# Quality and Product Differentiation: Theory and Evidence from the Mutual Fund Industry

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**Abstract**

We study product differentiation in the mutual fund industry. We design a model in which funds with heterogeneous perceived quality can choose their level of product differentiation. In equilibrium, high quality funds choose broad market designs (i.e., low differentiation) appealing to many investors, while low quality funds adopt niche designs (i.e., high differentiation) that investors either love or loath. Using as a measure of fund differentiation the degree of textual uniqueness of investment strategy description in fund prospectuses, we confirm empirically that funds with lower expected performance tend to differentiate more. We use the issuance of Morningstar rating to previously unrated funds as an exogenous shock to perceived quality to identify the economic mechanism. We find that funds receiving a low rating increase their product differentiation. The effect is mainly concentrated on funds run by small management companies, a feature associated with lower performance. This increase in product differentiation makes funds more likely to survive. It also has a market-level impact on the menu of funds available to investors.

*Keywords:* Market Structure, Product Differentiation, Ratings, Mutual Funds, Textual Analysis

# 1 Introduction

The U.S. mutual fund industry allocates over 20 trillion dollars of investor wealth, which represents one fourth of all financial assets held by U.S. households. The number of mutual funds has grown to almost 8,000 in 2019 in the U.S. alone.[1] There is a limited number of asset classes and investment styles that are increasingly "crowded"—with funds vying for investor wealth. One dimension of competition across funds is simply performance, and indeed a large literature studies the flow-performance relationship of mutual funds.[2] However, is performance the only dimension funds can compete on? In this paper, we provide evidence that beyond performance funds also strategically choose their ***product design***, that is their level of product differentiation to appeal to different investor clienteles.

Measuring mutual funds' levels of product differentiation is an empirical challenge. Comparing portfolio holdings across funds might confuse differentiation motives and performance considerations.[3] Instead, we rely on textual analysis of mutual fund prospectuses in which funds describe their investment strategies. Compared to holdings choice, how a fund describes its strategy in its prospectus has more to do with the fund's investment philosophy and objective, which is less mechanically correlated with incentives and skills to generate performance. Specifically, our textual analysis compares the prospectus of a fund to its peers' and generates a measure of fund uniqueness, which proxies for the fund's level of product differentiation. Intuitively, if a fund writes its prospectus in a more unique way, it is more likely to differentiate itself with respect to its peers.

We first provide some stylized facts on the ***uniqueness*** of active mutual funds according to our measure using prospectuses. We observe large variations in uniqueness, suggesting different levels of product differentiation across mutual funds. Figure 1 illustrates how fund uniqueness varies across two dimensions: Morningstar star ratings and management company size. Morningstar is one of the most important information intermediaries in the mutual fund space. For each mutual fund, it issues a 1 to 5-star rating entirely based on past fund performance relative to funds in the same category, where 1-star represents the worst performance and 5-star represents

[1] Cf., 2019 Investment Company Fact Book.

[2] See for instance Sirri and Tufano (1998); Berk and Green (2004); Barberis and Shleifer (2003). Note that finance researchers have made an extensive effort to infer fund manager skill to identify better-performing funds (e.g., Cremers and Petajisto, 2009; Amihud and Goyenko, 2013; Kacperczyk et al., 2014; Berk and Van Binsbergen, 2015; Jiang and Verardo, 2018; Hoberg et al., 2018).

[3] For example, Cremers and Petajisto (2009) show that more unique holdings compared to the benchmark index is a proxy for higher manager activeness and predicts higher return.

the best performance. Management companies are the qualified firms that run the funds for investors. Panel A of Figure 1 shows that low rated funds tend to be more ***unique*** than their more highly rated counterparts. While Panel B shows that smaller management companies (in terms of assets under management) provide more unique funds on average.

Figure 1 about here.

We adapt Bar-Isaac et al. (2012)'s theory of product differentiation to mutual funds. In our model, each investor randomly draws a fund and decides either to invest in it or in an exogenous outside option. Investors' expected utility from investing in a fund has two components: (i) the expected performance of the fund perceived by the market (common across all investors), and (ii) an investor-specific matching term. The latter captures the fact that different investors can derive different levels of expected utility from investing in the same fund, e.g., due to different hedging demand, beliefs or specific preferences. Mutual funds exogenously differ in their expected performance perceived by the market, i.e., their perceived ***quality***, and they seek to maximize profits. Funds can set their fees and ***product design***. The latter regards whether a fund chooses to be a ***broad*** fund or a ***niche*** fund. This choice affects the distribution of the investor-specific matching terms over the set of investors. If a fund chooses to be ***broad***, the matching term distribution is concentrated, which means that the fund is "somewhat equally attractive" to most investors. In contrast, if the fund chooses to be ***niche***, the distribution is more dispersed, implying that some investors find the fund very attractive (high matching term) while others find it not attractive at all (low matching term).

In equilibrium, funds with high expected performance—high quality funds—choose to be ***broad***, while funds with low expected performance—low quality funds—choose to be ***niche***. The intuition is that high quality funds can attract investors simply through high expected returns and thus maximize profits simply by avoiding a product design that would antagonize any clientele. Instead, low quality funds cannot compete on expected performance with high quality funds and therefore adopt a niche design, making them more appealing to a subset of investors than high quality funds with broad design. A novel prediction of our model is that lower quality funds might charge higher fees than higher quality funds. The intuition is that the low-quality-unique funds are niche funds and thus have more market power over their clientele.

We test our theory using data on US active mutual funds. We use fund prospectus uniqueness as a proxy for the level of fund product differentiation. Intuitively, the funds that write their prospectuses in a more unique way are more likely to be niche funds that appeal only to a subset of investors. To identify high (low) quality mutual funds we use two fund characteristics: (i) high (low) fund's Morningstar rating and (ii) high (low) fund's management company size in terms of assets under management. These two features are easily observable by investors and are directly linked to fund performance. Indeed, we confirm in our data set that funds with low Morningstar rating and low management company size have significantly lower gross and net returns. Rational investors can thus infer fund quality (expected performance) from these two features.[4]

We then provide empirical evidence supporting the predictions of our theoretical framework. We show that low quality funds (low rating funds and small management company funds) tend to have a higher level of differentiation, i.e., are more unique, as predicted by the theory. This is true according to both our measure of uniqueness relying on fund prospectus and uniqueness measured using portfolio holdings, controlling for category-month fixed effects and fund age. We also find that low quality funds charge higher fees than their high quality counterparts, again consistent with our theory.

Secondly, to address endogeneity concerns and pin down the economic mechanism at play, we study how funds change their level of product differentiation in reaction to an exogenous shock to their perceived quality. Specifically, we study how funds adapt their prospectuses following Morningstar publishing a fund's rating. Morningstar rates a mutual fund only once it has a 36 months track record. Given that a fund's rating is based solely on its performance ranking with respect to other funds in its category, if a fund receives an initial low rating, investors can learn 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.[5]

In a differences 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.[6] Instead, we do not find any significant change after a high initial rating.

[4] Research has shown that investors rely strongly on ratings to allocate their assets. See for instance Kaniel and Parham (2017), Ben-David et al. (2019) and Hartzmark and Sussman (2019).

[5] For funds with a track record of more than 36 months, Morningstar updates the star rating every month. 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 3 years of age. The timing of the publication of the rating is therefore exogenous to the fund. Instead, variations in ratings of previously rated funds can happen continuously and thus be caused by changes in the fund's behavior.

[6] As a robustness check, we confirm that this is also true using a measure of product differentiation based on

We find that conditional on receiving a low initial rating, more unique funds are more likely to survive than less unique funds. This suggests that there is a benefit for low quality funds to have a higher level of product differentiation after receiving a low rating. In contrast, survival is not statistically different for more unique funds following a high initial rating. We also conduct a triple differences analysis and show that the increase in uniqueness is driven by small management company funds, i.e., the funds with lowest initial perceived quality, which is consistent with our theory.

Last, we find that the funds' reactions to Morningstar ratings expand the menu of funds available to investors. Since low ratings lead to increased uniqueness for some funds, a more heterogeneous set of mutual funds is available to end investors after the ratings appear. Indeed, the distribution of uniqueness among rated funds is significantly shifted to the right (high uniqueness), compared to its distribution among unrated funds. Upon further investigation of the specific dimensions in which mutual funds are differentiating themselves, we find that unique funds' returns are less explained by common asset pricing factors, such as the market, size, value and momentum factors. We also find that the words used by unique funds appear to be related to ESG issues. We conclude that the unique funds allow investors to get exposure to or to hedge special risks, and cater for investors' special preferences.[7] This result is consistent with the recent literature showing that mutual fund investors value the sustainability of their investments (Hartzmark and Sussman, 2019; Bauer et al., 2021), and that investors are willing to forgo financial performance for social preferences (Riedl and Smeets, 2017; Brandon et al., 2021).

Our results have important implications for the mutual fund industry. To the best of our knowledge, this is the first paper that applies a general economic theory of product differentiation to the mutual fund industry to show that mutual funds respond strategically when their quality is "revealed". Our work can explain the puzzling fact that some low quality funds (i.e., with low returns) can persist in the universe of mutual funds in a rational framework. We also provide insights on why these low quality funds charge higher fees, a feature that is hard to rationalize without considering product differentiation (Gil-Bazo and Ruiz-Verdú, 2009; Cochrane, 2013). We also show that information intermediaries, such as Morningstar in the mutual fund industry, can have a general equilibrium effect on the supply of mutual funds, by providing investors

portfolio holdings.

[7] For example, Polkovnichenko et al. (2019) show that some investors have preferences for downside protection and upside potential in return distributions.

information on fund performance and shifting funds' perceived quality. They can thus shape product differentiation in the mutual fund industry and have an impact on the menu of funds available to investors.

Our paper is related to several areas of research. First, we contribute to the literature on the industrial organization of the mutual funds industry. Massa (1998), Khorana and Servaes (1999), Massa (2003), Del Guercio et al. (2010) and Betermier et al. (2020) study mutual fund product offering and in particular the incentives of fund families to offer non-performance related services.[8] Our model, based on Johnson and Myatt (2006) and Bar-Isaac et al. (2012), makes explicit fund product differentiation. It has the same spirit as Gennaioli et al. (2015)'s model, which incorporates an additional investor-specific component to fund return in investors' utility, namely "trust". We differ by providing a more general view regarding product differentiation beyond fund performance, and we highlight fund incentives to differentiate.[9] One paper close to our work is Hortaçsu and Syverson (2004), who study how non-portfolio fund differentiation and search frictions can explain the large number of S&P500 index funds and the dispersion in fund fees. Brown et al. (2020), Cooper et al. (2021), Akey et al. (2021), deHaan et al. (2021) also provide evidence that funds with same or lower performance charge higher fees in both active and passive spaces. While they attribute this phenomenon to investors' mistakes, our framework provides a rational explanation. Ben-David et al. (2021) show the existence of a separation between cheap broad ETFs and expensive specialized ETFs. Their work focuses on the passive ETF space, while we focus on active funds using a measure of product differentiation based on fund prospectuses and provide an empirical strategy to test our theory.

