using portfolio weights of a fund.

Panel A of Table 7 summarizes the results from regressions of valuation cost proxies of funds' stockholdings on their expense ratios. It shows that a one standard deviation increase in the fund's fee is associated with 0.14 standard deviation higher idiosyncratic volatility, 0.08 standard deviation lower asset tangibility, and 0.05 standard deviation higher analyst forecast dispersion. Lending early support to the valuation cost hypothesis, the results suggest that fund fees relate positively to each of the valuation difficulty proxies we consider.

To test the hypothesis further, we split a fund's reported expense ratio into the component that represents its asset management cost and the part that represents marketing and distribution cost. A typical fund's expense ratio consists of three main components: 12b-1 fee, management fee, and other operating expenses. Management fee and other operating expenses cover the cost of fund managers and daily operations, while 12b-1 fee is mainly used for the fund's marketing and distribution, for example, compensation to brokers who sell the fund to investors. Under the valuation cost hypothesis, funds investing in harder-to-value stocks should charge higher management fees to compensate managers for their efforts, but we do not expect marketing and distribution fees to relate to valuation difficulty of the stockholdings. We find this to be the case. Panel B of Table 7 shows that asset management fees relate significantly to the valuation cost of the underlying companies, while 12b-1 fees are negatively related or unrelated to the valuation cost, lending further support for the valuation cost hypothesis.

We find another piece of evidence that high-fee funds devote more research efforts when analyzing their investments by examining funds' prospectuses, which are known to provide valuable information on funds' investment strategies (Sheng, Xu, and Zheng 2022). Specifically, we study whether high- and low-fee funds describe investment approaches differently by analyzing differences in the "Principal Investment Strategies" (PIS) section of summary prospectus (forms 497K) available from EDGAR. To the extent that high- and low-fee funds differ in their investment styles, we expect to observe differences in the language in that section.

We find that high-fee funds tend to describe their investment strategies differently from low-fee funds. A typical PIS section of high-fee funds reads:

> [The fund] utilizes a *growth approach* to choosing securities based upon *fundamental research* which attempts to identify companies whose earnings growth rate exceeds that of their peer group, exhibit a competitive advantage in niche markets, or *do not receive significant coverage from other institutional investors*. (Emerald Mutual Fund)

By contrast, a typical low-fee fund describes its investment strategy as follows:

> The Fund invests, under normal circumstances, primarily in U.S. common stocks that are considered by the Fund's subadvisers to have above-average potential for growth. The subadvisers emphasize *stocks of well-established medium- and large-capitalization firms*. (The Vantagepoint Funds)

To test more formally whether high- and low-fee funds differ significantly in describing research activities central to their trading strategies, we perform textual analysis of the PIS sections. Specifically, we construct a "research index" to capture a fund's research activities by calculating the fraction of words that are related to research. We include the following words in the list: analysis, analyze, analyzes, analyzed, bottom-up, fundamentally-based, fundamentals-based, quantitative, qualitative, profitability, valuation, mispriced, under-valuation,

Table 8
Textual analysis of mutual fund prospectuses

	(1) *Research index*	(2) *Research index*	(3) *Research index*
Expense ratio$_t$	0.24***	0.21***	0.20***
	(5.65)	(4.52)	(4.13)
Constant	−0.09***	−0.01	−0.00
	(−23.90)	(−0.80)	(−0.41)
Observations	6,212	6,212	6,212
Adj. R^2	.005	.088	.109
Controls	No	Yes	Yes
Year × Style FEs	No	No	Yes

This table reports the results of panel regressions of the fraction of research-related words in funds' "Principal Investment Strategies" sections of summary prospectuses (Research index) on expense ratios and controls, which include fund size, fund age, and fund family size. All regressions include style-year fixed effects, where style is defined based on Lipper class code. Standard errors are clustered at the fund level.
$^*p < .1$; $^{**}p < .05$; $^{***}p < .01$.

over-valuation, under-valued, over-valued (with or without dashes), and research.[12] We then merge the text data with fund variables using the links in SEC's Investment Company Series and Class information. Limited data availability affects this textual analysis by narrowing the period from 2010 until 2016.

