Financial Product Incentives to Differentiate: Evidence from Mutual Funds*

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November 28, 2023

Abstract

We study the incentives of financial products to differentiate beyond performance, using mutual funds as our laboratory. We provide evidence consistent with product differentiation, reflected in fund prospectuses, enabling low-performing funds to compete for customers and charge higher fees by offering more niche products. Exploiting the issuance of Morningstar rating as a shock to perceived quality, we establish a causal link between low quality and increased differentiation. Funds receiving a low rating actively change their prospectus, increasing their product differentiation, which improves their survival likelihood. Much like other consumer products, mutual funds strategically pursue product differentiation to soften quality-based competition.

Keywords: Product Differentiation, Mutual Funds, Industrial Organization, Textual Analysis, Ratings

JEL codes: D22, L10, G11, G23

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*An earlier version of this paper was circulated under the title "Quality and Product Differentiation: Theory and Evidence from the Mutual Fund Industry". We would like to thank Pat Akey, Bruno Biais, Cecilia Bustamante, Vicente Cuñat, James Dow, Thierry Foucault, Francesco Franzoni, Denis Gromb, Augustin Landier, Jiang Luo, Albert Menkveld, Tamara Nefedova, Melissa Prado, Daniel Schmidt, Carlos Serrano, Boris Vallée, Florian Weigert and seminar participants at the Singapore Scholar Symposium 2023, Professional Asset Management Conference 2023, Research in Behavioral Finance Conference 2022, European Economic Association 2022, Future of Financial Information Conference 2022, FMA European Conference 2022, Financial Risks International Forum 2022, Australasian Finance and Banking Conference 2021, European Winter Meetings of the Econometric Society 2021 for helpful comments and feedback.

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1 Introduction

Product differentiation is a key feature of many consumer product markets, from durable goods like cars to non-durable goods like food items. Recent work has documented the existence of differentiation in financial products (e.g., Kostovetsky and Warner, 2020). Yet, there is limited research exploring the incentives of financial products to differentiate beyond mere financial performance. The goal of this paper is to address this gap by investigating why financial products actively engage in such differentiation, using mutual funds as our laboratory.

Based on the assumption that mutual fund customers' primary goal is to maximize capital growth, research on mutual funds has largely focused on fund performance.[1] This focus has led to a classic "puzzle" which remains largely unsolved: why do many funds with low performance continue to survive (Gruber, 1996)? However, mutual funds have many parallels with other non-financial consumer products studied by researchers in economics and marketing. When deciding which mutual fund to invest in, consumers typically have access to (i) the fund's historical performance (an element of "product quality"), and (ii) the fund's prospectus, a document describing the investment process (akin to a "product description"). Our contribution is to show that, despite operating in highly competitive markets, low-performing mutual funds can adopt product differentiation strategies through their prospectuses to escape performance-based competition.

We formalize our hypothesis in a theoretical framework based on Bar-Isaac et al. (2012). In our model, each consumer's expected utility from investing in a given fund ("product") has two components: (i) the expected performance, or "quality" of the product (shared across all consumers), and (ii) a fund-consumer-specific matching term, which captures consumer heterogeneity in expected utility from the same fund. This matching term can be explained by different factors, including but not limited to differences in hedging demand, beliefs or idiosyncratic preferences, which make some specific attributes of a fund—like its investment strategy or target market—differentially appealing to diverse investor profiles.

Funds differ in their quality and seek to maximize profits. They endogenously set (1) their fees, and (2) whether their product design caters to a "broad" or "niche" market. Product design affects the distribution of the fund-consumer-specific matching terms over the set of consumers. If a fund chooses to be broad, the matching term distribution is concentrated, which means that the fund is "somewhat equally attractive" to most consumers. If the fund chooses to be niche, the distribution is more dispersed, implying that some consumers find the fund very attractive

[1] See for instance Fama and French (2008); Kacperczyk et al. (2014); Berk and Van Binsbergen (2015).

(high matching term) while others find it not attractive at all (low matching term).

We show that in equilibrium, high-quality funds choose to be *broad*, while low-quality funds choose to be *niche*. High-quality funds can sufficiently attract consumers, and thus maximize profits, simply by avoiding a product design that antagonizes any specific customer segment. However, low-quality funds cannot compete with high-quality funds purely on financial performance. By contrast, they must adopt a niche design, making them more appealing to a subset of consumers (those with high matching terms). A prediction of our model is that lower quality funds might charge higher fees than higher quality funds. The intuition is that the low-quality funds cater to niche markets and thus have more market power over their customers.[2]

First, we provide evidence supporting these predictions using data on US active mutual funds over the 2011-2020 time period. Because the quality of a fund product is hard to quantify directly (unlike evaluating the ingredients in a food item or the materials in a car for instance), we use gross fund performance as a proxy for quality. To infer how broad or niche a fund is positioned, we use a textual analysis of the fund prospectus describing the investment strategy ("product description"). Building on Kostovetsky and Warner (2020), our textual analysis compares each product description to its peers' to generate a measure of product uniqueness. We use fund prospectus uniqueness as a proxy for the level of fund product differentiation. Consistent with Kostovetsky and Warner (2020), we observe large variations in uniqueness suggesting varying levels of product differentiation across mutual funds, with some positioned as more broad (low uniqueness) and some positioned as more niche (high uniqueness).

We find a strong negative relationship between uniqueness and gross fund performance (product quality), with lower quality funds having more unique product descriptions. This result holds controlling for fund category-month fixed effects and fund age. Consistent with Gil-Bazo and Ruiz-Verdú (2009), we also find that low-quality funds charge higher fees than their high-quality counterparts, a finding initially presented as puzzling but which is consistent with our theoretical framework. In addition, we find that funds with unique product descriptions are smaller according to their assets under management (AUM), consistent with catering to a more niche market.

Second, we add to these descriptive evidence by leveraging an identification strategy to show that low-quality funds actively *choose* to employ product differentiation and to become niche in order to escape performance-based competition. One major concern in the above findings

[2]This is consistent with evidence in other product categories that consumers become less price sensitive as product differentiation increases (Brynjolfsson et al., 2009).

is reverse causality. It could be that adopting a niche design *causes* funds to underperform, and not the reverse. To rule out this possibility, we study whether information about fund quality revealed by the most prominent information intermediary in the mutual fund industry (Morningstar) affects funds' level of product differentiation.

The menu of mutual funds offerings is an overwhelmingly large choice set for investors and calculating performance numbers for each product may not be feasible.[3] Morningstar therefore issues a 1 to 5-star (worst to best) rating based on past financial performance for each mutual fund, which is then made easily accessible to consumers who can use it to make decisions when purchasing products. Research has shown that investors rely strongly on ratings from Morningstar to allocate their assets (Nanda et al., 2004; Guercio and Tkac, 2008; Evans and Sun, 2021; Ben-David et al., 2022a).

Specifically, we study how funds adapt their product differentiation following Morningstar publishing a star rating. We exploit the fact that Morningstar rates every mutual fund only after it has exactly 36 months of financial performance. Therefore, the timing of the switch from unrated to rated is exogenous (although known) to the fund.[4] Morningstar ratings are always calculated by ranking funds in a given category according to their past financial performance. If a fund receives an initial low rating, consumers can infer that the fund has underperformed its peers, i.e., is of low-quality. Therefore, the publication of a low initial rating to a previously unrated fund can be viewed as a negative shock to the perceived quality of the fund.

Using a difference-in-differences analysis, we find that previously unrated funds significantly increase their product differentiation, i.e., make their prospectus more unique, after they receive a low initial rating. Funds that receive a 1-star rating become 13 p.p. more likely to change their prospectus (160% of the sample average) relative to 3-star funds, and increase their product uniqueness by 0.15 standard deviation. We do not find any significant change after a high initial rating. Importantly, despite modifications in the prospectus text of 1-star funds, there is no significant change in its complexity or readability, suggesting these funds do not react by engaging in more product obfuscation (Ellison and Ellison, 2009; Ghent et al., 2019; deHaan et al., 2021).

Moreover, we find that product differentiation is beneficial to low-quality funds. Conditional on receiving a 1-star rating, funds that change their prospectus become less likely to die and

[3] According to the 2019 Investment Company Fact Book, in 2019 there were almost 8,000 active mutual funds available to US investors.

[4] Adelino et al. (2023) develop a similar, albeit not identical, empirical strategy using Morningstar ratings.

collect more flows compared to similarly rated funds that do not. Specifically, after changing their prospectus, 1-star funds reduce their likelihood of death by 0.5 p.p., which is a 57% reduction compared to the average for 1-star funds. Additionally, these 1-star funds that change their prospectus enjoy an increase in their monthly inflows by 0.8%, relative to other 1-star funds that do not. In contrast, this disparity in survival rates and flows among funds that alter their prospectus is completely absent after receiving a high initial rating, consistent with high quality funds having little incentive to differentiate.

Upon further investigation of the specific dimensions across which funds were differentiating themselves over the time period studied, we find that the words more likely to be used in more unique product descriptions appear to be related to a number of different topics. One such topic is the investment process—for example, how quantitative is the investment approach described to investors (Abis, 2022). Another topic is environmental and sustainability issues, consistent with recent literature from finance showing that mutual fund investors value the sustainability of their investments (Hartzmark and Sussman, 2019; Bauer et al., 2021). We conclude that more unique funds cater for investors' idiosyncratic preferences, which change over time and might include different issues in the future.

Our paper contributes to several strands of literature. First, we contribute to the literature examining differentiation in financial products and its subsequent implications on the organization of the financial industry. Gennaioli et al. (2015) study trust beyond mere fund performance in delegated money management, while Hortaçsu and Syverson (2004) probe the role of non-portfolio fund differentiation in explaining the proliferation of index funds and variance in fund fees. Additionally, Célérier and Vallée (2017) and Brancaccio and Kang (2022) explore product design in the structured product and municipal bond markets, respectively. Ben-David et al. (2023) document that recently launched specialized passive funds (ETFs) cater to investor demand for popular and overvalued investment themes. Our paper shows that financial instruments competing over performance, such as active mutual funds, have incentives to employ product differentiation strategies throughout their lifecycle to escape quality-based competition, thereby affecting the menu of financial products offered to investors.

Second, our results have important implications for our understanding of the mutual fund industry, in particular the competition among mutual funds (Wahal and Wang, 2011; Khorana and Servaes, 2012). Employing a differentiation measure derived from fund prospectuses akin to Kostovetsky and Warner (2020), we add to their empirical findings by highlighting the underlying economic mechanism driving product differentiation among mutual funds.[5] To the best of our knowledge, this is the first paper that shows that funds respond strategically to investors' perception of their "quality" by adapting their product differentiation through their prospectus. This is consistent with Abis and Lines (2023) and Abis et al. (2022), which find that fund prospectuses contain information crucial to investors. Furthermore, we show that fund product differentiation may be one factor explaining the puzzling fact of low return funds charging higher fees and persisting in the universe of mutual funds—a fact initially explored by Gil-Bazo and Ruiz-Verdú (2009) and Cochrane (2013).

Third, we contribute to the literature on the role of information intermediaries in the mutual fund industry, in particular rating agencies such as Morningstar. Most prior works have focused on how ratings affect the *demand* side of the mutual fund market—the fact that investors chase ratings (Nanda et al., 2004; Guercio and Tkac, 2008; Hartzmark and Sussman, 2019; Ben-David et al., 2022a; Evans and Sun, 2021). We contribute to this literature by showing that the information provided by intermediaries can also have an effect on the *supply* side of the fund market. We show that mutual funds endogenously respond to the publication of ratings provided by intermediaries, by adapting their level of product differentiation.[6]

Last, our paper is related to the broader economics literature studying consumer product differentiation. Our theoretical framework is based on Johnson and Myatt (2006) and Bar-Isaac et al. (2012), which provide a tractable framework to study product differentiation. In particular, Bar-Isaac et al. (2012) predicts that high-quality firms choose to produce products with the most broad design (inoffensive to all consumers) while low-quality firms adopt the most niche design that consumers either love or loathe. Product designs are also studied by Kuksov (2004), Anderson and Renault (2009), Larson (2013), and Bar-Isaac et al. (2021). Our contribution is to provide empirical results supporting these theories, using the mutual fund industry as our laboratory.

[5] Prior work studying non-performance related aspects of mutual fund products also include Massa (2003) (switching costs across different funds) and Sialm and Starks (2012) (tax clienteles). Roussanov et al. (2021) show how funds' marketing efforts affect investor flows. Bergstresser et al. (2008), Christoffersen et al. (2013) and Guercio and Reuter (2014) study the role of brokers and advisors in the mutual fund market.

[6] Chen et al. (2021) and Kim (2021) show that the availability of ratings can affect fund managers' behavior, and their incentives to manipulate the information available to investors.

2 Theoretical Framework

We develop a theoretical framework based on the assumption that investors' utility, when investing in a fund, does not only depend on financial return ("quality"), but also encompasses an additional component: an investor-fund specific matching term. This term reflects the fact that some characteristics of a fund are valued differently by different investors. Our model focuses on how funds with different quality choose their product design.

2.1 Model

There is a continuum of funds and investors with mass 1 and m respectively. Each fund i is denoted by fund quality v_i. v is distributed according to some continuous density function $h(v)$ with support $[\underline{v}, \bar{v}]$. The term v_i captures a natural advantage of fund i. A higher v_i can be thought of as a better innate skill (i.e., ability to generate financial performance).

We consider a one period economy in which each investor randomly draws a fund from the population, and then choose to invest one unit of capital in the fund or to invest in an outside option. Each fund can endogenously set the *price* of its product and its *product design*. We describe investor and fund behaviors below.

A. Investors

A given investor l has the following (expected) utility function when investing in fund i at price p_i:

$$u_{li}(p_i) = v_i - p_i + \epsilon_{li}. \tag{1}$$

The term v_i captures the quality of fund i that is common across all investors. ϵ_{li} is a matching term between investor l and fund i. It captures idiosyncratic investor preferences for certain funds over others. The distribution of ϵ_{li} is described by the cumulative distribution function F_i, which is set by fund i and discussed below. We assume that realizations of ϵ_{li} are independent across funds and individual investors.

Note that the key difference between v_i and ϵ_{li} is that v_i gives the same utility to all investors, while ϵ_{li} differs across investors. In practice, v_i can be thought of as the (expected) financial return that a fund offers, and ϵ_{li} capturing the fact that some fund attributes—like its investment strategy or target market—can be more or less appealing to different investors. ϵ_{li} can be interpreted in several ways, including but not limited to: (a) If investors have different risk aversion, ϵ_{li} measures different required risk premium (net of v_i) across investors. (b) If investors have different hedging demand for some individual-specific exposures, ϵ_{li} measures the hedging benefit (or cost). (c) ϵ_{li} can measure the individual-specific (possibly biased) belief. (d) ϵ_{li} can also measure other individual-specific preferences, such as ESG concern or trust.

Each investor has an outside option providing expected utility U. U can be thought as the net return produced by a passive fund tracking the market. We assume U is exogenous and the same for all investors. Each investor l randomly draws a fund i and decides to invest one unit of capital in the fund if it provides more utility than the outside option, i.e., if

$$v_i - p_i + \epsilon_{li} > U. \tag{2}$$

B. Funds

Each fund i cannot choose v_i, its *quality*, but can set the price p_i and choose its product design. Following Bar-Isaac et al. (2012), we model product design choice by assuming that the fund can choose the distribution of the investor-fund specific matching term ϵ_{li}, by picking a design $s_i \in \{B, N\}$. Each fund can choose either a *broad* (B) or a *niche* design (N). Each design is associated with a distribution of ϵ_{li}. Specifically, the cumulative distribution function of ϵ_{li} is given by F_B (F_N) if the fund chooses the broad (niche) design. Following Bar-Isaac et al. (2012), we assume that F_B and F_N have log-concave densities, respectively f_B and f_N, that are positive everywhere.[7]

Figure 1 illustrates the density and cumulative distribution functions (c.d.f.) of ϵ for broad and niche designs. The niche design is the one associated with a more dispersed density function in Panel A. This is to reflect the fact that, for niche design, some investors "love" the fund (right tail of the distribution), while some other investors "loath" the fund (left tail of the distribution). On the contrary, for broad design, the fund is passable for the majority of investors. This is represented by a more concentrated distribution. The corresponding c.d.f. are presented in Panel B.

Figure 1 about here.

2.2 Fund Profit Maximization

Given (2), investors who draw a fund with quality v invest as long as they receive a match term ϵ such that $\epsilon > U - v + p_v$. Therefore, they invest in the fund with probability $1 - F_s(U - v + p_v)$,

[7] We further discuss that assumption in Internet Appendix A.

where $s \in \{B, N\}$ is the design chosen by the fund. Given that there is a mass m of investors and that each one randomly draws a fund, the demand for the fund with quality v that chooses a design s and price p is

$$m\left[1 - F_s(U - v + p)\right], \tag{3}$$

and its profit is

$$\Pi = pm\left[1 - F_s(U - v + p)\right]. \tag{4}$$

We proceed in two steps to derive the fund's choices of price and design. First, we derive the optimal price p taking design s as given. Then, we find which design is optimal for the fund.

Taking the first order condition to maximize fund profit in (4) with respect to price when design is s, we obtain that price is determined by

$$p_s(v) = \frac{1 - F_s(U - v + p_s(v))}{f_s(U - v + p_s(v))}, \tag{5}$$

where $p_s(v)$ is the price charged by a fund of quality v with product design s.[8]

Using (5), we can derive design choices. We show below that funds choose design according to a simple rule: if perceived quality v is high enough the fund chooses broad design, if not it chooses niche design. Specifically, we show in Proposition 1 that there exists a unique quality threshold V such that a fund with quality V is indifferent between choosing the broad or the niche design. As a consequence, funds with quality strictly greater than the threshold V choose broad design, while funds with quality strictly lower than the threshold choose niche design.

Proposition 1. *There exists a unique threshold V such that fund with quality V is indifferent between choosing a broad or a niche design, i.e.,*

$$p_B(V)\left[1 - F_B(U - V + p_B(V))\right] = p_N(V)\left[1 - F_N(U - V + p_N(V))\right].$$

As a consequence, all funds with quality lower than this threshold, $v < V$, choose a niche design, and all funds with $v > V$ choose a broad one.

The proof of Proposition 1 is provided in Internet Appendix A.

[8] As a consequence of the log-concavity assumption, $p_s(v)$ is well-defined as $[1 - F_s(x)]/f_s(x)$ is monotonic. In addition, it is such that higher quality funds charge higher prices conditional on design, and funds charge lower prices when investors are pickier, i.e., when investors have a higher value of outside option U.

2.3 Equilibrium Summary

A. Design Choice in Equilibrium

A key implication of Proposition 1 is that funds with lower quality are more likely to choose niche design. The intuition is that funds facing a disadvantage as compared to others need the investors to "love" the fund in order to invest. The chance that this happens increases with a niche design as it leads to a more dispersed distribution of matching terms. Instead, a high quality fund can appeal to many investors by adopting a broad design and, thereby, can minimize the chance that an investor observes such a bad match that she would prefer not to invest.

B. Price in Equilibrium

The design choice rule has an important implication for prices in equilibrium: price can decrease with quality. Because funds with perceived quality v above or below a certain threshold do not adopt the same design, there exist some funds with perceived quality v and v' such that $v < v'$ and $p_N(v) > p_B(v')$. We formalize that result in Proposition 2 below.

