Pricing Differentiated Funds: The Puzzle of ESG Fund Fees

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Abstract

We document a robust anomaly in the fee setting of U.S. mutual funds: ESG funds charge net expense ratios 11.5 basis points lower than those of conventional funds across providers, and 6.5 basis points lower within provider. Using panel data from 2011-2024, we show this fee gap persists across data sources, ESG classifications, and market segments. A Hotelling-style model of horizontal differentiation predicts that funds with higher returns and stronger differentiation should command higher fees. ESG funds have outperformed peers net-of-fees and exhibit greater textual differentiation, but nonetheless charge lower fees. The result is inconsistent with standard theories of fee setting based on performance signals or competitive differentiation.

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ESG products typically charge higher fees than more "plain vanilla" products. Globally, fee revenue from ESG-themed funds grew from $1.1 billion in 2020 to $1.8 billion in 2021. Touting a product as being "ESG" is good for business... A skeptic might believe that some ESG products are merely offered in order to extract higher management fees.

SEC Commissioner Mark T. Uyeda[1]
Jan. 27, 2023

1 Introduction

Products that cater to niche preferences and offer distinct characteristics typically command higher prices. Horizontal differentiation, whether it be offering cars in many colours or financial products with distinct thematic focuses, allows producers to weaken direct price competition and charge higher fees. In the mutual fund market, funds with environmental and social mandates ("ESG funds")[2] offer a clear example of horizontal differentiation: they appeal to a distinct set of investors and have no clear quality difference compared to conventional funds.

Economic theory and empirical work both suggest that such funds should be more expensive. ESG investors are willing to pay higher fees and accept lower returns for ESG funds (Baker et al., 2024; Barber et al., 2021; Bauer et al., 2021; Heeb et al., 2023; Riedl & Smeets, 2017). ESG funds may also incur higher marginal costs due to additional sustainability screening. Under standard models of pricing and fund competition, differentiation combined with willingness to pay and higher costs should result in higher fees.

Contrary to these expectations, this paper documents that from 2011 to 2024, ESG funds in the U.S. charged net expense ratios which were, on average, 11.5 basis points *lower* than conventional funds after controlling for fund characteristics. When comparing ESG and conventional funds within the same provider, ESG funds remain cheaper by 6.5 basis points. The result holds across four data sources, alternative ESG classifications (including Morningstar and Eikon labels), using matching methods, a non-U.S. sample, and alternative specifications. The finding also persists across market segments, including retail

[1]This quote is from a speech at the "California '40 Acts Group", which can be accessed here: https://www.sec.gov/newsroom/speeches-statements/uyeda-remarks-california-40-acts-group.

[2]We use the term "ESG" instead of "ES," although we only consider funds with environmental and social mandates, since the former term is more widely used. Other authors may use responsible investment, sustainable, or other terms to refer to funds with an environmental or social mandate.

vs. institutional funds, young vs. old funds, small vs. large funds, ETFs vs. traditional mutual funds, and equity vs. bond funds. Even funds that switch into ESG mandates exhibit lower fees while designated as ESG.

This finding presents a puzzle. ESG funds are horizontally differentiated products, marketed to investors with a demonstrated willingness to pay. Why, then, do they exhibit low fees?

To interpret this, we develop a simple model of horizontal differentiation in the style of Hotelling (1929). In the model, two funds compete for investors with heterogeneous locations along a continuum of sustainability preferences. In equilibrium, fund fees reflect expected returns and the extent of horizontal differentiation. The model generates clear, testable implications: (1) funds with lower expected returns charge lower fees; (2) funds facing less competition, proxied by uniqueness to global and local peers, charge lower fees.

We test these mechanisms. First, we show that ESG funds have outperformed comparable conventional funds net of fees in our sample. They also attract higher flows and exhibit stronger flow-performance sensitivity, suggesting that fund providers have room to raise fees. Second, we construct four measures of fund uniqueness based on textual descriptions investment strategies and portfolio holdings, each calculated relative to global and local peer groups. While ESG funds are textually unique, and textual uniqueness is generally associated with higher fees, this relationship does not hold within the ESG segment. Additionally, we show that holdings-based uniqueness has declined over time for ESG funds, particularly since 2018. Although this trend points to intensifying competition, it does not empirically explain the persistent fee gap.

In summary, we document a puzzle: ESG funds exhibit lower fees despite characteristics that, according to both investor-learning models and product differentiation theory, should support higher pricing. This suggests that standard frameworks may not fully explain how fees are set for differentiated financial products. Future models of fee setting may need to account for factors such as reputational incentives at the fund-family level, heterogeneity in investor performance and fee sensitivity, and the strategic pricing of new fund launches.

This paper contributes to several strands of the mutual fund literature. First, our findings relate to the literature on mutual fund fees and pricing anomalies. Khorana et al. (2009) document significant fee heterogeneity across countries and provide evidence on key determinants of fund fees. Some papers study the phenomenon of fee dispersion, particularly among index funds which are largely identical products (Choi et al., 2010; Elton et al., 2004; Hortaçsu & Syverson, 2004). In the model of Berk and Green (2004), and subsequent work such as Berk and van Binsbergen (2015), mutual fund fees reflect manager skill and are set such that expected net alphas are zero in equilibrium. Cooper et al. (2021) show that for investors fees are related to net-of-fee returns, supporting the view that fund fees matter for investors. We contribute to this literature by documenting a new pricing anomaly: ESG funds, despite being horizontally differentiated, charge significantly lower fees than comparable conventional funds. Appendix B reviews prior studies on ESG fund fees, most of which report mixed or context-specific findings. Our paper is the first to comprehensively document this pricing gap.

Second, our work contributes to the literature on mutual fund competition and differentiation. Prior studies show that competitive pressure leads to lower fees (Cremers et al., 2016; Hoberg et al., 2018; Sun, 2021; Wahal & Wang, 2011). For example, Hoberg et al. (2018) introduce a style-based spatial measure of competition and find that funds in less competitive segments charge higher fees. Li and Qiu (2014) show that funds with unique factor exposures exhibit greater market power and charge higher fees, while Bonelli et al. (2021) document that funds receiving unfavourable ratings respond by increasing differentiation to avoid direct competition. We show that while ESG funds show evidence of differentiation, particularly by using unique text in their investment strategies, this differentiation does not translate into higher fees. We replicate and extend prior uniqueness-fee relationships (Kostovetsky & Warner, 2020), but find that controlling for differentiation does not explain the ESG fee gap.

Third, we contribute to the literature on investor behaviour and the pricing of sustainable investments. Survey evidence shows that investors are willing to sacrifice financial returns for investments that align with their values (Bauer et al., 2021; Giglio et al., 2025; Riedl & Smeets, 2017). Experimental evidence confirms that investors are willing to pay higher fees for sustainable investments, but that WTP does not scale with the impact of the investment (Heeb et al., 2023). Barber et al. (2021) find that venture capital impact investors are willing to accept significantly lower expected returns, while Baker et al. (2024) show that WTP for ESG index funds fluctuated between 2019 and 2022, declining as sentiment toward ESG investing weakened. We find that ESG funds have outperformed conventional funds net-of-fees, and their flows respond more strongly to past returns. These results imply that ESG funds could charge more, and yet we find that they do not.

2 Data

This paper primarily uses data from the CRSP Survivor-Bias-Free U.S. Mutual Fund dataset and the SEC Mutual Fund Prospectus Risk/Return dataset.[3] Control variables are retrieved from CRSP and detailed fee data is from the SEC.[4] Additional data which is used in subsequent analysis is retrieved from Eikon (see Appendix G.3) and Morningstar (see Appendix G.2).

2.1 Sample Construction

The sample consists of quarterly observations of U.S. open-end mutual funds from Q1 2011 to Q4 2024. Exchange-traded funds (ETFs) and exchange-traded notes (ETNs) are also included, both of which are referred to as ETFs. The SEC dataset is merged with CRSP using fund series and class identifiers.

We conducted the following data cleaning steps. First, observations were excluded if fewer than ten unique ESG funds existed within a CRSP style classification across the sample, leaving 22 classifications. Second, the SEC fee variables were winsorized at the 1% level to mitigate the impact of reporting errors and extreme values. Third, since fund fees are often reported annually rather than quarterly, missing fee values were forward-filled up to three quarters. Finally, the panel was balanced such that the dependent variable and the control variables in the main specification were not missing.

The final sample contains over one million fund-quarter observations, covering 35,831 fund share classes from 13,019 fund series. Our main analysis is conducted at the share class level, since this is the level at which fees are determined. For brevity, we refer to a fund share class as a "fund," identified by a unique CRSP fund number.

2.2 Variable of Interest and Controls

The primary variable of interest is the (net) expense ratio, defined as net expenses divided by total net assets (TNA). Using the granular SEC data, the net expense ratio can be broken down into its components: gross expense ratio (comprised of management, dis-

[3]The SEC dataset can be accessed here: https://www.sec.gov/data-research/sec-markets-data/mutual-fund-prospectus-riskreturn-summary-data-sets.

[4]Since 2011, U.S. mutual funds have been required to file disclosures in XBRL format, allowing for standardized and structured reporting. As a result, the SEC dataset provides comprehensive coverage of the open-end mutual fund market in the U.S.

tribution, acquired, and other fees) and waivers. Appendix C contains more information about the decomposition of fees according to the SEC taxonomy.

We include a set of control variables which have been shown in the literature to explain variation in fees. Fund age in years since inception is used to account for potential effects of maturity on fees. We also include the square of age to control for non-linear age effects. Two controls capture economies of scale: $log(TNA)$ represents the natural logarithm of the fund's TNA (in USD), while $log(Family)$ measures the log of TNA at the fund family level. Indicator variables are used to identify index funds, ETFs, and institutional funds.

Appendix D reports the descriptive statistics. ESG funds have lower average unconditional fees. They are also younger and smaller, on average, but come from larger fund families. It is important to control for these variables in our baseline analysis. In addition, we conduct robustness checks using matching and entropy balancing approaches (in Appendix G.4) to ensure that differences in fund characteristics do not drive the observed fee patterns.

2.3 ESG Fund Classification

A key step in the analysis is the classification of ESG funds. We use a keyword-based approach, classifying a fund as an ESG fund if at least one ESG-related keyword appears in its name. The keyword list, detailed in Appendix A, aligns closely with those used by Andrikogiannopoulou et al. (2022), van der Beck (2021), and Michaely et al. (2024). We identify 1,577 ESG funds in the sample, which is about 4.4% of all funds.

There are benefits to using fund names rather than external labels for ESG fund classification. First, fund names are based on reliable regulatory filings. Mutual funds in the U.S. must have a name that accurately reflects their investment strategy as disclosed in regulatory filings.[5] This contrasts with third-party ESG classifications, which often rely on non-transparent methodologies. Second, fund names are salient and directly observable by investors. Unlike third-party ESG labels, which may not be widely recognized or consistently applied, a fund's name is prominently displayed in prospectuses, disclosures, and marketing materials, making it a first-order signal of its investment mandate. Third, using fund names allows for a more representative sample. External ESG labels are available only for a subset of funds, whereas names are reported for all funds across our datasets. Addi-

[5] See Rule 35d-1 of the SEC's Investment Company Act of 1940 here: https://www.ecfr.gov/current/title-17/chapter-II/part-270/section-270.35d-1.

tionally, fund names are available as a time series, allowing us to track mandate changes over time. In our sample, 396 funds changed their name to include or remove an ESG keyword. Finally, identifying ESG funds by name ensures alignment with fund providers' own classifications. Since fund managers determine both ESG positioning and fees, this method captures their intended strategy more accurately than third-party ratings, which may impose criteria that do not align with how funds actually position themselves in the market.

As a robustness check, we compare our classification with Eikon's responsible investment fund label in Appendix G.3. Using Q4 2023 data, we find a correlation coefficient of 0.82 between the two classifications, indicating that our keyword-based approach is broadly consistent with external ESG labels.

3 Fee Analysis

This section examines the relationship between ESG status and fund fees using panel regressions. We estimate how the fees of ESG funds compare to conventional funds, controlling for fund characteristics, time trends, and provider effects.

Table 1 presents the results from the baseline specifications. Panel A compares ESG funds to conventional funds across fund providers in the cross-section using year × CRSP style fixed effects. Panel B additionally includes fund-provider fixed effects to exploit within-provider variation. Standard errors are clustered at the fund provider level, since fee strategies are likely to be determined at the fund family level. This is also the most conservative choice, as it yields the largest standard errors across most specifications. Appendix E reports results using alternative clustering levels.

Across fund providers, ESG funds have net expense ratios that are, on average, 11.5 bps lower than those of conventional funds, which is 11.2% lower than the conventional fund mean (102.6 bps). Notably, this difference is not reflected in gross expense ratios (Column 2), where the ESG coefficient is statistically insignificant, but rather largely come from fee waivers (Column 3). Across the other fee components (Columns 4-7), we observe that ESG funds charge lower management, distribution, and acquisition fees, but higher "other" fees. The control variables exhibit expected signs, consistent with prior literature.

To address concerns that unobserved provider-level characteristics might jointly explain both lower fees and a higher likelihood of offering ESG funds, Panel B introduces

Table 1: **Fees of ESG versus Conventional Funds**
This table reports the results from panel regressions using fund fees as the dependent variable, with each specific dependent variable stated above the column number. Fees are reported in basis points and in annual terms. Panel A compares across fund providers, and Panel B uses fund-provider fixed effects to compare within fund provider. Panel B restricts the sample to fixed effects groups with variation in the *ESG* variable. All specifications use year × CRSP style classification fixed effects. Variable definitions can be found in the Appendix. Standard errors are clustered at the fund provider level and reported in parentheses.