Second, we contribute to the literature using textual analysis to study mutual funds. The paper that is the closest to ours is Kostovetsky and Warner (2020), who also use fund prospectuses to measure product differentiation. Their analysis provides descriptive evidence on how funds differentiate from each other. We add to their work by making clear the underlying economic mechanism driving product differentiation and we provide an identification strategy to support it. Abis et al. (2021) study fund prospectuses and introduce a framework featuring investors learning from funds' strategic disclosure. Instead, we focus on the strategic product differentiation of mutual funds and how quality, differentiation, and fees behave in equilibrium. Other papers have also used textual analysis in the mutual fund space. Abis and Lines (2020)

[8] Gantchev et al. (2021) study the tradeoff that mutual funds face between sustainability and performance when investors collectively value sustainability.

[9] We do not explicitly incorporate marketing in our framework as in Roussanov et al. (2021).

and Abis (2020) use fund prospectuses to better categorize mutual funds. Krakow and Schäfer (2020) and Sheng et al. (2021) compare the risk of mutual funds and the self-disclosed risk in prospectus. Hillert et al. (2016) and Du et al. (2019) study the tone of text from mutual funds' disclosures. Cooper et al. (2005) and Betermier et al. (2020) study the evolution of mutual fund names.

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 works in this area of research have focused on 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., 2020; Evans and Sun, 2021).[10] We contribute to this strand of literature by showing that the information provided by intermediaries can also have a general equilibrium effect on the supply side of the fund market. Mutual funds endogenously react to the rating disclosure by changing their product design and this has a market-level impact on the menu of funds available to investors.

The paper proceeds as follows. Section 2 presents a theoretical framework to study product differentiation by mutual funds. Section 3 presents the data and the measures we use in our empirical analysis. Section 4 presents the empirical results. Section 5 discusses in more details what our measure of product uniqueness captures in the mutual fund industry. Section 6 concludes.

## 2 Theoretical Framework

Most existing research on mutual funds takes the view that investors only value performance. We develop a different framework. We assume that return is not the only part in investors' utility function, and we introduce 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. The model abstracts away from funds' incentives to generate performance by assuming an exogenous perceived quality of each fund. We focus on how management companies choose the product design of their funds given their perceived quality.

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

## 2.1 Model

There is a continuum of management companies and investors with mass 1 and $m$ respectively. Each management company $i$ produces a single mutual fund and has an exogenous quality $v_i$, which captures the fund's perceived quality by the market. $v$ is distributed according to some continuous density function $h(v)$ with support $[\underline{v}, \bar{v}]$.

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

### 2.1.1 Investors

Each investor $l$ has the expected utility function described as follows when she invests 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 perceived quality of fund $i$, common across all investors. $\epsilon_{li}$ is a matching term between investor $l$ and fund $i$. It captures idiosyncratic investor preferences for certain funds over others. The distribution of $\epsilon_{li}$ is described by the cumulative distribution function $F_i$, which is set by management company $i$ and discussed below. We assume that realizations of $\epsilon_{li}$ are independent across management companies and individual investors.

Note that the key difference between $v_i$ and $\epsilon_{li}$ is that $v_i$ gives the same expected utility to all investors, while $\epsilon_{li}$ differs across investors. In practice, $v_i$ can be thought of as the expected return of a fund perceived by the market. $\epsilon_{li}$ can be interpreted in several ways: (a) If investors have different risk aversion, $\epsilon_{li}$ measures different required risk premium (net of $v_i$) across investors. (b) If investors have different hedging demand for some individual-specific exposures, $\epsilon_{li}$ measures the hedging benefit (or cost). (c) $\epsilon_{li}$ can measure the individual-specific belief about the fund expected return on top of the market belief. (d) $\epsilon_{li}$ can also measure other individual-specific preferences, such as ESG concern.

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 management company $i$ and decides to invest one unit of capital in the fund if it provides more expected utility than the outside option, i.e., if

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

### 2.1.2 Management companies

Each management company $i$ cannot affect $v_i$, its exogenous perceived 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 firm can affect the distribution of the match-specific component of investor tastes in (1), by picking a design $s_i \in \{B, N\}$. Management companies can choose either a ***broad*** $(B)$ or a ***niche*** design $(N)$. Each design is associated with a distribution of $\epsilon_{li}$. Specifically, the cumulative distribution function of $\epsilon_{li}$ is given by $F_B$ $(F_N)$ if the company 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.[11] We assume that there exists a rotation point $\theta^*$, 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 2 illustrates the density and cumulative distribution functions (c.d.f.) of $\epsilon$ 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 $\theta^*$ 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 $\epsilon$ is larger than a threshold, as shown in (2). If this threshold is below $\theta^*$, 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 $\theta^*$, 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.

[11] 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.

Figure 2 about here.

## 2.2 Management company profit maximization

Given (2), investors who draw a management company with perceived quality $v$ invest as long as they receive a match term $\epsilon$ such that $\epsilon > U - v + p_v$. Therefore, they invest in the fund with probability $1 - F_s(U - v + p_v)$, where $s \in \{B, N\}$ is the design chosen by the management company. Given that there is a mass $m$ of investors and that each one randomly draws a management company, the demand for the fund of a given management company 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 management company 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 firm.

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

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

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-perceived 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 $U$.

Using (5), we can derive design choices. We show below that management companies choose design according to a simple rule: if perceived quality $v$ is high enough the company 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 the company with perceived quality $V$ is indifferent between choosing the broad or the niche design. As a consequence, companies with quality strictly greater than the threshold $V$ choose broad design, while companies with quality strictly lower than the threshold choose niche design.

**Proposition 1.** *There exists a unique threshold $V$ such that management company with perceived quality $V$ is indi erent 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 firms with perceived quality lower than this threshold, $v < V$, choose a niche design, and all firms with $v > V$ choose a broad one.*

The proof of Proposition 1 is provided in Appendix B. It also allows to show that the following inequality holds: $p_B(V) < p_N(V)$. That is, management company with perceived quality $V$ is indifferent between choosing a broad design associated with larger demand but lower price, or the niche one with smaller demand and higher price.

## 2.3 Equilibrium summary

### 2.3.1 Design choice in equilibrium

A key implication of Proposition 1 is that management companies with lower perceived quality are more likely to choose niche design. The intuition is that companies 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-perceived 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.

### 2.3.2 Price in equilibrium

The design choice rule has an important implication for prices in equilibrium: price can decrease with perceived quality. Note that, even if $p_s(v)$ increases with $v$ conditional on design $s$, management companies with perceived quality $v$ above or below a certain threshold do not adopt the same design. This implies that there exists 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 management companies with perceived quality $v$ below the threshold $V$ that charge higher prices than companies with $v$ above the threshold.*

We provide the proof of Proposition 2 in Appendix B. Figure 3 illustrates how equilibrium price $p(v)$ varies by perceived quality $v$. There are two channels through which perceived quality affects price. The first channel is the most obvious one: better products are sold at higher price. As we show in Equation (5), price $p_s(v)$ is increasing in $v$ given $s$.

The second channel relates to the fact that quality affects the product design choice. When the perceived quality is lower than the threshold $V$, the firm is better-off by providing a niche product. The niche design gives the firm 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 $V$. The closer to $V$ from below the firm's quality $v$ is, the more likely its price will be larger than the one of the firm with quality just above $V$.[12] 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 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 firms charge a higher price than higher quality broad firms.

Figure 3 about here.

#### 2.3.3 Shock to perceived quality

We discuss below how a shock to the perceived quality of a fund can affect its product design choice. This discussion is helpful to match our theoretical framework to our empirical analysis using the issuance of Morningstar rating. Consider a fund with initial perceived quality $v$, and suppose it incurs a negative shock such that its perceived 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 initial quality was above the threshold $V$ but not large enough, i.e., if $v < V + \Delta v$, such that $v'$ is lower than $V$. This implies that, after a negative shock, the funds with the lowest quality among those with broad design will change their product to a more niche one. The closer to $V$ the initial quality, the higher the likelihood that a negative shock to perceived quality will push the fund to adopt a niche design. Likewise, after a positive shock, some funds will change the product design from niche to broad, and the closer to $V$ (from below) the initial quality, the higher the likelihood that the funds will change its design.

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

### 2.4 Empirical Predictions

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

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

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

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

This prediction follows from Proposition 2. Lower perceived 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 the perceived quality of funds, some funds become more niche. This e ect concentrates on the funds whose original perceived quality is not high enough.*

The first part of this prediction directly follows from Prediction 1. After a negative shock, some funds become more niche to compete and attract investors who receive a high matching term with them. However, not all funds change design. Funds whose original quality was quite high are still perceived as high quality funds despite the negative shock. Therefore, they are better-off keeping a broad design. On the contrary, broad funds with initial perceived quality not high enough have to adapt and become more niche.

## 3 Data

### 3.1 Product differentiation in the mutual fund industry

We test empirically our theory using data on U.S. Domestic Equity mutual funds. We focus on this set of funds simply because Domestic Equity funds are more comparable to each other, and computing their alpha is more straightforward.

To differentiate niche and broad funds, we generate a text uniqueness measure based on the prospectuses of funds. 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), text uniqueness can better predict whether funds are in the same category, compared to other measures such as holding uniqueness and return uniqueness. Second, because we seek to study the relationship between uniqueness and return, we want to avoid capturing mechanically previous findings from the mutual fund literature. Indeed, Cremers and Petajisto (2009) show that more unique holdings compared to index predict higher return. Amihud and Goyenko (2013) show that a lower $R^2$ in regressions of fund returns on factors predicts higher return. Therefore, we rely on text uniqueness because it is more orthogonal to fund return.

We compare funds' prospectuses and compute their text similarity. We take the negative of similarity as our measure of text uniqueness, i.e., how niche a fund is. The intuition is the following: 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 in a very different way from others, it is more likely to be a niche fund, seeking to attract specific investors who particularly like it.

We focus on two characteristics that can affect the perceived quality $v$ of a fund. The first one is the Morningstar rating. A large body of literature has documented that investors rely on these ratings to learn about funds' quality (e.g., Evans and Sun, 2021; Ben-David et al., 2019). We exploit the first issuance of a fund's Morningstar rating as an exogenous shock to its perceived quality. The second characteristic we use is the fund's management company size. Several papers have documented the role of mutual fund firms in the creation of value added (e.g., Fang et al., 2014; Berk et al., 2017; Luo et al., 2021; Zambrana and Zapatero, 2021) and we can arguably assume that investors have good reasons to believe that large companies provide products with higher performance than those issued by small companies. We verify this assumption in the empirical section. We provide more details about data, cleaning procedure and variable construction 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.[13] For each fund, we collect monthly TNA (Total Net Assets) and net return. We also collect expense ratios 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 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 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).[14]

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), 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 per 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

[13] 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".

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

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. 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 are corresponding 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 make uniqueness less noisy, we consider three measures, removing respectively the 10, 20 and 30 most commonly used words by all the funds.[15]

We 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.

## 3.3 Uniqueness measures

### A. Text uniqueness

Our main measure of uniqueness is based on the strategy description of fund prospectuses. 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

[15] Top 10 words are: fund, invest, secur, index, asset, market, compani, portfolio, includ, underli; Top 10-20 words are: equiti, stock, manag, advis, rate, income, capit, bond, alloc, instrument; Top 20-30 words are: time, strategi, exposur, seek, risk, deriv, return, fix, issuer, foreign

normalize the residuals $\epsilon_i$ and use them as the final uniqueness measure for fund $i$.

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

The uniqueness measure based on textual analysis of prospectuses was introduced by Kostovetsky and Warner (2020). The authors 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.