Proposition 2. *In equilibrium, there exist funds with quality v below the threshold V that charge higher prices than funds with v above that threshold.*

We provide the proof of Proposition 2 in Internet Appendix A. Figure 2 illustrates how equilibrium price $p(v)$ varies by quality v. There are two channels through which quality affects price. The first channel is the most obvious one: better quality funds are sold at higher price.[9] The second channel relates to the fact that quality affects the product design choice. When the fund quality is lower than the threshold V, the fund is better-off by adopting a niche design. The niche design gives the fund some market power to charge a higher price, as the investors who invest are those who "love" the fund.

The two channels are working in opposite directions, and the net effect depends on how close the quality is from the threshold V. As the fund's quality v approaches V from below, it becomes increasingly likely that its price will exceed that of a fund with a quality just slightly above V.[10] Indeed, as we show in Proposition 1, there exists a unique threshold V such that firm with quality V is indifferent between niche (higher price and lower quantity) and broad (lower

[9] As we show in Equation (5), price $p_s(v)$ is increasing in v given s.

[10] The exact space over which price is decreasing with quality depends on the functional forms of c.d.f. and parameters choice.

price and higher quantity) design. As a consequence, $P_N(V)$ is strictly higher than $P_B(V)$. As both $P_N(v)$ and $P_B(v)$ are continuous, there is a range of quality including V, over which lower quality niche funds charge a higher price than higher quality broad funds.

Figure 2 about here.

C. Shock to Fund Quality

We discuss below how a shock to fund quality can affect its product design choice. This discussion is helpful to match our theoretical framework to the empirical analysis in section 5. Note that in our empirical setting, we use the issuance of Morningstar rating, which can be viewed as a shock to fund *perceived* quality, changing the *expected* utility of investors. We provide more discussion in the empirical analysis. In this section, for brevity, we refer to a shock to fund quality.

Consider a fund with initial quality v, and suppose it incurs a negative shock such that its quality is now $v' = v - \Delta v$, with $\Delta v > 0$. Following the shock, the fund will change its product design from broad to niche if the new quality level is below the threshold V. This implies that, after a negative shock, some funds among those with broad design will switch their product to a more niche one.

2.4 Empirical Predictions

Based on our theoretical framework, we can make the following predictions:

Prediction 1. *Lower quality funds are more niche.*

This prediction follows directly from Proposition 1. Higher quality funds choose a broad design to be attractive to a larger set of investors, while lower quality funds choose niche design to attract investors who receive a high matching term with them.

Prediction 2. *Lower quality funds can charge higher fees.*

This prediction follows from Proposition 2. Lower quality funds choose a niche design in equilibrium. Because investors investing in those funds are the ones who receive a high matching term, the funds' market power on these investors allow them to charge higher fees.

Prediction 3. *After a negative shock to fund quality, some funds become more niche.*

This prediction directly follows from Prediction 1. After a negative shock to the quality of funds, some of them become more niche to compete and attract investors who receive a high matching term with them.

3 Data

3.1 Product Differentiation in the Mutual Fund Industry

We test our predictions using data on active U.S. Domestic Equity mutual funds. We focus on active mutual funds because they engage in competition by striving to deliver superior returns to their investors, in contrast to passive funds that provide exposure to specific indices, which falls outside the scope of our theoretical framework. We focus on Domestic Equity funds because they are more easily comparable, and computing their risk-adjusted return is more straightforward.

To differentiate niche and broad funds, we generate a text uniqueness measure in the spirit of Kostovetsky and Warner (2020) based on the strategy description of fund prospectuses. We use text uniqueness as our main measure because of two reasons. First, it is a more precise measure of product differentiation. As shown by Kostovetsky and Warner (2020), compared to other measures such as holding uniqueness and return uniqueness, text uniqueness is a better predictor of whether funds belong to the same category. Second, because we seek to study the relationship between performance (quality) and uniqueness (product differentiation), we want to avoid mechanically capturing previous findings from the mutual fund literature showing that there is a relationship between portfolio holdings and returns (Cremers and Petajisto, 2009; Amihud and Goyenko, 2013). Therefore, we rely on text uniqueness because it is, by nature, more "orthogonal" to fund return.

Intuitively, the text uniqueness measure captures how a fund describes its investments strategy differently than other funds in the same category. If the prospectus of a fund is written in a way that is similar to others, it is more likely to be a broad fund that is passable for most investors. If the prospectus of a fund is very unique, i.e., written using unique words differing from those used in other prospectuses, it is more likely to be a niche fund, seeking to attract specific investors with particular interests or tastes. The details on how we construct the measure are provided below.

3.2 Mutual Fund Data

The first data source we use is the CRSP Survivor-Bias-Free U.S. Mutual Fund Database (CRSP). This database includes all funds available at the time (including currently defunct funds) and therefore is not affected by survivorship bias. We focus on actively managed domestic equity mutual funds operating in the United States (with CRSP objective code "ED"). We remove all passive funds. We identify the latter using CRSP's flag indicating whether a fund is an index fund or an ETF. We also rely on fund names to identify additional passive funds not flagged by CRSP.[11] For each fund, we collect monthly TNA (total net assets) and net return. We also collect expense ratios, i.e., total fund fees, available from CRSP to compute monthly gross return. We replace any missing TNA or expense ratio by the most recent observation in the past. We drop remaining observations with missing TNA or net return. To address the possibility of incubation bias, we follow Kacperczyk et al. (2014) and exclude observations for which the date of the observation is prior to the reported fund's starting date as well as observations for which the names of the funds are missing in the CRSP database.

We compute each fund's age as the number of months between the date of the observation and the reported fund's starting date. Finally, we compute the fund risk-adjusted return ("alpha") using a rolling window of 24 months. The factor model we use contains the 3 Fama-French factors as well as the Momentum factor (all downloaded from Kenneth French's website).[12]

Following the mutual fund literature, we aggregate the different share classes of the same fund. We identify the different share classes of a mutual fund using the portfolio number provided by CRSP. For each fund, we take the sum of share classes' TNA and the TNA-weighted average of share classes' return, alpha and expense ratio. For age, we use the age of the oldest share class.

For each fund in our sample, we use the cusip and ticker to get additional data from the Morningstar Direct database. We download each fund's monthly Morningstar category as well as Morningstar star rating if available. We include in our final sample only funds that fall into one of the ten largest Morningstar fund categories: large blend (LB), large growth (LG), large value (LV), mid-cap blend (MB), mid- cap growth (MG), mid-cap value (MV), small blend (SB),

[11] We remove the fund if its name contains one of the following case insensitive character: "index", "idx", "indx", "mkt", 'market", "composite", "s&p", "russell","nasdaq", "dow jones", "wilshire", "nyse", "ishares", "spdr", "holdrs", "ETF", "Exchange-Traded Fund","Exchange Traded Fund", "PowerShares", "StreetTRACKS", "100", "400", "500", "600", "1000", "1500", "2000", "3000", "5000".

[12] See Fama and French (1993) for a complete description of the factor returns.

small growth (SG), small value (SV) and long-short (LS). In case of missing rating, we use the most recent rating available in the past. We give additional details on the rating methodology below and how it relates to our framework.

The third data source we use is from fund prospectuses. Each fund has to submit a prospectus to the SEC at least once a year. In the prospectus, the fund provides all the information that is relevant to investors, including strategy, risks, fees and performance. We collect all the fund prospectuses (Form N-1A) from SEC EDGAR (Electronic Data Gathering, Analysis, and Retrieval) system. We focus on the Principal Investment Strategy (PIS) section of the prospectus, as it is the most informative about the funds' characteristics. We extract the PIS section from the full prospectus, and forward fill the prospectus at the monthly frequency, i.e., we consider a fund has the same prospectus until it submits a new one. In case there are several prospectuses available in the same month for a given fund, we keep only the latest one. We merge the prospectus data with CRSP data using tickers.

We follow standard text cleaning procedures to clean the prospectus text. We only keep the English words in the prospectuses by removing numbers, symbols and special characters. We also remove all the stop words. In addition, we remove the words that correspond to the management company names or the advisor names, in order to remove any effect from mentioning brand names in the prospectuses. We stem each word to its root using the Porter stemmer algorithm (e.g. 'mathematic', 'mathematics', ... = 'mathemat'), to better compare the similarity between prospectuses. Finally, to reduce the noise in our uniqueness measure, we remove the 30 most commonly used words by all the funds.[13] This process aims to remove the uninformative words and make our measure less noisy. The economic magnitude of our results remains similar if instead we remove the 20 or 10 most commonly used words or if we do not remove any words.

Finally, we also obtain fund holdings data from CRSP. To compare the holding of the funds to their benchmark index, we collect holding of ETFs tracking the main benchmark in each category. For each category, we focus on ETFs tracking the most commonly used index and the holdings of the the largest corresponding ETFs. The list of indexes and ETFs can be found in Internet Appendix B.

[13]Top 30 words are: fund, invest, secur, index, asset, market, compani, portfolio, includ, underli, equiti, stock, manag, advis, rate, income, capit, bond, alloc, instrument, time, strategi, exposur, seek, risk, deriv, return, fix, issuer, foreign.

3.3 Uniqueness Measure

A. Text Uniqueness

Our measure of uniqueness is based on the strategy description of fund prospectuses and builds on Kostovetsky and Warner (2020). We first construct measures for the pairwise similarity between any two prospectuses. Let V_i and V_j be term frequency vectors from two prospectuses i and j. We compute the cosine similarity of two vectors, which is equation (6), where $\cdot$ is the dot product and $\| \ \|$ is the Euclidean norm.

$$Cosine\_Similarity_{\{i,j\}} = \frac{V_i \cdot V_j}{\|V_i\| \times \|V_j\|} \tag{6}$$

In each month, we calculate all the pairwise similarity between funds within a category. Then for each fund, we take the average of all its pairwise similarities with other funds in the same category that month. To remove any effect due to the length of the prospectus, we regress the minus cosine similarity on the prospectus' number of words, as defined in equation (7). We normalize the residuals ϵ_i and use them as the final uniqueness measure *TextUniq* for fund i.

$$-\,avg\_Cosine\_Similarity_{\{i,-i\}} = \beta_0 + \beta_1 \#Word + \epsilon_i. \tag{7}$$

Kostovetsky and Warner (2020) show that the text-based measure is superior at predicting unique fund types compared to return-based and holding-based measures. Note that Kostovetsky and Warner (2020) use the summarized strategy descriptions from Morningstar, which have an average text length of 70 words. We rather use the full PIS section from actual fund prospectuses, which have an average text length of 450 words and thus are more likely to capture specific fund characteristics.

Internet Appendix C gives examples of high and low uniqueness funds. The fund in C.1 mentions option strategy and VIX, which are unique words compared to other funds in the Large-Blend category. The fund in C.2 discusses its focus on climate change, sustainability and board diversity, which is unique in the Large-Growth category. Both funds in C.1 and C.2 have high *TextUniq* measures. In comparison, funds in C.3 and C.4 use general language to describe their strategy, such as earnings, dividend growth, strong financial condition, and management positions. As a result, their *TextUniq* measures are low. The examples above illustrate that our *TextUniq* measure can indeed capture the uniqueness of funds' strategy descriptions.

In addition, we also generate time-series similarity of prospectuses $TS\ TextSim$. It is defined as the cosine similarity (same as equation 6) between the current and previous prospectus of the same fund. This measure captures how much a fund has updated the strategy description in its prospectus. As such, a low *TS TextSim* indicates that the fund has changed a lot its prospectus.

B. Additional Holding-based Uniqueness Measures

We also construct uniqueness measures based on holdings to perform robustness tests. We follow a procedure similar to the one used to compute prospectus uniqueness. In each month, for each pair of funds in the same category, we calculate the pairwise cosine similarity of holding vectors.[14] For each fund, we take the average of these pairwise measures with other funds in the same category that month. We normalize the similarity, and multiply it by -1 to obtain our measure of holding uniqueness.

We also construct the similarity with respect to the index. We construct the measure by calculating the cosine similarity between the holdings of a fund and those of the ETF that tracks the main benchmark index of the fund's category.[15] For each category, we use the most commonly used index and the largest index ETF tracking it (cf., Internet Appendix B). Note that there is no index for the Long-Short category, and as a consequence the index similarity measure is missing for all the funds in that category.

3.4 Morningstar Star Rating

The identification strategy developed in Section 5 relies on Morningstar ratings for mutual funds. The original star rating was introduced in 1985 by Morningstar, who have since become one of the most important information intermediaries in the mutual fund space. The 1 to 5-star rating is based on past financial performance, and is made easily accessible to consumers, who can then use the rating to make decisions about an otherwise overwhelming menu of mutual funds.

Morningstar rates funds with respect to other peers in a given Morningstar category, such that fund ratings are balanced across each Morningstar category. The star ratings are formulaically calculated in two steps. First, for each fund with at least 36 continuous months of

[14] We only use holdings with available cusip code.

[15] We follow Kostovetsky and Warner (2020) and measure portfolio similarity using cosine similarity of portfolio holdings. Note that this measure is different from the "active share" measures by Cremers and Petajisto (2009) and Doshi et al. (2015), which measure the activeness of funds through the absolute value of difference between portfolio weights and indices. The cosine similiarity measures the angle of two portfolio holding vectors, while the "active share" measures the relative size of the long-short portfolio that deviates from the indices.

returns, Morningstar calculates a performance measure using past returns, with minor adjustments based on return volatility. Second, Morningstar ranks funds by their performance measure and assigns ratings. Importantly, each mutual fund gets rated as soon as it has a track record of at least 36 months. In addition, the ratings receive no subjective input, and therefore do not take into consideration any product differentiation measures. We give additional details on the rating methodology in Internet Appendix D. Note that Morningstar rates each share class of a mutual fund separately because each share class might have different fees and total return time periods available.[16] We aggregate the Morningstar ratings of the different share classes of the same fund by taking the TNA-weighed average of share class ratings.

Funds that are the highest outperformers in their group receive a 5-star rating, and funds that are the lowest underperformers in their group receive a 1-star rating. If a fund receives an initial 1-star rating, we posit that consumers can infer that the product is of "low-quality". Therefore, the publication of a low initial rating to a previously unrated fund can be viewed as a negative shock to the perceived quality of the fund. The main advantage of using the publication of an initial rating instead of the variation in the rating of a previously rated funds is that the initial rating is published exactly when the fund reaches three years of age. The timing of the publication of the initial rating is therefore exogenous to the fund.

Prior research has shown that investors rely on simple signals to decide fund allocation (e.g., Kaniel and Parham, 2017). Several papers show that Morningstar ratings have a strong impact on flows from both retail and institutional investors (Nanda et al., 2004; Guercio and Tkac, 2008; Evans and Sun, 2021; Ben-David et al., 2022a; Adelino et al., 2023). Key to our framework, these papers show that it is the discrete change in the star rating itself and not the change in the underlying performance that drives flow. This suggests that mutual fund investors chase fund performance via Morningstar ratings. Therefore, we interpret the release of fund ratings as a shock to the fund quality perceived by investors.

3.5 Summary Statistics

Our sample contains monthly observations at the fund level from 2011 to 2020. We focus on this period because the structure of the prospectus data available from EDGAR before 2011

[16] However, the distribution of funds among the star ratings depends on the number of mutual funds evaluated within the category rather than the number of share classes. The Morningstar official methodology explains how Morningstar prevents multi-share funds from taking up a disproportionate amount of space in any one rating level. Cf., https://www.morningstar.com[...]771945_Morningstar_Rating_for_Funds_Methodology.pdf.

does not allow us to scrape and parse them. Our sample features 2,592 distinct mutual funds managed by 698 different management companies. We provide summary statistics of the main variables used in our empirical analysis in Table 1.

Fund monthly gross and net returns are on average 1% while fund alphas are on average virtually zero. Note that the lower number of observations for fund alpha is due to the fact that we use a 24-month rolling window to estimate factor regressions. Gross cumulative return is 24-month cumulative return using the same rolling window in alpha estimation. Expense ratio, i.e., fund fee, is on average 1.1% per annum. By construction, the Morningstar rating has a mean and a median of 3. Note that about 20,000 observations (20% of the sample) have missing rating. Those observations correspond to funds with less than 36 months of track record, which are not yet rated by Morningstar. TNA (total net assets) has a median of about \$270 million and a mean of \$1.7 billion. $Fund\ Age$, the number of month since the reported fund's starting date, is on average 144, i.e., 12 years. $InstFund$, the fraction of institutional share classes of the funds, is on average 45%.

$Nb.\ Word$ is the total number of words appearing in the fund's prospectus after removing stop words. We observe that fund prospectuses feature on average respectively 171 words (after removing uninformative words as described in Section 3.2). $TextUniq$ refers to funds' text uniqueness measure, which is computed based on the method described in section 3.2. By construction, $TextUniq$ has a mean of zero and a standard deviation of one. Therefore, uniqueness measures are expressed in number of standard deviations from the mean. $TS\ TextSim$ corresponds to funds' time-series text similarity between two consecutive prospectuses. It has a mean of 0.98 and its 25% percentile is 0.99, i.e., most of the funds do not update their prospectuses at all, which implies that fund prospectuses are quite persistent over time.

$Fund\ Flow$ is the monthly flow of funds, i.e., the cash that flows into and out of the fund in a month, defined for fund i in month t as $Fund\ Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + Ret_{i,t-1})}{TNA_{i,t-1}}$. $HoldUniq$ measures the uniqueness of the fund portfolio holdings as defined in section 3.3, and is also expressed in number of standard deviations from the mean. $SimIdx$ refers to holding similarity between the fund and the most common index used as benchmark in the fund's category. On average, fund holdings are 30% "similar" to their benchmark index's holdings. $SimIdx$ is missing for funds in the Long-Short category as the latter does not have a proper benchmark index.

$\boxed{\text{Table 1 about here.}}$

4 Empirical Analysis of Quality and Production Differentiation

4.1 Measurements

In the following section, we explain how our empirical measures map to our theoretical framework. Fund quality v is measured through the gross (before-fee) return of funds. Fund prices are measured by the fees charged by mutual funds.[17] As a result, the utility of the investors before any gains from differentiation $(v - p)$ is the net return of funds. Our main measure of product differentiation is the uniqueness of a fund's prospectus as calculated using our textual analysis of fund prospectuses, which is designed to capture how differently a fund's prospectus is written compared to other funds in the same category.

A. Fund Quality

To measure the quality of a fund, we use the monthly before-fee return, which is the return obtained by the fund's investment strategy. We acknowledge that returns might be noisy, however, if it is a noisy measure of quality, it will simply lead to attenuation bias in our regressions. We use both monthly contemporaneous return and cumulative return over the following 24 months to measure the realized quality of funds. Because existing finance research has highlighted that a key driver of a fund return is its exposure to risk factors, we also use risk-adjusted return ("alpha") estimated through a 4-factor model using the same 24-month period.

In addition, we use Morningstar rating to measure the quality of funds. We use this additional measure for two reasons. First, prior research in finance has shown that it might be difficult for investors to learn about the (relative) performance of funds and that they rely on Morningstar ratings to select funds (e.g., Evans and Sun, 2021; Ben-David et al., 2022b). Second, we use the issuance of Morningstar ratings in our identification strategy to establish a causal link between quality and product differentiation. Morningstar ratings are based on after-fee returns within fund categories. The Morningstar rating methodology is explained in Section 3.4 and more details are provided in Internet Appendix D. In Internet Appendix Table A.5, we confirm that Morningstar ratings are correlated with future realized return of funds.

[17] In practice, mutual funds charge an annual fee (in percentage of total amount invested) to their investors. This is also known as *expense ratio*, which includes the payment for portfolio management, administration, marketing, and distribution, among other expenses.