Panel A	Exp. Ratio	Gross Exp. Ratio	Waiver	Mgmt. Fee	Dist. Fee	Acq. Fee	Other Fee
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ESG	-11.525***	0.023	-12.174**	-2.844*	-4.238***	-4.254*	10.376**
	(1.467)	(5.540)	(5.125)	(1.458)	(1.467)	(2.306)	(5.099)
Age	1.748***	-1.734***	3.475***	0.082	1.057***	0.521***	-2.813***
	(0.113)	(0.329)	(0.307)	(0.074)	(0.094)	(0.151)	(0.315)
Age^2	-0.029***	0.023***	-0.052***	-0.0004	-0.019***	-0.013***	0.044***
	(0.002)	(0.005)	(0.005)	(0.001)	(0.001)	(0.003)	(0.005)
$log(TNA)$	-5.278***	-15.231***	9.825***	-0.241	-3.643***	-0.857***	-10.993***
	(0.256)	(0.978)	(0.980)	(0.150)	(0.199)	(0.185)	(0.994)
$log(Family)$	-3.656***	-6.710***	2.801***	-3.767***	1.587***	0.686***	-4.545***
	(0.368)	(0.814)	(0.779)	(0.350)	(0.389)	(0.254)	(0.751)
Index	-29.500***	-33.381***	4.831	-21.098***	-5.449***	-14.786***	-2.813
	(3.853)	(5.012)	(3.897)	(2.378)	(1.476)	(2.430)	(4.203)
ETF	-9.634***	-24.240***	13.735***	-0.543	1.567	8.591***	-25.323***
	(3.258)	(5.578)	(3.803)	(2.091)	(1.007)	(2.031)	(4.257)
Inst.	-40.733***	-44.840***	4.014*	-4.801***	-32.693***	0.641	-8.699***
	(1.373)	(2.530)	(2.311)	(0.729)	(1.093)	(0.845)	(2.322)
Observations	1,076,077	1,076,077	1,076,077	1,074,054	982,693	353,364	1,076,077
R^2	0.532	0.281	0.140	0.465	0.355	0.293	0.155
Adj. R^2	0.532	0.281	0.140	0.465	0.355	0.292	0.155
Panel B	Exp. Ratio	Gross Exp. Ratio	Waiver	Mgmt. Fee	Dist. Fee	Acq. Fee	Other Fee
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ESG	-6.509***	9.766	-16.495**	0.019	-4.555***	-3.886***	16.818**
	(1.068)	(7.437)	(7.501)	(0.829)	(0.987)	(1.404)	(7.498)
Age	2.206***	-0.515	2.735***	0.386***	1.363***	0.436**	-2.235***
	(0.179)	(0.636)	(0.592)	(0.118)	(0.122)	(0.176)	(0.594)
Age^2	-0.032***	0.005	-0.038***	-0.005***	-0.022***	-0.008**	0.033***
	(0.003)	(0.009)	(0.009)	(0.002)	(0.002)	(0.003)	(0.009)
$log(TNA)$	-4.630***	-11.588***	6.890***	-0.207	-3.471***	-0.794**	-7.655***
	(0.266)	(1.228)	(1.212)	(0.130)	(0.239)	(0.326)	(1.173)
$log(Family)$	-0.667	-4.154	3.412	0.513	0.199	-0.439	-4.594*
	(0.797)	(2.983)	(2.710)	(0.920)	(0.371)	(1.108)	(2.714)
Index	-32.265***	-35.160***	3.345	-28.122***	-0.185	-10.054***	-5.024
	(3.222)	(8.749)	(6.784)	(2.522)	(2.501)	(3.432)	(6.637)
ETF	1.616	-21.630***	23.034***	4.505	4.333***	10.848***	-28.587***
	(3.063)	(7.386)	(5.531)	(3.173)	(1.484)	(2.541)	(5.667)
Inst.	-42.352***	-48.752***	6.954**	-3.478***	-35.730***	0.095	-10.425***
	(1.556)	(3.732)	(3.126)	(1.185)	(1.441)	(0.666)	(3.156)
Observations	139,471	139,471	139,471	139,443	125,026	31,674	139,471
R^2	0.682	0.411	0.266	0.621	0.495	0.459	0.278
Adjusted R^2	0.681	0.409	0.264	0.620	0.493	0.453	0.276

fund-provider fixed effects. We also restrict the sample to provider-year-style groups where at least one ESG and one conventional fund exist, ensuring within-provider comparisons. The results in Panel B mirror those in Panel A. ESG funds have lower net expense ratios, distribution fees, and acquired fees compared to conventional funds offered by the same fund provider. The reduction in net expense ratios remains statistically and economically meaningful at 6.5 basis points (Column 7). Both across and within fund providers, the lower fees of ESG funds can largely be attributed to larger waivers. In additional to larger waiver amounts, we report in Appendix F using logit regression that ESG funds are more likely to issue waivers.

3.1 Fee Differences Across Market Segments

To assess whether the fee gap between ESG and conventional funds is concentrated in particular segments of the market, we repeat the analysis across a series of subsamples. The results are presented in Table 2. Column (1) and (2) split the sample by institutional status. Columns (3) and (4) by index fund status. Columns (5) and (6) distinguish between younger (less than or equal to 3 years) and older funds, addressing concerns about incubation bias (Evans, 2010). Columns (7) and (8) split by total net assets relative to the annual median. Columns (9) and (10) distinguish between equity and fixed income funds. Columns (11) and (12) distinguish between load and no-load funds, and Columns (13) and (14) distinguish ETFs from non-ETFs. All specifications include the earlier controls, as well as year $\times$ CRSP style fixed effects.

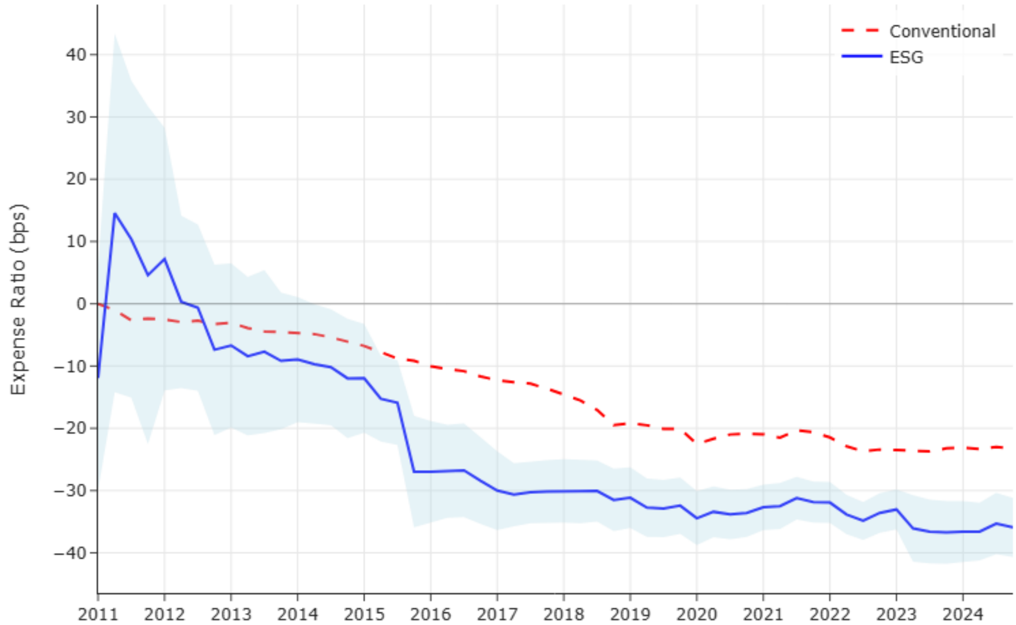
Across all subsamples, ESG funds continue to exhibit lower net expense ratios relative to conventional funds. While the magnitude of the coefficient on the ESG indicator varies (as does the average fee level across segments), it remains consistently negative and statistically significant. This suggests that the observed fee gap is not driven by any single segment of the market but reflects a broad-based pattern across fund types.

3.2 Fee Differences Over Time

To explore the evolution of fund fees over time, we estimate panel regression which interact the quarter indicator variables with the ESG coefficient. As before, we also control for CRSP style. Panel A of Figure 1 plots the time effects for ESG and conventional funds and includes a 95% confidence interval around the ESG fund line. Both ESG and conventional funds exhibit a downward trend in expense ratios over the sample period. The fee difference began to emerge in late 2015 and persisted throughout the sample.

Panel B plots the residual fees of ESG funds calculated from panel regressions of fees on standard set of controls, excluding the ESG coefficient. New ESG funds are coloured

Panel A:



Panel B:

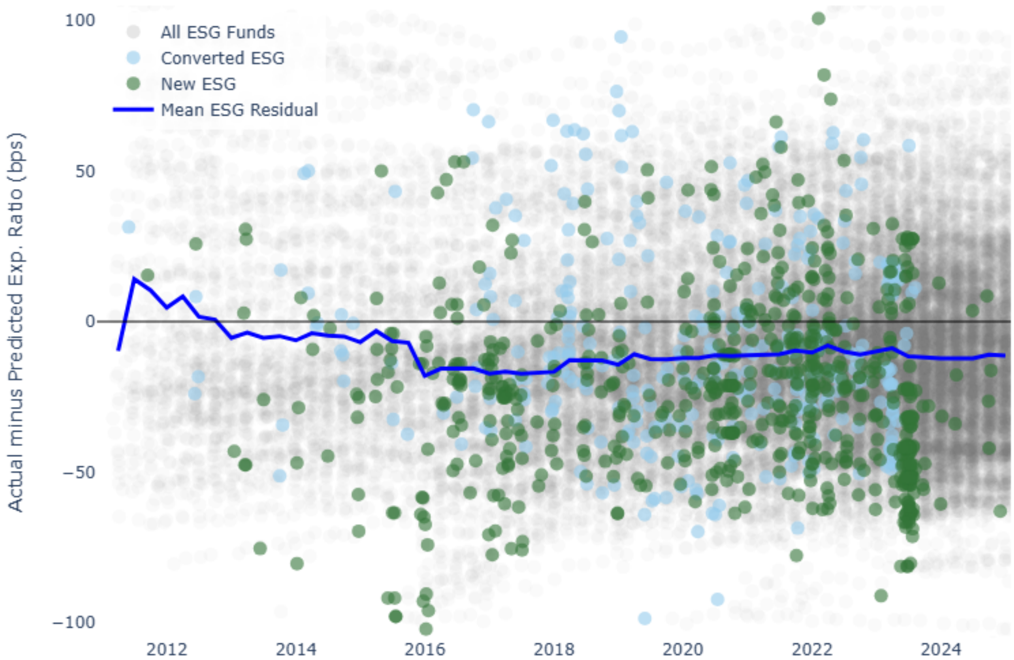


Figure 1: **Time Series and Residual Analysis of ESG Fund Fees**
This figure plots the evolution of fund fees. Panel A plots net expense ratios over time, estimated from a panel regression with ESG interacted with quarter fixed effects and controls for fund characteristics. Panel B plots the residuals from a regression of net expense ratios on fund controls (excluding the ESG indicator). Each dot represents an ESG fund at a given time, jittered for visibility. Green dots represent new ESG funds when they first appear in CRSP, and light blue dots represent converted ESG funds.

Table 2: **Fees Across Market Segments**
This table reports the results from panel regressions using expense ratio as the dependent variable, where the sample is subject to certain conditions. Columns (1) and (2) restrict by institutional fund status, Columns (3) and (4) on index fund status, Columns (5) and (6) by fund age, Columns (7) and (8) by fund TNA versus the median in that quarter, Columns (9) and (10) by fund type (i.e., equity or fixed income), Columns (11) and (12) by whether the fund has load fees, and Columns (13) and (14) by ETF status. Expense ratios are reported in basis points and in annual terms. All specifications use year × CRSP style classification fixed effects. Unreported control variables include fund age and age squared, log fund size, log family size, and indicator variables for index, ETF, institutional status. Variable definitions can be found in the Appendix. Standard errors are clustered at the fund provider level and reported in parentheses.

	Dependent variable: Exp. Ratio						
	Non-Inst.	Inst.	Non-Index	Index	Age≤3	Age>3	TNA≤Med.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ESG	-13.986***	-9.748***	-10.490***	-13.525***	-5.464***	-10.275***	-7.653***
	(2.746)	(1.366)	(1.812)	(3.118)	(1.839)	(1.790)	(1.641)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	461,550	614,527	981,689	94,388	192,984	883,093	538,199
R^2	0.383	0.462	0.494	0.590	0.544	0.534	0.493
Adj. R^2	0.382	0.462	0.494	0.590	0.544	0.534	0.493

	TNA>Med.	Equity	Fixed Inc.	No Load	Load	Non-ETF	ETF
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ESG	-11.835***	-9.757***	-15.308***	-10.877***	-13.283***	-12.138***	-5.318***
	(1.555)	(1.596)	(2.394)	(1.556)	(3.358)	(1.698)	(1.686)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	537,878	752,131	323,945	949,054	127,023	1,013,264	62,813
R^2	0.532	0.523	0.471	0.544	0.511	0.505	0.437
Adj. R^2	0.532	0.523	0.471	0.544	0.511	0.505	0.436

green, and converted ESG funds, i.e., former conventional funds which switched to being ESG funds, are labelled in light blue. The fee divergence shown in both panels appears to be driven by several new funds which entered the sample in late 2015.

3.3 Robustness Checks

We conduct a number of robustness checks to challenge the finding that ESG exhibit lower expense ratios. The results are robust to alternative data sources, ESG classification methods, and specifications. Figure 2 summarizes the results by plotting the coefficient on the ESG identifier across the various robustness checks.