Table 8 summarizes the results of regressions of the *research index* on the expense ratio and control variables. The coefficients for the expense ratio are positive and significant in all specifications, consistent with high-fee funds focusing more on research in formulating their investment strategies and lends further support to the valuation cost hypothesis. The economic magnitude is large as well. For example, the coefficient in specification (3) suggests that one standard deviation increase of fees is associated with 0.006 increase in a fund's research index, a magnitude that represents 8.2% of the mean of the research index.

Lastly, we show that funds that tilt their portfolios strongly toward difficult-to-value companies deliver better performance per unit of fees they charge. Specifically, we split all mutual funds into quintiles based on the average percentile rank of the three valuation cost proxies.[13] This average rank, which we call the "valuation cost score," captures the difficulty of valuing the stocks that a mutual fund invests in. We then assess the relation between expenses and before-fee five-factor alphas for each quintile of funds separately. Under the valuation cost hypothesis, we expect funds with greater tilts toward hard-to-value companies to generate higher before-fee alpha per unit of fees charged. In other words, funds that invest in hard-to-value companies

[12] This so-called "dictionary-based method" is well-accepted in the finance literature. For example, Loughran and MacDonald (2011) use a similar method to develop a dictionary to measure sentiment for 10K filings. Baker, Bloom, and Davis (2016) follow this approach to construct economic policy uncertainly index. Fisher, Martineau, and Sheng (2022) use a similar approach to construct macroeconomic attention indexes from news articles, and Liu and Matthies (2022) also use it to construct a measure of consumption based on news articles.

[13] We first convert each fund-level proxy of valuation cost into a cross-sectional percentile rank and then take the average of the three percentile ranks. Note that we rank funds with high asset tangibility as low valuation cost and low asset tangibility as high valuation cost.

Table 9
Fee-performance relation conditional on valuation difficulty of fund stockholdings

	Valuation difficulty				
	Low	Q2	Med	Q4	High
Expense ratio$_{t-1}$	0.12	0.31	0.96**	1.00**	1.52***
	(0.35)	(0.90)	(2.25)	(2.20)	(3.23)
log(Fund size$_{t-1}$)	0.00	−0.09	0.10	0.05	0.12
	(0.03)	(−1.11)	(1.13)	(0.60)	(1.14)
log(Fund age$_{t-1}$)	−0.11	0.12	−0.15	0.06	−0.08
	(−0.71)	(0.76)	(−0.97)	(0.33)	(−0.40)
log(Fund family size$_{t-1}$)	0.06	0.09**	0.11**	0.09**	0.12**
	(1.55)	(2.13)	(2.45)	(2.08)	(2.39)
Observations	67,190	65,392	65,890	64,317	63,208
Adj. R^2	.171	.178	.182	.183	.189
Style × Month FEs	Yes	Yes	Yes	Yes	Yes

This table presents the results of panel regressions of before-fee five-factor alphas on lagged expense ratios, both in percent per month, and other fund characteristics in different subsamples of mutual funds. Control variables include the logarithm of fund size, fund age, and fund family size. Funds are grouped into quintiles based on the average percentile rank of the three valuation cost proxies (e.g., idiosyncratic volatility, asset tangibility, and analyst dispersion). Each column corresponds to one quintile of mutual funds with column 1 corresponding to funds investing in stocks that are least difficult to value. Regressions include style-month fixed effects, where style is defined based on Lipper class code. Standard errors are clustered at both fund and month levels.
*$p < .1$; **$p < .05$; ***$p < .01$.

and compensate managers richly to induce greater valuation effort should generate better before-fee performance. Table 9 provides evidence supporting this conjecture. Column 1 shows the fee-performance relation for mutual funds that invest in companies with the lowest valuation difficulty, while column 5 shows the fee-performance relation of mutual funds that invest in companies with highest valuation difficulty. The coefficients for the expense ratio increases monotonically from column 1 to column 5, consistent with our hypothesis that the return to active research by a mutual fund increases with the valuation difficulty of the stocks it invests in. As a result, mutual funds that are willing to spend more effort in valuing companies choose to invest more in hard-to-value firms because the potential reward for their valuation effort is greater. Taken together, the evidence in Tables 7 through 9 provides strong support for the valuation cost hypothesis.

5. Robustness and Additional Results

In this section, we conduct several robustness tests of our results: we consider including index funds in the sample, using alternative factor models that control for exposures to profitability and investment factors, and modifying the empirical specifications.