B. Fund Product Differentiation

Our main measure of product differentiation is based on the strategy descriptions of fund prospectuses. Intuitively, the measure captures how unique the investment strategy description of a fund is compared to other funds within the same category. In additional tests, we also use holding uniqueness and similarity to index. Holding uniqueness captures how unique a fund's holdings are compared to those of other funds in the same category. The similarity to index measure captures how similar the fund's holdings are compared to those of the most common benchmark index in the fund's category. The construction methods are detailed in Section 3.3.

C. Fund Price

We use the expense ratio of funds to measure fund "prices". Fund expense ratio captures the fees charged by the fund managers (as a percentage of assets invested). It includes management fees, as well as any advertising and promotion expenses (known as 12b-1 fees).

4.2 Relationship between Quality, Production Differentiation and Fees

In this section, we test the predictions from our theoretical framework. First we test how the text uniqueness of funds correlates with their quality. Specifically, we estimate the following regression:

$$TextUniq_{i,t} = \alpha + \beta\, Quality_{i,t} + \gamma \log(age)_{i,t} + \delta_{cat\times t} + \epsilon_{i,t} \tag{8}$$

where $TextUniq_{i,t}$ is the prospectus uniqueness measure of fund i in month t defined in Section 3.3. $Quality_{i,t}$ indicates gross return in month t, cumulative gross return over months $[t, t+23]$, 4-factor gross alpha estimated over months $[t, t+23]$, or Morningstar rating. $\log(age)_{i,t}$ is the logarithm of the age of fund i in month t. $\delta_{cat\times t}$ indicates category-month fixed effects. The standard errors are clustered at the fund level. Note that we do not control for fund size in the regressions, because our theoretical framework predicts that fund size is an outcome variable jointly determined with fund uniqueness. We use the sample of funds with available Morningstar ratings.[18]

Table 2 about here.

[18] Summary statistics are provided in Appendix Table A.2.

The estimation results are presented in Table 2. Columns (1), (2) and (3) use gross return, cumulative gross return and gross alpha as measures of quality respectively. Column (1) shows a strong and negative association between fund prospectus uniqueness and gross return. In terms of economic magnitude, a 10 p.p. decrease in gross return is associated with a 0.06 standard deviation increase in text uniqueness of funds.[19] The results are qualitatively similar and remain statistically significant when using cumulative return and alpha as alternative measures of fund quality (Columns (2) and (3)). In Internet Appendix Table A.5, we show that low Morningstar rating funds have more unique investment strategy descriptions than high Morningstar rating funds. 1-star funds are more unique than 3-star funds by 0.2 standard deviation and 2-star funds are more unique than 3-star funds by 0.05 standard deviation. We do not observe a statistical difference between 3-star and 5-star funds. The difference in uniqueness across funds with different Morningstar ratings is illustrated in Figure 3.

In column (4) of Table 2, we use as independent variable the logarithm of the fund's TNA. We observe a strong negative relationship between prospectus uniqueness and fund size. The magnitude suggests that doubling fund size is associated with a decline of 0.02 standard deviations in uniqueness. This suggests that more unique funds tend to be smaller, consistent with these funds catering to a more niche market.

The evidence above supports **Prediction 1** that lower quality funds choose more niche design on average. Internet Appendix Table A.4 presents the same regressions using holding-based uniqueness measures as dependent variables, and supports the same conclusion.

We next move on to test whether fund fees differ across funds with different levels of quality. We estimate the following regression:

$$FundFees_{i,t} = \alpha + \beta\, Quality_{i,t} + \gamma \log(age)_{i,t} + \delta_{cat\times t} + \epsilon_{i,t} \tag{9}$$

where $FundFees_{i,t}$ is the expense ratio of fund i in year t, and other variables are the same as in equation 8.

The estimation results are shown in columns (5) to (8) of Table 2. Column (5), (6) and (7) use gross return, cumulative gross return and gross alpha as measures of quality respectively. Column (5) implies a strong negative association between fund fees and gross return. In terms of economic magnitude, a 10 p.p. decrease in gross return is associated with a 0.06 p.p. increase in fund fees. This result is also robust to using cumulative return and alpha as alternative measures

[19]The uniqueness measure is normalized to have a mean of zero and a standard deviation of one.

of fund quality (columns (6) and (7)), and is consistent with Gil-Bazo and Ruiz-Verdú (2009) who find that funds with worse before-fee performance charge higher fees.[20]

In Internet Appendix Table A.5, we show that low Morningstar rating funds charge higher fees than high rating funds. 1-star funds are more expensive than 3-star funds by 0.47% per year (1.01 standard deviation). 2-star funds are more expensive than 3-star funds by 0.15% per year (0.32 standard deviation). These effects are economically significant when compared to the average expense ratio of 1.1% in our sample. An obvious concern is the fact that Morningstar rating methodology is based on after-fee return. However, we show that our results do not come from a pure mechanical effect of fund fees. As shown in Internet Appendix Table A.5, low rating funds have lower *before-fee* returns, and charge a higher fee, which makes their net-of-fee return even worse.

In column (8) of Table 2, we use as independent variable the logarithm of the fund's TNA. We observe a strong negative relationship between fund fees and size, consistent with niche (smaller) funds charging higher fees. The magnitude suggests that doubling fund size is associated with a decline of 0.08% in fund fees.

The above evidence supports **Prediction 2** that lower quality funds can charge higher fees to investors. Overall, the empirical results presented above are consistent with the predictions generated by our theoretical framework: Lower quality funds offer more niche products and charge higher fees.

5 Shock to Fund (Perceived) Quality

The previous results highlight correlations, prompting concerns regarding potential reverse causality. Specifically, one might hypothesize that adopting a niche design, as reflected in more unique prospectus text, lead to underperformance, rather than the inverse. In that case, funds characterized by higher uniqueness might also display lower performance and assets under management. To rule out this possibility, one needs to show that an exogenous shock to fund quality affects a fund's product differentiation decision. Realistically, identifying such a clear shock to fund quality is challenging. However, in practice, what determines investor demand is their *perceived* quality of funds, which, in turn, defines their *expected* utility from investing. In the

[20] In practice, some funds also charge investors an additional fee when they acquire or redeem fund shares, namely "fund loads". Appendix Table A.3 shows that the negative relationship between quality and fees is robust to including fund loads as part of fund fees.

subsequent section, we introduce an empirical approach leveraging a shift in perceived fund quality, using ratings from a leading information intermediary in the mutual fund industry.

5.1 Empirical Strategy

We use the issuance of the initial Morningstar rating of a fund as a quasi-exogenous shock to the fund perceived quality. Each fund gets rated by Morningstar from the month it reaches a track record of 36 months. When the rating is released, investors can learn from this additional signal: If a fund gets a high (low) rating, it is more likely to be of high (low) quality. Therefore, the release of the initial rating can be considered as a plausibly exogenous shock to investors' expectation of the fund quality. This setting allows us to test whether funds that are "revealed" to be of low quality actively choose to become more niche.

We acknowledge the fact that the initial rating of a fund is to some extent predictable, as Morningstar's rating methodology is publicly available and can be used to compute the fund rating before it is officially published. Indeed, in the following section, we show some evidence suggesting that the funds themselves are predicting the rating in advance. However, this does not necessarily go against our central prediction. Our empirical strategy requires that a significant group of investors gain additional information from the publication of Morningstar ratings, even if some sophisticated investors are able to predict the rating before its publication.[21] Ben-David et al. (2022b) show that mutual fund investors have limited financial sophistication and rely on Morningstar ratings to make investment decisions. We therefore expect most investors to update their perception of fund quality at the time a rating is made public. This makes the publication of Morningstar ratings a plausibly exogenous shock to fund perceived quality.

We exploit the issuance of fund initial rating in a staggered differences-in-differences framework. To do so, we use the subsample of funds that enter our sample before they get rated and therefore for which we can observe the initial Morningstar rating, which includes 474 funds.[22] Internet Appendix Table A.6 presents detailed summary statistics for this subsample. We con-

[21] In practice, predicting a fund's Morningstar rating before its publication requires skills: collecting the fund and its peers' performance, running regressions, and ranking funds based on different conditions, which are presumably challenging to an average investor.

[22] In our analysis, we include funds that enter our sample prior to reaching 24 months of age, ensuring we observe their prospectus for at least one year before their initial rating. Our findings remain robust even when we expand the sample to funds that enter before they attain exactly 36 months of age. It is worth noting that funds created after 2018 do not receive ratings during our sample period. Nevertheless, we retain these funds in our sub-sample for this particular analysis.

sider a specification featuring different "treatment" effects which depend on the initial rating obtained by funds. Specifically, we estimate the following regression:

$$\begin{aligned} TextUniq_{i,t} = \alpha &+ \beta_1 Post \times 1^* \, Rating_{i,t} \\ &+ \beta_2 Post \times 2^* \, Rating_{i,t} \\ &+ \beta_3 Post \times 3^* \, Rating_{i,t} \\ &+ \beta_4 Post \times 4^* \, Rating_{i,t} \\ &+ \beta_5 Post \times 5^* \, Rating_{i,t} \\ &+ \gamma \log(age)_{i,t} + \delta_{cat \times t} + \lambda_i + \epsilon_{i,t}, \end{aligned} \tag{10}$$

where $TextUniq$ is the text uniqueness measure of fund i in month t. $Post$ is a dummy which is equal to one if the fund is rated. 1^* to 5^* $Rating$ are dummy variables indicating whether the initial rating of the fund is equal to the corresponding star rating. $\log(age)_{i,t}$ is the logarithm of fund age. As in previous regressions, we include category-month fixed effects $\delta_{cat \times t}$. We also include fund fixed effects λ_i. Standard errors are clustered at the fund level. Again, we do not control for fund size in the regressions, because fund size is an outcome variable jointly determined with fund uniqueness.

The regression in (10) compares how funds that get rated (treated group) change their prospectus uniqueness compared to not yet rated funds (control group). The fund fixed effects fully control for differences between funds that are constant over time. The category-month fixed effects control for fluctuations that are specific to the fund's Morningstar category. The coefficients βs are the estimates of the effect of the publication of a specific rating. For example, β_1 captures the average variation in uniqueness before vs. after a fund receives a 1 star rating, with respect to not yet rated funds in the same category over the same period. Note that the rating issuance date is fund-specific. Therefore, the staggered differences-in-differences specification (10) means that our control group is not restricted to funds that are never rated in our sample. In fact, equation (10) takes as the control group all funds that do not have yet a rating in month t, even if they will get rated later on.

We further consider a specification adding fund age fixed effects to regression (10). Because such fixed effects are perfectly collinear with the timing of the release of ratings (ratings are mechanically released after a fund reaches 36 months), we omit the interaction $Post \times 3^* \, Rating$ in this specification. Therefore, in that case, the βs coefficients estimate the effect of the publication of a specific rating, relative to funds of the same age but which get a 3-star rating at the same period.

Finally, to ensure our effects are estimated by comparing funds with similar "initial" uniqueness levels, we also consider a specification adding fixed effects based on the combination of initial uniqueness quintiles and fund age. Specifically, we categorize funds into five groups based on their initial prospectus text uniqueness (ranging from low to high) and we incorporate fixed effects capturing each group-age combination. In that case, the βs coefficients estimate the effect of the publication of a specific rating, relative to funds of the same age with same initial uniqueness level and which get a 3-star rating over the same period.

5.2 Main Results

Table 3 shows the estimation results of the regressions. In column (1), we do not control for fund age. The coefficient on $Post \times 1^{*}Rating$ is positive and statistically significant at the 1% level. After receiving a 1-star rating, a fund increases its prospectus uniqueness by 0.15 standard deviations. The coefficient on $Post \times 2^{*}Rating$ is also positive but not significant, with an economic magnitude of 0.04 standard deviations.

Table 3 about here.

Mechanically, the timing of the release of a fund's Morningstar rating is perfectly correlated with the fund's age (36 months). Therefore, comparing rated funds with not yet rated funds may capture some life cycle effects of fund uniqueness. We alleviate this concern in two ways. First, we add the natural logarithm of fund age as control variable into the regression. As shown in column (2) in Table 3, the results are similar when adding this control variable. Column (3) replaces $Post \times 3^{*}Rating$ by the dummy $Post$ and test whether the changes in text uniqueness for funds receiving a 1, 2, 4 or 5-star rating are statistically different from the changes for funds receiving a 3-star rating. The results suggest that funds that receive a 1-star rating increase their prospectus uniqueness significantly more than 3-star funds.

Second, in column (4), we estimate the effect by adding fund age (in months) fixed effects, which fully absorbs the $Post$ coefficient in the regression. This specification further restricts the comparison between funds that are of the same age, but receive different ratings. The results suggest that funds receiving a 1-star rating significantly increase their fund prospectus uniqueness, compared to 3-star rated fund of exactly the same age. This specification absorbs any life-cycle effects in fund uniqueness. Finally, in column (5), we replace fund age fixed effects by fixed effects capturing the combination of initial uniqueness quintiles and fund age. The magnitude and statistical significance of the coefficients remain similar.

To study the timing of this change in funds' uniqueness design choice, we estimate a specification similar to regression (10) but with month-specific dummies indicating 24 months before rating, the month of rating, and 36 months or more after the rating. This allows us to analyze the dynamics of the effect of the ratings on funds' uniqueness, relative to the month in which the rating is made public by Morningstar. We use a specific set of coefficients for each category of ratings.

Figure 4 about here.

Figure 4 presents the estimated coefficients. We find that funds that receive a 1-star rating increase their prospectus uniqueness following the rating shock, as illustrated in Panel A. Notably, an increase emerges three months prior to the official rating release. We posit that funds—supported by the management company's marketing and sales teams who typically monitor the release of such ratings—adjust their product differentiation during the preceding quarter in anticipation of the forthcoming disclosure of the rating to underlying investors. Nevertheless there is a clear structural change before vs. after receiving 1 star. In contrast, prospectus uniqueness does not change significantly after the rating disclosure for the funds that receive a 5-star rating (cf., Panel B in Figure 4). In Internet Appendix Figure A.1, we present the coefficients for funds that receive 2 and 4 stars. We observe non-significant change.[23]

To further confirm that funds actively update their own prospectus, in Table 4, we re-estimate the regressions presented in Table 3 but replace the dependent variable with a dummy indicating a change in the prospectus text. This variable is equal to one if the time-series prospectus similarity, $TS\ TextSim$, which measures how similar a fund prospectus is compared

[23]The anticipatory effect observed in Panel A of Figure 4 raises the concern that the increase in uniqueness three months prior to the release of Morningstar's ratings might drive down the fund's returns, and be the cause of the one-star rating. Two points are essential to mention here. First, the last three months exert only a limited influence on the rating, as it is based on the aggregate returns over the preceding 36 months. Second, we can assess whether there is an actual decline in fund returns during the three months leading up to the one-star rating. To test this, we estimate the regression underlying Figure 4, using the fund's monthly gross return as the dependent variable. The estimated coefficients are presented in Internet Appendix Figure A.2. The findings indicate no significant fluctuation in fund returns in the three months leading up to the one-star rating release. This suggests that the rise in uniqueness observed in Figure 4 is not likely the cause of the subsequent low rating.

to the previous prospectus of the same fund, is strictly lower than 0.95. In instances where there is no change in the prospectus text, $TS\ TextSim$ is equal to one. Therefore a value of $TS\ TextSim$ below 0.95 indicates a non negligible update to the prospectus text in comparison to the previous version. Internet Appendix Table A.7 presents the estimation results using the continuous $TS\ TextSim$ measure as the dependent variable.

Table 4 about here.

In Table 4, columns (1) and (2) reveal that funds that receive a 1-star rating become more likely to update their prospectus than unrated ones, whereas 3-star-rated funds show a decreased likelihood to do so. Column (3) further shows that 1-star-rated funds become significantly more likely to update their prospectuses than their 3-star counterparts. This result remains consistent even after accounting for fund age fixed effects, as presented in column (4), and upon integrating initial uniqueness × fund age fixed effects in column (5). In terms of economic magnitude, the increase in the likelihood of a prospectus change for funds that receive a 1-star relative to 3-star funds is approximately 13 percentage points. This is economically large as the average of the dependent variable is 0.08, indicating the general stability and persistence of prospectuses over time. Internet Appendix Table A.7 shows that our conclusion remains the same when using the continuous $TS\ TextSim$ measure as the dependent variable: Funds that receive a 1-star rating update more (decline in $TS\ TextSim$) their prospectuses, compared to unrated funds and 3-star funds.

5.3 Additional Tests

The above results are consistent with **Prediction 3** in Section 2 that funds adapt and become more niche after a negative shock to their (perceived) quality. Funds that are likely to be now considered as low-quality funds become more unique according to their prospectus and, as such, target a smaller segment of the market. Below, we discuss additional tests.

In Internet Appendix Table A.8, we estimate the same regressions as in Table 3 using text uniqueness as dependent variable, but controlling for funds' past 12-month return. Our results remain robust, which is consistent with the fact that Morningstar rating brings new information to investors.

A recent econometrics literature documents that estimators in difference-in-difference regressions with time and unit fixed effects, known as two-way fixed effects (TWFE) estimators, may be biased if there exists treatment effect heterogeneity across treated groups or over time (cf., De Chaisemartin and d'Haultfoeuille, 2022, for a survey). As a robustness check, in Internet Appendix Table A.9, we re-estimate the results using the imputation estimator of Borusyak et al. (2022). We obtain similar coefficients and the conclusions remain the same.

Internet Appendix Table A.10 presents difference-in-difference regression results with portfolio holding uniqueness (Panel A) and similarity to the index (Panel B) as dependent variables. Our findings modestly suggest that the funds receiving a 1-star rating also react by holding more unique portfolios. However, it is worth noting that these results are statistically significant in only a small set of our regression analyses.

We run the same regressions with fund fees as dependent variables to test whether funds change their fees after receiving a low Morningstar ratings. As shown in Internet Appendix Table A.11, we do not find any significant results (neither positive nor negative).[24]

Finally, we also explore whether funds might obfuscate poor performance by increasing the complexity of their investment strategy descriptions within their prospectuses, echoing the ideas on obfuscation in Ellison and Ellison (2009) and deHaan et al. (2021). To investigate this, we estimate difference-in-differences regressions with several metrics assessing the complexity of the prospectus language as our dependent variables. The results are presented in Internet Appendix Table A.12. Notably, there does not appear to be any significant increase in the complexity of the prospectus language after funds receive a low rating.

6 Benefits of Product Differentiation

Prior research has shown that fund prospectuses provide important information regarding fund strategy to investors (Abis and Lines, 2023; Abis et al., 2022).[25] Morningstar also provides synopses of the strategy descriptions in fund prospectuses to help investors pick mutual funds, and it appears that investors do pay attention to this information (Kostovetsky and Warner, 2020). In this section, we investigate whether the changes in fund prospectuses that we document in Section 5 affect investor behavior and consequently fund outcomes.

[24]Note that this does not necessarily go against our theoretical framework. As shown in Section 2, two forces drive fund fees. A negative shock decreases perceived quality which has a negative effect on fees, but it should increase product differentiation which has a positive effect on fees. The net effect is therefore ambiguous.

[25]The SEC has implemented regulations to make fund prospectuses more easily understandable to investors, which affect investors' investment decisions (deHaan et al., 2021).