We replicate the analysis using three additional data sources: CRSP (Appendix G.1), Morningstar (Appendix G.2), and Eikon (Appendix G.3). The CRSP analysis uses Total Shareholder Cost (TSC), which incorporates load fees. The Morningstar analysis uses the Morningstar sustainability rating (i.e., "globes") to classify ESG funds. The Eikon analysis

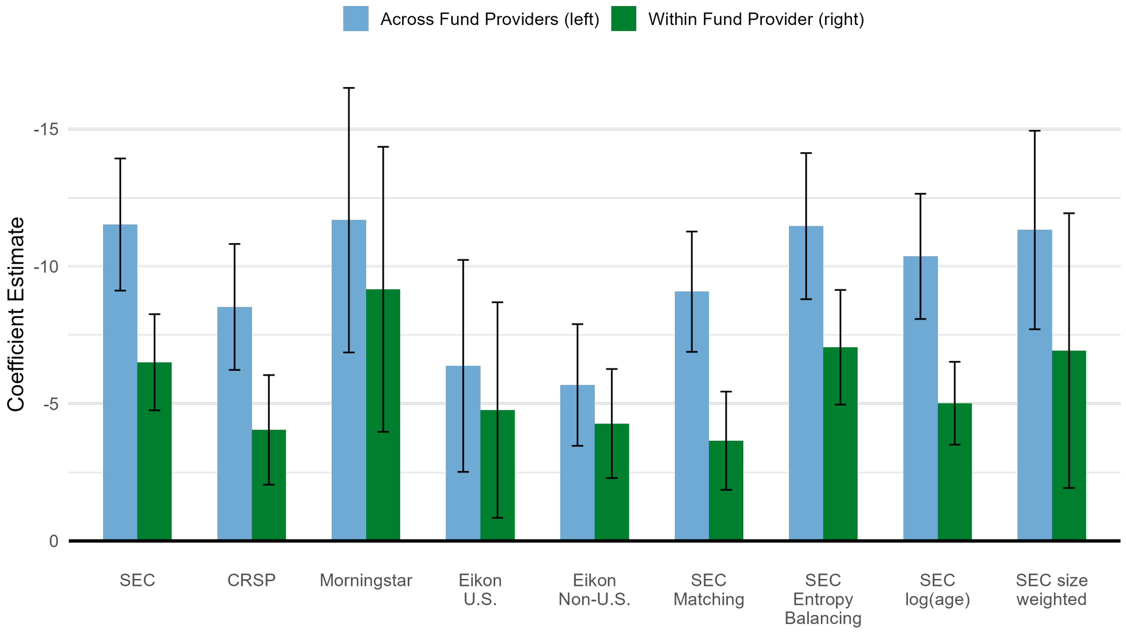


Figure 2: **Robustness of ESG Fund Fee Difference**
This figure presents the estimated difference in net expense ratios between ESG and conventional funds across various robustness checks. Note that the y-axis is inverted. Each bar represents a different specification and/or dataset. The blue bars (left) show results using the baseline specification which uses year $\times$ CRSP style fixed effects, while the green bars (right) include additional fund provider fixed effects. Error bars represent 90% confidence intervals. Standard errors are clustered at the fund provider level. Details on each robustness check are provided in the respective sections of the Appendix. "SEC" corresponds to Columns (1) and (8) in Table 1. "CRSP" corresponds to Appendix G.1. "Morningstar" corresponds to Appendix G.2. "Eikon U.S." and "Non-U.S." correspond to Appendix G.3. "SEC Matching" and "Entropy Balancing" correspond to Appendix G.4. "SEC log(age)" denotes additional specifications using the natural log of age instead of the quadratic form. "SEC size weighted" denotes additional regressions which run the baseline specification using weighted regressions, where weights are set to funds' TNA in the across-provider specification and fund family TNA in the within-provider specification.

uses Eikon's "responsible investment" fund label to classify ESG funds. It also reports similar results using a non-U.S. sample.

We also implement two methods to account for differences in fund characteristics (Appendix G.4). First, we use propensity score matching to pair each ESG fund observation with a conventional fund similar in observable characteristics. Second, we implement entropy balancing, which reweights conventional funds so that the weighted means of key covariates match those of ESG funds. Both approaches produce results consistent with our baseline results.

Our robustness checks yield results in line with the baseline specification, reinforcing the conclusion that ESG funds charge lower fees.

4 Model

Fundamentally, the emergence of ESG funds is a case of product differentiation. This section introduces a model of horizontal differentiation, in the style of Hotelling (1929).[6] The model examines how two mutual funds compete on fees in a market where investors have heterogeneous preferences. We first outline the structure of the model and its key components before deriving the equilibrium fund fees. Finally, we discuss the model's implications and how it explains the observed fee differences between funds.

The market is represented as a unit interval, $[0,1]$, where two mutual funds compete for investors. A conventional fund, C, is located at a, and an ESG fund, E, is located at $1-b$. Both funds are located within the unit interval, i.e., $0 \leq a \leq 1$ and $0 \leq b \leq 1$, with C being located to the left of E, i.e., $1-b-a \geq 0$.

Investors are distributed along the interval according to a continuous density function $g(x)$. For simplicity, we assume that this follows a uniform distribution. As is typical in Hotelling-style models, this continuum represents a preference space, where investor positions reflect their inclination toward ESG-related attributes. Since fund E is located to the right of fund C, a higher value of x corresponds to a stronger preference for ESG investing. Funds compete by simultaneously setting fees in a Bertrand competition setting. Both fund and investor locations are exogenous.

Investors can choose to invest in one of the two funds. Each investor i derives utility from investing in fund $j \in [C, E]$, given by:

$$U_{i,j} = R_j - f_j - t(x_i - x_j)^2 \tag{1}$$

where R_j is the expected return of the fund, f_j is the fee, x_i is the location of the investor along the continuum, and x_j is the location of the fund. The term t is the transport cost parameter, which captures the utility loss an investor incurs when investing in a fund that does not fully align with their preferences. A higher t implies that investors are more sensitive to deviations from their ideal fund. Transport costs are assumed to be quadratic

[6] This model is similar to the one presented in Chapter 7 of Tirole (1988). It is also similar to that of Dumitrescu and Gil-Bazo (2024), with a few notable exceptions. The model of Dumitrescu and Gil-Bazo (2024) is more complex, since it covers four funds: two ESG and two conventional funds, each group having a high- and low-quality fund. The model also has wider implications, covering certain aspects beyond fee setting. In their model, ESG funds have average fees which are equal to or higher than that of conventional funds in a covered market.

for tractability.[7] We also assume that the market is fully covered, and that no single fund dominates the entire market.

Each fund is managed by a fund manager who maximizes profit. The profit function for fund j is:

$$\Pi_j = (f_j - c_j)\, D_j - F_j \tag{2}$$

where F_j and c_j are the fixed and marginal costs, respectively, and D_j is the demand. In equilibrium, the fees f_C and f_E are set to maximize each fund's profit, given the demand of investors and the response of the other fund.

Since we assume a covered market, the total demand is fully allocated between the two funds. There exists a marginal investor at location $\tilde{x}$ who is indifferent between investing in C and E. Investors to the left of $\tilde{x}$ chose C, while investors to the right choose E. The location of this indifferent investor is determined by setting the utilities of both funds equal at $\tilde{x}$. This results in the following demand for C:

$$\tilde{x} = D_C\,(R_C, R_E, f_C, f_E) = a + \frac{1-a-b}{2} + \frac{(R_C - f_C) - (R_E - f_E)}{2t\,(1-a-b)} \tag{3}$$

Note that when $R_C - f_C = R_E - f_E$, i.e., when the expected return excess of fees is equal for each fund, demand is purely a function of the funds' locations. Demand for E is simply $D_E = 1 - \tilde{x}$.

Given the profit maximization problem faced by the fund managers, and the demand functions of the funds, we can solve for the reaction functions of the funds. Solving this system of equations results in the following equilibrium fees:

$$f_C^* = t\,(1-a-b)\left(1 - \frac{a-b}{3}\right) + \frac{R_C - R_E}{3} + \frac{2c_C + c_E}{3}, \tag{4}$$

$$f_E^* = t\,(1-a-b)\left(1 - \frac{b-a}{3}\right) + \frac{R_E - R_C}{3} + \frac{2c_E + c_C}{3} \tag{5}$$

These equilibrium fees illustrate how investor preferences, fund locations, expected returns, and marginal costs jointly determine pricing in equilibrium. While the model differs in setup and assumptions, the equilibrium fees are conceptually related to those in Berk and

[7] As shown by d'Aspremont et al. (1979), quadratic transport costs ensure the existence of a pure-strategy equilibrium, unlike linear transport costs, which often lead to price undercutting and discontinuous demand functions.

Green (2004), where fees reflect manager ability (captured in returns) and costs. The key distinction is that the Hotelling-style model employed here explicitly incorporates investor heterogeneity in preferences, allowing us to capture the role of horizontal differentiation in determining fees.

To analyze the potential drivers of fee differences between ESG and conventional funds, we express the equilibrium fee difference as follows:

$$\Delta f = f_E^* - f_C^* = \underbrace{\frac{2t}{3}(1-a-b)(a-b)}_{\text{positioning}} + \underbrace{\frac{2}{3}(R_E - R_C)}_{\text{(expected) returns}} + \underbrace{\frac{1}{3}(c_E - c_C)}_{\text{costs}} \tag{6}$$

Each term in this equation represents a distinct force influencing the relative pricing of the two funds. The first term captures the effect of fund positioning, i.e., horizontal differentiation. The expression $(1-a-b)$ captures the distance between the two funds in the product space: greater distance reduces direct competition and allows for a larger difference in fees. The expression $(a-b)$ reflects the relative locations of the funds: if $b > a$, the ESG fund is closer to the centre of investor preferences than the conventional fund, which means $f_E^* < f_C^*$, holding all else constant. In other words, ESG funds that are closer to conventional funds (i.e., less horizontally differentiated) experience greater competitive pressure and set lower fees in equilibrium.

The second term captures the role of expected returns. All else equal, investors require lower fees to compensate for lower expected performance. If ESG funds deliver lower returns than conventional funds, this term contributes negatively to Δf, consistent with lower ESG fees in equilibrium. This mechanism aligns with Berk and Green (2004), where fees have a positive relationship with fund manager skill. If investors use past returns to proxy for expected returns because it is a signal of skill, then funds with higher past performance can sustain higher fees.

The third term reflects differences in marginal cost, with greater costs contributing to higher fees. In summary, this decomposition provides a simple framework for interpreting the equilibrium fee gap. Each component offers a potential explanation (albeit not mutually exclusive) for why ESG funds might charge lower fees in equilibrium.

5 Empirical Tests of Model Implications

In this section, we test whether one of the channels is driving the fee difference. More specifically, we examine whether ESG funds (1) have delivered lower returns, and (2) are more or less horizontally differentiated from conventional funds. Since we do not observe marginal costs of funds, this differences can only be speculated upon based on the results of the performance and differentiation analyses.

5.1 Performance

First, we examine whether ESG funds underperform conventional funds in terms of realized and risk-adjusted returns. The model suggests that, all else equal, if ESG funds have lower returns than conventional funds, they should offer lower fees in equilibrium. This would also be consistent with Berk and Green (2004), where investors interpret low realized returns as a signal of lower skill and consequently demand lower fees.

To test this, we restrict the sample to active (i.e., non-index) equity funds and estimate panel regressions of realized returns and risk-adjusted returns (alphas) on a set of fund-level controls.[8] The results are presented in Table 3. We use the same sample as the baseline analysis, but use monthly observations for returns. Returns are calculated over a rolling 36-month window, and alphas are estimated from rolling 36-month time-series regressions using standard factor models. All specifications include year-month $\times$ CRSP style fixed effects. Several specifications also include fund provider fixed effects, allowing us to compare funds within the same family. Standard errors are clustered at the fund provider level. Controls include the standard deviations of returns, fund age, lagged values of fund size and family size, and institutional fund status.

Across all specifications, ESG funds exhibit significantly higher realized and risk-adjusted returns relative to conventional funds. This holds across multiple factor models. The estimated ESG coefficient ranges from approximately 4.6 to 7.8 bps per month, implying an annualized outperformance of 55 to 95 bps. The results suggest that ESG funds do not offer lower fees due to inferior performance, weakening the return-based explanation. All returns are measured net of fees, so the performance differential cannot be mechanically attributed to lower fees.

[8] Note that the fee gap is also present in this subsample of active equity funds; ESG funds exhibit expense ratios which are 9.2 bps lower than conventional funds after controlling for the baseline covariates. When comparing within fund provider, they exhibit expense ratios which are 5.9 bps lower. See Table 2 for the baseline specification split into the market segments of index funds and equity funds separately.

Table 3: **Realized and Risk-Adjusted Returns**
This table reports the results from regressions of monthly realized returns or alpha at the fund level on a set of control variables. The sample is restricted to active (i.e., non-index) equity funds. Returns are expressed net of fees. Alphas are calculated using monthly data and a 36 month window, and are reported in basis points and in monthly terms. Three-Factor α is from the model of Fama and French (1993). Four-Factor α is is from the model of Carhart (1997). Five-Factor α is is from the model of Fama and French (2015). Unreported control variables include fund age and age squared, lagged log fund size, lagged log family size, and an indicator variable denoting institutional status. All specifications use year-month × CRSP style classification fixed effects. Variable definitions can be found in the Appendix. Standard errors are clustered at the fund provider level and reported in parentheses.

	Returns		CAPM α		Three-Factor α		Four-Factor α		Five-Factor α	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ESG	4.588***	5.797***	5.998***	7.428***	6.507***	7.845***	6.118***	7.241***	5.385***	6.728***
	(1.432)	(1.781)	(1.741)	(2.419)	(1.637)	(2.212)	(1.622)	(2.164)	(1.886)	(2.518)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provider FE		Yes		Yes		Yes		Yes		Yes
Observations	2,371,854	2,371,854	1,400,812	1,400,812	1,400,247	1,400,247	1,399,598	1,399,598	1,399,519	1,399,519
R^2	0.702	0.725	0.437	0.497	0.489	0.552	0.452	0.519	0.469	0.535
Adjusted R^2	0.701	0.725	0.436	0.495	0.488	0.551	0.451	0.517	0.468	0.533

To assess whether outperformance is concentrated in specific periods, we plot the average four-factor α spread over time in Figure 3. We select the four-factor model of Carhart (1997) to control for momentum returns. The return spread was particularly high between 2020 and 2023, aligning with the theoretical framework of Pástor et al. (2021) and the empirical evidence by Pástor et al. (2022), which suggest that shifting investor preferences can temporarily boost performance in sustainable assets, and have done so in recent years.