5.1 Including index funds in the sample

While our focus is on the actively managed funds, it is informative to augment the analysis by including index funds. Absent investor segmentation between active and passive funds, Berk and Green (2004) model predicts that no fund should dominate others and future net-of-fee performance should not be different for active and index funds. As a first test, we compare performance of index funds with performance of active funds in the lowest fee decile. This comparison is suitable because the average fee of index funds (0.58% per year) is similar to the average fee of active funds in the lowest fee decile (0.57% per year). Consistent with the intuition in Berk and Green, we find that when using the five-factor model, future net-of-fee performance is similar for index funds and the decile of the lowest-fee active funds (−0.61% vs. −0.62% per year). The difference, at 0.01%, is statistically indistinguishable from zero ($t = 0.04$).

For a more formal assessment of how our results are affected by the inclusion of index funds into the sample, we build on the tests from Table 3 by running regressions of before- or after-fee alphas on expense ratios and controls in the sample that contains both active and index funds. The results of this analysis, summarized in Table IA1 of the Internet Appendix, show that our conclusions remain unaffected: in this broader sample, fees are positively related to gross five-factor alphas and are unrelated to net five-factor alphas.

5.2 Using alternative factor models

Given that mutual funds that charge different expenses invest in stocks that differ substantially along their profitability and investment characteristics, it is important to control for those attributes when measuring fund performance. In the analysis above, we have done so using the Fama-French (2015) five-factor model. We now evaluate the robustness of our results to using other models that control for the profitability and investment factors. The first three models we consider augment the Fama-French five-factor model with the momentum factor, the Pastor and Stambaugh (2003) liquidity factor, or both factors. We also consider Hou et al. (2021) five-factor model and the Barillas and Shanken (2018) six-factor model. The results of this analysis, summarized in Table IA2 of the Internet Appendix, are similar to our main findings in Table 3: the before-fee alpha relates positively and significantly to fees while the after-fee alpha is unrelated to expenses. Overall, these results suggest that controlling for investment and profitability factors is critical to assess the fee-performance relation.

5.3 Additional results

In our next set of robustness tests, we evaluate whether the propensity of high-fee funds to hold high-growth low-profitability firms is driven by other characteristics of the stocks in the portfolio. To this end, we reun regression (1) of average portfolio characteristics on expense ratios after adding averages of CAPM betas, market capitalizations, return run-ups, and book-to-market ratios of the stockholdings as regressors. The results, summarized in Table IA3 of the Internet Appendix, remain little affected relative to those in the base-case analysis in Table 2.