6.1 Survival and Flows

Specifically, we ask the following question: Do low-quality funds accrue benefits from becoming more unique products? We examine whether low-rated funds that update their prospectus face a reduced probability of market exit and collect more asset flows, compared to similar low-rated funds that do not. Essentially, we aim to test whether product differentiation helps low-quality funds to survive. We analyze the combined impact of a low rating and a prospectus update on a fund's likelihood to die, i.e., to exit the market, within a given month. Specifically, we estimate the following regression:

$$\begin{aligned} Dead_{i,t} = \alpha &+ \gamma_1\, 1^*\, Rating_{i,t} + \beta_1\, 1^*\, Rating_{i,t} \times ChangedProspectus_{i,t} \\ &+ \gamma_2\, 2^*\, Rating_{i,t} + \beta_2\, 2^*\, Rating_{i,t} \times ChangedProspectus_{i,t} \\ &+ \beta_3\, 3^*\, Rating_{i,t} \times ChangedProspectus_{i,t} \\ &+ \gamma_4\, 4^*\, Rating_{i,t} + \beta_4\, 4^*\, Rating_{i,t} \times ChangedProspectus_{i,t} \\ &+ \gamma_5\, 5^*\, Rating_{i,t} + \beta_5\, 5^*\, Rating_{i,t} \times ChangedProspectus_{i,t} \\ &+ \gamma \mathbf{X_{i,t}} + \delta_{cat \times t} + \theta_{age} + \epsilon_{i,t}, \end{aligned} \tag{11}$$

where $Dead_{i,t}$ is a dummy indicating whether fund i exits the market, i.e., dies in month t. 1^* to 5^* $Rating_{i,t}$ are dummy variables indicating whether the initial rating we observe for fund i is equal to the corresponding star rating. We consider observations exclusively from rated funds, setting 3-star funds as the benchmark in regression (11). $ChangedProspectus_{i,t}$ is a dummy variable equal to one if fund i has changed its prospectus by time t. A prospectus change is defined as in section 5.2, i.e., if the fund *TS TextSim*, which measures how similar the fund prospectus is compared to the previous prospectus of the same fund, is strictly lower than 0.95. $\mathbf{X_{i,t}}$ is a vector of fund characteristics used as controls, which include the logarithm of fund size (TNA), the fund fees, and the fraction of institutional share classes in the fund. As in previous regressions, we include category-month fixed effects $\delta_{cat \times t}$. We also include fund age fixed effects θ_{age} to capture life cycle effects. The coefficients of interest are β_1, β_2, β_3, β_4 and β_5, which capture the effect of changing prospectus on funds' likelihood of dying after receiving a given rating.

The estimation results are shown in columns (1) to (4) of Table 5. Note that all coefficients are multiplied by 100 and must be interpreted in p.p.. Column (1) confirms the significant influence of the initial rating on fund survival probabilities. In a given month, compared to 3-star funds, 1-star (2-star) funds are 0.44 p.p. (0.22 p.p.) more likely to die, and 5-star (4-star) funds are 0.11 p.p. (0.10 p.p.) less likely to do so. Controlling for fund size, fees and fraction of institutional share classes affects the magnitude of the coefficients but leads to the same conclusion that 1-star and 2-star funds are more likely to exit the market than 3-star funds (column (2)).

In column (3), the coefficient on the interaction between a 1-star rating and prospectus change is significantly negative, which indicates that 1-star funds that update their prospectus decrease their likelihood of death. The coefficient is also economically large: A prospectus update is associated with a decrease in the likelihood of death by 0.49 p.p. for 1-star funds, which almost annihilate the negative effect of receiving a 1-star rating (cf., the coefficient of 0.59 on 1* *Rating* in column (3)). Changing prospectus also decreases the likelihood of death of 2-star funds, while the coefficient is smaller in magnitude. We do not observe significant effect for 4-star and 5-star funds. In column (4), we add control variables and we reach the same conclusion.

Table 5 about here.

We also estimate regression (11) using as dependent variable the monthly percentage flow of the fund. The estimation results are shown in columns (5) to (8) of Table 5. Columns (5) and (6) reveal that higher-rated funds tend to attract larger flows than lower-rated funds. In column (7) and (8), which include the interactions between each rating and prospectus change, we observe that a prospectus update has a positive and significant effect on fund flows for low rated funds. The estimated coefficients suggest that 1-star funds that update their prospectus increase their monthly flow by 0.8 p.p.. 2-star and 3-star that do also increase their flows, though to a lower extent, by 0.6 p.p. and 0.3 p.p. respectively. We do not observe a significant effect of prospectus change for 4-star and 5-star funds.

These results are consistent with the notion that being more unique allows low-quality funds to attract the set of investors who gain additional utility from investing in these differentiated products. As a result, uniqueness increases the likelihood of survival for low-quality funds. This rationalizes the behavior of funds that we identified in our differences-in-differences analysis: Low quality funds become more unique in order to increase their chances of survival and collect more flows.

Note that our results provide a novel potential explanation for the survival of low-return funds in the mutual fund space. One conventional view might be that investors are simply naive and do not know (or do not spend enough attention to the fact) that they could achieve higher return by relocating their capital to a better fund. However, in such a framework, there should not be any impact of uniqueness on survival of low-return funds. Our framework provides a "rational" explanation: Low return funds optimally become more unique and attract the investors who can gain additional utility beyond financial return, and therefore survive in equilibrium.

6.2 Market-level Impact of Ratings

In this section we ask whether mutual funds' reaction to the release of Morningstar rating influences the degree of product differentiation in the mutual fund market. Intuitively, if low-rated funds increase their product differentiation in response to Morningstar ratings, then, one should observe that, overall, rated funds offer greater product differentiation compared to unrated funds.

To validate this hypothesis empirically, we examine the uniqueness distribution across rated and unrated funds. Specifically, we split funds that get eventually rated in our sample into two categories: those whose initial rating is low (1- or 2-star) and those whose initial rating is high (above 3-star). Then, within each subsample, we compare the text uniqueness distribution for pre- and post-rating observations. Our objective is to assess whether there are shifts in the overall uniqueness distribution induced by the rating release. To absorb potential time and age effects, we first regress text uniqueness on category-month fixed effects and age: $TextUniq_{i,t} = \alpha + \beta_1 \log(age)_{i,t} + \delta_{cat\times t} + \epsilon_{i,t}$. We then estimate the kernel density of the residuals ϵ.

Panel A of Figure 5 presents the density estimates for rated versus unrated observations of funds with initial 1-star or 2-star ratings.[26] Panel A suggests a marked difference in the uniqueness distributions. Prior to the release of Morningstar ratings ("Unrated"), a dense concentration is evident around the average text uniqueness. In contrast, post-disclosure of a low Morningstar rating reveals a more pronounced skewness towards funds with above-average prospectus uniqueness. Interestingly, this pattern does not appear when considering funds with high initial rating. As shown in Panel B of Figure 5, the uniqueness distributions between rated and unrated observations remain largely unchanged for funds whose initial rating is 3 to 5 stars.

Figure 5 about here.

To test the significance of the observed distributional differences in Panel A of Figure 5, we employ the Mann-Whitney U Test. This non-parametric test assesses the equality of two distributions. The results, presented in Table 6, corroborate our previous observations. Specifically,

[26] We pool 1- and 2-star funds and 3-, 4- and 5-star funds to obtain smoother density kernels estimation.

there is a significant difference in the uniqueness distributions of funds pre- and post-rating issuance when their initial rating is low. Conversely, for funds with high initial rating, the distributions before and after the rating disclosure remain statistically indistinguishable.

Table 6 about here.

These results suggest that the disclosure of Morningstar ratings might play a role in shaping the market-wide landscape of mutual funds. The release of these ratings prompt certain mutual funds to adjust their product uniqueness. Such changes appear to lead to an increased presence of "niche" funds, offering more specialized products than what might have potentially emerged in the absence of Morningstar ratings. However, it is important to approach this interpretation with caution, as we cannot directly observe how the mutual fund landscape might have evolved in the absence of Morningstar ratings.

7 Discussion: What is Uniqueness Measuring?

In this section, we explore the different dimensions through which mutual funds differentiate themselves according to the text uniqueness measure. We examine three potential explanations for what the text uniqueness measure captures: specific investor preferences, unique factor exposures, and investor sentiment.[27]

7.1 Investor Preferences

We investigate whether unique funds offer products which cater for specific investor preferences, e.g., environmental concerns. We first construct a measure of *word uniqueness* by taking, for each word, the average text uniqueness of all prospectuses mentioning that word.[28] From there, we rank all the words by their respective *word uniqueness*. Intuitively the top of the list contains the words which appear mostly in unique funds' prospectuses and the words with low uniqueness are those which are used by the average fund.

Table 7 about here.

[27] As Kostovetsky and Warner (2020), we find that text uniqueness attenuates the flow-performance relation, reducing the risk of investor outflows. We do not report these results as they are similar to this prior work.

[28] We focus on words that are mentioned by at least 10 funds to limit the uniqueness "noisiness" of words.

Table 7 illustrates the words with highest uniqueness and the words with uniqueness close to zero. One set of words which clearly pop out are those related to environmental, social and corporate governance, or "ESG" concerns, a topic which has received increased interest from investors in the past decade. Some investors believe that exposure to ESG-focused funds is a moral imperative, even if it is means giving up higher fund performance in a non-ESG focused alternative. The niche funds in our data are more likely to mention words which indicate a stance on the environmental impact of their investment portfolio such as "climate", "coal" and "nuclear". Niche funds are also more likely to mention words which indicate a stance on the social impact of their investment portfolio such as "controversial" and "vote". Furthermore, niche funds may have words addressing corporate governance issues, including "workplace". Another set of words which pop out indicate more targeted investment philosophies such as "database" and "media".

In contrast, when it comes to commonly used–not unique–words which are found in "average" prospectuses, we find more generic references to fund terms (e.g. "discount" and "expense") or general fund investment strategies (e.g. "model" and "dividend").

To better understand the time-variation of funds' differentiation, we investigate how the funds' usage of unique words evolves over time. We first manually categorize top 50 unique words into three categories: ESG, investment strategy and others. Detailed categorization is shown in Internet Appendix Table A.13. Then we plot the word ratio in each category (number of words in each category divided by total number of words in fund prospectuses) by year.

As shown in Figure 6, interestingly, there is a large increase in the usage of ESG-related words in high-uniqueness fund prospectuses, which is consistent with the recent rise of ESG in the asset management industry. While the usage of unique strategy-related words are stable over time. We conclude that funds differentiate by catering to investor preferences, which could vary over time.

Figure 6 about here.

7.2 Factor Exposures

We also test whether unique funds provide alternative factor exposures to investors, i.e., beyond standard asset pricing models. These alternative factors may attract investors with specific hedging demand or belief in the superior risk-adjusted return of these factors. If this is the case, standard factor models should explain a lower fraction of variations in the returns of unique funds. To test this, we run the following regression:

$$Y_{i,t} = \alpha + \gamma TextUniq_{i,t} + \lambda_{cat \times t} + \epsilon_{i,t} \tag{12}$$

where $Y_{i,t}$ is eitheir $R^2_{i,t}$ or $\beta_{i,t}$, which are respectively the R-square and factor loadings from the 4-factor regression (3 Fama-French factors as well as the Momentum factor) of fund i in month t, estimated using a rolling window of 24 months. $TextUniq_{i,t}$ is the prospectus uniqueness of fund i in month t. $\lambda_{cat \times t}$ are category-month fixed effects.

Internet Appendix Table A.14 shows the estimation results of the above regressions. Consistent with Kostovetsky and Warner (2020), we find that variations in unique funds' returns are explained to a lower extent by standard risk factors. An increase by one standard deviation in prospectus uniqueness is associated with a 0.73 percentage point decrease in R^2 of the factor regressions. Unique funds also load less on the market factor: A one standard deviation increase in prospectus uniqueness is associated with a 0.01 lower market beta. Unique funds also load more on the value factor. However, there is no significant difference regarding the exposure to the size or momentum factors. Overall these results suggest that unique funds might differentiate themselves from broad funds by providing exposure to uncommon factors.

7.3 Investor Sentiment

Finally, we investigate whether unique funds offer products that cater for investor sentiment (or grabbing investors' attention). Ben-David et al. (2023) show that "specialized" ETF offer portfolios in which the stocks experience over-valuation and attract investors' attention. We examine whether this is also true in the active mutual fund space. Specifically, we test whether unique funds hold stocks that have higher valuations. We construct fund-level market-to-book ratio by value-weighted individual stock's market-to-book ratios (market equity divided by book equity) in the portfolio. We estimate the following regression:

$$Market\text{-}to\text{-}Book_{i,t} = \alpha + \beta Uniqueness_{i,t} + \gamma \mathbf{X_{i,t}} + \lambda_{cat \times t} + \epsilon_{i,t} \tag{13}$$

where $Market\text{-}to\text{-}Book_{i,t}$ is the market-to-book ratio of fund i in month t. $Uniqueness_{i,t}$ is the uniqueness measures of fund i in month t. $\mathbf{X_{i,t}}$ is a vector of other fund characteristics as controls, which include the logarithm of fund age, the logarithm of total asset under management, the expense ratio of the fund, and the fraction of institutional shares in the fund. The variable of interest is β, which captures how fund uniqueness correlates with market to book ratio.

Internet Appendix Table A.15 shows the estimation results. Both text and holding uniqueness are negatively correlated with market-to-book ratio, and the similarity to index is positively correlated with market-to-book ratio. More unique funds hold portfolios that have a lower valuation. This is inconsistent with the view that unique funds hold more popular stocks to attract investors' sentiment or attention.

8 Conclusion

In this paper we provide evidence on the incentives of financial product to differentiate beyond performance, using mutual funds as our laboratory. We show that mutual funds behave like many other consumer products in their use of product differentiation to mitigate quality-based competition.

We present a theoretical framework to understand how funds choose their product design to cater for different investor clienteles. In our model, each consumer's expected utility from investing in a given mutual fund is made up of the fund's expected performance (product quality) and a fund-consumer-specific matching term. Mutual funds then set their (i) fees (product price) and (ii) product design, i.e., whether the fund prefers to cater to a broad or niche market of consumers. We show that, in equilibrium, high-quality funds choose to be broad, while low-quality funds choose to be niche. Furthermore, a novel prediction of our model is that lower quality funds might charge higher fees than higher quality counterparts.

We present evidence supporting these predictions using data on US active mutual funds. Mutual funds with lower performance are more likely to adopt a niche product design, as reflected in their prospectus text (akin to product description), to cater for a smaller set of investors. Furthermore, since these funds have more market power over their investors, they tend to charge higher fees—providing a potential explanation for the puzzle of why low-quality mutual funds can survive in a crowded menu of options for investors. Finally, using the initial publication of a Morningstar rating as a shock to (perceived) quality, we find that funds which receive a low rating respond strategically by becoming more unique. This change increases the probability of survival for these low-rated fund.

Our findings provide a potential explanation for the growing array of mutual funds in a relatively constrained set of asset classes and fund categories and open up new questions about the ways in which financial products differentiate.

Figures

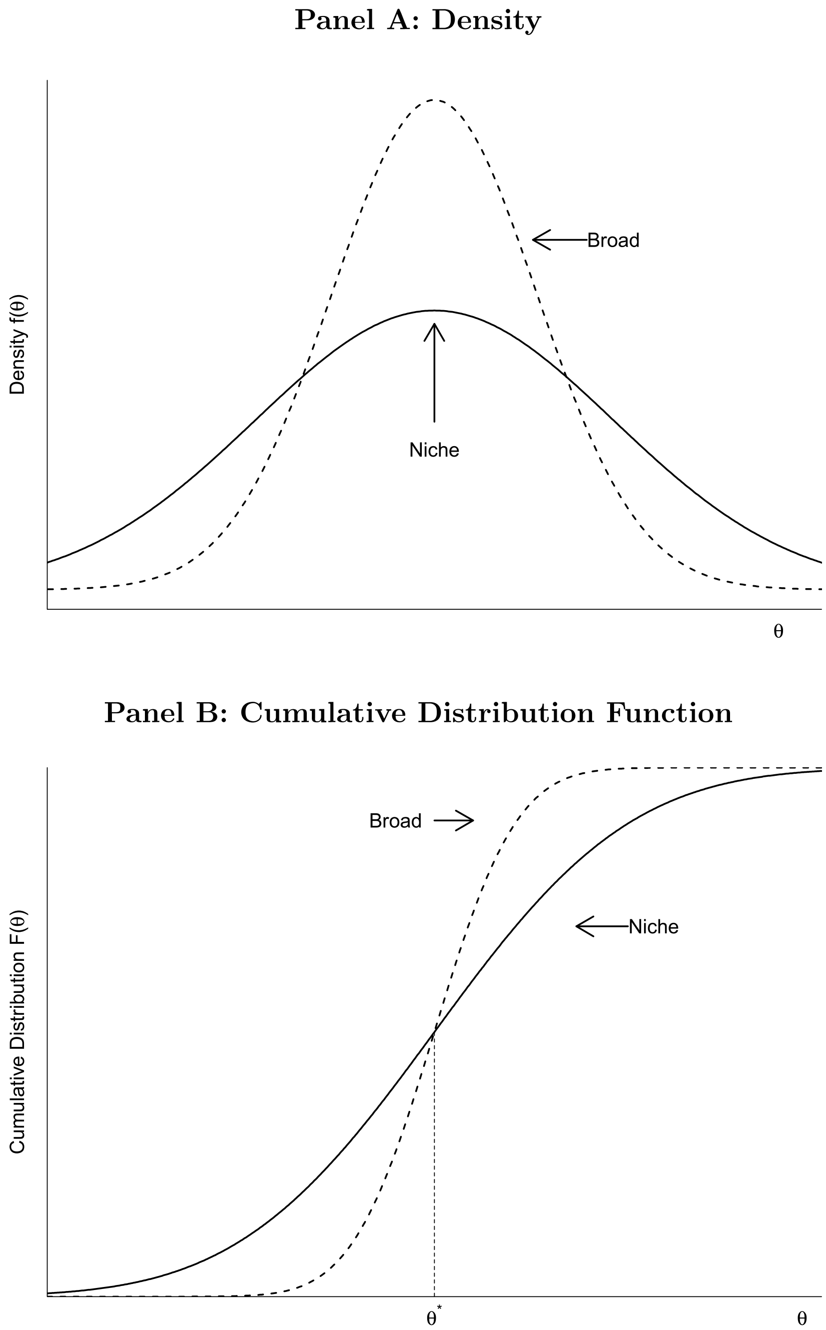


Figure 1: **Density and c.d.f. of matching terms with broad and niche product design**: This figure illustrates the density and c.d.f. of the matching term ϵ, with broad and niche fund design. In both panels, the dotted line corresponds to the broad design, and the solid line corresponds to the niche design. θ^* in panel B is the rotation point discussed in Internet Appendix A.