These findings contribute to the central puzzle: if ESG funds have delivered higher after-fee performance, why have they not charged higher fees?

5.1.1 Flows

In Berk and Green (2004), fees, performance, and flows are jointly determined. Investors allocate capital to funds with higher expected after-fee returns, and in doing so, drive alphas to zero. Thus, higher observed performance should be accompanied by higher flows if investors reward skill through capital reallocation. One potential way to reconcile high performance with low fees is if ESG investors are less responsive to returns. This would dampen the link between performance and fees. Kostovetsky and Warner (2020) find that funds with more unique strategies (measured by textual similarity of fund prospectuses) exhibit lower flow-performance sensitivity, suggesting that product differentiation weakens competitive pressure.

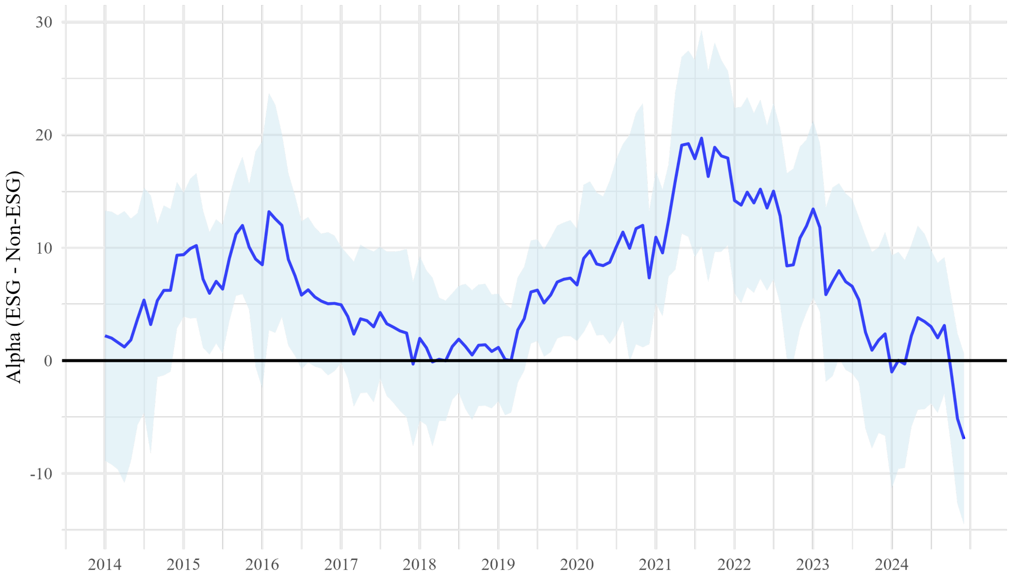


Figure 3: **Time Series of ESG Risk-Adjusted Monthly Return Differential**
This figure plots the average four-factor α difference between ESG and conventional active equity funds, in basis points per month. The shaded area represents 95% confidence intervals based on standard errors clustered at the provider level. The time series begins in 2014, as estimates prior to this period are volatile due to a smaller and less stable sample of ESG equity funds.

To test this, we estimate regressions at the fund level using percentage net flow as the dependent variable. Flows for fund i were calculated using the standard calculation from the literature:

$$Flow_t = \frac{TNA_t}{TNA_{t-1}} - (1 + R_t)$$

The key independent variables are ESG, lagged annualized eight-quarter performance ($R_{t-8,t-1}$) net of fees, and lagged net expense ratio (f_{t-1}), along with interactions. Control variables are the same as the baseline regression, with the addition of turnover ratio. All regressions include CRSP style $\times$ year fixed effects, and standard errors are clustered at the fund level. The results are reported in Table 4.

We find that ESG funds experience significantly higher flows: around 1.45 percentage points per quarter without any controls (Column 1). This effect remains statistically significant after controlling for performance (Column 2) and persists in specifications with interaction terms (Column 3). As expected, funds with stronger past performance receive greater flows. Notably, the interaction between ESG and past performance is positive and significant, suggesting that flows into ESG funds are more sensitive to returns than those into conventional funds (Columns 3 and 6).[9] This stands in contrast to the results of

[9]The higher flow-performance sensitivity for ESG funds is not driven by differences in age. While Berk and Green (2004) show that as a fund becomes older, there is more past information about the fund performance, and flows are less responsive to returns. However, we control for fund age and age squared.

Table 4: **Flows of ESG versus Conventional Funds**
This table reports the results from panel regressions using net fund flows (in percentage) as the dependent variable. The sample is restricted to active (non-index) funds. All specifications include CRSP style classification × year fixed effects. Returns ($R_{t-8,t-1}$) are the annualized cumulative (net-of-fee) returns from the previous eight quarters, lagged, and reported in percentage points. Net expense ratios (f_{t-1}) are lagged and reported in basis points. Unreported control variables include turnover ratio, fund age and age squared, log fund size, log family size, and indicator variables for ETF and institutional share classes. All specifications use year × CRSP style classification fixed effects. Variable definitions can be found in the Appendix. Standard errors are clustered at the fund level and reported in parentheses.

	Dependent variable: $Flow_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
ESG_t	1.455***	1.273***	0.680**	0.905***	0.372	-0.051
	(0.316)	(0.309)	(0.314)	(0.309)	(0.677)	(0.663)
$R_{t-8,t-1}$		0.344***	0.341***			0.333***
		(0.007)	(0.007)			(0.007)
$ESG \times R_{t-8,t-1}$			0.093***			0.100***
			(0.028)			(0.027)
f_{t-1}				-0.055***	-0.055***	-0.054***
				(0.001)	(0.001)	(0.001)
$ESG \times f_{t-1}$					0.005	0.002
					(0.005)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	723,085	723,085	723,085	723,085	723,085	723,085
R^2	0.032	0.037	0.037	0.038	0.038	0.043
Adj. R^2	0.032	0.037	0.037	0.037	0.037	0.042

Kostovetsky and Warner (2020), who show that funds with more unique strategies exhibit lower flow-performance sensitivity.

Together, this makes the low fees charged by ESG funds even more puzzling. From the perspective of Berk and Green (2004), stronger past performance, together with higher return sensitivity, should justify *higher* fees, not lower. Additionally, we find no evidence of stronger fee sensitivity that might explain such pricing.

5.2 Positioning, Uniqueness, and Competition

The model predicts that fees decline when competition intensifies, represented by funds being located closer together in the product space. This prediction aligns with the literature linking product differentiation to pricing power in mutual funds. For example, Hoberg et al. (2018) observe that funds experiencing less competition in the style space earn higher fees. Wahal and Wang (2011) show that incumbent funds lower their fees following the arrival of an entrant with high portfolio overlap. Similarly, Li and Qiu (2014) show that funds with more unique factor exposures charge higher fees.

Empirically, the product space is unobservable, but we approximate it using text-based and holdings-based similarity measures. More specifically, we construct two types of uniqueness measures: global and local. These correspond to the separate effects in the positioning component of Equation 6: $(1 - a - b)(a - b)$.

The term $(1 - a - b)(a - b)$ captures two features: the distance between the ESG and conventional fund (through $1 - a - b$) and their relative location in the market (through $a - b$). In a simple two-fund model such as our own, these are tightly linked. However, in a richer setting with many funds, these components can be conceptually separated. Our global uniqueness measure captures how far a fund is from the rest of the market, i.e., how central it is positioned relative to all other funds. This maps to the $a - b$ term, which determines the effect on fees due to relative location along the continuum.[10] Local uniqueness focuses on the proximity to the most similar competitors, and maps to the $1 - a - b$ component which determines the effect on fees due to how tightly clustered the competitors are.[11]

These uniqueness measures are derived from both the textual descriptions of the investment strategy and portfolio holdings. We begin by computing cosine similarity between all eligible fund pairs in each quarter, using either (1) TF-IDF vectors of the Principal Investment Strategy (PIS) text or (2) portfolio weight vectors. The pairwise cosine similarity measures are aggregated to the fund level by averaging over all other funds (for the global measure) and over the ten closest peers in terms of cosine similarity and subject to filtering conditions such as being from a different fund family and matching on CRSP style (for the local measure). Finally, following Kostovetsky and Warner (2020) uniqueness values are calculated by orthoganalizing the cosine similarity measures to (1) number of unique words in the PIS or (2) number of holdings. Appendix H provides further details on the construction of the measures.[12]

[10] Remember that the conventional and ESG funds are located at a and $1 - b$, respectively, so if $b > a$, then the ESG fund is located closer to the centre of the continuum. This means the term $a - b$ is negative.

[11] Remember that since the funds are located at a and $1 - b$, the term $1 - a - b$ denotes the distance between the two funds.

[12] This approach is conceptually similar to the Broad Similarity and Product Similarity measures of Hoberg and Phillips (2010), where global uniqueness resembles the former and local uniqueness the latter.

Figure 4 plots the time series estimates of ESG fund uniqueness relative to conventional funds, estimated from panel regressions including the standard controls. All specifications include CRSP style fixed effects. Each panel reports the ESG coefficient by quarter, with shaded bands denoting 95% confidence intervals based on standard errors clustered at the provider level. The sample is restricted to equity funds which have values for all four measures of uniqueness.

Panels A and B present results for text-based uniqueness (U^{Global}_{Text} and U^{Local}_{Text}). ESG funds exhibit persistently high global text uniqueness (Panel A), with values well above one standard deviation above the mean for much of the sample. While the level gradually declines, it remains large and significant throughout. The local text uniqueness estimates (Panel B) show a similar pattern, albeit at a slightly lower level and with a more pronounced decline in 2016. These results are consistent with the idea that ESG funds use distinct language in their strategy, especially relative to nearby peers, which is evidence of horizontal differentiation. Panels C and D show the corresponding estimates for holdings-based uniqueness ($U^{Global}_{Hold.}$ and $U^{Local}_{Hold.}$). Both global (Panel C) and local (Panel D) uniqueness measures decline steadily over the sample period. Since 2015, ESG funds are less unique than the average conventional fund in the universe (i.e., global) in terms of holdings. While ESG funds exhibited high local holdings uniqueness early in the sample, the difference was insignificant by 2018, suggesting that ESG funds increasingly resembled their closest peers in terms of portfolio composition.

In summary, this suggests that while ESG funds have consistently positioned themselves as textually unique, their actual portfolio differentiation has weakened over time, particularly relative to close competitors.

To validate the measures of uniqueness, and to show the link between fees and uniqueness, we run regressions of net expense ratios on the global and local holdings measures and the set of control variables. Following Kostovetsky and Warner (2020), some specifications interact uniqueness with log fund family TNA to explore whether the relationship varies based on fund family size. The results are reported in Table 5. The results are consistent with Kostovetsky and Warner (2020) and show that more unique funds, particularly locally, charge higher fees. The effect is stronger for smaller fund families.

Crucially, however, controlling for uniqueness does not eliminate the ESG fee gap. The difference between the *ESG* coefficient in Column (1) and the other columns which control for uniqueness (Columns 2-7) is not significant, since it is often less than the

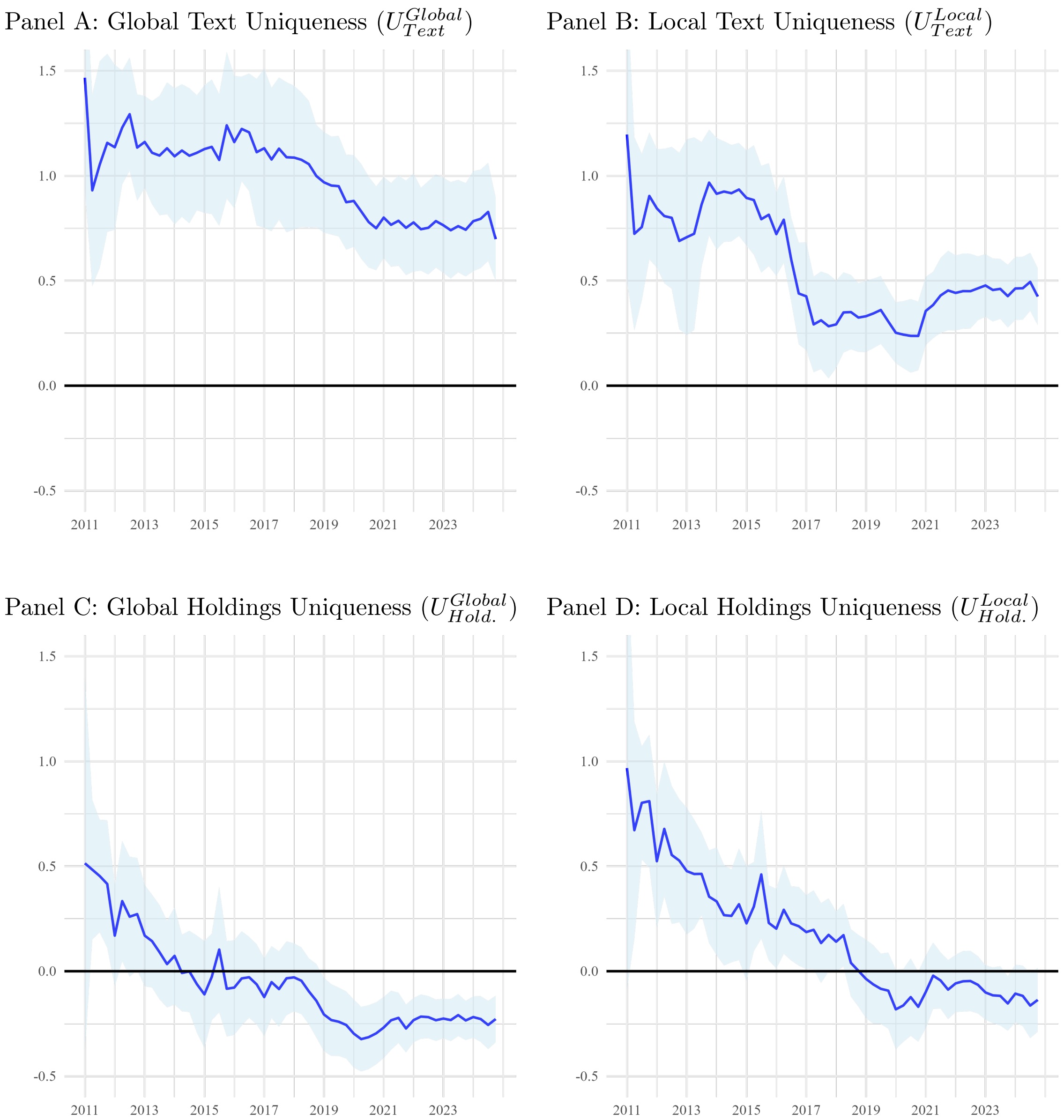


Figure 4: **Time Series of Global and Local Uniqueness for ESG Funds**
This figure presents the estimated time trends in uniqueness for ESG funds along two dimensions: text-based and holdings-based, each computed at both the global and local levels. The sample is restricted to equity funds which have values for all four measures of uniqueness. Each panel shows quarterly coefficient estimates from regressions of the respective uniqueness measure on ESG status, controlling for fund age, age squared, log total net assets, log family total net assets, index fund status, ETF status, and institutional share class. The regressions include CRSP style and quarter fixed effects. Shaded areas represent 95% confidence intervals based on standard errors clustered at the fund provider level.

standard error on the coefficient (i.e., 1.64). If uniqueness were the driver of low ESG fund fees, then the coefficient on ESG should have lost significance or flipped sign when uniqueness is controlled for. This reinforces the puzzle by providing evidence that the low fees of ESG funds are not driven by low uniqueness, or more generally, heightened competition.