**B. Holding uniqueness and similarity to index**

We also construct uniqueness measures based on holdings. 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.[16] 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 of an ETF that tracks the main benchmark index. For each category, we use the most commonly used index and the largest index ETF tracking it. The list of indexes and ETFs can be found in Appendix E. 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 original Morningstar Rating was introduced in 1985. Over our sample period, Morningstar assigns ratings based on comparisons of all funds within a given Morningstar category. Specifically, Morningstar rates all mutual funds on their performance ranking in their peer group. By design, fund ratings are balanced across Morningstar categories.

Morningstar ratings are updated every month and the calculation consists in two steps. First, for each fund with at least 36 continuous months of returns, Morningstar calculates performance

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

measures using past returns (with minor adjustments based on return volatility). Second, Morningstar ranks funds by the performance measure and assigns ratings. We give additional details on the rating methodology below.[17] Importantly, note that each mutual fund gets rated as soon as it has a track record of at least 36 months. Morningstar fund analysts don't assign star ratings and have no subjective input into the ratings. Furthermore, the ratings do not take into consideration any product differentiation measures. Therefore, the Morningstar rating gives investors straightforward information regarding how a fund has performed relative to similar funds.

Several papers have shown that Morningstar ratings of performance have a strong and significant impact on investor flows from both retail and institutional investors (Nanda et al., 2004; Guercio and Tkac, 2008; Evans and Sun, 2021; Ben-David et al., 2020). 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 measure that drives flow. This suggests that mutual fund investors chase fund performance *via* Morningstar ratings. Therefore, we interpret the release of a fund's rating as a shock to its perceived quality by investors.

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):

$$MRAR_i^T(\gamma) = \left[\frac{1}{T}\sum_{t=1}^{T}(1 + r_{i,t} - r_t^f)\right]^{-\frac{12}{\gamma}} - 1, \tag{8}$$

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 $\gamma$ converges to 0, $MRAR_i^T(0)$ is equal to the annualized geometric mean of excess returns. When $\gamma$ 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.

[17] Morningstar ratings are strongly correlated with other standard performance measures such as cumulative return, alpha and return rank, as shown for instance in Guercio and Tkac (2008).

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.

Note that Morningstar rates each share class of a mutual fund separately because each share class has different fees and total return time periods available.[18] We aggregate the Morningstar ratings of the different share classes of the same fund by taking the TNA-weighed average of share class ratings.

### 3.5 Summary statistics

Our sample contains monthly observations at the fund level from 2011 to 2020. We focus on this period because the prospectus data available from EDGAR are not well-structured and we are unable to scrape them before 2011. 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 alpha has a slightly negative mean of -0.1%. 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. Expense ratio is on average 1.1%. 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, that are not yet rated by Morningstar.

$IsDead$ is a dummy that is equal to one if the fund dies at the end of that month, zero otherwise.[19] 0.4% of observations in our sample correspond to fund death. This relates to the

[18] 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.

[19] Specifically, $isDead$ is equal to one if the fund is a dead fund according to CRSP and the observation is the last one for that fund.

exit of 862 funds, i.e., one third of the funds appearing in our sample are dead by the end of 2020.

$TNA$ (fund total net assets) has a median of $263 million and a mean of $1.7 billion. We compute management company TNA by taking the sum of fund TNA over all Equity Domestic mutual funds managed by the company in that month. $Mgmt\ Company\ TNA$ has a median of $13 billion and a mean of $108 billion. For all funds, we also compute the corresponding management company TNA in 2009 (two years before the beginning of our sample). We use that variable in our empirical analysis in order to avoid concerns about endogeneity of current firm size. *Fund Age* is the number of month since the reported fund's starting date.

$\#Word$ and $\#UniqueWord$ are respectively the total number of words and the number of words appearing at least once, in the fund's prospectus after removing stop words. We observe that fund prospectuses feature on average respectively 171 and 91 words and unique words. *TextUniq*(10), *TextUniq*(20) and *TextUniq*(30) are funds' text uniqueness measures, which are computed after removing the 10, 20 and 30 most commonly used words, listed in section 3.2. They are mean zero and have a standard deviation of one. Therefore, uniqueness measures are expressed in number of standard deviations from the mean.

$\#Asset$ refers to the number of assets with available cusip in the fund portfolio. On average, funds hold 231 securities. *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.

Table 1 about here.

# 4 Empirical results

## 4.1 Performance of funds

In this section, we provide evidence on how funds' realized performance relates to two observable features: Morningstar rating and management company size. We show that low rating funds and funds managed by small companies have inferior performance. Because investors can learn from these two characteristics, they expect low rating funds and funds managed by small companies to have lower performance (i.e., lower perceived quality).

We focus on funds with available Morningstar ratings. To capture a fund having a low rating, we define a dummy variable ***Low Rating*** which is equal to one if the fund's rating is equal to or less than two stars. This specifically captures funds which are "below average" in each category. Similarly, we capture small management company size by defining a dummy variable *Small Mgmt Company* equal to one if the firm's TNA in 2009 (two years prior to the start of our sample) belongs to the bottom three management TNA quintiles. We use the management TNA in 2009 because we want to avoid the mechanical effect that higher performance leads to larger company size. We use funds managed by companies belonging to the bottom three quintiles to keep our sample relatively balanced between small and large company funds. Indeed large management companies have more funds and therefore represent more observations. 28% of the fund observations are in the bottom three management TNA quintiles, while 49% are in the top quintile.

To test the cross-sectional relation between performance and ratings and company size, we estimate the following regression:

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

where $Perf_{i,t}$ is the realized performance of fund $i$ in month $t$, measured by before-fee return, after-fee return, and net alpha. *Characteristics* includes the dummies *Low Rating*, *Small Mgmt Company*, and their interaction *Low Rating* $\times$ *Small Company*. $\log(age)$ is the logarithm of fund age, included to control for the correlation between age and performance. In all the regressions we include $\delta_{cat \times t}$, which corresponds to $Month \times Category$ fixed effects. We cluster standard errors at the fund level.

Table 2 shows the estimation results. Both *Low Rating* and *Small Mgmt Company* are significantly negatively correlated with funds' performance measures. The effect of rating is quite expected, as ratings are constructed based on recent relative performance of funds in the same category. In column 1 of Panels A, B and C, we find that low rating is associated with between 0.26% and 0.34% lower monthly performance depending on the measure. Note that because we include $Month \times Category$ fixed effects, the coefficients have to be interpreted relative to the average performance in the fund's category in a given month. Perhaps more surprisingly, this relationship is directionally the same for small management company size. In column 2 of Panels A, B and C, we find that *Small Mgmt Company* is associated with between 0.05% and 0.10% lower monthly performance. This might be due to the fact that large companies have an advantage to generate higher performance (e.g., better access to information or better execution). In Table A2, we run the same regression but replacing management company size with management company age. The management company age has the similar effect on performance.

Note that Morningstar rating is a more informative signal than company size. For gross return and alpha (Panels A and C respectively), the coefficient on *Small Mgmt Company* is no longer significant in column 3, when we include rating in the regression, while the coefficient on rating remains significantly negative in all specifications. Interestingly, the coefficient on the interaction between the two features is also significantly negative for all dependent variables (cf. column 4 in Panels A, B and C). Indeed, a low rating fund managed by a small company has a monthly return that is between 0.08% and 0.09% lower than that of a low rating fund managed by a large company. This implies that management size can give additional information to investors, on top of rating.

Therefore, we expect investors to form expectations of the performance of a fund by observing its rating and the size of its management company. We rely on this fact in section 4.3, by using the release of the first Morningstar rating of a fund as a shock to its perceived quality. We assess the heterogenous effects across management companies of the release of a low rating.

Table 2 about here.

## 4.2 Production differentiation and fees

We now move on to testing the specific predictions made by our theoretical framework. We first test how the text uniqueness of funds is correlated with the perceived quality of funds. Specifically, we estimate the following regression:

$$TextUniq_{i,t} = \alpha + \beta Low\ Perceived\ Quality_{i,t} + \gamma \log(age)_{i,t} + \delta_{cat\times t} + \epsilon_{i,t}, \tag{10}$$

where $TextUniq_{i,t}$ is the prospectus uniqueness measure of fund $i$ in month $t$ defined in Section 3.3. *Low Perceived Quality* includes the dummies *Low Rating*, *Small Mgmt Company*, and their interaction *Low Rating* $\times$ *Small Company*, which are defined in Section 4.1.

The results of the regressions are shown in Table 3. When the dummies *Low Rating* and *Small Mgmt Company* are the only variables entering into the regressions, the corresponding coefficients are significantly positive, suggesting that low rating funds and small company funds have more unique fund prospectus. Based on our uniqueness measure, low rating funds are more unique than high rating funds by 0.08 standard deviation.[20] Funds in small management companies are more unique than funds in large companies by 0.14 standard deviation. When both measures enter into the regressions, the coefficients remain significant and positive. Interestingly, in column 4, the coefficient on the interaction of *Low Rating* and *Small Mgmt Company* indicates that low-rated funds in small companies, i.e., the lowest perceived quality funds according to our previous results, are particularly likely to be more unique than all other groups. The evidence supports **Prediction 1** that lower perceived quality funds choose more niche design on average.

Table 3 about here.

Second, we investigate whether a similar relationship holds when we focus on funds' actual holdings. We estimate the same regression as in (10) but with holding uniqueness as the dependent variable:

$$HoldUniq_{i,t} = \alpha + \beta Low\ Perceived\ Quality_{i,t} + \gamma \log(age)_{i,t} + \delta_{cat\times t} + \epsilon_{i,t}, \tag{11}$$

where $HoldUniq_{i,t}$ is the holding uniqueness of funds or alternatively the similarity of holdings with respect to the index of the corresponding category. The results are presented in Table 4. Panel A shows that low rating funds and funds in small companies hold more unique portfolios than high rating funds and funds in large companies. Low rating funds' portfolios are more unique than high rating funds' by 0.29 standard deviation. The portfolios of small company funds are more unique than portfolios of funds in large companies by 0.36 standard deviation. The results in Panel B, with portfolio similarity with respect to the index as dependent variable, are consistent with this evidence. The portfolios of low rating funds and small company funds are less similar to the benchmark index' of their category. Overall, these results show that the effects we captured using prospectus measures are not merely marketing. Low rating and small company funds are more unique according to their prospectuses and also do differentiate more according to their actual holdings.

[20] The uniqueness measure is normalized to mean 0 and standard deviation 1.

Table 4 about here.

Finally, we test whether fees differ across funds with different levels of perceived quality. We estimate the following regression:

$$ExpRatio_{i,t} = \alpha + \beta Low\ Perceived\ Quality_{i,t} + \gamma \log(age)_{i,t} + \delta_{cat\times t} + \epsilon_{i,t} \tag{12}$$

where $ExpRatio_{i,t}$ is the expense ratio of the fund. The estimation results are shown in Table 5. Low rating funds and funds in small companies charge higher fees on average than high rating funds and funds in large companies, which is consistent with **Prediction 2**. Fees charged by low rating funds are higher than fees charged by high rating funds by 27 basis points. Fees charged by small company funds are higher than fees charged by large company funds by 28 basis points. These effects are economically significant compared to average expense ratio of 110 basis points in our sample. The coefficient on the interaction of the two dummies is also significantly positive in column 4. Low rating funds in small companies, i.e., the lowest perceived quality funds, charge the highest fees among all the funds.