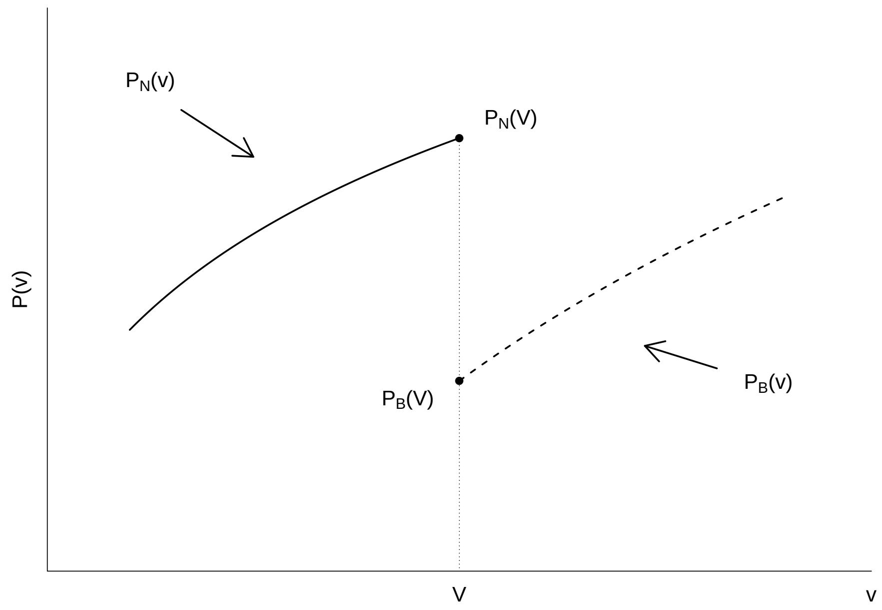


Figure 2: **Price in equilibrium**: This figure illustrates how equilibrium price changes with fund quality. The y-axis is the equilibrium price and the x-axis is the perceived quality v. V is the quality for which the fund is indifferent between choosing broad or niche designs. The solid (dashed) line shows how price changes with v in niche (broad) design.

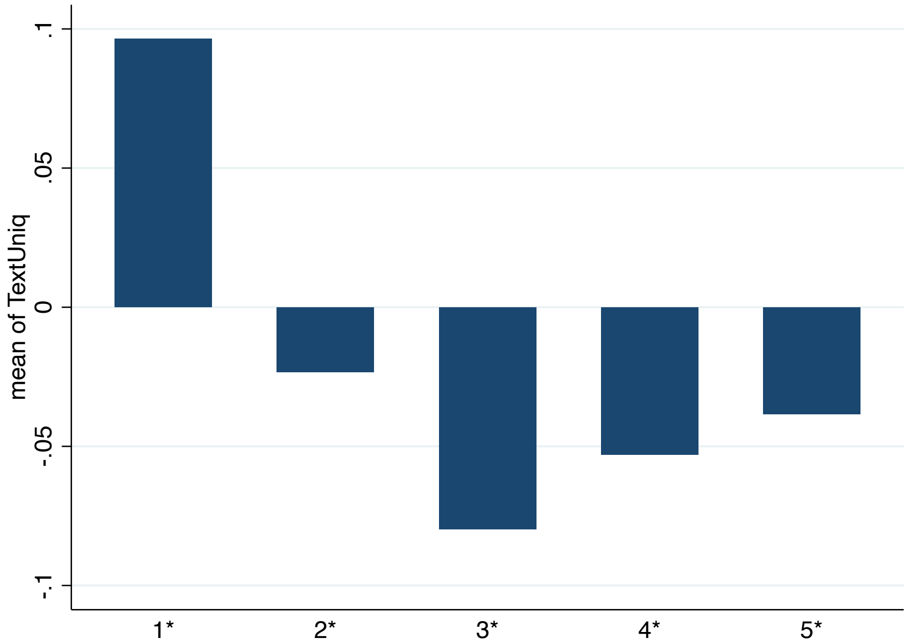
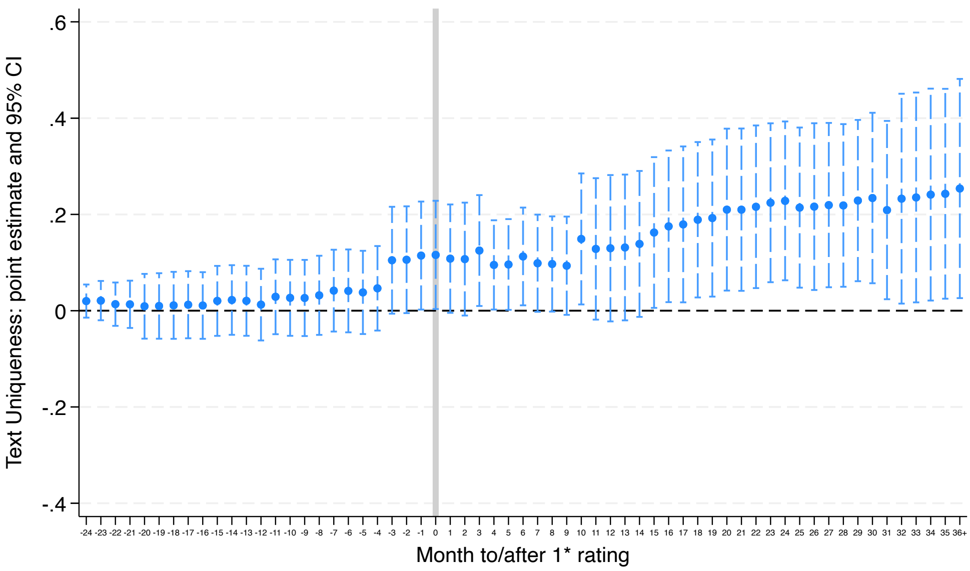


Figure 3: **Product uniqueness over rating:** This figure reports the average of prospectus text uniqueness by Morningstar rating. On the x-axis is the Morningstar rating. On the y-axis is the mean of text uniqueness of funds with that rating.

Panel A: After 1* Rating



Panel B: After 5* Rating

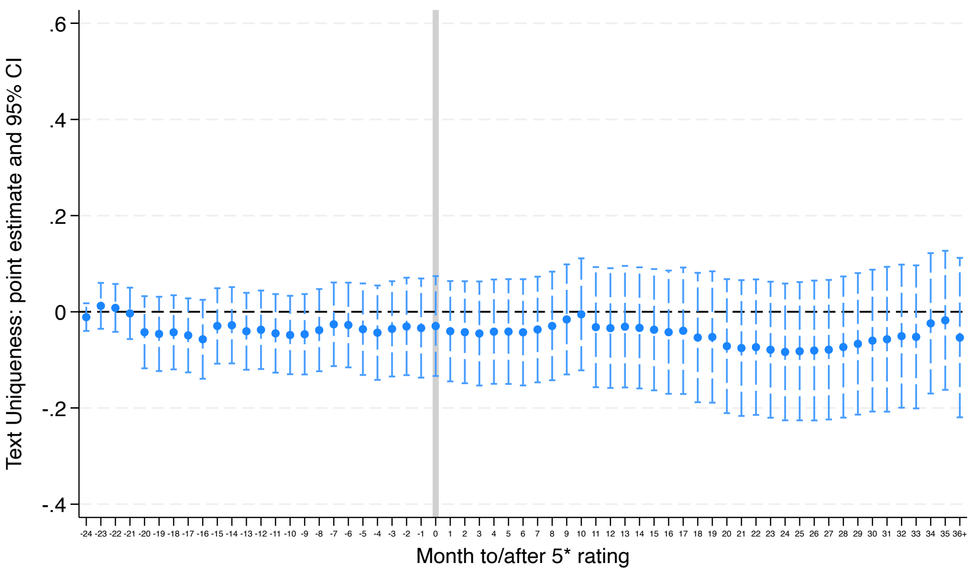
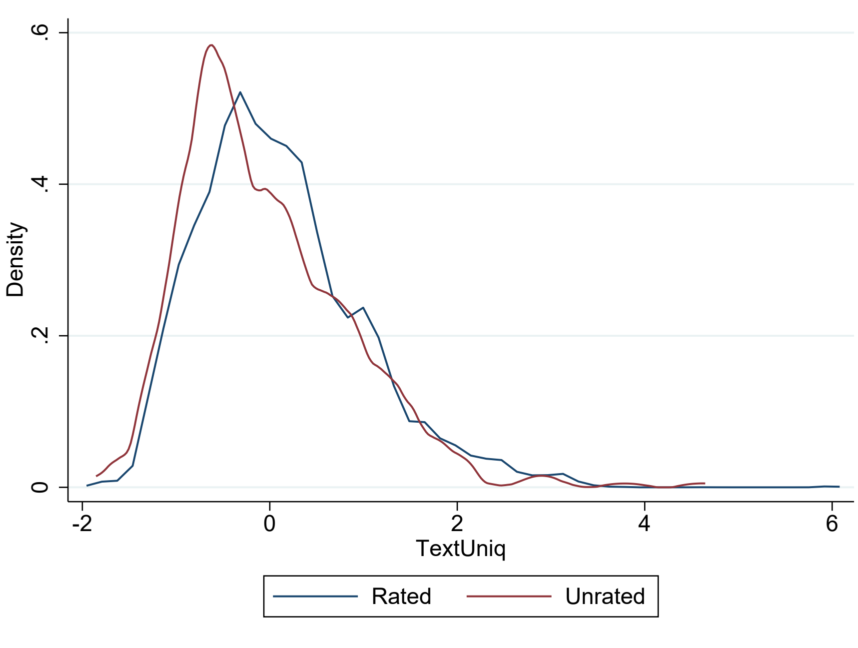


Figure 4: **Effect of rating disclosure on fund prospectus text uniqueness**: This figure presents the coefficient estimates $\beta_{k,1^*}$ (Panel A) and $\beta_{k,5^*}$ (Panel B) as well as 95% confidence intervals against month to the disclosure of rating, from the following regression:

$TextUniq_{i,t} = \sum_{rating \in \{1^*,2^*,4^*,5^*\}} \left\{ \sum_k \beta_{k,rating} \{month\ k\ to\ rating\}_{i,t} \right\} + \gamma \log(age)_{i,t} + \delta_{cat \times t} + \lambda_i + \epsilon_{i,t}$.

The dependent variable is the fund's prospectus text uniqueness. $\delta_{cat \times t}$ and λ_i are month-Morningstar category fixed effects and fund fixed effects respectively. Standard errors are clustered at the fund level. The regression includes only the sub-sample of funds entering our sample one year before they get rated.

Panel A: Text uniqueness distribution for 1^* and 2^* funds



Panel B: Text uniqueness distribution for 3^*, 4^* and 5^* funds

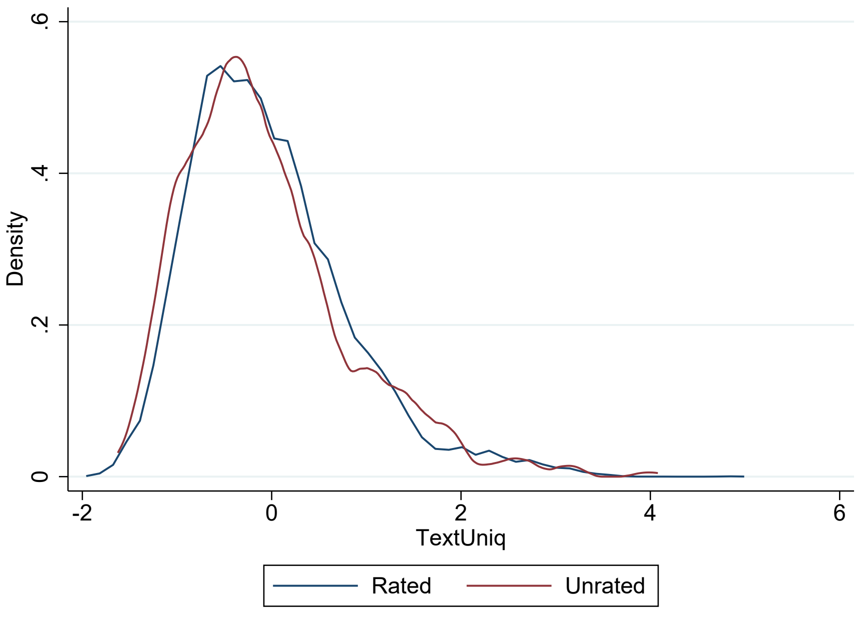


Figure 5: **Distribution of text uniqueness before and after rating:** The graphs show the kernel estimates of the distribution of text uniqueness of funds. The variable used is the residual $\epsilon_{i,t}$ of the regression:
$TextUniq_{i,t} = \alpha + \beta_1 \log(age)_{i,t} + \delta_{cat \times t} + \epsilon_{i,t}$.
Blue lines represent the distribution among rated funds' observations and red lines represent the distribution among unrated funds' observations. Panel A presents distribution for the funds which will receive (for unrated funds) or have received (for rated funds) 1 or 2 stars. Panel B presents distribution for the funds which will receive (for unrated funds) or have received (for rated funds) 3, 4 or 5 stars.

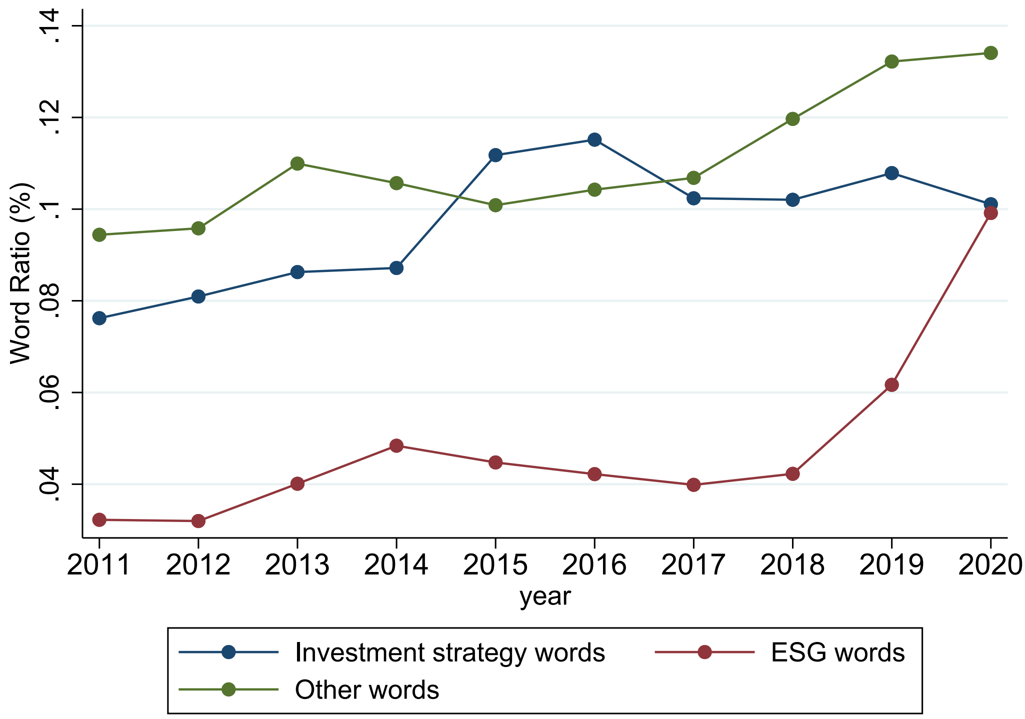


Figure 6: **Dynamics of unique word category:** The graph shows the time variation of word ratio by categories of top 50 unique words. On the y-axis is the unique word ratio, defined as number of unique words in each category divided by total number of words in prospectuses. On the x-axis is the year of prospectuses. Detailed categorization of top 50 unique words is exhibited in Internet Appendix Table A.13.

Tables

	Obs	Mean	Sd	5%	25%	50%	75%	95%
Gross Ret (%)	187,052	1.05	4.70	-7.13	-1.15	1.31	3.50	7.84
Fund Fees (%, annual)	187,052	1.10	0.47	0.46	0.87	1.06	1.28	1.86
Net Ret. (%)	187,052	0.95	4.70	-7.23	-1.24	1.22	3.42	7.75
TNA (mill)	187,052	1,720.67	5,453.66	5.70	51.00	266.50	1,270.25	7,788.90
Fund Age (month)	187,052	144.00	122.85	14.00	57.00	121.00	199.00	340.00
InstFund	187,052	0.45	0.41	0.00	0.00	0.39	0.91	1.00
Nb. Words	187,052	171.08	103.42	43.00	105.00	156.00	212.00	351.00
TextUniq	187,052	-0.05	0.97	-1.44	-0.74	-0.17	0.51	1.70
TS TextSim	161,197	0.98	0.05	0.91	0.99	1.00	1.00	1.00
Gross Cum. Ret (%)	129,976	21.22	16.32	-4.86	10.94	21.06	32.80	45.68
Gross Alpha (%)	129,976	-0.02	0.32	-0.50	-0.18	-0.02	0.15	0.47
Rating	167,743	3.02	1.04	1.00	2.00	3.00	3.97	5.00
Fund Flow (%)	184,635	-0.04	5.55	-5.75	-1.51	-0.51	0.59	6.89
HoldUniq	186,358	0.08	0.99	-1.79	-0.68	0.42	0.90	1.23
SimIdx	179,134	0.34	0.23	0.05	0.16	0.30	0.50	0.76

Table 1: **Summary statistics**: This table reports summary statistics for the main variables used in our analysis from 2011 to 2020. Variables are defined at the fund level at the monthly frequency. $Nb. Words$ refers to the number of words in the fund prospectus (after removing stopping words and other meaningless words). $TextUniq$ is the text uniqueness measure defined in section 3.3. $TS\,TextSim$ refers to the time-series similarity of prospectuses of the same fund. $HoldUniq$ measures the uniqueness of the fund portfolio holdings and is defined in section 3.3. $SimIdx$ refers to holding similarity between the fund and the most common index used as benchmark in the fund's category.