Table 5: **Explaining Fees using Uniqueness**
This table reports the results from panel regressions using expense ratio as the dependent variable. Expense ratios are reported in basis points and in annual terms. Unreported control variables include fund age and age squared, log fund size, log family size, and indicator variables for index, ETF, institutional status. All specifications use year × CRSP style classification fixed effects. Variable definitions can be found in the Appendix. Standard errors are clustered at the fund provider level and reported in parentheses.

	Dependent variable: Exp. Ratio						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ESG	-8.869***	-8.075***	-7.960***	-7.035***	-9.057***	-8.840***	-8.857***
	(1.640)	(1.668)	(1.654)	(1.679)	(1.675)	(1.653)	(1.684)
U_{Text}^{Global}		13.414***		12.077**			
		(4.759)		(4.750)			
$U_{Text}^{Global} \times log(Fam.)$		-0.578***		-0.530***			
		(0.199)		(0.199)			
$U_{Hold.}^{Global}$			17.662***	17.128***			
			(4.010)	(3.994)			
$U_{Hold.}^{Global} \times log(Fam.)$			-0.523***	-0.501***			
			(0.160)	(0.159)			
U_{Text}^{Local}					28.760***		26.393***
					(5.137)		(5.108)
$U_{Text}^{Global} \times log(Fam.)$					-1.141***		-1.061***
					(0.215)		(0.214)
$U_{Hold.}^{Local}$						18.824***	17.782***
						(4.115)	(4.078)
$U_{Hold.}^{Local} \times log(Fam.)$						-0.586***	-0.549***
						(0.168)	(0.166)
log(Fam.)	-1.880***	-2.000***	-1.729***	-1.851***	-1.362***	-1.659***	-1.199***
	(0.263)	(0.275)	(0.265)	(0.278)	(0.256)	(0.257)	(0.253)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	407,261	407,261	407,261	407,261	407,261	407,261	407,261
R^2	0.561	0.562	0.565	0.565	0.563	0.565	0.567
Adjusted R^2	0.561	0.561	0.565	0.565	0.563	0.565	0.567

To isolate the effect of ESG classification on fund characteristics and fees, we estimate panel regressions with fund fixed effects. This approach absorbs all time-invariant differences across funds and providers. It enables us to examine whether outcomes change within the same fund when it switches ESG status and begins to compete in the ESG market segment. The analysis focuses on a subset of 396 funds that switch ESG classification during the sample period: 330 funds adopt an ESG mandate, 94 remove it, and 28 switch in both directions.

We begin by testing whether funds become more or less differentiated when they adopt an ESG mandate. Table 6 shows that ESG classification is associated with a statistically significant increase in textual uniqueness, both globally and locally. In contrast, global holdings uniqueness remains unchanged, while local holdings uniqueness increases modestly. These results reinforce our earlier finding: ESG funds primarily differentiate themselves through how they describe their strategy, rather than through distinct portfolio choices. If horizontal differentiation enables higher pricing power, one would expect funds to charge higher fees when they are more unique.

Table 6: **Uniqueness and Fees of Converted ESG Funds**
This table reports the results from within-fund panel regressions. The dependent variable is stated above the column number. The sample is restricted to funds with experience a change in the *ESG* varible in the sample, i.e., funds which experienced a change in ESG mandate. Expense ratios are reported in basis points and in annual terms. All specifications use year × CRSP style classification fixed effects in addition to fund fixed effects. Unreported control variables include fund age and age squared, log fund size, log family size, and indicator variables for index, ETF, institutional status. Variable definitions can be found in the Appendix. Standard errors are clustered at the fund provider level and reported in parentheses.

	Dependent variable:				
	U^{Global}_{Text}	U^{Local}_{Text}	$U^{Global}_{Hold.}$	$U^{Local}_{Hold.}$	Exp. Ratio
	(1)	(2)	(3)	(4)	(5)
ESG	0.482***	0.423***	-0.044	0.076*	-3.486***
	(0.067)	(0.052)	(0.058)	(0.045)	(1.102)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	14,458	13,994	7,933	7,866	15,265
R^2	0.865	0.809	0.912	0.873	0.973
Adjusted R^2	0.859	0.799	0.908	0.867	0.972

However, Column (5) of Table 6 reveals the opposite. Funds charge significantly lower net expense ratios, by approximately 3.5 basis points, during periods when they are classified as ESG. This is consistent with evidence by Gibbon et al. (2025), who find lower fees for funds that rename to become ESG funds.

The combination of these results reinforces the central puzzle. ESG funds become more unique in terms of disclosure, and only slightly less unique in terms of holdings, yet they charge *lower* fees. This pattern is difficult to reconcile with standard models of horizontal differentiation, where greater substitutability (i.e., lower uniqueness) increases competitive pressure and drives prices down. Both theory and prior empirical work suggest there is a negative relationship between differentiation and fees (e.g., Bonelli et al., 2021; Cremers et al., 2016; Hoberg et al., 2018; Kostovetsky & Warner, 2020; Li & Qiu, 2014; Sun, 2021; Wahal & Wang, 2011). If competition were the driver of our findings, we would expect switching funds to become less unique upon entering the ESG segment, and for that loss of uniqueness to correspond to lower fees. Instead, we observe the opposite: funds become more textually unique and yet charge lower fees. This contradiction between theoretical prediction and empirical outcome deepens the central puzzle motivating our analysis.

6 Discussion

Our empirical tests rule out two explanations from the literature as to why ESG funds exhibit low fees. First, in the framework of Berk and Green (2004), higher past performance signals manager skill and supports higher fees in equilibrium. We find that ESG funds exhibit stronger past performance and greater sensitivity of flows to performance, yet they charge *lower* fees. Second, the literature on product differentiation shows that uniqueness is associated with reduced competition and greater pricing power (e.g., Hoberg et al., 2018; Kostovetsky & Warner, 2020; Li & Qiu, 2014). While ESG funds are textually more differentiated, this does not translate into higher fees. Controlling for textual and holdings-based uniqueness fails to eliminate the fee gap.

In this section, we discuss six alternative explanations. We begin with three less plausible explanations before turning to three more plausible explanations.

First, it is unlikely that ESG funds have lower marginal costs than conventional funds. It can easily be argued that ESG funds incur higher research costs due to additional investment screening and purchasing of third-party data, and due to additional governance structures such as advisory/oversight committees. These features suggest that ESG funds should face higher, not lower, marginal costs. Also, while it is plausible that ESG funds experience cost savings due to lower turnover (60% compared to 77% for conventional funds, see Appendix D), these trading costs are reflected in the return, not the fees.[13] Overall, the cost structure of ESG funds should, if anything, support higher fees.

Second, we find no evidence that ESG funds use low initial fees as a strategy to attract investors and subsequently raise fees. This is suggested by Christoffersen (2001) as a potential explanation for the use of waivers. In Appendix I, we show that ESG funds decrease their fees more than conventional funds, even when they discontinue a waiver.

[13] More information about this can be found here: https://www.sec.gov/news/studies/feestudy.htm.

Third, the ESG fee gap is not a byproduct of distribution channel effects. Sun (2021) observes that funds which are directly sold to investors (as opposed to through a broker) exhibit lower fees, largely due to competitive pressure from low-cost Vanguard index funds. While a higher portion of ESG funds are in the direct sold channel (68% of fund-quarter observations, versus 57% for conventional funds), this does not explain the fee gap when controlled for in panel regressions. When we run the baseline regressions on direct-sold and broker sold funds separately (as done in Table 2) using the proxy proposed by Sun (2021), we find that across fund providers, direct-sold ESG funds have fees 6.9 bps lower (8.9% of the mean), and broker-sold ESG funds have fees 13.3 bps lower (9.4% of the mean) than conventional funds.

A more plausible explanation is that ESG funds generate reputational benefits for providers. Offering ESG products may help asset managers retain investors by aligning with their values, satisfy internal sustainability goals, or reduce reputational and regulatory risks. These benefits may offset part of the marginal cost of offering ESG products, allowing for lower fees in equilibrium. If reputational gains include a fixed-cost component, they could also lower the effective breakeven point for launching ESG funds and increase market entry, intensifying competition even without marginal cost advantages.

Another possibility is that fund providers overestimated the growth potential of ESG investing and priced ESG funds under the assumption that they would quickly reach a large scale. Expecting high future assets under management, fund providers may have entered the market with low fees to attract early flows. Given that fee increases are uncommon in the mutual fund industry, these low initial fees may have persisted even as asset growth fell short of expectations.

Finally, on the demand side, a plausible explanation is that ESG investors are more sensitive to fees when selecting among funds. While our flow-fee regressions find no clear difference in price sensitivity between ESG and conventional funds, this may be due to the low time-series variation in fees. Additionally, fee sensitivity may matter most at the time of fund entry, and our analysis excludes very young funds due to return lags. While we have no direct evidence of heightened fee sensitivity among ESG investors, it remains plausible based on prior literature. Pool et al. (2024) find that 401(k) plan fees are lower for residents of more educated and higher-income areas in the U.S., and Giglio et al. (2025) show that wealthier investors tend to allocate more of their portfolio to ESG investments. This could result in a form of Simpson's paradox: within each market segment defined by fee sensitivity, ESG funds may charge higher fees, but the overall correlation between ESG status and lower fees may arise because ESG funds are more prevalent in segments with higher fee sensitivity.

In summary, while the proposed explanations for the ESG fee gap are plausible, they rely on unobservable factors such as internal cost structures, growth expectations, and reputational motives, making them difficult to test directly outside of an experimental or proprietary data setting. Nonetheless, they point to a broader need for models that incorporate investor heterogeneity, fund-family objectives, and strategic pricing decisions in explaining how fees are set in differentiated mutual fund markets.

7 Conclusion

This paper documents a robust anomaly in the pricing of U.S. mutual funds: ESG funds charge lower net expense ratios than conventional funds, despite offering horizontal differentiation and targeting investors with a demonstrated willingness to pay. Using comprehensive panel data from 2011 to 2024, we show that ESG funds are 11.5 basis points cheaper than conventional funds across providers, and 6.5 basis points cheaper within providers. This pricing gap persists across ESG classifications, market segments, and empirical specifications.

To interpret this finding, we develop a Hotelling-style model of horizontal differentiation in which fees reflect expected returns and the degree of product differentiation. The model predicts that funds with lower expected returns and greater competition should charge lower fees. We empirically test both channels. First, we show that ESG funds have outperformed conventional funds net-of-fees, and attract both stronger flows and greater flow-performance sensitivity. Second, we construct four measures of differentiation using both investment strategy text and portfolio holdings, both calculated relative to global and local peers. ESG funds exhibit greater textual uniqueness, and this form of differentiation is positively associated with fees in the broader market, but not for ESG funds. Additionally, portfolio uniqueness among ESG funds has declined over time, suggesting increasing competition. However, this does not explain the fee gap.

These findings are not consistent with the two dominant frameworks used to explain mutual fund fee setting. In models of rational investor learning, such as Berk and Green (2004), stronger performance and higher return sensitivity should justify higher fees. In industrial organization models, greater product differentiation reduces competitive pressure and supports higher fees. ESG funds contradict both predictions: they perform well, are more differentiated, yet charge lower fees. This suggests that existing models may be incomplete in capturing how fees are set for differentiated financial products, and that new frameworks should account for reputational incentives, investor heterogeneity, and the strategic pricing of new fund offerings.