Overall, the evidence is consistent with the predictions generated by our theoretical framework. Lower perceived quality funds offer more niche products and charge higher fees.

Table 5 about here.

In Appendix C, we check that the dummies *Low Rating*, *Small Mgmt Company*, and their interaction *Low Rating*×*Small Company* are negatively correlated with fund size. We estimate the same regression as in (10) but with the logarithm of fund TNA as dependent variable. The results are presented in Table A1. As expected, we find that smaller management companies produce significantly smaller funds. We also find that low rating funds are significantly smaller, on average, than high rating funds. This supports our previous findings and suggests that low rating funds and small company funds, which are typically more unique than their counterparts, tend to target a niche (smaller) market. In Table A3, A4 and A5, we run the same set of regressions but replacing management company size with management company age. The results are qualitatively similar. Like small management company, funds in young management companies are also perceived as low quality, and have a niche product design.

### 4.3 The effects of a negative shock to perceived quality of funds

One concern from the regressions above is that rating and company size are potentially correlated with other latent fund characteristics, which might drive our results on fund uniqueness. In this section, we use the issuance of the initial Morningstar rating of a fund as an exogenous shock to its perceived quality, to validate causality between perceived quality and product design. Each fund gets rated by Morningstar from the month it reaches a track record of 36 months. For funds that are younger than 3-year old, investors can observe the fund's company size but there is no rating available. 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 appearance of the initial rating can be considered as a shock to investors' perceived quality of funds. This setting allows us to further test our theoretical framework and in particular the prediction that low perceived quality funds choose more niche designs.

We exploit the issuance of the initial rating in a staggered differences in differences framework. We consider different "treatment" effects depending on whether the initial rating of the fund is low or high. Specifically, we estimate the following regression:

$$\begin{aligned} Uniqueness_{i,t} = \alpha &+ \beta_1 Post \times Low\ Rating_{i,t} \\ &+ \beta_2 Post \times Med\text{-}High\ Rating_{i,t} \\ &+ \gamma \log(age)_{i,t} + \delta_{cat \times t} + \lambda_i + \epsilon_{i,t}, \end{aligned} \tag{13}$$

where *Uniqueness* is the text or holding uniqueness measure of fund $i$ in month $t$. *Post* is a dummy which is equal to one if the fund is rated. *Low Rating* is a dummy which is equal to one if the initial rating the fund gets is equal to or below 2 stars. *Med-High Rating* is a dummy which is equal to one if the initial rating the fund gets is larger than 2 stars. As in the cross-sectional regressions, we control for the natural logarithm of the age of the funds and include category-month fixed effects $\delta_{cat \times t}$. We also include fund fixed effects $\lambda_i$.

Our methodology fully controls for fixed differences between funds via the fund fixed effects, while controlling for fund age. The category-month fixed effects control for fluctuations that are specific to the fund's Morningstar category. $\beta_1$ ($\beta_2$) is our estimate of the effect of the release of a low (medium-high) rating. $\beta_1$ captures the average variation in uniqueness before and after a fund gets a low rating, with respect to other unrated 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 (13) means that our control group is not restricted to funds that are never rated in our sample. In fact, equation (13) takes as the control group all funds that do not have a rating in month $t$, even if they will get rated later on.

Table 6 shows the estimation results of the regressions above. The coefficients on *Post* $\times$ *Low Rating* is significant in regressions for all uniqueness measures. After receiving a low rating, a fund's prospectus becomes more unique by 0.06 standard deviations. Moreover, after receiving a low rating, the fund starts holding a more unique portfolio, which is less similar to the benchmark index. This behavior is consistent with the first part of **Prediction 3** that funds adapt after a negative shock to their perceived quality, by becoming more unique and targeting a more niche market.

Table 6 about here.

To confirm that the rating issuance is the driver of this change in funds' uniqueness design choice, we estimates a specification similar to (13) but with specific dummies indicating whether the rating is released in each of the next two years, the current year, and in each of the previous four years or more. This allows us to analyze the dynamics of the effect of the rating on funds' uniqueness. We use a specific set of coefficients for low, medium and high rated funds. We corroborate that the funds whose initial rating is low significantly increase their prospectus uniqueness in the year following the rating shock (cf., Panel A in Figure 4), and there is no pre-trend before the shock. In contrast, prospectus uniqueness does not change significantly after the rating disclosure for the funds whose initial rating is medium or high (cf., Panels B and C in Figure 4).

Figure 4 about here.

Moreover, given the earlier empirical evidence that small management company size is associated with lower performance, we estimate an additional specification with a triple interaction. We further interact the *Low Rating* dummy with dummies capturing the size of the fund's management company. Specifically, we estimate the following regression:

$$\begin{aligned} Uniqueness_{i,t} = \alpha &+ \beta_{11} Post \times Low\ Rating_{i,t} \times Small\ Mgmt\ Company \\ &+ \beta_{12} Post \times Low\ Rating_{i,t} \times Large\ Mgmt\ Company \\ &+ \beta_2 Post \times Med\text{-}High\ Rating_{i,t} \\ &+ \gamma \log(age)_{i,t} + \delta_{cat \times t} + \lambda_i + \epsilon_{i,t}, \end{aligned} \tag{14}$$

where *Small Mgmt Company* (*Large Mgmt Company*) is a dummy equal to one if the firm's TNA in 2009 belongs to the bottom three (top two) management TNA quintiles, zero otherwise. As shown in Table 7, the effect on uniqueness we observed really concentrates on the funds which belong to small management companies. It is these funds that significantly increase their prospectus and holding uniqueness on average after receiving a low rating, i.e., a negative shock to their perceived quality. This result further supports the second part of **Prediction 3**, that the effect of a negative shock to perceived quality (the low rating shock) is concentrated on the funds whose original perceived quality was not high enough. In other words, even if some large management company funds receive low ratings, because their initial perceived quality is not low enough, the low rating shock does not drive a significant uniqueness increase.

Overall our results are consistent with the theoretical framework developed in section 2. We observe that funds that are less likely to deliver high performance relative to their peers differentiate more through their prospectuses and holdings. When an additional signal about funds' expected performance is made available to investors, mutual funds adapt their product design choice. Funds that are likely to be now considered as low quality funds, i.e., expected to deliver poor performance, become more unique in terms of prospectus and holdings. As such, they target a smaller segment of the market, i.e., they become more niche.

Table 7 about here.

Note that all the results presented in this section remain valid when we use the management company age instead of its size. Additional results are presented in Appendix D.

### 4.4 Uniqueness and survival

A natural question that arises is whether the observed fund response to low rating has any impact on funds' success. In this section, we show that becoming more unique after a low rating has a real impact on the fund's likelihood of survival.

Specifically, we estimate the Kaplan-Meier failure function of mutual funds in our sample, conditioning on funds' characteristics. The Kaplan-Meier function is a nonparametric estimation of the likelihood of failure. Denoting $T$ the duration of fund life, the hazard rate or exit probability is $\theta_t = P(T = t \mid T \geq t)$. It can be estimated empirically in our sample using the ratio of the number of funds that die at age $t$ and the number of funds that die at age equal to or larger than $t$. The Kaplan-Meier failure function $F(t)$ is an estimate of the probability that fund life is no longer than $t$ and is defined as follows: $F(t) = 1 - S(t)$, where $S(t) = \prod_{j=1}^{t}(1 - \theta_j)$. We graph the Kaplan–Meier estimates as a function of fund age for different groups of funds.

In Figure 5, we split our sample of rated funds into two subsamples: those whose initial rating is low (equal to or lower than two stars) in Panel A, and those whose initial rating is medium or high (above two stars) in Panel B. In each subsample, we graph the Kaplan-Meier failure function, conditioning on prospectus text uniqueness. We define a dummy variable $HighTextUniq$ that is one if the fund's prospectus uniqueness measure is above the median uniqueness in its category-month. By looking at hazard plots of fund failure rate broken out by Morningstar rating, we see that conditional on low initial rating, funds with high prospectus uniqueness are more likely to survive in the years following (see Panel A). Meanwhile, the uniqueness of a fund's prospectus has virtually no impact on survival rate for funds with with medium or high initial rating (see Panel B).

In Figure 6, we focus on funds with low initial rating. We split this sample between funds that belong to small management companies and funds that belong to large management companies. In each subsample, we graph the Kaplan-Meier failure function, conditioning on prospectus text uniqueness. By breaking out the failure function by management company size, we observe that the effect of uniqueness on survival is more pronounced for funds which receive a low rating and are managed by small companies (see Panel A). While higher prospectus uniqueness still has a negative impact on death rate for low-rated funds from larger management companies, the effect is not nearly as pronounced (see Panel B).

Figure 5 about here.

Figure 6 about here.

We support these descriptive results with regressions analyzing the effect of a low rating on the likelihood of the fund dying in a given month. Specifically, we run the following regression:

$$\begin{aligned} IsDead_{i,t} = \alpha &+ \beta_1 Low\ Rating + \beta_2 HighTextUniq \\ &+ \beta_3 Low\ Rating \times HighTextUniq \\ &+ \gamma \log(age)_{i,t} + \delta_{cat \times t} + \epsilon_{i,t} \end{aligned} \tag{15}$$

where $IsDead$ is a dummy indicating death of fund $i$ in month $t$. $HighTextUniq$ is a dummy variable that is equal to one if the prospectus uniqueness of the fund is above the median uniqueness of its Morningstar category in that month. And all other variables are defined as in Section 4.1. The variable of interest is $\beta_3$, which captures the effect of fund uniqueness on the fund's likelihood of dying when the fund's initial rating is low.

The estimation results are shown in Table 8. Note that all coefficients are multiplied by 100 and must be interpreted in pp. Table 8 confirms our results obtained with hazard function estimates. Low rating significantly increases the probability of a fund dying, whereas the interaction of receiving a low rating and having a more unique fund prospectus lowers the probability of fund death (Panel A). The effect is economically large. Compared to low rating funds that are not unique, the low rating unique funds have a likelihood of dying that is 18 basis points lower. Given that the unconditional mean of the dependant variable is 0.4, this implies a drop in the likelihood of dying by almost 50% relative to the sample mean. We estimate the same regressions on two subsamples: funds that belong to small and large management companies. Consistent with our differences in differences regression results, the drop in the likelihood of dying due to high prospectus uniqueness concentrates on funds in small companies (Table 8 Panel B), but is not as strong in large companies (Table 8 Panel C).

Again, these results are consistent with our theoretical framework that low perceived quality funds are better-off being more unique. Hazard plots and regressions in Table 8 also rationalize the behavior of funds that we identified in our differences in differences analysis: low perceived quality funds become more unique in order to increase their chances of survival.

Table 8 about here.

### 4.5 Market-level impact of ratings

In this section we show that the mutual funds' reaction to the release of Morningstar rating has a broad impact on the overall product differentiation in the mutual fund industry. We first compare the distribution of uniqueness among rated and unrated funds. Specifically, we split all funds that get eventually rated in our sample into two subsamples: those whose initial rating is low and those whose initial rating is high. Then, in each subsample, we compare the distribution of text uniqueness for observations before and after the issuance of the rating. Our goal is to assess whether there is a change in the distribution of uniqueness that is triggered by the released rating. In order to absorb any 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 $\epsilon$, the residual uniqueness of funds.