	TextUniq				Fund Fees			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gross Ret (%)	-0.006***				-0.006***			
	(0.002)				(0.002)			
Gross Cum. Ret (%)		-0.005***				-0.004***		
		(0.001)				(0.001)		
Gross Alpha (%)			-0.081**				-0.064*	
			(0.039)				(0.036)	
log(TNA)				-0.025**				-0.111***
				(0.010)				(0.007)
log(Fund Age)	-0.013	-0.021	-0.023	0.016	-0.017	-0.027*	-0.028*	0.112***
	(0.028)	(0.031)	(0.031)	(0.029)	(0.014)	(0.015)	(0.015)	(0.016)
Year-Month × Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	167,393	116,474	116,474	167,393	167,393	116,474	116,474	167,393
R^2	0.22	0.22	0.22	0.22	0.11	0.11	0.10	0.32

Table 2: **Relationship between quality, product differentiation and fees**: This table reports results for regressions investigating how the text uniqueness of funds is associated with fund return and fund size. In columns (1)-(4), the dependent variable is the text uniqueness of funds (normalized negative cosine similarity of text, adjusted for number of words). In columns (5)-(8), the dependent variable is the annual expense ratio of funds (in percentage points). *Gross Ret* is the before-fee monthly return of funds, measured in percentage points. *Gross Cum. Ret* is the cumulative before-fee return of funds for the following 24 months, measured in percentage points. *Gross Alpha* is monthly before-fee alpha estimated through a 4-factor (FF 3 factor + momentum) model, using the return of following 24 months, measured in percentage points. $log(TNA)$ is the natural logarithm of the size of funds. $log(Fund\ Age)$ is the natural logarithm of the age of funds. All regressions include month-Morningstar category fixed effects. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

	TextUniq				
	(1)	(2)	(3)	(4)	(5)
Post × 1^* Rating	0.146***	0.150***	0.149***	0.149***	0.151***
	(0.051)	(0.050)	(0.055)	(0.055)	(0.054)
Post × 2^* Rating	0.041	0.046	0.045	0.045	0.053
	(0.033)	(0.033)	(0.045)	(0.045)	(0.045)
Post × 3^* Rating	-0.003	0.002			
	(0.027)	(0.026)			
Post × 4^* Rating	-0.019	-0.013	-0.015	-0.018	-0.027
	(0.030)	(0.029)	(0.040)	(0.041)	(0.038)
Post × 5^* Rating	-0.025	-0.021	-0.023	-0.023	-0.007
	(0.038)	(0.037)	(0.047)	(0.047)	(0.045)
Post			0.002		
			(0.026)		
log(Fund Age)		-0.017	-0.017		
		(0.017)	(0.017)		
Year-Month × Cat. FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Fund Age FE	No	No	No	Yes	No
Initial Uniqueness × Fund Age FE	No	No	No	No	Yes
Observations	32,427	32,427	32,427	32,427	32,427
R^2	0.96	0.96	0.96	0.96	0.96

Table 3: **Change in text uniqueness after the release of Morningstar ratings**: This table reports estimation results for difference-in-differences regressions investigating how the text uniqueness of funds change after receiving different Morningstar ratings. The dependent variable is the text uniqueness of funds (normalized negative cosine similarity of text, adjusted for number of words). *Post* is a dummy variable that is equal to 1 if the fund has received a Morningstar rating in the month. 1*, 2*, 3*, 4* and 5* *Rating* are dummy variables that are equal to one if the initial rating of the fund is 1, 2, 3, 4, or 5 stars respectively. $log(Fund\ Age)$ is the natural logarithm of the age of funds. All regressions include only the sub-sample of funds entering our sample one year before they get rated. All regressions include month-Morningstar category fixed effects and fund fixed effects. Column (4) also includes fund age (in months) fixed effects. In column (5), we replace fund age fixed effects by fixed effects capturing the combination of initial uniqueness quintiles and fund age. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

	Change Prospectus				
	(1)	(2)	(3)	(4)	(5)
Post × 1* Rating	0.083** (0.038)	0.080** (0.038)	0.134*** (0.041)	0.126*** (0.041)	0.123*** (0.043)
Post × 2* Rating	-0.014 (0.025)	-0.017 (0.026)	0.037 (0.031)	0.034 (0.032)	0.037 (0.031)
Post × 3* Rating	-0.051** (0.022)	-0.053** (0.024)			
Post × 4* Rating	-0.044 (0.027)	-0.047 (0.028)	0.007 (0.033)	0.001 (0.033)	-0.004 (0.033)
Post × 5* Rating	-0.024 (0.033)	-0.026 (0.034)	0.028 (0.037)	0.026 (0.037)	0.026 (0.038)
Post			-0.053** (0.024)		
log(Fund Age)		0.008 (0.025)	0.008 (0.025)		
Year-Month × Cat. FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Fund Age FE	No	No	No	Yes	No
Initial Uniqueness × Fund Age FE	No	No	No	No	Yes
Observations	29,119	29,119	29,119	29,119	29,119
R^2	0.26	0.26	0.26	0.27	0.28

Table 4: **Likelihood to change prospectus text after the release of Morningstar ratings**: This table reports estimation results for difference-in-differences regressions investigating whether funds' tendency of updating fund prospectuses change after receiving different Morningstar ratings. The dependent variable is a dummy variable that is equal to 1 if the fund prospectus similarity to the last prospectus (*TS TextSim*) is lower than 0.95. *Post* is a dummy variable that is equal to 1 if the fund has received a Morningstar rating in the month. 1*, 2*, 3*, 4* and 5* *Rating* are dummy variables that are equal to one if the initial rating of the fund is 1, 2, 3, 4, or 5 stars respectively. *log*(*Fund Age*) is the natural logarithm of the age of funds. All regressions include only the sub-sample of funds entering our sample one year before they get rated. All regressions include month-Morningstar category fixed effects and fund fixed effects. Column (4) also includes fund age (in months) fixed effects. In column (5), we replace fund age fixed effects by fixed effects capturing the combination of initial uniqueness quintiles and fund age. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

	Dead × 100				Fund Flow (%)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1* Rating	0.441***	0.199*	0.589***	0.340**	-0.105	0.022	-0.214*	-0.077
	(0.104)	(0.108)	(0.129)	(0.133)	(0.125)	(0.137)	(0.124)	(0.135)
2* Rating	0.215***	0.094*	0.300***	0.182***	-0.114	-0.083	-0.202*	-0.169
	(0.055)	(0.056)	(0.070)	(0.070)	(0.089)	(0.091)	(0.107)	(0.108)
4* Rating	-0.103***	-0.014	-0.097**	0.003	0.197***	0.206***	0.342***	0.353***
	(0.035)	(0.037)	(0.043)	(0.045)	(0.075)	(0.075)	(0.086)	(0.086)
5* Rating	-0.116***	0.041	-0.089	0.085	0.236**	0.294***	0.342***	0.404***
	(0.045)	(0.047)	(0.056)	(0.059)	(0.100)	(0.100)	(0.114)	(0.114)
1* Rating × Changed Prospectus			-0.494***	-0.523***			0.803**	0.802**
			(0.185)	(0.185)			(0.320)	(0.325)
2* Rating × Changed Prospectus			-0.190**	-0.240**			0.562***	0.573***
			(0.093)	(0.094)			(0.156)	(0.154)
3* Rating × Changed Prospectus			0.072	0.035			0.288***	0.299***
			(0.057)	(0.056)			(0.108)	(0.108)
4* Rating × Changed Prospectus			0.056	-0.019			-0.153	-0.152
			(0.050)	(0.053)			(0.115)	(0.115)
5* Rating × Changed Prospectus			-0.008	-0.093			-0.038	-0.037
			(0.073)	(0.075)			(0.178)	(0.178)
log(TNA)		-0.201***		-0.202***		-0.047**		-0.046**
		(0.013)		(0.013)		(0.019)		(0.019)
Fund Fees		-0.198***		-0.198***		-0.411***		-0.415***
		(0.054)		(0.053)		(0.095)		(0.094)
InstFund		-0.006		-0.009		0.073		0.081
		(0.047)		(0.047)		(0.080)		(0.080)
Year-Month × Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	166,033	166,033	166,033	166,033	166,033	166,033	166,033	166,033
R^2	0.02	0.03	0.02	0.03	0.03	0.03	0.03	0.03

Table 5: **The effect of rating and prospectus change on fund death and flows**: This table reports results for regressions investigating how prospectus updates affect fund likelihood of death and fund flows, depending on their Morningstar rating. In columns 1-4, the dependent variable is an indicator that equals 100 if the fund closes in the next month. In columns 5-8, the dependent variable is the (percentage) monthly fund flow. 1*, 2*, 3*, 4* and 5* *Rating* are dummy variables that are equal to one if the fund rating is 1, 2, 3, 4, or 5 stars respectively. *ChangedProspectus* is a dummy variable equal to one if the fund has changed its prospectus by that time. A prospectus change is identified if the fund *TS TextSim*, which measures how similar the fund prospectus is compared to the previous prospectus of the same fund, is strictly lower than 0.95. $log(TNA)$ is the natural logarithm of the fund's assets under management. *FundFees* is the fund expense ratio. *InstFund* is the fraction of institutional share classes in the fund. All regressions include month-Morningstar category fixed effects and fund age fixed effects. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

	1^* and 2^* Rating	3^*, 4^*, and 5^* Rating
U statistic	-13.030	-1.131
P value	0.000	0.258

Table 6: **Mann-Whitney U Test for equality of distributions:** This table reports the Mann-Whitney tests for distributions of uniqueness among unrated and rated funds. The null hypothesis is that the text uniqueness distribution of rated and unrated funds' observations are the same. The first column reports the result for the sample of funds whose initial rating is 1 or 2 stars. The second column focuses on the sample of funds whose initial rating is 3, 4 or 5 stars.

Panel A: Unique words

formula	dictat	appropri	wholli	putnam	cornerston	controversi	foster	subsidiari	correct
activist	proxi	climat	sampl	help	personnel	subset	float	coal	nuclear
centuri	bargain	essenti	workplac	guidanc	prioriti	pure	reveal	compens	express
databas	expir	ident	carri	propos	emot	spdr	esg	assumpt	twelv
outweigh	edg	settl	transport	vote	mind	ascertain	withstand	media	inflow

Panel B: Broad words

inform	regular	drive	model	acceler	effort	absolut	lend	releas	arrang
compli	consider	discount	pool	resourc	lowest	creat	expens	increment	dividend
applic	protect	captur	summari	techniqu	acquisit	rapid	behav	materi	build
senior	caus	judg	opportunist	visit	collar	norm	screen	recommend	exceed
versu	diversif	result	moodi	broader	magnifi	structur	control	world	theme

Table 7: **Unique and broad words**: This table shows the unique and broad words in fund prospectuses. Panel A shows the words that are ranked top 50 on "word uniqueness" (meaning they are found in mostly unique funds' prospectuses). Green words are the words related to ESG issues. Red words are the words related to investment strategies. Black words are uncategorized words. Panel B shows the words that rank low on "word uniqueness" (around 0, meaning they are found in almost all the prospectuses).

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Internet Appendix

Financial Product Incentives to Differentiate: Evidence from Mutual Funds

(not intended for publication)

A Theoretical Framework

A.1 Modeling Assumptions

Following Bar-Isaac et al. (2012), we assume that F_B and F_N have log-concave densities, respectively f_B and f_N, that are positive everywhere.[29] We assume that there exists a rotation point θ^*, such that $F_B(\theta) < F_N(\theta)$ if $\theta < \theta^*$, and $F_B(\theta) > F_N(\theta)$ if $\theta > \theta^*$. We explain the intuition of this assumption below.

Figure 1 in the paper illustrates the density and cumulative distribution functions (c.d.f.) of ϵ for broad and niche designs. The niche design is the one associated with a more dispersed density function in Panel A. This is to reflect the fact that, for niche design, some investors "love" the product (right tail of the distribution), while some other investors "loath" the product (left tail of the distribution). On the contrary, for broad design, the product is passable for the majority of investors. This is represented by a more concentrated distribution.

The corresponding c.d.f. are presented in Panel B. The intuition behind θ^* relates to the demand faced by a fund. Given v_i and p_i, the investor will invest in the fund if the matching term ϵ is larger than a threshold, as shown in (2). If this threshold is below θ^*, it means it is relatively easy for the fund to attract investors. As a result, the fund will have larger demand if it chooses a broad design, as it doesn't take the risk that an investor will "dislike" the fund, due to a low matching term. On the contrary, if the threshold is above θ^*, it means that it is harder for the fund to attract investors. The fund will therefore have larger demand if it chooses a niche design. This is because investors need to "love" the fund in order to invest in, and the chance that this happens increases with a design that leads to dispersed matching terms.

A.2 Proof of Proposition 1

We follow Bar-Isaac et al. (2012) to derive the proof of Proposition 1. Consider V such that fund with perceived quality V is indifferent between choosing a broad or a niche design, i.e.,

$$p_B(V)\,[1 - F_B(U - V + p_B(V))] = p_N(V)\,[1 - F_N(U - V + p_N(V))]\,. \tag{A.1}$$

By definition of $p_B(v)$ and $p_N(v)$, which are the profit maximizing prices when the fund

[29]The assumption of log-concavity ensures that the failure rate $f_{s_i}(\theta)/(1-F_{s_i})$ is monotonic and, so, guarantees existence of a profit-maximizing price, which is continuous and increasing in perceived quality conditional on design. We refer to Bagnoli and Bergstrom (2005) for a discussion of log-concavity and functions that do and do not satisfy this condition.

chooses respectively broad and niche design, we have

$$p_N(V)\left[1 - F_N(U - V + p_N(V))\right] \geq p_B(V)\left[1 - F_N(U - V + p_B(V))\right],$$

and

$$p_B(V)\left[1 - F_B(U - V + p_B(V))\right] \geq p_N(V)\left[1 - F_B(U - V + p_N(V))\right].$$

Using equality (A.1), it follows that

$$1 - F_B(U - V + p_B(V)) \geq 1 - F_N(U - V + p_B(V)), \tag{A.2}$$

and

$$1 - F_N(U - V + p_N(V)) \geq 1 - F_B(U - V + p_N(V)). \tag{A.3}$$

This implies that $p_N(V) > p_B(V)$. To see this, remember that the c.d.f. F_B and F_N are defined such that $F_B(x) > F_N(x)$ if $x > \theta^*$, and $F_B(x) < F_N(x)$ if $x < \theta^*$. Suppose $U - V + p_B(V) > \theta^*$. It implies

$$1 - F_B(U - V + p_B(V)) < 1 - F_N(U - V + p_B(V)),$$

which is in contradiction with inequality (A.2). Therefore $U - V + p_B(V) \leq \theta^*$.

Suppose now that $p_N(V) < p_B(V)$. Then, we have

$$\theta^* \geq U - V + p_B(V) > U - V + p_N(V),$$

which implies

$$1 - F_N(U - V + p_N(V)) < 1 - F_B(U - V + p_N(V)),$$

which is in contradiction with inequality (A.3). Therefore $p_N(V) > p_B(V)$ and from (A.1) we get

$$1 - F_B(U - V + p_B(V)) > 1 - F_N(U - V + p_N(V)). \tag{A.4}$$

Going back to the profit of the firm given in (4), define

$$\Pi_{vs} = mp_s(v)\left[1 - F_s(U - v + p_s(v))\right],$$

with $s = B, N$. Since the price is chosen to maximize profits, by the envelope theorem, we have $\partial p_s(v)/\partial v = 0$. It implies that

$$\frac{\partial \Pi_{vs}}{\partial v} = mp_s(v) f_s(U - v + p_s(v)) = mp_s(v)\left[1 - F_s(U - v + p_s(v))\right],$$

where the second equality follows from the price definition in (5). Because of (A.4), we get that $\partial(\Pi_{vB} - \Pi_{vN})/\partial v > 0$. This implies that $(\Pi_{vB} - \Pi_{vN})$ is strictly increasing and therefore there exists a unique V such that $\Pi_{VB} = \Pi_{VN}$. As a consequence, if $v > V$, $\Pi_{vB} > \Pi_{vN}$ and the fund chooses broad design. If $v < V$, $\Pi_{vB} < \Pi_{vN}$ and the fund chooses niche design.

A.3 Proof of Proposition 2

We show that there exist funds with perceived quality v below V that charge higher prices than companies with v above the threshold. To see this, we use a Taylor expansion argument. Because of the log-concavity assumption, the price $p_s(v)$ defined in (5) is a well behaved function of which we can take derivative. Consider Taylor expansions of $p_B(v)$ and $p_N(v)$ around V:

$$p_B(V+\delta) = p_B(V) + \delta \frac{\partial p_B(v)}{\partial v}\bigg|_{v=V} + R_B(\delta), \tag{A.5}$$

and

$$p_N(V-\delta) = p_N(V) - \delta \frac{\partial p_N(v)}{\partial v}\bigg|_{v=V} + R_N(\delta), \tag{A.6}$$

with $\delta > 0$ and $\lim_{\delta\to 0} R_s(\delta)/\delta = 0$, $s = B, N$. Taking the difference between (A.6) and (A.5), we get

$$p_N(V-\delta) - p_B(V+\delta) = (p_N(V) - p_B(V)) - \delta \frac{\partial (p_N(v) + p_B(v))}{\partial v}\bigg|_{v=V} + (R_N(\delta) - R_B(\delta)) \,.$$

Because we have shown in the proof of Proposition 1, that $p_N(V) > p_B(V)$, we can find an arbitrarily small δ, such that $p_N(V-\delta) > p_B(V+\delta)$. As a consequence, the price charged by fund with perceived quality $V-\delta < V$ is higher than the price charged by fund with quality $V+\delta > V$.

B Indexes and ETFs

Category	Index	ETF
Large Blend	S&P 500 Index	Vanguard S&P 500 Index Fund; ETF Shares
Large Growth	Russell 1000 Growth Index	Vanguard Russell 1000 Growth Index Fund; ETF Shares
Large Value	Russell 1000 Value Index	Vanguard Russell 1000 Value Index Fund; ETF Shares
Mid-Cap Blend	S&P Mid-Cap 400 Index	Vanguard S&P Mid-Cap 400 Index Fund; ETF Shares
Mid-Cap Growth	Russell Midcap Growth Index	iShares Russell Midcap Growth Index Fund; ETF Shares
Mid-Cap Value	Russell Midcap Value Index	iShares Russell Midcap Value Index Fund; ETF Shares
Small Blend	Russell 2000 Index	Vanguard Russell 2000 Index Fund; ETF Shares
Small Growth	Russell 2000 Growth Index	Vanguard Russell 2000 Growth Index Fund; ETF Shares
Small Value	Russell 2000 Value Index	Vanguard Russell 2000 Value Index Fund; ETF Shares

Table A.1: **ETFs used to construct the index similarity**: This table reports the ETFs, from which the holdings are used to construct index similarity. For funds in each of the category, we calculate the cosine similarity of holdings compared to the holdings of ETFs in the table.

C Examples of Fund Prospectuses

C.1 Example 1 - Niche Fund

Virtus Rampart Enhanced Core Equity Fund, 2018 (Large Blend), **TextUniq=4.3**

The fund seeks to achieve its investment objectives by investing in securities and/or Exchange Traded Funds ("ETFs") representing the S&P 500 Index. Allocations are based on a **proprietary rules-based model** that seeks to **overweight those segments of the market that have experienced stronger recent relative performance.**

An options strategy is employed for the purpose of seeking to generate additional returns. The strategy utilizes **index-based, out-of-the-money put and call credit spreads**. The strategy is driven by the relationship between **implied volatility, as measured by the CBOE Volatility Index (VIX), and the realized volatility of the S&P 500 Index.** The strategy seeks to exploit **pricing inefficiencies in the S&P 500 Index options market.**

C.2 Example 2 - Niche Fund

John Hancock ESG All Cap Core Fund, 2017 (Large Growth), **TextUniq=1.67**

Under normal market conditions, the fund invests at least 80% of its net assets (plus any borrowings for investment purposes) in equity securities of any market capitalization or sector that meet the manager's **sustainability criteria**. Equity securities include common and preferred stocks and their equivalents. The manager seeks companies meeting its **sustainability criteria with high-quality characteristics including strong environmental, social, and governance ("ESG") records.**

The manager employs a bottom-up financial analysis that includes **a review of ESG issues** and how they may impact stock valuation or performance. ESG factors reflect a **variety of key sustainability issues that can influence company risks and opportunities and span a range of metrics including board diversity, climate change policies, and supply chain and human rights policies. Companies that meet the manager's ESG requirements or sustainability criteria typically have strong sustainability data and policy reporting, for example publishing a comprehensive corporate sustainability report.** The fund may also invest up to 20% of its total assets in the equity securities of foreign issuers, including American Depositary Receipts ("ADRs") and Global Depositary Receipts ("GDRs"). The fund may focus its investments in a **particular sector or sectors of the economy**.The manager may sell stocks for several reasons, including when the stock no longer **meets the manager's ESG or sustainability criteria,** or when the stock declines in value and no longer reflects the manager's investment thesis. The fund will not invest in any companies with material exposure to **agricultural biotechnology, coal mining, hard rock mining, nuclear power, tar sands, tobacco, or weapons/firearms. The fund also will not invest in any companies with major recent or ongoing controversies involving animal welfare, environmental, governance, human rights, product safety, or workplace matters.**

C.3 Example 3 - Broad Fund

Legg Mason ClearBridge Equity Fund, 2013 (Large Blend), **TextUniq=-0.98**

Under normal circumstances, the fund invests at least 80% of its assets in equity securities. The fund invests primarily in common stock or securities convertible into common stock of companies in industries the portfolio manager believes have the potential to grow at a **faster rate than the economy** as a whole and that appear to have **above-average earnings and dividend growth potential**.

The fund emphasizes investments in U.S. stocks with large capitalizations, but the fund also invests in stocks with small and medium capitalizations. The fund may invest up to 25% of its assets in foreign securities, including up to 10% of its assets in securities of emerging market issuers.