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Appendices

A Variable Definitions

Variable Name	Variable Definition
ESG	A dummy variable which takes the value of one if the fund has an ESG keyword in its name. The keywords are the following: • Case sensitive: ESG, CSR, SRI, SDG. • Case insensitive: enviro, ethic, responsib, sustain, climate, carbon, clean, social, diversity, governance, impact, green, just, renewable, pollution, human rights, fossil, fossil free, net zero, women in leadership, gender, better world, screen, earth, solar, wind energy, conscious, transition, biological, toxic, pax, parnassus, equality, ecolog, epiphany. Note that some terms include leading and trailing spaces so that funds are not misclassified solely based on company name (e.g., Greenhill & Co.). Additionally, following Michaely et al. (2024), the following exclusions are applied to prevent false positives: sustainable dividend, sustainable growth, sustainable momentum, social media.
Age	Age of the fund in years since the first offer date (CRSP variable `CALDT` for current date and `FIRST_OFFER_DT` for first offer date).
$log(TNA)$	The natural log of the TNA of the fund (CRSP variable `TNA_LATEST`).
$log(Family)$	The natural log of the TNA of the fund family, where family is defined as the fund management company (CRSP variable `MGMT_CD`).
Index	A dummy variable which takes the value of one if the fund is an index fund (CRSP variable `INDEX_FUND_FLAG`). We also label a fund as an index fund if the term "index" is used in the fund name.
ETF	A dummy variable which takes the value of one if the fund is an ETF or ETN (CRSP variable `ET_FLAG`).
Inst.	A dummy variable which takes the value of one if the fund is an institutional fund (CRSP variable `INST_FUND`).
Dead	A dummy variable which takes the value of one if the fund is no longer active (CRSP variable `DEAD_FLAG`).
Turnover Ratio	The turnover ratio of the fund in percent. This is defined by CRSP as the "minimum (of aggregated sales or aggregated purchases of securities), divided by the average 12-month total net assets of the fund" (CRSP variable `TURN_RATIO`).
(Net) Expense Ratio (SEC)	"Total annual fund operating expenses after fee waiver or expense reimbursement" as a percentage of assets, according to the *Mutual Fund Risk/Return Summary Taxonomy Preparers Guide* from the SEC. The file can be accessed here. SEC variable `NetExpensesOverAssets`.
Gross Expense Ratio (SEC)	"Total annual fund operating expenses" as a percentage of assets, according to the SEC. This is the sum of management, distribution, acquired, and other fees. SEC variable `ExpensesOverAssets`. If this value is missing, we take the sum of the individual fee components, defined below.
Management Fee (SEC)	Management fees as a percentage of assets. These fees are "generally paid out of fund assets to its adviser in exchange for managing the fund," according to the SEC (see the SEC Glossary here). SEC variable `ManagementFeesOverAssets`.
Distribution Fee (SEC)	Marketing, promotion, service, and distribution expenses as a percentage of assets. This corresponds to the sum of the following SEC variables: `DistributionAndService12b1FeesOverAssets` and `DistributionOrSimilarNon12b1FeesOverAssets`. If both values are not reported, this is considered zero.

Continued on next page

Variable Name	Variable Definition
Acquired Fee (SEC)	Fees originating from funds held by the fund as a percentage of assets, therefore relevant for "fund-of-funds." SEC variable `AcquiredFundFeesAndExpensesOverAssets`.
Other Fee (SEC)	All other expenses as a percentage of assets which are not included in management, acquired, or distribution fees, and can include legal, custodian, accounting, administration, and transfer agency fees. This is SEC variable `OtherExpensesOverAssets`, or, if the value is missing, the sum of `Component1OtherExpensesOverAssets`, `Component2OtherExpensesOverAssets`, and `Component3OtherExpensesOverAssets`. If all values are missing, this is considered zero.
Waiver Amount (SEC)	Fee waivers or reimbursements as a percentage of assets. A negative value indicates a positive waiver, i.e., a fee reimbursement given to investors. SEC variable `FeeWaiverOrReimbursementOverAssets`.
$Waiver$	A dummy variable which takes the value of one if the fund has reported a waiver/reimbursement.
CRSP Style	The CRSP style code (variable `CRSP_OBJ_CD`). Refer to the CRSP Survivor-Bias-Free US Mutual Fund Guide for a breakdown of the classification and a mapping to Lipper, Strategic Insights, and Wiesenberger fund codes.
(Net) Expense Ratio (CRSP)	The expense ratio of the most recently completed fiscal year. Reported as a percent of total assets, in basis points (CRSP variable `EXP_RATIO`). As stated in the CRSP Survivor-Bias-Free US Mutual Fund Guide: "[this data point] may include waivers and reimbursements, causing it to appear less than the management fee."
Management Fee (CRSP)	The management fee of the most recently completed fiscal year. Reported as a percent of total assets, in basis points (CRSP variable `MGMT_FEE`). As stated in the CRSP Survivor-Bias-Free US Mutual Fund Guide: "The management fee can be offset by fee waivers and/or reimbursements which will make this value differ from the contractual fees found in the prospectus. Reimbursements can lead to negative management fees."
Distribution Fee (CRSP)	The actual 12b-1 fee of the most recently completed fiscal year. Reported as a percent of total assets, in basis points (CRSP variable `ACTUAL_12B1`).
TSC (CRSP)	Total Shareholder Cost, which is calculated as the sum of the maximum front and rear load (after five years of holding), divided by five, plus the net expense ratio. Load fees and expense ratios are from CRSP.
$FrontLoad$	A dummy variable which takes the value of one if the fund has a front load. Load data is from CRSP.

B Literature on ESG Fund Fees

Authors	Type	ESG Fees	ESG Identification	Sample Period	Sample Location	Data Source	Fee Analysis	Source in Paper	Comments
Cao et al. (2023)	Journal article	Higher	Label (Morningstar)	2004-2016	US	Morningstar; CRSP	Descriptive statistics	Table A1 (Appendix)	Asset-weighted mean expense ratio by fund category
Fisch and Robertson (2023)	Journal article	Lower	Keywords	2015-2021	US	CRSP	Regressions	Table 2	ESG funds are matched to sister funds in the same family
Geczy et al. (2021)	Journal article	Higher	Mixed	1963-2001	US	CRSP	Descriptive statistics	Table 2	Small sample: 36 ESG funds
Gibbon et al. (2025)	Journal article	Lower	Keywords	2015-2023	US	Eikon	Descriptive statistics	Table A9 (Appendix)	Covers renamed funds
Gil-Bazo et al. (2010)	Journal article	Similar / Lower	Label (Social Investment Forum)	1997-2005	US	CRSP	Regressions	Table V to X	Performs matching
Henke (2016)	Journal article	Lower	Label (Social Investment Forum)	2001-2014 (US); 2010-2014 (Europe)	US and Europe	CRSP (US) and Bloomberg (Europe)	Descriptive statistics	Table 1	Covers bond mutual funds. ESG fund fees are lower both in the US and Europe.
Raghunandan and Rajgopal (2022)	Journal article	Similar/ Higher	Label (Morningstar)	2010-2018	US	Morningstar; CRSP; SEC	Regressions	Table 9	Depends on regression specification; overall, no fee difference (Column 2), but non-low carbon ESG funds have higher fees (Column 4).
Andrikogiannopoulou et al. (2022)	Working paper	Similar	Mixed: keywords	2011-2020	US	CRSP; SEC	Descriptive statistics	Table 1	
Baker et al. (2024)	Working paper	Lower	Mixed: label (Morningstar)	2019-2023	US	Morningstar; CRSP	Descriptive statistics	Table 1	
Cremers et al. (2024)	Working paper	Similar	Mixed: keywords, label (Morningstar)	2003-2021	US	CRSP	Descriptive statistics	Table 1	

Continued on next page

Authors	Type	ESG Fees	ESG Identification	Sample Period	Sample Location	Data Source	Fee Analysis	Source in Paper	Comments
Csiky et al. (2024)	Working paper	Higher	Keywords	2000-2022	US	Morningstar	Descriptive statistics	Table 1	
Huij et al. (2023)	Working paper	Higher	Mixed: keywords, label (Morningstar)	2007-2015	US	Morningstar; CRSP; SEC	Regressions	Table 3	Some regression specifications show insignificant fee differences. Data is aggregated from share class to fund level.
Lowry et al. (2022)	Working paper	Mixed	ESG Score (MSCI)	2013-2020	US	CRSP	Descriptive statistics	Table 2	Depends on whether fund is "committed," i.e., has large ESG investments
Darpeix (2024) /AMF	Report	Lower	Mixed: keywords, label	2017-2022	France	Internal	Regressions	Table 9	
ESMA (2022a, 2022b)	Report	Lower	Label (Morningstar)	2019-2021	Europe	Internal	Regressions	Tables 5 and 6	
FMA (2022)	Report	Similar/ Lower	Label	2024	Austria	Internal	Regressions	Table 7	Depends on label; the "EcoLabel 49" funds have lower fees, whereas Article 8 and 9 SFDR do not

C Additional Information on Fee Decomposition

Figure 5 illustrates the decomposition of reported annual fee items according to the XBRL U.S. Mutual Fund Risk/Return Summary Taxonomy from the SEC. All fee items are expressed as a percentage of TNA in annual terms and reported in basis points.

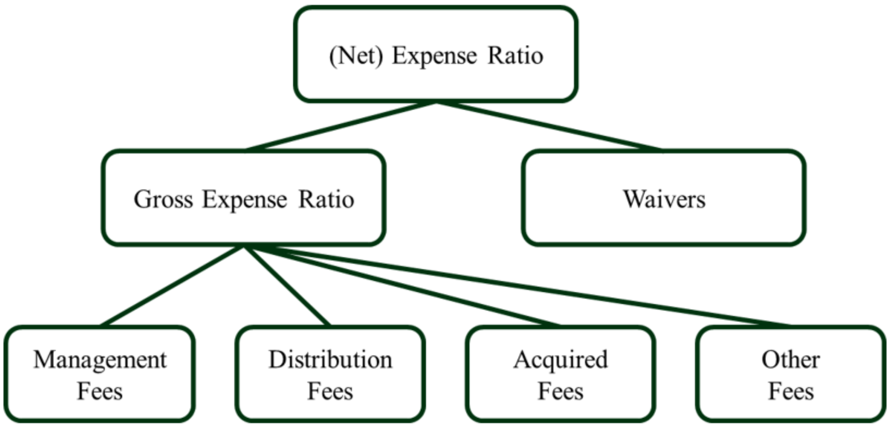

Figure 5: **Annual Fee Decomposition**
This figure presents the decomposition of reported annual fee items according to the XBRL US Mutual Fund Risk/Return Summary Taxonomy. A link denotes that the lower item is a subset of the upper item (e.g., the net expense ratio is calculated as the sum of the gross expense ratio and waivers). For further details, refer to the "Mutual Fund Risk/Return Summary Taxonomy Preparers Guide" from the SEC, available at: https://xbrl.sec.gov/rr/rrsummaryfilinginfo.htm. This decomposition does not include load fees, which are not part of the annual expense ratio. Variable definitions can be found in the Appendix.

The net expense ratio consists of the gross expense ratio and waivers. The gross expense ratio includes all costs associated with operating the fund, including contracted fees covering management, marketing and distribution, administration, and custodial services. Any increase in contracted fees requires approval from the fund's Board of Directors. Waivers, on the other hand, are voluntary reductions applied by the fund management to lower contractual fees, thereby reducing the net expense ratio. Christoffersen (2001) provides a detailed discussion of the use of waivers in mutual funds. Acquired fees arise from funds within a fund's portfolio, and are only relevant for "funds-of-funds." Distribution fees, commonly referred to as 12b-1 fees in the U.S., cover marketing and promotional expenses. "Other fees" include legal, custodian, accounting, administration, and transfer agency fees, none of which fall under management, acquired, or distribution fees.

D Descriptive Statistics

Table 9: **Descriptive Statistics**
This table reports the descriptive statistics of the sample, grouped by *ESG*. The t-stat is from a Welch's t-test comparing the means across the groups. Continuous values are winsorized at the 1% level across the sample. Panel A contains fee data points in annual terms at the fund-quarter level. Panel B contains additional variables at the fund-quarter level. Panel C contains variable at the fund-month level. Variable definitions can be found in Appendix A. Fees and returns are displayed in basis points.

	Conventional Funds						ESG Funds						
Panel A	Count	Mean	Std	25%	50%	75%	Count	Mean	Std	25%	50%	75%	t-Stat
(Net) Exp. Ratio	1,049,348	102.61	54.21	65	95	135	26,729	84.49	50.06	48	75	113	-58.31
Gross Exp. Ratio	1,049,348	137.31	132.93	72	108	160	26,729	145.70	155.73	61	103	170	8.72
Waiver Amt.	1,049,348	-34.03	117.02	-17	-1	0	26,729	-60.98	140.58	-50	-8	0	-31.07
Mgmt. Fee	1,047,325	53.52	31.35	30	55	75	26,729	50.85	26.02	30	50	71	-16.49
Dist. Fee	959,006	25.18	33.84	0	7	25	23,687	19.33	31.26	0	0	25	-28.39
Acquired Fee	348,081	27.55	29.87	1	14	51	5,283	19.96	24.25	1	5	42.50	-22.49
Other Fees	1,049,348	51.25	119.39	11	23	42	26,729	73.81	142.52	7	27	69	25.66
Panel B	Count	Mean	Std	25%	50%	75%	Count	Mean	Std	25%	50%	75%	t-Stat
Age (years)	1,049,348	11.50	9.13	5	9	16	26,729	8.62	8.37	2	5	12	-55.31
TNA (m. USD)	1,049,348	903.75	5869.10	5.60	44.80	277.40	26,729	253.11	981.79	2.30	17.40	121.60	-78.39
Fam. TNA (b. USD)	1,049,348	392.87	872.21	19.64	88.09	283.17	26,729	643.83	1316.78	9.88	58.38	353.92	30.99
Index	1,049,348	0.09	0.28	0	0	0	26,729	0.19	0.39	0	0	0	42.36
ETF	1,049,348	0.06	0.23	0	0	0	26,729	0.15	0.36	0	0	0	43.17
Inst.	1,049,348	0.57	0.50	0	1	1	26,729	0.63	0.48	0	1	1	19.57
Dead	1,049,348	0.27	0.44	0	0	1	26,729	0.17	0.37	0	0	0	-41.73
Turnover Ratio (%)	930,046	77.16	177.66	22	43	80	23,161	60.22	102.66	21	36	65	-24.22
Flow (%)	1,038,380	5.27	37.27	-4.96	-1	4.21	26,012	7.45	36.38	-3.32	0.10	6.61	9.51
Returns ($R_{t-8,t-1}$)	886,131	621.65	851.25	84.58	464.48	1086.75	19,142	686.56	1032.83	-30.32	511.21	1326.10	8.63
U^{Global}_{Text}	967,530	-0.18	0.96	-0.89	-0.22	0.43	26,360	0.68	0.92	-0.02	0.67	1.37	150.23
U^{Local}_{Text}	949,659	-0.06	0.96	-0.70	-0.05	0.62	24,967	0.70	0.79	0.24	0.75	1.28	149.52
$U^{Global}_{Hold.}$	464,041	-0.07	0.96	-0.84	0.34	0.67	15,573	-0.38	0.98	-1.26	-0.14	0.51	-39.06
$U^{Local}_{Hold.}$	453,560	-0.04	0.92	-0.71	0.09	0.68	15,402	-0.13	0.87	-0.82	-0.01	0.58	-12.06
Panel C	Count	Mean	Std	25%	50%	75%	Count	Mean	Std	25%	50%	75%	t-Stat
Monthly Ret.	3,098,626	55.52	353.83	-89.21	44.71	218.98	77,613	62.48	420.97	-167.41	68.23	301.26	4.57
CAPM α	1,549,937	-27.47	40.52	-45.07	-22.10	-4.16	38,515	-22.38	41.36	-39.84	-15.79	0.04	23.87
Three-Factor α	1,549,365	-24.97	34.73	-38.44	-19.48	-4.82	38,515	-21.44	37.71	-37.39	-15	-1.05	18.21
Four-Factor α	1,548,667	-23.32	32.43	-36.77	-18.53	-4.44	38,470	-20.38	36.26	-36.10	-14.54	-0.78	15.75
Five-Factor α	1,548,565	-22.58	35.02	-37.29	-18.03	-3.05	38,473	-21.85	39.07	-39.81	-15.86	-1.26	3.62

E Level of Clustering

We opt for using clustered standard errors in our analysis to allow for some amount of residual correlation. Fees are fairly stable over time for funds, so it could be argued that residuals are correlated over time for the same fund. However, clustering only by time might not be suitable because it assumes that standard errors in the cross-section are not correlated.