Panel A of Figure 7 presents the density estimates for rated and unrated observations of funds whose initial rating is equal or lower than 2 stars. It appears that there is a clear difference in the uniqueness distribution prior to receiving the Morningstar rating—with a denser distribution around average text uniqueness—and following the disclosure of a low Morningstar rating, with a greater mass of funds having higher than average fund prospectus uniqueness. In contrast, there is virtually no difference in the distributions of uniqueness between rated and unrated funds' observations when we focus on funds whose initial rating is above 2 stars (Panel B of Figure 7).

Figure 7 about here.

To formally test whether the difference in distributions we observe in Panel A of Figure 7 is meaningful, we rely on the Mann-Whitney U Test to test the equality of two distributions. The results of the tests (Table 9) confirm our previous observations. The distributions of funds' uniqueness for observations before and after the rating release are significantly different when the initial rating is low (equal to or less than two stars). The two distributions are not significantly different when we focus on funds whose initial rating is high.

Table 9 about here.

These results show that the disclosure of Morningstar ratings have a market-level impact on the uniqueness distribution of available mutual funds. Specifically, the issuance of ratings leads some mutual fund to adapt their product uniqueness. As a consequence, we observe an increase in the availability of "niche" funds which employ more unique strategies than would exist without the existence of Morningstar ratings.

# 5 Discussion: What is uniqueness measuring?

In the analysis above, we treat mutual funds as financial products and use a novel measure of text uniqueness to measure product differentiation. In this section, we investigate the specific dimensions in which mutual funds are differentiating themselves. We propose two explanations for what our text uniqueness measure captures in the mutual fund context: unique factor exposures and investor preferences.

### 5.1 Factor Exposures

First we test whether unique funds provide alternative factor exposures to investors, i.e., outside standard 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:

$$Y_{i,t} = \alpha + \gamma TextUniq_{i,t} + \lambda_{cat\times t} + \epsilon_{i,t} \tag{16}$$

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.

Table 10 shows the estimation results of the above regressions. We find that variations in the unique funds' returns are less explained by the factor model. 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: 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 but there is no significant difference regarding the size or momentum factor exposures. Overall this suggests that the unique funds might differentiate from broad funds by providing more exposure to uncommon factors.

Table 10 about here.

### 5.2 Investor Preferences

Next we investigate whether the unique funds offer products which cater for specific investor preferences, e.g. environmental concerns. To answer this question, we first construct a measure of *word uniqueness* by taking, for each word, the average text uniqueness of all prospectuses which use that word. 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 bottom of the list features the words which appear mostly in broad funds' prospectuses. The words with 0 uniqueness are those which are used by an average fund.

Table 11 about here.

Table 11 illustrates the words with highest uniqueness and the words with uniqueness close to 0. 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 which employ more unique strategies in our data are more likely to have words which indicate a stance on the environmental impact of their investment portfolio such as "climate," "coal" and "nuclear". Niche funds in our data are also more likely to have 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 focusing on a specific sector (e.g. "retail") or strategy (e.g. "activist").

When it comes to commonly used – not unique – words which are found in average prospectuses, we find more generic references to fund terms and marketing strategy. The top 5% least unique words include financial terms such as "expense," "discount" and "lowest". Least unique words also include verbs describing growth such "create," "drive," and "accelerate". Finally, words regarding a fund manager's process, such as "consider," "effort", and "model" are highly common. This evidence suggests that the words in unique funds may reflect investors' preferences stemming from their specific investment mandate.

Overall, we conclude that the unique funds are differentiated through two ways. They provide the investors with special factor exposures (for hedging or speculating), and they cater for particular investor preferences, such as on ESG concerns.

# 6 Conclusion

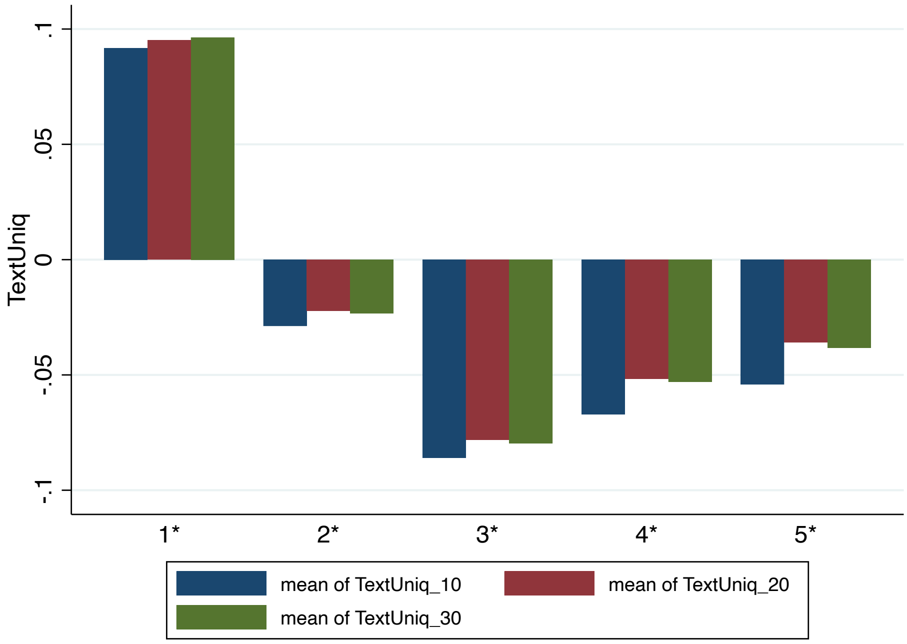
In this paper we have shown evidence that major financial products—mutual funds—behave like many other consumer products in their focus on product differentiation in addition to quality. We present a theoretical model to understand how funds choose product design to cater for different investor clienteles and the incentives of doing so.

We find evidence supporting our model's predictions in empirical data on US active mutual funds. Mutual funds with lower perceived quality, as suggested by lower Morningstar rating and smaller management company size, are more likely to adopt a ***niche*** product design to cater for a smaller set of investors. In contrast, mutual funds with higher perceived quality are more likely to adopt a ***broad*** product design to make the funds acceptable to most investors. Unique funds enjoy a higher market power, allowing them to charge higher fees. Using the revealing of the Morningstar's rating as a shock, we find that funds which receive a low initial rating respond strategically by becoming more unique, and this change increases the probability of survival for a low-rated fund.

These findings question the traditional view that investors only care about performance attributes, and provide a potential explanation for the growing array of mutual funds in a relatively constrained set of asset classes and fund categories. As funds adapt their strategies to meet specific investor preferences, the "menu" of funds may be more heterogeneous and less crowded than it initially appears. Our findings therefore open up new questions about how financial products differentiate themselves in order to appeal to a subset of investors and increase their chance of survival.

# Figures

Panel A: Uniqueness across Morningstar ratings




Panel B: Uniqueness over management company size

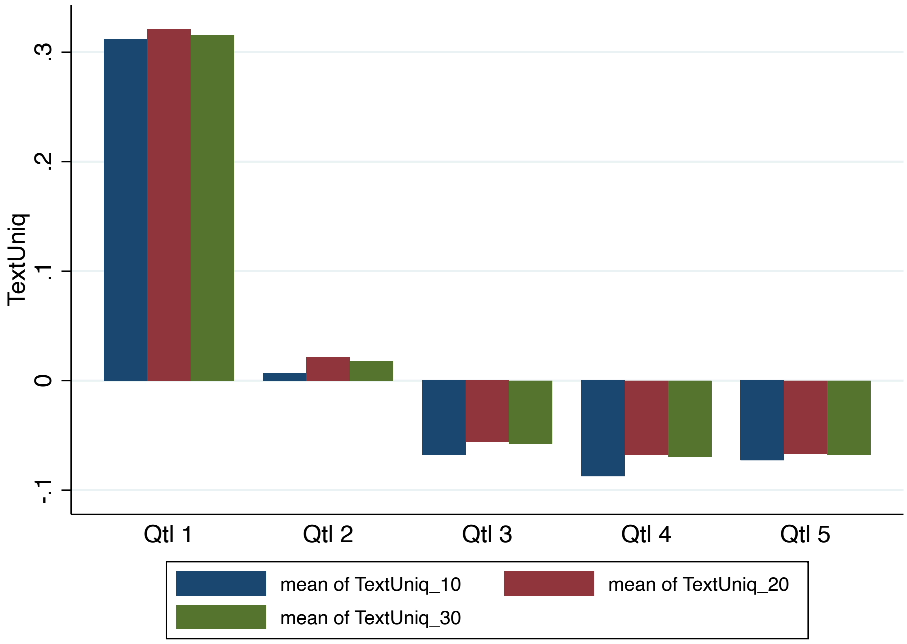
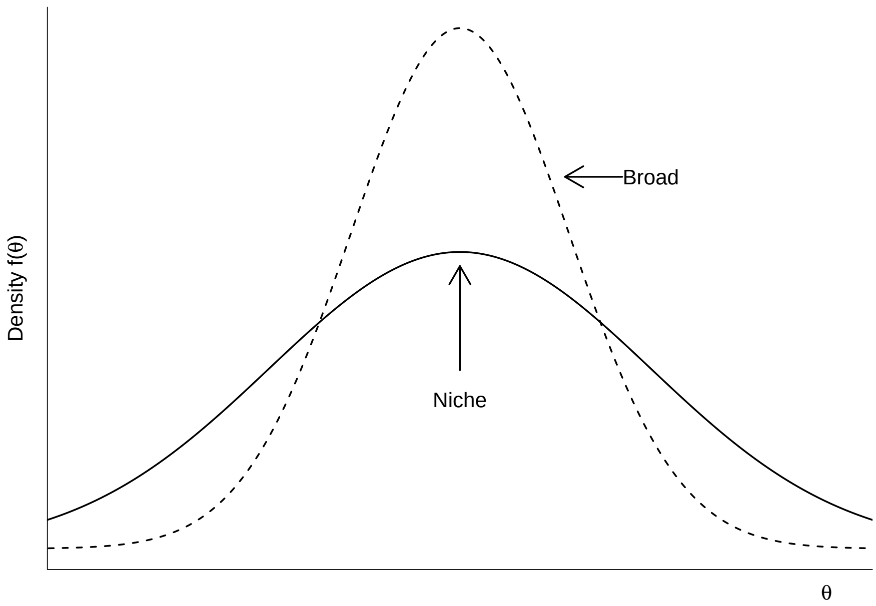



Figure 1: **Product uniqueness over rating and Mgmt Company size:** This figure reports the average of prospectus text uniqueness by rating and management company size quintiles, for rated funds. In Panel A, it shows the average of the text uniqueness across Morningstar fund ratings. In Panel B, it shows the average text uniqueness across the management company size quintiles.