C.4 Example 4 - Broad Fund

Beacon Holland Large Cap Growth Fund, 2011 (Large Growth), **TextUniq=-1.12**

The Fund seeks to achieve its investment objective by investing primarily in common stocks of mid- to large-capitalization growth companies. In pursuing its investment objective, the Fund maintains a diversified portfolio of equity securities of companies that Holland Capital Management LLC (the "Adviser") regards as high-quality companies based on earnings growing faster than the general market, **reasonable valuations, strong financial condition, strong management and superior industry positions.** Equity securities include preferred stocks, convertible securities, rights and warrants. The Fund invests primarily in U.S. companies. The Fund may invest up to 20% of its total assets in securities of foreign issuers that exhibit the growth characteristics mentioned above.

D Details of Morningstar Star Rating Methodology

Morningstar proceeds as follows to rate funds. First, the so called Morningstar risk-adjusted return ($MRAR$) is computed over a 3-year horizon (36 months):

$$MRAR_i^T(\gamma) = \left[\frac{1}{T}\sum_{t=1}^{T}(1 + r_{i,t} - r_t^f)\right]^{-\frac{12}{\gamma}} - 1, \tag{A.7}$$

where $r_{i,t}$ is the monthly return of fund i net of management fees, r_t^f is the risk-free rate monthly return computed using three-month T-bills, and $\gamma = 2$ is the risk aversion coefficient. The formula penalizes funds with higher return volatility. Indeed, when γ converges to 0, $MRAR_i^T(0)$ is equal to the annualized geometric mean of excess returns. When γ is set to be greater than 0, holding the geometric mean return constant, the formula yields a lower $MRAR$ value for funds whose monthly returns deviate more from their mean.

All funds in the Morningstar category are then sorted by three-year $MRAR$ % rank in descending order. The funds with a rank that does not exceed 10% receive a 5-star rating. Funds with a rank greater than or equal to 10% but that does not exceed 32.5% receive a 4-star rating. Funds with a rank greater than or equal to 32.5% but that does not exceed 67.5% receive a 3-star rating. Funds with a rank greater than or equal to 67.5% but that does not exceed 90% receive a 2-star rating. The remaining funds receive 1 star.

If the data are available, 5-year ratings are assigned using 60 months of data and 10-year ratings are assigned using 120 months of data. The overall star rating for each fund is based on a weighted average of the number of stars assigned to it in the 3-, 5-, and 10-year rating periods. For funds with more than three years but less than five years of data, the overall rating is just the three-year rating. For funds with more than five years but less than 10 years of data, the overall rating assigns 60% and 40% weights on the five-year and three-year ratings. For those with more than 10 years of data, 50%, 30%, and 20% weights are assigned on the 10-year, 5-year, and 3-year ratings, respectively.

E Appendix Tables

	Obs	Mean	Sd	5%	25%	50%	75%	95%
Gross Ret (%)	167,393	1.06	4.76	-7.27	-1.16	1.34	3.54	7.93
Fund Fees (%, annual)	167,393	1.10	0.46	0.48	0.87	1.06	1.26	1.83
Net Ret. (%)	167,393	0.97	4.76	-7.36	-1.25	1.25	3.45	7.85
TNA (mill)	167,393	1,886.68	5,716.84	10.10	72.30	342.60	1,471.40	8,358.80
Fund Age (month)	167,393	158.38	121.85	33.00	75.00	135.00	209.00	353.00
InstFund	167,393	0.43	0.40	0.00	0.00	0.33	0.86	1.00
Nb. Words	167,393	166.30	99.93	43.00	103.00	152.00	206.00	336.00
TextUniq	167,393	-0.04	0.96	-1.43	-0.73	-0.16	0.51	1.68
TS TextSim	146,464	0.98	0.05	0.91	0.99	1.00	1.00	1.00
Gross Cum. Ret (%)	116,473	21.39	16.13	-4.86	11.13	21.32	33.03	45.60
Gross Alpha (%)	116,473	-0.02	0.32	-0.50	-0.18	-0.02	0.15	0.47
Rating	167,393	3.02	1.04	1.00	2.00	3.00	3.97	5.00
Fund Flow (%)	165,691	-0.40	4.92	-5.75	-1.57	-0.59	0.37	5.08
HoldUniq	166,877	0.04	0.99	-1.82	-0.72	0.37	0.87	1.21
SimIdx	162,420	0.35	0.23	0.05	0.16	0.31	0.51	0.76

Table A.2: **Summary statistics for rated funds only**: This table reports summary statistics for the main variables used in our analysis from 2011 to 2020. Statistics are reported for the subsample of funds with available Morningstar rating. Variables are defined at the fund level at the monthly frequency. $Nb. Words$ refers to the number of words in the fund prospectus (after removing stopping words and other meaningless words). $TextUniq$ is text uniqueness measures of the funds and is defined in section 3.3. $TS TextSim$ refers to the time-series similarity of prospectuses of the same fund. $HoldUniq$ measures the uniqueness of the fund portfolio holdings and is defined in section 3.3. $SimIdx$ refers to holding similarity between the fund and the most common index used as benchmark in the fund's category.

	Fund Fees, including Loads (%)			
	(1)	(2)	(3)	(4)
Gross Ret (%)	-0.006**			
	(0.003)			
Gross Cum. Ret (%)		-0.003**		
		(0.001)		
Gross Alpha (%)			-0.069*	
			(0.041)	
log(TNA)				-0.120***
				(0.009)
log(Fund Age)	-0.247***	-0.261***	-0.262***	-0.096***
	(0.019)	(0.020)	(0.020)	(0.022)
Year-Month × Cat. FE	Yes	Yes	Yes	Yes
Observations	130,778	92,252	92,252	130,778
R^2	0.18	0.19	0.19	0.34

Table A.3: **Fund fees and Product Quality, including fund loads**: This table reports results for regressions investigating how fund fees (including fund loads) are associated with fund return. The dependent variable is the sum of annual expense ratio and one seventh of fund loads (assuming a holding period of 7 years), which is the sum of front loads and rear loads charged by the funds. The front loads and rear loads are percentage fees, average across different thresholds of AUM invested. *Gross Ret* is the before-fee monthly return of funds, measured in percentage points. *Gross Cum. Ret* is the cumulative before-fee return of funds for the following 24 months, measured in percentage points. *Gross Alpha* is monthly before-fee alpha estimated through a 4-factor (FF 3 factor + momentum) model, using the return of following 24 months, measured in percentage points. $log(TNA)$ is the natural logarithm of the size of funds. $log(Fund\ Age)$ is the natural logarithm of the age of funds. All regressions include month-Morningstar category fixed effects. All regressions include month-Morningstar category fixed effects. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

	HoldUniq				SimIdx			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gross Ret (%)	-0.016***				0.004***			
	(0.002)				(0.000)			
Gross Cum. Ret (%)		-0.010***				0.003***		
		(0.001)				(0.000)		
Gross Alpha (%)			-0.070***				0.009	
			(0.026)				(0.008)	
log(TNA)				-0.066***				0.016***
				(0.007)				(0.002)
log(Fund Age)	-0.102***	-0.087***	-0.090***	-0.026	0.026***	0.021***	0.022***	0.008
	(0.018)	(0.020)	(0.020)	(0.020)	(0.005)	(0.006)	(0.006)	(0.006)
Year-Month × Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	166,877	116,239	116,239	166,877	162,420	113,924	113,924	162,420
R^2	0.65	0.65	0.64	0.67	0.41	0.40	0.40	0.43

Table A.4: **Holding Uniqueness and Product Quality**: This table reports results for regressions investigating how the holding uniqueness of funds is associated with fund return. In Panel columns (1)-(4), the dependent variable is the uniqueness of fund portfolio holdings. In columns (5)-(8), the dependent variable is the similarity of fund portfolio holdings compared to the index of the category. *Gross Ret* is the before-fee monthly return of funds, measured in percentage points. *Gross Cum. Ret* is the cumulative before-fee return of funds for the following 24 months, measured in percentage points. *Gross Alpha* is monthly before-fee alpha estimated through a 4-factor (FF 3 factor + momentum) model, using the return of following 24 months, measured in percentage points. $log(TNA)$ is the natural logarithm of the size of funds. $log(Fund\ Age)$ is the natural logarithm of the age of funds. All regressions include month-Morningstar category fixed effects. All regressions include month-Morningstar category fixed effects. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

	TextUniq	Fund Fees	Gross Ret (%)	Net Ret (%)	Gross Alpha (%)	Net Alpha (%)
	(1)	(2)	(3)	(4)	(5)	(6)
1* Rating	0.203***	0.465***	-0.425***	-0.464***	-0.067**	-0.106***
	(0.058)	(0.065)	(0.024)	(0.026)	(0.027)	(0.030)
2* Rating	0.053**	0.154***	-0.180***	-0.192***	-0.009	-0.024***
	(0.027)	(0.015)	(0.010)	(0.010)	(0.008)	(0.008)
4* Rating	0.006	-0.081***	0.122***	0.129***	0.024***	0.031***
	(0.024)	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)
5* Rating	0.044	-0.088***	0.379***	0.387***	0.049***	0.057***
	(0.044)	(0.015)	(0.016)	(0.016)	(0.010)	(0.010)
log(Fund Age)	-0.008	-0.003	0.005	0.005	0.001	0.002
	(0.028)	(0.013)	(0.006)	(0.006)	(0.006)	(0.006)
Year-Month × Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	167,393	167,393	167,393	167,393	116,474	116,474
R^2	0.22	0.20	0.91	0.91	0.14	0.15

Table A.5: **Ratings, uniqueness and fund fees**: This table reports results for regressions investigating whether Morningstar ratings are correlated with uniqueness, expense ratios and realized return of funds. In columns 1 to 6, the dependent variables are (1) the text uniqueness of funds (normalized negative cosine similarity of text, adjusted for number of words), (2) expense ratio of funds, (3) monthly before-fee return of funds, (4) monthly after-fee return of funds, (5) monthly before-fee alpha estimated through a 4-factor (FF 3 factor + momentum) model, using the return of following 24 months, and (6) monthly after-fee alpha estimated through a 4-factor (FF 3 factor + momentum) model, using the return of following 24 months. 1*, 2*, 4* and 5* *Rating* are dummies corresponding to each Morningstar rating. $log(Fund\ Age)$ is the natural logarithm of the age of funds. All regressions include month-Morningstar category fixed effects. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

	Obs	Mean	Sd	5%	25%	50%	75%	95%
Gross Ret (%)	32,427	0.97	4.65	-6.91	-1.07	1.19	3.34	7.73
Fund Fees (%, annual)	32,427	1.12	0.45	0.43	0.87	1.08	1.34	1.95
Net Ret. (%)	32,427	0.87	4.65	-6.99	-1.17	1.09	3.24	7.65
TNA (mill)	32,427	513.63	1,697.39	2.80	18.40	63.70	273.60	2,329.00
Fund Age (month)	32,427	46.71	30.16	8.00	24.00	41.00	65.00	102.00
InstFund	32,427	0.65	0.39	0.00	0.26	0.84	1.00	1.00
Nb. Words	32,427	204.62	123.77	59.00	132.00	185.00	243.00	422.00
TextUniq	32,427	-0.17	0.98	-1.51	-0.88	-0.30	0.39	1.67
Change Prospectus	29,119	0.08	0.27	0.00	0.00	0.00	0.00	1.00
TS TextSim	29,119	0.98	0.05	0.92	0.99	1.00	1.00	1.00
Gross Cum. Ret (%)	21,031	18.15	16.17	-8.27	8.41	18.02	28.91	43.27
Gross Alpha (%)	21,031	-0.02	0.33	-0.55	-0.19	-0.02	0.16	0.50
Rating	18,752	3.00	1.12	1.00	2.00	3.00	4.00	5.00
Fund Flow (%)	32,016	1.43	7.31	-6.49	-1.11	0.16	2.25	14.19
HoldUniq	32,180	0.35	0.95	-1.65	-0.19	0.75	1.07	1.30
SimIdx	28,177	0.29	0.22	0.04	0.11	0.22	0.42	0.73

Table A.6: **Summary statistics for funds switching from unrated to rated**: This table reports summary statistics for the main variables used in our analysis from 2011 to 2020 in Section 5. Statistics are reported for funds switching from unrated to rated over our sample period and that we can observe at least one year before their first rating. Variables are defined at the fund level at the monthly frequency. $Nb.Words$ refers to the number of words in the fund prospectus (after removing stopping words and other meaningless words). $TextUniq$ is text uniqueness measures of the funds and is defined in section 3.3. $TSTextSim$ refers to the time-series similarity of prospectuses of the same fund. $HoldUniq$ measures the uniqueness of the fund portfolio holdings and is defined in section 3.3. $SimIdx$ refers to holding similarity between the fund and the most common index used as benchmark in the fund's category.

	TS TextSim				
	(1)	(2)	(3)	(4)	(5)
Post × 1* Rating	-0.012**	-0.012**	-0.022***	-0.020***	-0.020***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Post × 2* Rating	-0.001	-0.001	-0.011*	-0.010*	-0.011*
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Post × 3* Rating	0.010**	0.010*			
	(0.004)	(0.005)			
Post × 4* Rating	0.004	0.004	-0.006	-0.004	-0.003
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Post × 5* Rating	0.002	0.002	-0.008	-0.007	-0.007
	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
Post			0.010*		
			(0.005)		
log(Fund Age)		0.000	0.000		
		(0.006)	(0.006)		
Year-Month × Cat. FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Fund Age FE	No	No	No	Yes	No
Initial Uniqueness × Fund Age FE	No	No	No	No	Yes
Observations	29,119	29,119	29,119	29,119	29,119
R^2	0.27	0.27	0.27	0.29	0.30

Table A.7: **Prospectus time-series similarity after the release of Morningstar ratings**: This table reports estimation results for difference-in-differences regressions investigating how the time-series similarity of fund prospectuses change after receiving different Morningstar ratings. The dependent variable is the time-series similarity of fund prospectuses (cosine similarity of two consecutive prospectuses of the same fund). In instances with no prospectus change, the dependent variable is equal to one. *Post* is a dummy variable that is equal to 1 if the fund has received a Morningstar rating in the month. 1*, 2*, 3*, 4* and 5* *Rating* are dummy variables that are equal to one if the initial rating of the fund is 1, 2, 3, 4, or 5 stars respectively. *log(Fund Age)* is the natural logarithm of the age of funds. All regressions include only the sub-sample of funds entering our sample one year before they get rated. All regressions include month-Morningstar category fixed effects and fund fixed effects. Column (4) also includes fund age (in months) fixed effects. In column (5), we replace fund age fixed effects by fixed effects capturing the combination of initial uniqueness quintiles and fund age. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

Panel A: Text Uniqueness

	TextUniq				
	(1)	(2)	(3)	(4)	(5)
Post × 1* Rating	0.126**	0.123**	0.138**	0.137**	0.139**
	(0.052)	(0.051)	(0.055)	(0.056)	(0.055)
Post × 2* Rating	0.045	0.042	0.057	0.056	0.060
	(0.035)	(0.034)	(0.045)	(0.045)	(0.046)
Post × 3* Rating	-0.012	-0.015			
	(0.026)	(0.025)			
Post × 4* Rating	-0.020	-0.024	-0.008	-0.013	-0.023
	(0.029)	(0.029)	(0.039)	(0.039)	(0.038)
Post × 5* Rating	-0.023	-0.027	-0.011	-0.013	-0.001
	(0.036)	(0.035)	(0.043)	(0.043)	(0.042)
Post			-0.015		
			(0.025)		
Past 12-month NetRet	-0.085	-0.084	-0.084	-0.078	-0.107
	(0.075)	(0.075)	(0.075)	(0.075)	(0.073)
log(Fund Age)		0.012	0.012		
		(0.036)	(0.036)		
Year-Month × Cat. FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Fund Age FE	No	No	No	Yes	No
Initial Uniqueness × Fund Age FE	No	No	No	No	Yes
Observations	29,280	29,280	29,280	29,280	29,280
R^2	0.96	0.96	0.96	0.96	0.96

Panel B: Prospectus Time-Series Similarity

	TS TextSim				
	(1)	(2)	(3)	(4)	(5)
Post × 1* Rating	-0.012*	-0.015**	-0.021***	-0.020***	-0.019***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Post × 2* Rating	-0.001	-0.005	-0.011*	-0.010	-0.011*
	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)
Post × 3* Rating	0.010**	0.006			
	(0.004)	(0.006)			
Post × 4* Rating	0.003	-0.001	-0.007	-0.005	-0.004
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Post × 5* Rating	0.003	-0.001	-0.007	-0.006	-0.006
	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)
Post			0.006		
			(0.006)		
Past 12-month NetRet	0.020	0.020	0.020	0.019	0.020
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
log(Fund Age)		0.015	0.015		
		(0.012)	(0.012)		
Year-Month × Cat. FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Fund Age FE	No	No	No	Yes	No
Initial Uniqueness × Fund Age FE	No	No	No	No	Yes
Observations	27,832	27,832	27,832	27,832	27,832
R^2	0.27	0.27	0.27	0.29	0.30

Table A.8: **Robustness test: Controlling for past performance**: This table reports results for the regressions investigating how text uniqueness of funds and time-series similarity of prospectus change after receiving different Morningstar ratings, controlling for past returns. In Panel A, the dependent variable is the text uniqueness of funds (normalized negative cosine similarity of text, adjusted by number of words). In Panel B, the time-series similarity of fund prospectuses (cosine similarity of two consecutive prospectuses of the same fund). *Post* is a dummy variable that is equal to 1 if the fund has received a morningstar rating in the month. 1*, 2*, 3*, 4* and 5* *Rating* are dummy variables that are equal to one if the initial rating of the fund is 1, 2, 3, 4, or 5 stars respectively. $log(Fund\ Age)$ is the natural logarithm of the age of funds. $Past12-monthNetRet$ is the net return of past 12 months. All regressions include only the sub-sample of funds entering our sample one year before they get rated. All regressions include month-Morningstar category fixed effects and fund fixed effects. Column (4) also includes fund age (in months) fixed effects. In column (5), we replace fund age fixed effects by fixed effects capturing the combination of initial uniqueness quintiles and fund age. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

	TextUniq				
	(1)	(2)	(3)	(4)	(5)
Post × 1* Rating	0.122*** (0.029)	0.124*** (0.028)	0.122*** (0.033)	0.122*** (0.033)	0.120*** (0.032)
Post × 2* Rating	0.045 (0.033)	0.050 (0.033)	0.048 (0.044)	0.048 (0.045)	0.056 (0.045)
Post × 3* Rating	-0.003 (0.027)	0.002 (0.026)			
Post × 4* Rating	-0.016 (0.030)	-0.010 (0.030)	-0.012 (0.041)	-0.016 (0.041)	-0.026 (0.039)
Post × 5* Rating	-0.023 (0.038)	-0.019 (0.037)	-0.021 (0.047)	-0.021 (0.047)	-0.004 (0.045)
Post			0.002 (0.026)		
log(Fund Age)		-0.018 (0.017)	-0.018 (0.017)		
Year-Month × Cat. FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Fund Age FE	No	No	No	Yes	No
Initial Uniqueness × Fund Age FE	No	No	No	No	Yes
Observations	32,427	32,427	32,427	32,427	32,427