There is no consensus in the literature on the level of clustering of standard errors for regressions of fund fees on fund characteristics. Dannhauser and Spilker (2023), Gil-Bazo and Ruiz-Verdú (2009), Khorana et al. (2009), and Li and Qiu (2014) use standard errors clustered at the fund level. Cooper et al. (2021) and Wahal and Wang (2011) do not cluster standard errors, but rather use Fama and MacBeth (1973) t-statistics, which account for cross-sectional correlation. Some analyses uses two-way clustering: Sun (2021) clusters at the fund family and year level, Cremers et al. (2016) cluster at the country of domicile and year level, and Khomyn et al. (2024) cluster at the fund and year level.

For completeness, we show results using several levels of clustering and present it in Figure 6. The across fund provider specification corresponds to Column (1) in Table 1 and the within fund provider corresponds to Column (8). The circles are the point estimates, and the lines represent the 95% confidence intervals. In the baseline specification, the results remain significant across clustering levels. In our main analysis, we decided to cluster on the fund provider level, since it is likely that the fees and fund characteristics are correlated within fund provider. It also takes a more conservative approach than the previous literature, as clustering at the fund provider produces the largest standard errors in the within fund provider specifications, and nearly the largest standard errors in the across fund provider specifications.

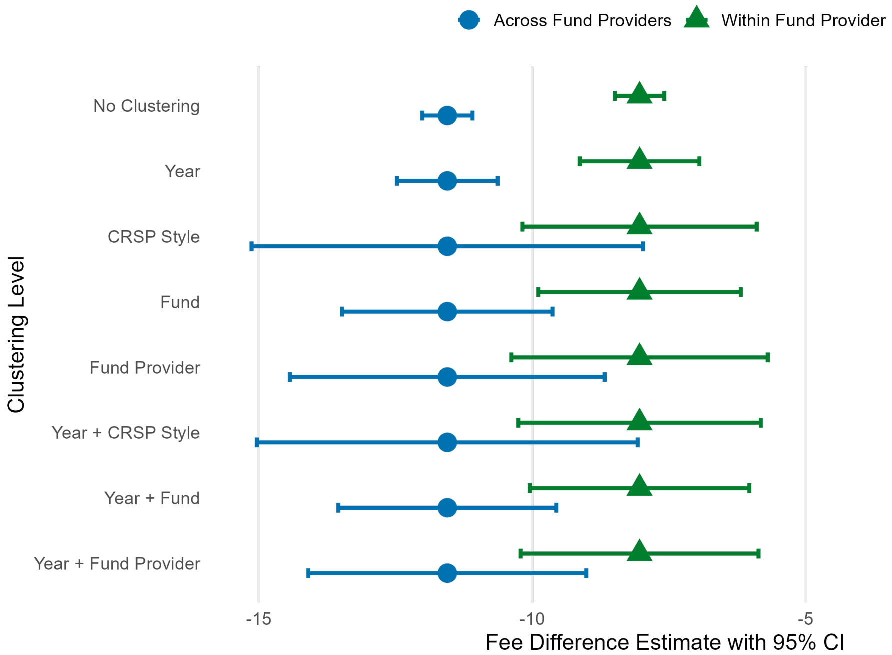

Figure 6: **Choosing an Appropriate Level of Standard Error Clustering**
This figure plots the point estimates and 95% confidence intervals on the coefficient of *ESG* in the baseline specifications of Table 1 using different levels of clustering. The across fund provider specification corresponds to Column 1 (Panel A) and the within fund provider corresponds to Column 7 (Panel B).

F Use of Waivers

Table 10 reports the results of logistic regressions of the indicator variable $Waiver$ on a set of control variables, to examine whether ESG funds are more likely to offer waivers. The coefficients on the control variables align with the findings of Wahal and Wang (2011): older, larger funds and those part of larger fund families are less likely to offer waivers. The coefficient on ESG is positive across specifications, indicating that ESG funds are more likely to offer waivers than conventional funds. The coefficient ranges from 0.136 to 0.390, corresponding to odds ratios of 1.15 to 1.48. This means that the odds of an ESG fund offering a waiver are 15 to 48% higher than for conventional funds.

Table 10: **Waiver Usage of ESG versus Conventional Funds**
This table reports the results from logistic regressions to explain the usage of waivers. The dependent variable, $Waiver$, takes the value of one if the fund uses a waiver. Reported coefficients are in log-odds units. All specifications use year and CRSP style classification fixed effects. Variable definitions can be found in the Appendix. Standard errors are clustered at the fund provider level and reported in parentheses.

	Dependent variable: Waiver			
	(1)	(2)	(3)	(4)
ESG	0.390***	0.143***	0.136***	0.245***
	(0.013)	(0.014)	(0.014)	(0.014)
Age		−0.029***	−0.032***	−0.042***
		(0.000)	(0.000)	(0.001)
Age^2		0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)
$log(TNA)$		−0.180***	−0.181***	−0.164***
		(0.001)	(0.001)	(0.001)
$log(Family)$		−0.083***	−0.082***	−0.089***
		(0.001)	(0.001)	(0.001)
$FrontLoad$			0.352***	0.394***
			(0.007)	(0.007)
$Index$				0.049***
				(0.009)
ETF				−1.522***
				(0.012)
$Inst.$				0.164***
				(0.005)
Deviance	1,464,482	1,365,330	1,362,498	1,339,782
Num. obs.	1,076,077	1,076,077	1,076,077	1,076,077

G Robustness Checks of the Fee Regressions

G.1 CRSP Fee Data

To ensure the robustness of our findings, we repeat the baseline regressions using fee data from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database.

Table 11 presents the results. The dependent variable is stated above the column number. Following previous literature (e.g., Cremers et al., 2016; Khorana et al., 2009), Total Shareholder Cost (TSC) is calculated as the net expense ratio plus one-fifth of the maximum load (front plus rear), assuming a five-year holding period. This measure captures a more complete view of investor costs, including load fees. While the SEC data separately report each fee component (including waivers), the CRSP dataset only includes expense ratio, management fee, and distribution fee. In CRSP, waivers are netted from the management fee field, which can result in negative management fees when waivers exceed the reported fee.

Across all specifications, ESG funds have significantly lower fees than conventional funds, even after controlling for fund provider fixed effects. These results reinforce the main finding that ESG funds are priced lower.

Table 11: **Fees of ESG versus Conventional Funds - CRSP Data**
This table reports the results from panel regressions using fee data from CRSP. Each dependent variable is stated above the column number. Fees are reported in basis points and in annual terms. All specifications use CRSP style × year fixed effects, and some columns use fund provider fixed effects. Variable definitions can be found in the Appendix. Standard errors are clustered at the fund provider level and reported in parentheses.

	Exp. Ratio		Mgmt. Fee		Dist. Fee		TSC	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ESG	-8.524***	-4.046***	-20.663***	-23.172***	-5.007**	-6.582***	-7.382***	-2.899**
	(1.399)	(1.217)	(4.083)	(6.874)	(2.152)	(1.334)	(1.735)	(1.172)
Age	1.719***	2.205***	2.752***	2.769***	1.163***	1.755***	1.682***	2.088***
	(0.115)	(0.181)	(0.228)	(0.432)	(0.118)	(0.172)	(0.126)	(0.213)
Age^2	-0.026***	-0.032***	-0.043***	-0.041***	-0.019***	-0.027***	-0.021***	-0.029***
	(0.002)	(0.003)	(0.004)	(0.007)	(0.002)	(0.003)	(0.002)	(0.004)
$log(TNA)$	-4.685***	-4.448***	9.406***	6.504***	-4.195***	-5.505***	-4.041***	-3.434***
	(0.279)	(0.301)	(1.021)	(1.171)	(0.313)	(0.415)	(0.364)	(0.375)
$log(Family)$	-3.688***	0.137	-2.716***	3.220	2.126***	0.741	-3.512***	-0.593
	(0.343)	(0.871)	(0.690)	(2.199)	(0.431)	(0.522)	(0.475)	(0.739)
Index	-25.048***	-30.788***	-14.960***	-27.179***	-12.908***	-4.337	-30.084***	-35.168***
	(3.945)	(3.767)	(4.733)	(6.354)	(3.304)	(6.471)	(4.531)	(5.369)
ETF	-10.349***	2.541	4.706	21.935***	-7.573	14.298***	-8.051**	3.676
	(3.006)	(2.994)	(3.545)	(5.163)	(4.764)	(2.051)	(3.439)	(4.091)
Inst.	-40.437***	-41.586***	-2.380	1.990	-19.713***	-23.205***	-66.605***	-64.407***
	(1.329)	(1.506)	(2.461)	(3.086)	(1.758)	(2.554)	(2.054)	(2.799)
Provider FE		Yes		Yes		Yes		Yes
Observations	1,111,133	131,931	1,119,172	132,692	517,807	52,114	1,111,133	131,931
R^2	0.520	0.656	0.156	0.273	0.172	0.355	0.567	0.689
Adjusted R^2	0.520	0.655	0.155	0.271	0.172	0.350	0.567	0.688

G.2 Morningstar Data

Table 12 presents results of the baseline fee regressions using fund-level data from Morningstar Direct. The dependent variable is the annual net expense ratio. Column (1) shows that ESG funds charge, on average, 11.7 basis points less than conventional funds. Column (2) restricts the comparison to within fund providers that offer both ESG and conventional funds, yielding a fee gap of 9.2 basis points. Columns (3) and (4) replace the ESG indicator with the Morningstar Sustainability Rating (M* Globes). A one-globe increase is associated with a 1.8 basis point reduction in fees (Column 3), though this effect weakens and becomes statistically insignificant once provider fixed effects are included (Column 4).

Control variables behave as expected and align with prior findings. Overall, these results reinforce the core finding: ESG funds tend to charge lower net fees than conventional funds, even after accounting for fund provider and other fund characteristics.

Table 12: **Fees of ESG versus Conventional Funds - Morningstar Data**
This table reports the results from panel regressions using fee data from Morningstar Direct. Annual net expense ratios are reported in basis points. *M*Globes* is the Morningstar fund sustainability rating. *M*Rating* is the Morningstar fund rating. All specifications use fund type (i.e., equity or fixed income) × year fixed effects, and some columns use fund provider fixed effects. Variable definitions can be found in the Appendix. Standard errors are clustered at the fund provider level and reported in parentheses.

	Dependent variable: Annual Net Expense Ratio			
	(1)	(2)	(3)	(4)
ESG	-11.683***	-9.164***		
	(2.938)	(3.165)		
M* Globes			-1.826**	-0.555
			(0.736)	(0.836)
M* Rating	-3.342***	-1.700*	-2.371**	-1.267
	(0.806)	(0.907)	(0.965)	(1.134)
Age	0.931***	1.297***	1.149***	1.496***
	(0.256)	(0.383)	(0.318)	(0.483)
Age^2	-0.010***	-0.014***	-0.013***	-0.016***
	(0.003)	(0.004)	(0.003)	(0.005)
$log(TNA)$	-3.843***	-3.593***	-4.860***	-4.574***
	(0.636)	(0.934)	(0.736)	(1.030)
$log(Family)$	-6.070***	-1.042	-6.253***	1.554
	(0.627)	(2.962)	(0.582)	(3.115)
Inst.	-7.516**	-0.367	-8.343***	-0.326
	(3.148)	(4.770)	(3.211)	(5.200)
Provider FE		Yes		Yes
Observations	36,075	13,058	22,351	8,706
R^2	0.308	0.462	0.291	0.475
Adjusted R^2	0.308	0.458	0.290	0.470

G.3 Eikon Data

Table 13 presents results of the baseline fee regressions using fund-level data from Eikon. The analysis is in the style of Table 2, where the regressions are repeated over certain market segments. Panel A uses a sample of non-US-domiciled funds, and Panel B uses a sample of US-domiciled funds. All specifications use year $\times$ Lipper classification fixed effects, and Panel A also uses domicile fixed effects. This is important, since country of domicile explains a significant amount of fee variation (Khorana et al., 2009). The dependent variable is Total Expense Ratio (TER), and the variable of interest is $RI, Eikon$, which is Eikon's label of "responsible investment" funds. The results are consistent with the baseline results: across fund providers, ESG funds exhibit lower expense ratios.