**Panel A: Density**




**Panel B: Cumulative Distribution Function**

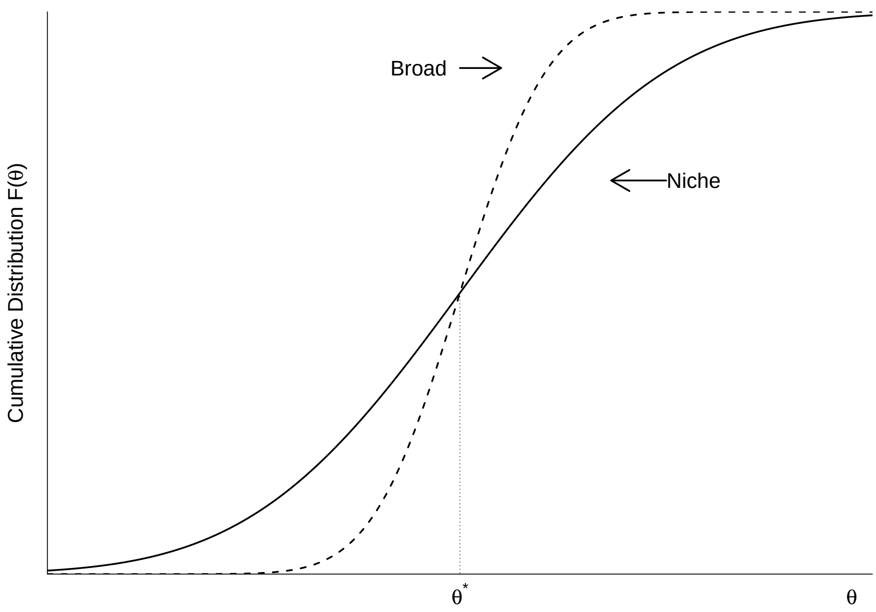



Figure 2: **Density and c.d.f. of matching terms with broad and niche product design**: This figure illustrates the density and c.d.f. of the matching term $\epsilon$, with broad and niche fund design. In both panels, the dotted line corresponds to the broad design, and the solid line corresponds to the niche design. $\theta^*$ in panel B is the rotation point defined in Section 2.1.2.

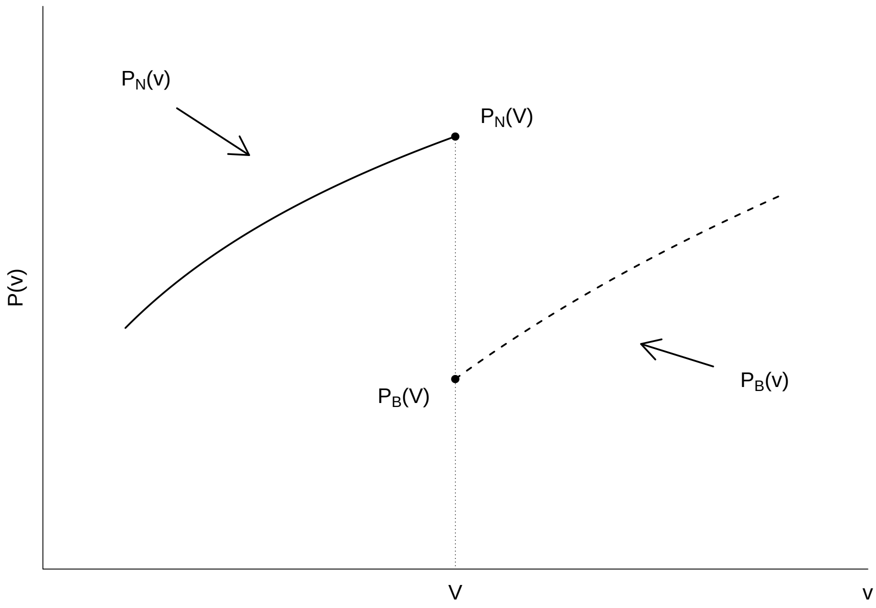
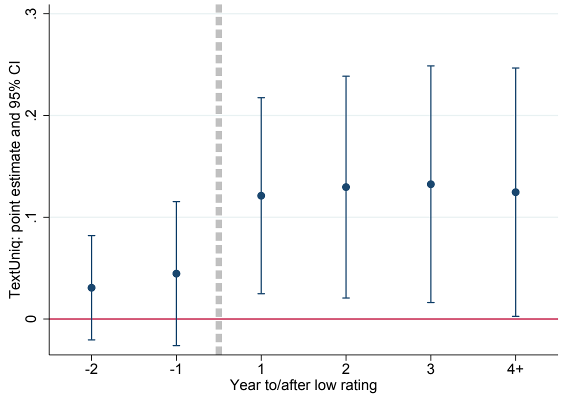
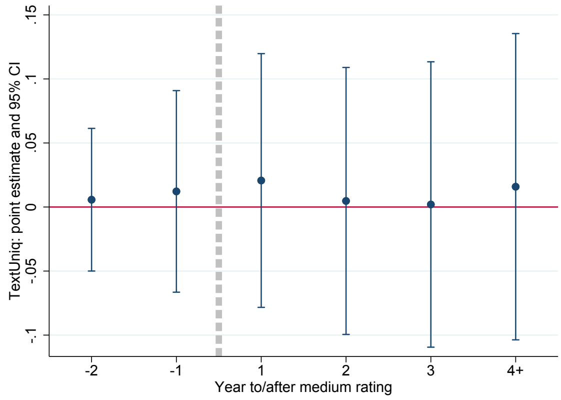



Figure 3: **Price in equilibrium**: This figure illustrates how equilibrium price changes with quality. The y-axis is the equilibrium price and the x-axis is the perceived quality $v$. $V$ is the quality for which the management company is indiﬀerent between choosing broad or niche designs. The solid (dashed) line shows the how price changes with $v$ in niche (broad) design.

**Panel A: Prospectus text uniqueness before/after low rating**




**Panel B: Prospectus text uniqueness before/after medium rating**




**Panel C: Prospectus text uniqueness before/after high rating**

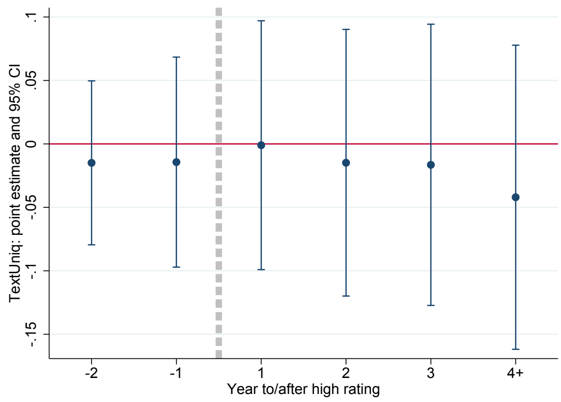
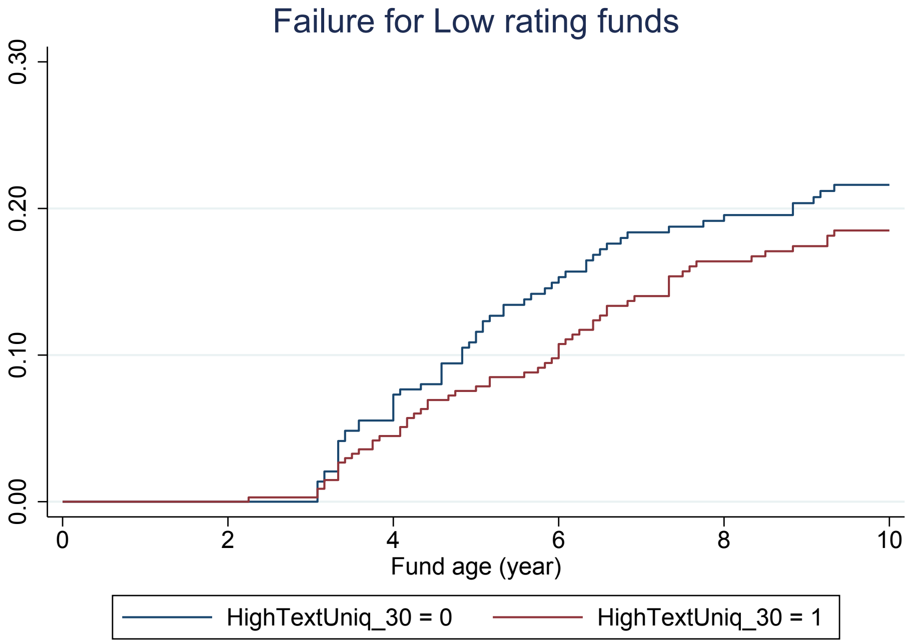



Figure 4: **Effect of rating disclosure on fund prospectus uniqueness**: This figure presents the coefficient estimates $\beta_{k,Low}$ (Panel A), $\beta_{k,Med}$ (Panel B) and $\beta_{k,High}$ (Panel C) as well as 95% confidence intervals against year to the disclosure of rating:

$TextUniq_{i,t} = \sum_{rating \in \{Low,Med,High\}} \{\sum_k \beta_{k,rating}\{year\ k\ to\ rating\}_{i,t}\} + \log(age)_{i,t} + \delta_{cat \times t} + \lambda_i + \epsilon_{i,t}$.

The dependent variable is the fund's prospectus text uniqueness. $Low\ Rating$ is a dummy variable that is equal to 1 if a fund's initial rating is equal or less than 2 stars. $Med - High\ Rating$ is a dummy variable that is equal to 1 if a fund's initial rating is more than 2 stars. $log(age)$ is the natural logarithm of the age of funds. All regressions include month-Morningstar category fixed effects and fund fixed effects. Standard errors are clustered at the fund level. Panels A, B and C show the dynamic effect of low, medium and high rating respectively, on text uniqueness.

**Panel A**




**Panel B**

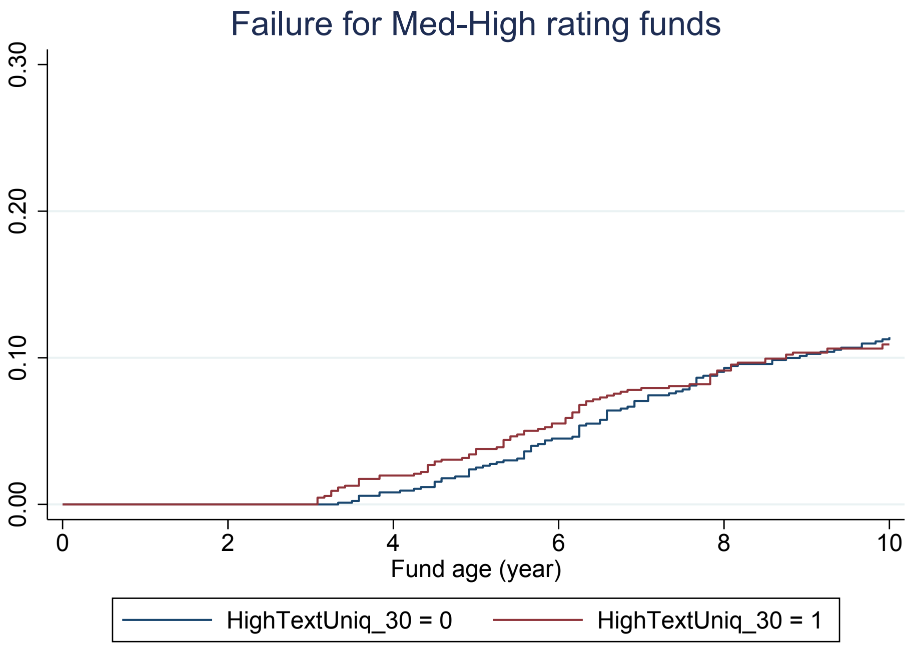
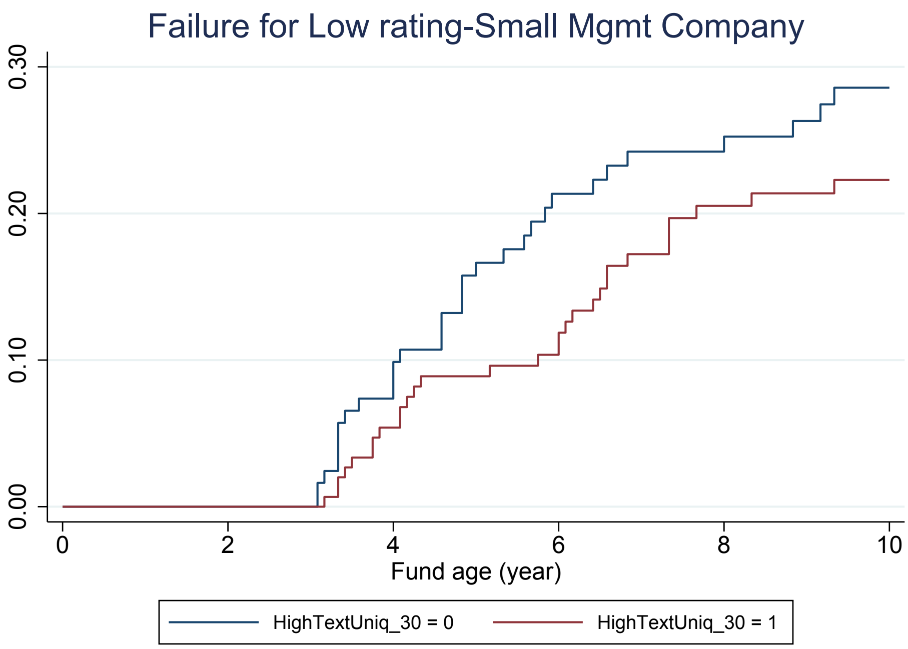