Table A.9: **Robust difference-in-differences estimator using Borusyak et al. (2022)**: This table reports results for the regressions investigating how text uniqueness of funds change after receiving different Morningstar ratings. The coefficients are estimated using the methods by Borusyak et al. (2022). The dependent variable is the text uniqueness of funds (normalized negative cosine similarity of text, adjusted by number of words). *Post* is a dummy variable that is equal to 1 if the fund has received a Morningstar rating in the month. 1*, 2*, 3*, 4* and 5* *Rating* are dummy variables that are equal to one if the initial rating of the fund is 1, 2, 3, 4, or 5 stars respectively. *log*(*Fund Age*) is the natural logarithm of the age of funds. All regressions include only the sub-sample of funds entering our sample before they get rated. All regressions include month-Morningstar category fixed effects and fund fixed effects. Column (4) also includes fund age (in months) fixed effects. In column (5), we replace fund age fixed effects by fixed effects capturing the combination of initial uniqueness quintiles and fund age. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

Panel A: Holding Uniqueness

	HoldUniq				
	(1)	(2)	(3)	(4)	(5)
Post × 1* Rating	0.046*	0.046**	0.033	0.031	0.029
	(0.024)	(0.023)	(0.029)	(0.028)	(0.030)
Post × 2* Rating	0.030	0.030	0.017	0.014	0.015
	(0.027)	(0.025)	(0.036)	(0.036)	(0.035)
Post × 3* Rating	0.013	0.013			
	(0.023)	(0.022)			
Post × 4* Rating	0.004	0.004	-0.008	-0.010	-0.009
	(0.026)	(0.026)	(0.032)	(0.032)	(0.031)
Post × 5* Rating	0.007	0.007	-0.006	-0.009	-0.018
	(0.027)	(0.027)	(0.032)	(0.032)	(0.031)
Post			0.013		
			(0.022)		
log(Fund Age)		-0.000	-0.000		
		(0.015)	(0.015)		
Year-Month × Cat. FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Fund Age FE	No	No	No	Yes	No
Initial Uniqueness × Fund Age FE	No	No	No	No	Yes
Observations	32,180	32,180	32,180	32,180	32,180
R^2	0.96	0.96	0.96	0.96	0.96

Panel B: Holding Similarity to the Index

	SimIdx				
	(1)	(2)	(3)	(4)	(5)
Post × 1* Rating	-0.007	-0.007	-0.001	-0.000	-0.001
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Post × 2* Rating	-0.008	-0.008	-0.003	-0.001	-0.002
	(0.009)	(0.008)	(0.011)	(0.011)	(0.011)
Post × 3* Rating	-0.006	-0.005			
	(0.007)	(0.007)			
Post × 4* Rating	-0.002	-0.002	0.003	0.004	0.004
	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)
Post × 5* Rating	0.008	0.008	0.013	0.015	0.017
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
Post			-0.005		
			(0.007)		
log(Fund Age)		-0.001	-0.001		
		(0.005)	(0.005)		
Year-Month × Cat. FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Fund Age FE	No	No	No	Yes	No
Initial Uniqueness × Fund Age FE	No	No	No	No	Yes
Observations	28,177	28,177	28,177	28,177	28,177
R^2	0.93	0.93	0.93	0.93	0.94

Table A.10: **Change in holding uniqueness after the release of Morningstar ratings**: This table reports results for difference-in-differences regressions investigating how the holding uniqueness of funds change after receiving different Morningstar ratings. In Panel A, the dependent variable is the holding uniqueness of funds. In Panel B, the dependent variable is the similarity of fund portfolio holdings compared to index. *Post* is a dummy variable that is equal to 1 if the fund has received a Morningstar rating in the month. 1*, 2*, 3*, 4* and 5* *Rating* are dummy variables that are equal to one if the initial rating of the fund is 1, 2, 3, 4, or 5 stars respectively. *log(Fund Age)* is the natural logarithm of the age of funds. All regressions include only the sub-sample of funds entering our sample before they get rated. All regressions include month-Morningstar category fixed effects and fund fixed effects. Column (4) also includes fund age (in months) fixed effects. In column (5), we replace fund age fixed effects by fixed effects capturing the combination of initial uniqueness quintiles and fund age. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

	Fund Fees (%)				
	(1)	(2)	(3)	(4)	(5)
Post × 1* Rating	-0.011	-0.007	0.010	0.008	0.000
	(0.045)	(0.045)	(0.049)	(0.049)	(0.050)
Post × 2* Rating	-0.024	-0.020	-0.003	-0.004	-0.004
	(0.024)	(0.024)	(0.027)	(0.027)	(0.027)
Post × 3* Rating	-0.022	-0.017			
	(0.014)	(0.014)			
Post × 4* Rating	-0.020	-0.015	0.002	0.007	0.008
	(0.017)	(0.016)	(0.021)	(0.020)	(0.020)
Post × 5* Rating	0.003	0.006	0.024	0.024	0.017
	(0.019)	(0.019)	(0.023)	(0.023)	(0.023)
Post			-0.017		
			(0.014)		
log(Fund Age)		-0.014	-0.014		
		(0.010)	(0.010)		
Year-Month × Cat. FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Fund Age FE	No	No	No	Yes	No
Initial Uniqueness × Fund Age FE	No	No	No	No	Yes
Observations	32,427	32,427	32,427	32,427	32,427
R^2	0.95	0.95	0.95	0.95	0.95

Table A.11: **Change in fund fees after the release of Morningstar ratings**: This table reports results for the difference-in-differences regressions investigating how fund fees change after receiving different Morningstar ratings. The dependent variable is the expense ratio of funds. *Post* is a dummy variable that is equal to 1 if the fund has received a morningstar rating in the month. 1*, 2*, 3*, 4* and 5* *Rating* are dummy variables that are equal to one if the initial rating of the fund is 1, 2, 3, 4, or 5 stars respectively. $log(Fund\ Age)$ is the natural logarithm of the age of funds. All regressions include only the sub-sample of funds entering our sample before they get rated. All regressions include month-Morningstar category fixed effects and fund fixed effects. Column (4) also includes fund age (in months) fixed effects. In column (5), we replace fund age fixed effects by fixed effects capturing the combination of initial uniqueness quintiles and fund age. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

	Flesch Reading Ease		Fog Index		log(Nb. Words Per Sentence)		log(Nb. Characters)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post × 1^* Rating	-0.540	-0.384	0.016	-0.017	-0.005	0.001	-0.053**	-0.047
	(0.484)	(0.543)	(0.123)	(0.138)	(0.008)	(0.009)	(0.026)	(0.031)
Post × 2^* Rating	0.191	0.340	-0.135	-0.165	0.001	0.008	-0.022	-0.016
	(0.310)	(0.428)	(0.087)	(0.123)	(0.007)	(0.009)	(0.021)	(0.028)
Post × 3^* Rating	-0.123		0.019		-0.008		-0.005	
	(0.283)		(0.079)		(0.006)		(0.019)	
Post × 4^* Rating	0.136	0.315	-0.051	-0.084	-0.008	-0.002	-0.024	-0.017
	(0.299)	(0.398)	(0.089)	(0.116)	(0.007)	(0.009)	(0.016)	(0.023)
Post × 5^* Rating	0.137	0.285	-0.078	-0.106	-0.015**	-0.008	-0.005	0.002
	(0.399)	(0.491)	(0.111)	(0.137)	(0.007)	(0.009)	(0.021)	(0.028)
log(Fund Age)	0.391*		-0.129**		-0.004		-0.024*	
	(0.202)		(0.059)		(0.005)		(0.013)	
Year-Month × Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Age FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	32,427	32,427	32,427	32,427	32,427	32,427	32,427	32,427
R^2	0.93	0.93	0.92	0.92	0.93	0.93	0.93	0.94

Table A.12: **Complexity of prospectus text after the release of Morningstar ratings**: This table reports estimation results for difference-in-differences regressions investigating how text complexity and readability of fund prospectuses change after receiving different Morningstar ratings. The dependent variables are measures of readability and complexity of fund prospectuses. In columns (1)-(2), the dependent variable is the Flesch Reading Ease Index (Flesch, 1948). In columns (3)-(4), the dependent variable is the Fog Index (Gunning, 1952). In columns (5)-(6), the dependent variable is the natural logarithm of average number of words per sentence. In columns (7)-(8), the dependent variable is the natural logarithm of total number of characters in the fund prospectuses. *Post* is a dummy variable that is equal to 1 if the fund has received a Morningstar rating in the month. 1^*, 2^*, 3^*, 4^* and 5^* *Rating* are dummy variables that are equal to one if the initial rating of the fund is 1, 2, 3, 4, or 5 stars respectively. *log(Fund Age)* is the natural logarithm of the age of funds. All regressions include only the sub-sample of funds entering our sample one year before they get rated. All regressions include month-Morningstar category fixed effects and fund fixed effects. Columns 2, 4, 6 and 8 also include fund age (in months) fixed effects. Standard errors in parentheses are clustered at the fund level. * $p<.10$; ** $p<.05$; *** $p<.01$.

Investment Strategy	formula, wholli, foster, correct, proxi, bargain, essenti, guidanc, prioriti, reveal, express, databas, expir, ident, emot, assumpt, outweigh, edg, mind, ascertain
ESG	dictat, controversi, activist, climat, help, personnel, coal, nuclear, workplac, pure, compens, propos, esg, transport, vote, withstand
Others	appropri, putnam, cornerston, centuri, spdr, subsidiari, proxi, sampl, subset, float, carri, twelv, settl, media

Table A.13: **Categorization of unique words:** Sample of words which rank high on “uniqueness” (in the top 5% of the uniqueness measure, meaning they were found mostly in unique funds’ prospectus) or low on “uniqueness” (around 0, meaning they were found in almost all of the prospectuses).

	R^2	β_Mkt-Rf	β_SMB	β_HML	β_MOM
	(1)	(2)	(3)	(4)	(5)
TextUniq	-0.722***	-0.010***	-0.001	0.012***	0.002
	(0.210)	(0.003)	(0.003)	(0.003)	(0.002)
log(Fund Age)	0.969***	0.013***	-0.004	-0.002	-0.002
	(0.173)	(0.003)	(0.004)	(0.004)	(0.002)
Year-Month × Cat. FE	Yes	Yes	Yes	Yes	Yes
Observations	175,642	175,642	175,642	175,642	175,642
R^2	0.26	0.29	0.76	0.52	0.22

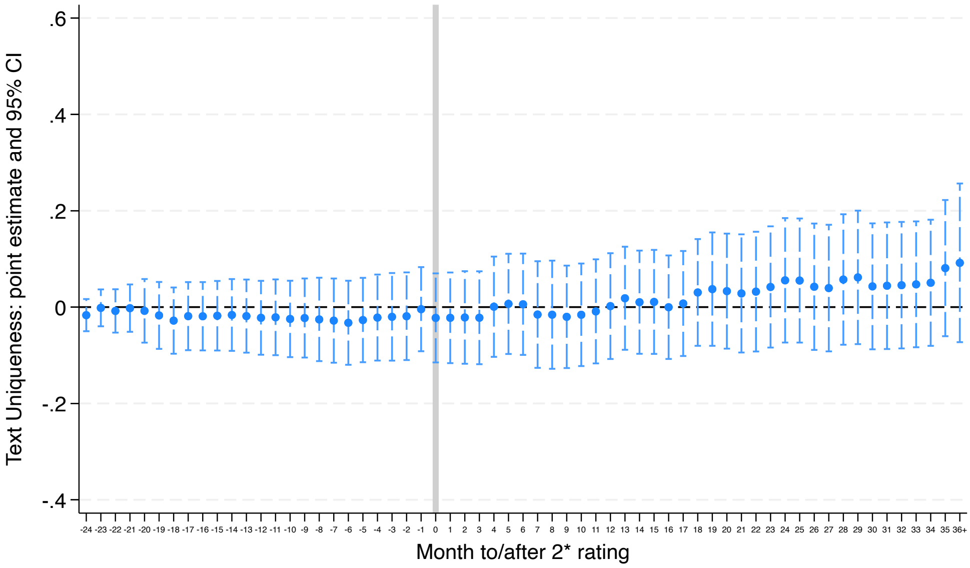
Table A.14: **R-Square and Betas and prospectus uniqueness**: This table reports results for regressions of R^2 and factor loadings on fund uniqueness. The independent variable is the prospectus uniqueness. In columns (1) to (5), the dependent variables are respectively R^2 (%), loading on the market factor, loading on the size factor, loading on the value factor, and loading on the momentum factor. All are estimated through a 4-factor (FF 3 factor + momentum) regression with a rolling window of 24 months. All regressions include month-Morningstar category fixed effects. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

	Market-to-Book Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
TextUniq	-0.131***	-0.119***				
	(0.034)	(0.034)				
HoldUniq			-0.787***	-0.830***		
			(0.055)	(0.056)		
SimIndex					2.136***	2.201***
					(0.187)	(0.196)
log(Fund Age)	-0.019	-0.047	-0.086***	-0.104***	-0.069**	-0.100***
	(0.028)	(0.033)	(0.027)	(0.031)	(0.028)	(0.033)
log(TNA)		0.041***		0.017		0.036**
		(0.014)		(0.014)		(0.015)
Fund Fees		0.036		0.276***		0.245***
		(0.080)		(0.080)		(0.089)
InstFund		0.137**		0.032		0.087
		(0.068)		(0.064)		(0.068)
Year-Month $\times$ Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	180,325	180,325	180,325	180,325	174,643	174,643
R^2	0.64	0.64	0.66	0.66	0.66	0.66

Table A.15: **Market-to-book ratio and fund uniqueness**: This table reports results for regressions of fund market-to-book ratio on fund uniqueness. The dependent variable is fund-level market-to-book ratio, calculated as the value-weighted average of stock-level market-to-book (market equity divided by book equity) ratios in the portfolio. *TextUniq* is the text uniqueness of funds (normalized negative cosine similarity of text, adjusted by number of words). *HoldUniq* is the holding uniqueness of funds (normalized negative cosine similarity of portfolio holdings). *SimIdx* is the similarity to index (cosine similarity with respect to the index of the corresponding category). *log(Fund Age)* is the natural logrithm of the age of the funds, *log(TNA)* is the natural logrithm of the asset under management of the funds, *Fund Fees* is the expense ratio of the funds, and *InstFund* is the fraction of institutional shares of the funds. All regressions include month-Morningstar category fixed effects. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

F Appendix Figures

Panel A: After 2* Rating



Panel B: After 4* Rating

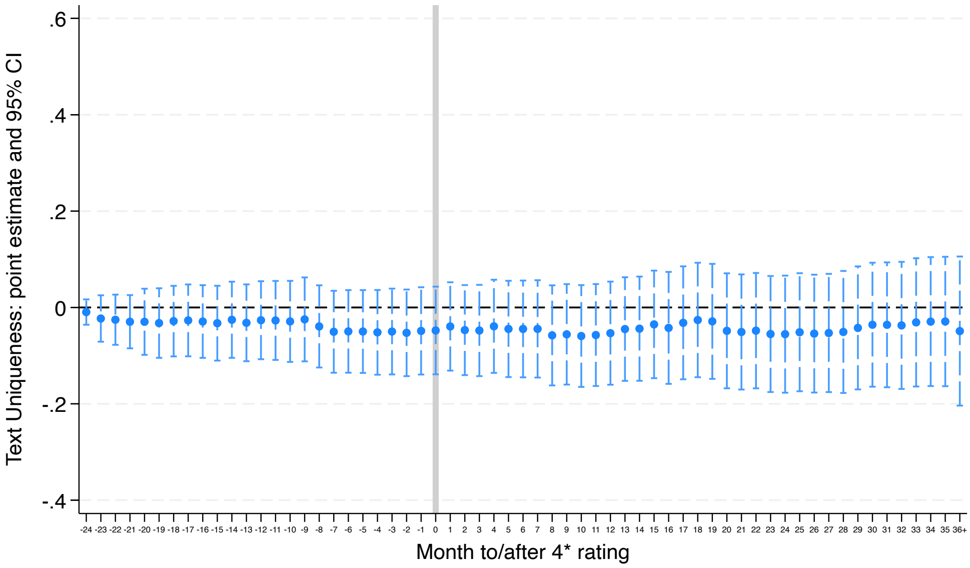


Figure A.1: **Effect of rating disclosure on fund prospectus uniqueness**: This figure presents the coefficient estimates $\beta_{k,2^*}$ (Panel A) and $\beta_{k,4^*}$ (Panel B) as well as 95% confidence intervals against year to the disclosure of rating, from the following regression:

$TextUniq_{i,t} = \sum_{rating \in \{1^*,2^*,4^*,5^*\}} \{\sum_k \beta_{k,rating}\{month\ k\ to\ rating\}_{i,t}\} + \gamma \log age_{i,t} + \delta_{cat \times t} + \lambda_i + \epsilon_{i,t}$.

The dependent variable is the fund's prospectus text uniqueness. $\delta_{cat \times t}$ and λ_i are month-Morningstar category fixed effects and fund fixed effects respectively. Standard errors are clustered at the fund level. The regression includes only the sub-sample of funds entering our sample one year before they get rated.

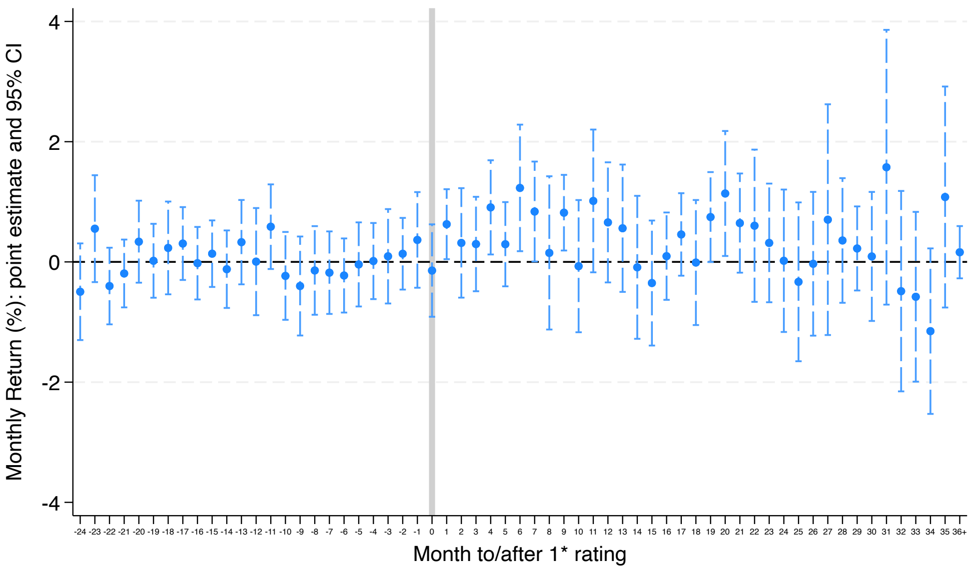


Figure A.2: **Fund returns before and after 1* rating**: This figure presents the coefficient estimates $\beta_{k,1^*}$ as well as 95% confidence intervals against month to the disclosure of rating, from the following regression:

$Ret_{i,t} = \sum_{rating \in \{1^*,2^*,4^*,5^*\}} \left\{ \sum_k \beta_{k,rating} \{month\ k\ to\ rating\}_{i,t} \right\} + \gamma \log age_{i,t} + \delta_{cat \times t} + \lambda_i + \epsilon_{i,t}$.

The dependent variable is the fund's gross monthly return. $\delta_{cat \times t}$ and λ_i are month-Morningstar category fixed effects and fund fixed effects respectively. Standard errors are clustered at the fund level. The regression includes only the sub-sample of funds entering our sample one year before they get rated.