The robustness checks in Figure 2 also use Eikon data. The within-provider specifications, use year $\times$ *type* fixed effects, whereas the across provider analysis in Table 13 uses year $\times$ *classification* fixed effects. This is to avoid over parametrization, since we are also using domicile and fund provider fixed effects, and there are several hundred Lipper classifications.

Table 13: **Fees Across Market Segments - Eikon Data**
This table reports the results from panel regressions using fund fees as the dependent variable, using data from Eikon. Panel A shows results for a sample of non-U.S.-domiciled funds, Panel B for U.S.-domiciled funds. Panel A also includes domicile fixed effects. All specifications use year × Lipper fund classification fixed effects. Fees are reported in basis points and in annual terms. Variable definitions can be found in the Appendix. Standard errors are clustered at the fund provider level and reported in parentheses.

	Dependent variable: TER						
Panel A	All Funds	Age≤3	Age>3	Inst.	Non-Inst.	Passive	Active
RI, Eikon	-5.680***	-3.403**	-5.819***	-13.424***	-5.731***	3.306	-6.285***
	(1.351)	(1.641)	(1.489)	(2.901)	(1.384)	(4.405)	(1.369)
Age	2.550***	10.974***	2.109***	2.431***	2.493***	1.767***	2.491***
	(0.214)	(1.674)	(0.242)	(0.505)	(0.218)	(0.441)	(0.219)
Age2	-0.049***	-1.792***	-0.039***	-0.041**	-0.047***	-0.040***	-0.046***
	(0.006)	(0.375)	(0.006)	(0.017)	(0.005)	(0.013)	(0.005)
log(TNA)	-1.121***	-1.045***	-1.247***	-3.542***	-1.040***	-0.999	-1.118***
	(0.312)	(0.263)	(0.401)	(0.464)	(0.310)	(0.697)	(0.308)
log(Family)	-2.984***	-2.240***	-3.177***	-4.008***	-2.915***	-2.528**	-2.929***
	(0.563)	(0.542)	(0.623)	(0.780)	(0.582)	(1.146)	(0.576)
Inst.	-45.041***	-46.065***	-45.257***			-14.963***	-49.205***
	(2.642)	(2.610)	(3.017)			(2.787)	(2.883)
Passive	-63.846***	-59.914***	-65.045***	-39.164***	-67.240***		
	(2.722)	(3.221)	(2.841)	(4.296)	(2.999)		
Observations	691,559	144,986	546,573	36,742	654,817	39,295	652,264
R^2	0.558	0.544	0.577	0.578	0.546	0.615	0.546

Panel B	All Funds	Age≤3	Age>3	Inst.	Non-Inst.	Passive	Active
RI, Eikon	-6.376***	-6.750*	-5.927**	-8.138***	-4.761	-18.159	-6.079**
	(2.354)	(3.455)	(2.697)	(2.140)	(3.667)	(11.099)	(2.365)
Age	0.926***	-1.621	0.854***	0.684***	1.211***	2.124**	0.902***
	(0.123)	(2.554)	(0.122)	(0.161)	(0.187)	(1.009)	(0.128)
Age2	-0.010***	0.602	-0.009***	-0.009***	-0.013***	-0.057*	-0.010***
	(0.002)	(0.499)	(0.002)	(0.003)	(0.002)	(0.034)	(0.002)
log(TNA)	-3.947***	-0.940	-4.597***	-2.358***	-5.701***	-7.024***	-3.743***
	(0.398)	(0.683)	(0.428)	(0.437)	(0.627)	(2.622)	(0.342)
log(Family)	-5.933***	-5.936***	-5.766***	-6.130***	-5.476***	-8.667***	-5.803***
	(0.548)	(0.560)	(0.593)	(0.674)	(0.570)	(2.050)	(0.553)
Inst.	-20.081***	-15.423***	-20.463***			-17.796**	-20.174***
	(2.003)	(3.338)	(2.039)			(8.908)	(2.018)
Passive	-36.174***	-45.359***	-35.608***	-37.016***	-35.908***		
	(6.230)	(5.701)	(6.524)	(4.653)	(10.495)		
Observations	68,328	6,729	61,599	27,878	40,450	3,326	65,002
R^2	0.622	0.654	0.629	0.642	0.598	0.739	0.611

G.4 Matching and Entropy Balancing

Table 14 repeats the baseline analysis with samples constructed using (1) nearest-neighbour matching and (2) entropy balancing.

The matching approach aims to pair ESG funds with conventional funds that share similar characteristics, mitigating potential confounding effects. To identify close funds, a propensity score for each fund is estimated using a logistic regression model. The model estimates the likelihood of a fund being classified as an ESG fund based on the standard control variables (i.e., Age, Age^2, $log(TNA)$, $log(Family)$, $Index$, ETF, and $Inst.$) and year $\times$ CRSP style fixed effects. We conduct two matching methods: (1) exact matching on the CRSP style, year, age, and $Index$, ETF, and $Inst.$, and (2) exact matching on the CRSP style, year, and fund provider. For each method, nearest-neighbour matching is performed with a 1:1 ratio and with replacement, ensuring that each ESG fund is paired with the most similar conventional fund based on its propensity score. Matching method 1 is used in the specifications for Columns (1) and (2), and matching method 2 is used in the specifications for Columns (3) and (4).

The entropy balancing approach retains the full sample, but assigns weights to observations to balance the means of the covariates of the ESG and conventional funds. We balance on the same control variables used in the baseline regression: Age, $log(TNA)$, $log(Family)$, $Index$, ETF, and $Inst.$ Both methods produce results which are consistent with the baseline results.

Table 14: **Explaining Fees using Matching and Entropy Balancing**
This table reports the results from panel regressions using expense as the dependent variable. Columns (1) and (2) use a sample where ESG funds are matched 1:1 on CRSP style, year, age, *Index*, *ETF*, and *Inst.*. Columns (3) and (4) use a sample where ESG funds are matched 1:1 on CRSP style, year, and fund provider. Columns (5) and (6) run weighted regressions, where weights are assigned to balance covariates across ESG and conventional fund groups. Expense ratios are reported in basis points and in annual terms. All specifications use year × CRSP style classification fixed effects. Variable definitions can be found in the Appendix. Standard errors are clustered at the fund provider level and reported in parentheses.

	Dependent variable: Exp. Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
ESG	-9.079***	-3.651***	-5.025***	-4.494***	-11.467***	-7.054***
	(1.336)	(1.091)	(1.231)	(1.124)	(1.623)	(1.273)
Age	3.493***	3.401***	3.527***	3.002***	1.759***	1.635***
	(0.291)	(0.330)	(0.367)	(0.311)	(0.114)	(0.105)
Age^2	-0.079***	-0.079***	-0.072***	-0.061***	-0.029***	-0.027***
	(0.008)	(0.009)	(0.010)	(0.008)	(0.002)	(0.002)
$log(TNA)$	-5.033***	-4.298***	-5.218***	-4.553***	-5.282***	-4.468***
	(0.386)	(0.371)	(0.488)	(0.446)	(0.256)	(0.179)
$log(Family)$	-3.070***	0.744	-2.446***	-1.627**	-3.676***	0.216
	(0.399)	(0.545)	(0.732)	(0.817)	(0.370)	(0.418)
Index	-36.590***	-37.420***	-41.151***	-34.508***	-29.232***	-27.005***
	(2.600)	(2.802)	(2.915)	(2.827)	(3.913)	(2.955)
ETF	2.506	1.796	8.021***	3.428	-9.891***	-8.917***
	(2.822)	(3.404)	(2.882)	(3.214)	(3.282)	(3.395)
Inst.	-42.565***	-41.746***	-44.260***	-43.325***	-40.762***	-40.803***
	(1.734)	(1.663)	(2.336)	(2.418)	(1.373)	(1.006)
Method	Match 1	Match 1	Match 2	Match 2	Ent. Bal.	Ent. Bal.
Provider FE		Yes		Yes		Yes
Observations	42,570	42,570	26,870	26,870	1,076,077	1,076,077
R^2	0.599	0.725	0.651	0.742	0.532	0.650
Adjusted R^2	0.596	0.716	0.648	0.738	0.532	0.649

H Constructing the Uniqueness Measures

This appendix describes the construction of the fund-level uniqueness measures used to proxy for horizontal differentiation in the product space. The approach follows the intuition in Hoberg and Phillips (2010) and the implementation in Kostovetsky and Warner (2020), with minor adjustments.

Overview and Data Sources

We construct two types of uniqueness measures, based on either (i) textual descriptions of the fund's investment strategy or (ii) portfolio holdings. Each type yields two measures: global uniqueness, reflecting a fund's distinctiveness relative to the overall market, and local uniqueness, reflecting its distinctiveness relative to its closest competitors.

The text-based measures use the Principal Investment Strategy (PIS) text retrieved from the SEC Mutual Fund Prospectus Risk/Return dataset. Texts are preprocessed by lowercasing, removing stop words and punctuation, lemmatizing, and then transformed into TF-IDF (term frequency–inverse document frequency) vectors, where a value in the vector corresponds to the TF-IDF value of a given unique word in the set of all words used that quarter by all funds in the dataset. The resulting vectors are at the series-quarter level.

The holdings-based measures are based on the CRSP Mutual Fund Holdings database. The sample is restricted to active (i.e., non-index) equity funds. We ensure that we only consider equity positions in stocks, and not cash positions or holdings in other mutual funds. We require at least 50% of the fund's portfolio to be reported in the CRSP data (i.e., to be in stocks with a CUSIP number) to calculate this measure. We rescale the portfolio weights so they sum to one, resulting in a vector of weights per CRSP portfolio number.

Following the calculations (outlined below), we merge the text-based measures to our sample at the series level and the holdings-based measures at the CRSP portfolio number level.

Cosine Similarity Calculation

Let $\mathbf{x}_i$ and $\mathbf{x}_j$ denote vector representations of fund i and j, with vectors (defined above) constructed from either (1) TF-IDF vectors from the fund's Principal Investment Strategy

(PIS) text, or (2) portfolio weight vectors. Cosine similarity is defined as:

$$CS_{ij} = \frac{\mathbf{x}_i^\intercal \mathbf{x}_j}{||\mathbf{x}_i||\,||\mathbf{x}_j||}$$

The global cosine similarity of a fund i is defined as the average cosine similarity across the entire universe of funds in a given quarter:

$$CS_i^{\text{Global}} = \frac{1}{N-1} \sum_{j \neq i} CS_{ij}$$

Local similarity is a more refined, peer-based measure created using a filtered sample of local competitors. For each fund i, we retain only the top ten most similar peers (based on global cosine similarity) that meet a set of matching criteria: the peer fund must (1) belong to a different fund family, (2) share the same CRSP style, as well as index, ETF, and institutional status, and (3) be older than one year. These pairwise combinations also need to be in the top 20% most similar fund pairs.

Local cosine similarity is then defined as:

$$CS_i^{\text{Local}} = \frac{1}{|\mathcal{P}_i|} \sum_{j \in \mathcal{P}_i} CS_{ij}$$

where $\mathcal{P}_i$ is the peer set of fund i.

Uniqueness Calculation

To turn the average similarity measure into a uniqueness score, we follow Kostovetsky and Warner (2020) and multiply the cosine similarity by negative one, standardize it in the cross-section, and then regress it on either (i) the natural log of the number of unique words in the PIS, or (ii) the log of the number of holdings in the portfolio. The uniqueness value is the residual of this regression. The standardization and the regressions are performed each quarter.

I Fee Increase Following Waiver Discontinuation

Table 15 reports the results from regressions of changes in expense ratios from quarter t to $t+4$ or $t+8$ on a set of control variables. This analysis examines whether ESG funds that use fee waivers subsequently increase their fees, consistent with the hypothesis that waivers are used strategically to build investor base and later raise prices. This is a potential explanation for the use of waivers put forth by Christoffersen (2001).

Columns (1) to (4) use the full sample, while Columns (5) to (8) restrict the sample to funds that discontinue a waiver in quarter $t+1$ (i.e., the fund has a waiver in t but not in $t+1$). All specifications include control variables for fund age and age squared, log fund size, log family size, and indicator variables for index, ETF, institutional status. Year $\times$ CRSP style fixed effects are used in all specifications, and some specifications use fund provider fixed effects. Standard errors are clustered at the fund level.

Across specifications, we find no evidence that ESG funds are more likely to increase fees following a waiver discontinuation. If anything, the estimated coefficients on the ESG indicator are negative, suggesting that ESG funds experience smaller subsequent fee increases relative to conventional funds. This pattern holds for both four- and eight-quarter horizons and remains robust in the subsample of waiver discontinuations. The results do not support the notion that ESG fund providers use waivers as an option to raise fees in the future.

Table 15: **Future Fee Increases**
This table reports the results from panel regressions using change in fund fees from t to $t+4$ or $t+8$ as the depended variable. Columns (1) to (4) considers the entire sample, and Columns (5) to (8) restrict the sample to observations with a waiver discontinuation in time $t+1$, i.e., with a waiver at t but no waiver at $t+1$. Fees are reported in basis points and in annual terms. All specifications use year $\times$ CRSP style classification fixed effects. Unreported control variables include fund age and age squared, log fund size, log family size, and indicator variables for index, ETF, institutional status. Variable definitions can be found in the Appendix. Standard errors are clustered at the fund level and reported in parentheses.

	Entire Sample				Waiver Discontinuation in $t+1$			
	$\Delta f_{t,t+4}$		$\Delta f_{t,t+8}$		$\Delta f_{t,t+4}$		$\Delta f_{t,t+8}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ESG	-0.196***	-0.062	-0.726***	-0.347**	-0.054	-1.017*	-0.743	-1.763**
	(0.066)	(0.068)	(0.153)	(0.157)	(0.421)	(0.521)	(0.629)	(0.781)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provider FE		Yes		Yes		Yes		Yes
Observations	921,850	921,850	797,632	797,632	8,324	8,324	7,423	7,423
R^2	0.019	0.056	0.032	0.090	0.137	0.419	0.142	0.443
Adjusted R^2	0.019	0.054	0.032	0.088	0.106	0.349	0.109	0.374