Table 10
Fee-performance relation: Robustness to methodological choices

	(1)	(2) Before-fee alpha	(3)	(4)	(5) After-fee alpha	(6)
	FF5	FFC6	FFC6+Liq	FF5	FFC6	FFC6+Liq
A. Sample period starts in 1998						
Expense ratio$_{t-1}$	0.88***	0.65**	0.78***	−0.08	−0.31	−0.18
	(3.13)	(2.37)	(2.82)	(−0.28)	(−1.11)	(−0.65)
Observations	327,464	327,464	327,464	327,464	327,464	327,464
Adj. R^2	.181	.175	.171	.180	.175	.171
Month × Style FEs	Yes	Yes	Yes	Yes	Yes	Yes
Fund-level controls	Yes	Yes	Yes	Yes	Yes	Yes
B. Fama-MacBeth regressions						
Expense ratio$_{t-1}$	1.17***	0.72**	0.86***	0.26	−0.19	−0.05
	(3.50)	(2.24)	(2.66)	(0.78)	(−0.59)	(−0.15)
Observations	367,928	367,928	367,928	367,928	367,928	367,928
Average R^2	.026	.025	.025	.026	.025	.025
Fund-level controls	Yes	Yes	Yes	Yes	Yes	Yes
C. Loadings estimated in 36-month windows						
Expense ratio$_{t-1}$	0.99***	0.66**	0.70***	0.06	−0.28	−0.23
	(3.38)	(2.55)	(2.67)	(0.20)	(−1.06)	(−0.88)
Observations	444,932	444,932	444,932	444,932	444,932	444,932
Adj. R^2	.168	.154	.152	.168	.154	.152
Month × Style FEs	Yes	Yes	Yes	Yes	Yes	Yes
Fund-level controls	Yes	Yes	Yes	Yes	Yes	Yes
D. Controlling for turnover ratio and distribution channel						
Expense ratio$_{t-1}$	1.03***	0.76***	0.88***	0.11	−0.16	−0.04
	(3.74)	(2.72)	(3.10)	(0.41)	(−0.56)	(−0.15)
Observations	337,900	337,900	337,900	337,900	337,900	337,900
Adjusted R-squared	.176	.169	.165	.176	.169	.165
Month × Style FEs	Yes	Yes	Yes	Yes	Yes	Yes
Fund-level controls	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results of regressions of fund alphas on lagged expense ratios, both in percent per month, and other fund-level control, which include the logarithm of fund size, fund age, and fund family size. Alphas are computed using the Fama-French five-factor model (FF5), Fama-French five-factor augmented with Carhart momentum factor model (FFC6), and Fama-French five-factor augmented with Carhart momentum factor and Pastor-Stambaugh liquidity factor model (FFC6+Liq). The dependent variables in columns 1 to 3 are before-fee alphas. The dependent variables in columns 4 to 6 are after-fee alphas. In panel A, the results are based on the 1998–2017 sample. Panel B shows results from Fama-MacBeth regressions. Factor loadings for each fund in each month in both panels A, B, and D are estimated based on 5-year rolling regression windows. In panel C, alphas are measured using factor loadings estimated from 3-year rolling windows. In panel D, we include turnover ratio and broker share as additional control variables. Standard errors in panels A, C, and D, are clustered at the fund and month levels.
*$p < .1$; **$p < .05$; ***$p < .01$.

Finally, we modify various aspects of our empirical methods. In panel A of Table 10, we run the analysis on the more recent sample covering spanning 1998 to 2017 and find that our results are similar to those in Table 3. In panel B, we run Fama-MacBeth regressions of monthly alpha from different models on expense ratios and other fund-level controls. We find that the relation between the expenses ratio and alphas is similar to the one we observed using panel regressions. In panel C of Table 10, we use a shorter 3-year rolling window to calculate factor loadings of the funds. Again, the results remain robust, further confirming that after controlling for exposures to profitability and investment factors, we find high-fee funds significantly outperform low-fee funds before deducting expenses and perform equally well net of fees. In panel D, we include two additional control variables: the turnover ratio and the distribution channel proxied by broker share. The conclusions remain unaffected after adding these controls. Finally, our results are robust to using net management expense (i.e., the expense ratio net of 12b-1 fees) as a proxy of management cost (see Tables IA4 and IA5 in the Internet Appendix).

6. 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 and the apparent misallocation of capital in the mutual fund industry.

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 surplus by charging high fees, and call into question the widely offered advice to prefer low-fee funds over high-fee counterparts.

Appendix

Variable Definition

Variable	Definition
Analyst dispersion	The standard deviation of analyst forecast of a company's quarterly earnings divided by the stock price
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 assets are measured as of the fiscal year-end: $AG_{i,t} = \ln\frac{Asset_{i,t}}{Asset_{i,t-1}}$
B/M ratio	The ratio of stock i's book equity at the end of its fiscal year to its December end market capitalization. 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 $B/M_{i,t} = \frac{BE_{it}}{ME_{it}}$
CAPM beta	We estimate a stock's CAPM beta as the regression coefficient from regressing the stock's monthly excess return on the market excess return over the prior 5 years
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 $EI_{i,t} = \ln\frac{Adjusted\ \ Shares\ \ Outstanding_{i,t}}{Adjusted\ \ Shares\ \ Outstanding_{i,t-1}}$
Idiosyncratic volatility	We measure a stock's idiosyncratic volatility as the standard deviation of the residual of daily Fama-French three-factor regression estimated over a rolling 3-month horizon as in Ang et al. (2006)
Market capitalization	The natural logarithm of stock i's market capitalization, measured in the end of December of each year
MAX	Maximum daily stock return over the past month
Momentum	The cumulative return of a stock from January to November of each year
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 $OP^{stock}_{i,t} = \frac{(REV-COGS-SG\&A-INT\ \ EXP)_{i,t}}{Book\ \ Equity_{i,t}}$
Stock age	Number of years a stock is publicly listed
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

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