Figure 5: **Failure function of funds by rating and prospectus text uniqueness**: This figure presents the Kaplan-Meier estimator of the failure function of mutual funds conditional on initial rating and prospectus text uniqueness. $HighTextUniq$ is a dummy variable that is equal to 1 if the prospectus uniqueness of the fund is above the median of its Morningstar category in that month. Panel A shows the failure functions only for funds with a initial rating less than or equal to 2 conditional on $HighTextUniq$. Panel B shows the failure functions only for funds with a initial rating strictly above 2 conditional on $HighTextUniq$.

**Panel A**




**Panel B**

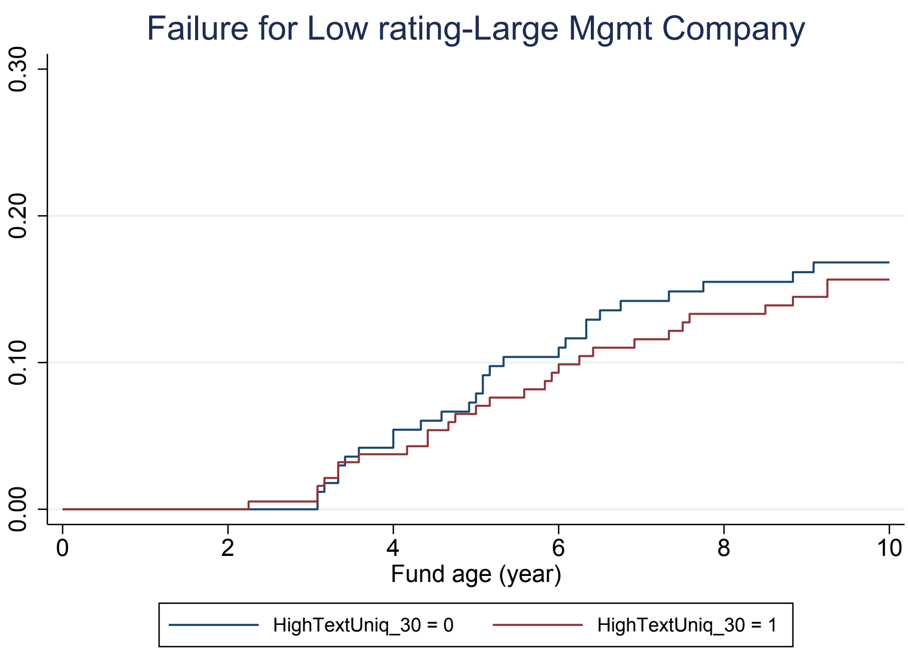
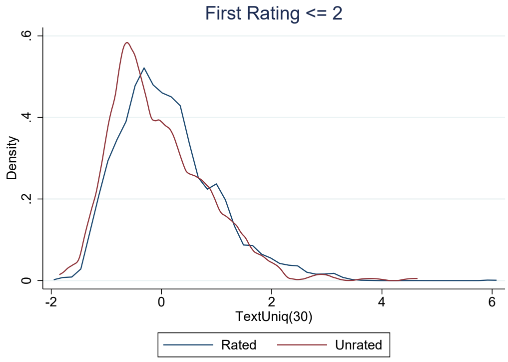



Figure 6: **Failure function of low rating funds by Mgmt company size and prospectus text uniqueness**: This figure presents the Kaplan-Meier estimator of the failure function of mutual funds with low initial rating, conditional on Mgmt Company size and prospectus text uniqueness. Small Mgmt Company corresponds to management companies with 2009 TNA in the bottom three quintiles while Large Mgmt Company corresponds to management companies with 2009 TNA in the top two quintiles. $HighTextUniq$ is a dummy variable that is equal to 1 if the prospectus uniqueness of the fund is above the median of its Morningstar category in that month. Panel A shows the failure functions only for funds with a initial rating less than or equal to 2 and that belongs to a small management company conditional on $HighTextUniq$. Panel B shows the failure functions only for funds with a initial rating less than or equal to 2 and that belongs to a large management company conditional on $HighTextUniq$.

## Panel A




## Panel B

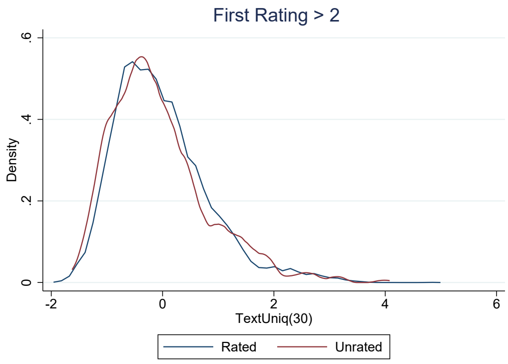



Figure 7: **Distribution of prospectus uniqueness before and after rating:** The graphs show the kernel estimates of the distribution of text uniqueness of funds. The variable used is the residual of the regression:
$TextUniq_{i,t} = \alpha + \beta_1 \log(age)_{i,t} + \delta_{cat \times t} + \epsilon_{i,t}$.
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 whose initial rating is lower or equal to two stars. Panel B focuses on the funds whose initial rating is higher than two stars.

# Tables

| | Obs | Mean | Sd | 5% | 25% | 50% | 75% | 95% |
|---|---|---|---|---|---|---|---|---|
| Gross Ret. (%) | 187,052 | 1.0 | 4.7 | -7.1 | -1.1 | 1.3 | 3.5 | 7.8 |
| Net Ret. (%) | 187,976 | 1.0 | 4.7 | -7.2 | -1.2 | 1.2 | 3.4 | 7.8 |
| Alpha (%) | 176,287 | -0.1 | 0.3 | -0.6 | -0.3 | -0.1 | 0.1 | 0.4 |
| Exp. Ratio (%) | 187,052 | 1.1 | 0.5 | 0.5 | 0.9 | 1.1 | 1.3 | 1.9 |
| Rating | 167,970 | 3.0 | 1.0 | 1.0 | 2.0 | 3.0 | 4.0 | 5.0 |
| IsDead ($\times$ 100) | 187,976 | 0.4 | 6.5 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| TNA (mill) | 187,976 | 1,713.9 | 5,441.5 | 5.5 | 50.1 | 263.4 | 1,262.9 | 7,750.9 |
| Mgmt Company TNA (bill) | 187,972 | 107.7 | 332.7 | 0.0 | 0.9 | 13.3 | 39.9 | 833.4 |
| Mgmt Company TNA 2009 (bill) | 187,972 | 33.7 | 88.1 | 0.0 | 0.3 | 4.2 | 21.8 | 361.2 |
| Fund Age (month) | 187,976 | 198.0 | 161.8 | 19.0 | 86.0 | 173.0 | 258.0 | 500.0 |
| # Word | 187,976 | 171.2 | 103.6 | 43.0 | 105.0 | 156.0 | 212.0 | 351.0 |
| # UniqueWord | 187,976 | 91.3 | 40.8 | 30.0 | 63.0 | 89.0 | 113.0 | 162.0 |
| TextUniq(10) | 187,976 | -0.1 | 1.0 | -1.4 | -0.7 | -0.2 | 0.5 | 1.7 |
| TextUniq(20) | 187,976 | -0.0 | 1.0 | -1.4 | -0.7 | -0.2 | 0.5 | 1.7 |
| TextUniq(30) | 187,976 | -0.0 | 1.0 | -1.4 | -0.7 | -0.2 | 0.5 | 1.7 |
| # Asset | 187,254 | 231.9 | 454.0 | 28.0 | 48.0 | 79.0 | 152.0 | 1,264.0 |
| HoldUniq | 187,254 | 0.1 | 1.0 | -1.8 | -0.7 | 0.4 | 0.9 | 1.2 |
| SimIdx | 179,956 | 0.3 | 0.2 | 0.0 | 0.2 | 0.3 | 0.5 | 0.8 |

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. # Word and # UniqueWord refer respectively to the number of words and number of unique words in the fund prospectus. TextUniq(10), TextUniq(20) and TextUniq(30) are text uniqueness measures of the funds, which are computed after removing the 10, 20 and 30 most commonly used words, listed in section 3.2. # Asset refers to the number of assets with available cusip in the fund portfolio. 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.

**Panel A**

| | Gross Ret. | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | -0.34*** | | -0.34*** | -0.31*** |
| | (0.01) | | (0.01) | (0.01) |
| Small Mgmt Company | | -0.08*** | -0.01 | 0.01 |
| | | (0.01) | (0.01) | (0.01) |
| Small Mgmt Company × Low Rating | | | | -0.08*** |
| | | | | (0.02) |
| log(Fund Age) | 0.01 | 0.00 | 0.00 | 0.00 |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,393 | 167,393 | 167,393 | 167,393 |
| $R^2$ | 0.91 | 0.90 | 0.91 | 0.91 |

**Panel B**

| | Net Ret. | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | -0.36*** | | -0.36*** | -0.32*** |
| | (0.01) | | (0.01) | (0.01) |
| Small Mgmt Company | | -0.10*** | -0.03*** | -0.00 |
| | | (0.01) | (0.01) | (0.01) |
| Small Mgmt Company × Low Rating | | | | -0.09*** |
| | | | | (0.02) |
| log(Fund Age) | 0.01 | 0.00 | 0.00 | 0.00 |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,618 | 167,618 | 167,618 | 167,618 |
| $R^2$ | 0.91 | 0.90 | 0.91 | 0.91 |

**Panel C**

| | Alpha | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | -0.26*** | | -0.26*** | -0.23*** |
| | (0.01) | | (0.01) | (0.01) |
| Small Mgmt Company | | -0.05*** | 0.00 | 0.03*** |
| | | (0.01) | (0.01) | (0.01) |
| Small Mgmt Company × Low Rating | | | | -0.08*** |
| | | | | (0.02) |
| log(Fund Age) | -0.01*** | -0.01** | -0.01*** | -0.01*** |
| | (0.00) | (0.01) | (0.00) | (0.00) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,546 | 167,546 | 167,546 | 167,546 |
| $R^2$ | 0.25 | 0.13 | 0.25 | 0.25 |

Table 2: **Performance and perceived quality of funds**: This table reports results for regressions investigating how the performance of funds depends on the Morningstar ratings and management company size. In Panel A, the dependent variable is the gross (before-fee) return (in pp) of funds. In Panel B, the dependent variable is the net (after-fee) return (in pp) of funds. In Panel C, the dependent variable is the net alpha of funds, estimated from a 4-factor model (FF 3 factors + momentum factor) using a rolling window of 24 months. *Low Rating* is a dummy variable that is equal to 1 if a fund's rating is equal or less than 2 stars. *Small Mgmt Company* is a dummy variable that is equal to 1 if the TNA of the fund's management company in 2009 (before the beginning of our sample) belongs to the bottom three management size quintiles, 0 otherwise. *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.

**Panel A**

| | TextUniq(10) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | 0.08*** | | 0.06* | 0.02 |
| | (0.03) | | (0.03) | (0.04) |
| Small Mgmt Company | | 0.13*** | 0.12*** | 0.08* |
| | | (0.04) | (0.04) | (0.05) |
| Small Mgmt Company × Low Rating | | | | 0.12* |
| | | | | (0.06) |
| log(Fund Age) | -0.02 | 0.00 | 0.00 | 0.00 |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,618 | 167,618 | 167,618 | 167,618 |
| $R^2$ | 0.22 | 0.23 | 0.23 | 0.23 |

**Panel B**

| | TextUniq(20) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | 0.08** | | 0.06* | 0.02 |
| | (0.03) | | (0.03) | (0.04) |
| Small Mgmt Company | | 0.14*** | 0.13*** | 0.09** |
| | | (0.04) | (0.04) | (0.05) |
| Small Mgmt Company × Low Rating | | | | 0.10 |
| | | | | (0.06) |
| log(Fund Age) | -0.01 | 0.01 | 0.01 | 0.01 |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,618 | 167,618 | 167,618 | 167,618 |
| $R^2$ | 0.22 | 0.22 | 0.22 | 0.22 |

**Panel C**

| | TextUniq(30) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | 0.08*** | | 0.06* | 0.02 |
| | (0.03) | | (0.03) | (0.04) |
| Small Mgmt Company | | 0.14*** | 0.12*** | 0.09* |
| | | (0.04) | (0.04) | (0.05) |
| Small Mgmt Company × Low Rating | | | | 0.11* |
| | | | | (0.06) |
| log(Fund Age) | -0.01 | 0.01 | 0.01 | 0.01 |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,618 | 167,618 | 167,618 | 167,618 |
| $R^2$ | 0.22 | 0.22 | 0.22 | 0.22 |

Table 3: **Text Uniqueness and rating in the mutual fund industry**: This table reports results for regressions investigating how the text uniqueness of funds depends on the Morningstar ratings and management company size of funds. In Panel A, Panel B and Panel C, the dependent variables are the text uniqueness of funds (normalized negative cosine similarity of text, adjusted by number of words) after removing 10, 20, and 30 common words of text respectively. $Low\ Rating$ is a dummy variable that is equal to 1 if a fund's rating is equal or less than 2 stars. $Small\ Mgmt\ Company$ is a dummy variable that is equal to 1 if the TNA of the fund's management company in 2009 (before the beginning of our sample) belongs to the bottom three management size quintiles, 0 otherwise. $log(Fund\ Age)$ is the natural logarithm of the age of funds. All regressions include month-Morningstar category fixed e□ects. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

**Panel A**

| | HoldUniq | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | 0.29*** | | 0.23*** | 0.24*** |
| | (0.02) | | (0.02) | (0.03) |
| Small Mgmt Company | | 0.36*** | 0.31*** | 0.32*** |
| | | (0.03) | (0.03) | (0.03) |
| Small Mgmt Company × Low Rating | | | | -0.03 |
| | | | | (0.04) |
| log(Fund Age) | -0.09*** | -0.04** | -0.04** | -0.04** |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,102 | 167,102 | 167,102 | 167,102 |
| $R^2$ | 0.66 | 0.67 | 0.68 | 0.68 |

**Panel B**

| | SimIdx | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | -0.08*** | | -0.06*** | -0.07*** |
| | (0.01) | | (0.01) | (0.01) |
| Small Mgmt Company | | -0.10*** | -0.09*** | -0.09*** |
| | | (0.01) | (0.01) | (0.01) |
| Small Mgmt Company × Low Rating | | | | 0.01 |
| | | | | (0.01) |
| log(Fund Age) | 0.02*** | 0.01* | 0.01* | 0.01* |
| | (0.00) | (0.01) | (0.00) | (0.00) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 162,637 | 162,637 | 162,637 | 162,637 |
| $R^2$ | 0.43 | 0.45 | 0.46 | 0.46 |

Table 4: **Holding Uniqueness, rating and company size in the mutual fund industry**: This table reports results for regressions investigating how the holding uniqueness of funds depends on the Morningstar ratings and management company size of funds. In Panel A the dependent variable is the holding uniqueness of funds (normalized negative cosine similarity of portfolio holdings). In Panel B, the dependent variable is the similarity with respect to the benchmark index (cosine similarity with respect to the index of the corresponding category). $Low\ Rating$ is a dummy variable that is equal to 1 if a fund's rating is equal or less than 2 stars. $Small\ Mgmt\ Company$ is a dummy variable that is equal to 1 if the TNA of the fund's management company in 2009 (before the beginning of our sample) belongs to the bottom three management size quintiles, 0 otherwise. $log(Fund\ Age)$ 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.

| | Exp. Ratio | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | $0.27^{***}$<br>(0.02) | | $0.23^{***}$<br>(0.02) | $0.17^{***}$<br>(0.02) |
| Small Mgmt Company | | $0.28^{***}$<br>(0.03) | $0.24^{***}$<br>(0.02) | $0.18^{***}$<br>(0.02) |
| Small Mgmt Company × Low Rating | | | | $0.16^{***}$<br>(0.05) |
| log(Fund Age) | -0.01<br>(0.01) | $0.03^{*}$<br>(0.02) | $0.03^{**}$<br>(0.01) | $0.03^{*}$<br>(0.01) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,393 | 167,393 | 167,393 | 167,393 |
| $R^2$ | 0.17 | 0.18 | 0.22 | 0.23 |

Table 5: **Fees and perceived quality in the mutual fund industry**: This table reports results for regressions investigating how the fees of funds depends on the Morningstar ratings and management company size of funds. The dependent variables are the expense ratio (in pp) of the funds. *Low Rating* is a dummy variable that is equal to 1 if a fund's rating is equal or less than 2 stars. *Small Mgmt Company* is a dummy variable that is equal to 1 if the TNA of the fund's management company in 2009 (before the beginning of our sample) belongs to the bottom three management size quintiles, 0 otherwise. *log(Fund Age)* is the natural logarithm of the age of funds. All regressions include month-Morningstar category fixed eects. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

| | TextUniq(10) | TextUniq(20) | TextUniq(30) | HoldUniq | SimIdx |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Post × Low Rating | $0.060^{**}$<br>(0.028) | $0.062^{**}$<br>(0.027) | $0.060^{**}$<br>(0.028) | $0.035^{*}$<br>(0.021) | $-0.012^{*}$<br>(0.007) |
| Post × Med-High Rating | 0.007<br>(0.018) | 0.008<br>(0.018) | 0.006<br>(0.018) | 0.004<br>(0.013) | 0.001<br>(0.004) |
| log(Fund Age) | -0.017<br>(0.016) | -0.015<br>(0.015) | -0.015<br>(0.015) | -0.012<br>(0.010) | 0.002<br>(0.003) |
| Time × Cat. FE | Yes | Yes | Yes | Yes | Yes |
| Fund FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 187,969 | 187,969 | 187,969 | 187,247 | 179,951 |
| $R^2$ | 0.92 | 0.93 | 0.93 | 0.95 | 0.92 |

Table 6: **Low Rating and Uniqueness of funds**: This table reports results for the di-in-di regressions investigating how the uniqueness of funds change after receiving Morningstar Ratings. In Column (1) - Column (3), the dependent variables are the text uniqueness of funds (normalized negative cosine similarity of text, adjusted by number of words) after removing 10, 20, and 30 common words of text respectively. In Column (4), the dependent variable is the holding uniqueness of funds (normalized negative cosine similarity of portfolio holdings). In Column (5), the dependent variable is the similarity to index (cosine similarity with respect to the index of the corresponding category). *Post* is a dummy variable that is equal to 1 if a fund is rated. *Low Rating* is a dummy variable that is equal to 1 if a fund's initial rating is equal or less than 2 stars. $Med-High\ Rating$ is a dummy variable that is equal to 1 if a fund's initial rating is more than 2 stars. *log(Fund Age)* is the natural logarithm of the age of funds. All regressions include month-Morningstar category fixed eects and fund fixed eects. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

| | TextUniq(10) | TextUniq(20) | TextUniq(30) | HoldUniq | SimIdx |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Post $\times$ Low Rating $\times$ Small Mgmt Company | 0.079** (0.038) | 0.079** (0.037) | 0.080** (0.037) | 0.050** (0.025) | -0.015** (0.007) |
| Post $\times$ Low Rating $\times$ Large Mgmt Company | 0.027 (0.034) | 0.033 (0.035) | 0.027 (0.037) | 0.011 (0.037) | -0.007 (0.013) |
| Post $\times$ Med-High Rating | 0.008 (0.018) | 0.008 (0.018) | 0.006 (0.018) | 0.004 (0.013) | 0.001 (0.004) |
| log(Fund Age) | -0.017 (0.016) | -0.015 (0.015) | -0.015 (0.015) | -0.012 (0.010) | 0.002 (0.003) |
| Time $\times$ Cat. FE | Yes | Yes | Yes | Yes | Yes |
| Fund FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 187,969 | 187,969 | 187,969 | 187,247 | 179,951 |
| $R^2$ | 0.92 | 0.93 | 0.93 | 0.95 | 0.92 |

Table 7: **Low Rating and Uniqueness of funds**: This table reports results for the diff-in-diff regressions investigating how the uniqueness of funds change after receiving Morningstar Ratings. In Column (1) - Column (3), the dependent variables are the text uniqueness of funds (normalized negative cosine similarity of text, adjusted by number of words) after removing 10, 20, and 30 common words of text respectively. In Column (4), the dependent variable is the holding uniqueness of funds (normalized negative cosine similarity of portfolio holdings). In Column (5), the dependent variable is the similarity to index (cosine similarity with respect to the index of the corresponding category). $Post$ is a dummy variable that is equal to 1 if a fund is rated. $Low\ Rating$ is a dummy variable that is equal to 1 if a fund's initial rating is equal or less than 2 stars. $Med-High\ Rating$ is a dummy variable that is equal to 1 if a fund's initial rating is more than 2 stars. $Small\ Mgmt\ Company$ is a dummy variable that is equal to 1 if the management firm's size in 2009 (before the beginning of our sample) belongs to the bottom three size quintiles, 0 otherwise. $Large\ Mgmt\ Company$ is a dummy variable that is equal to 1 if the management firm's size in 2009 (before the beginning of our sample) belongs to the top two size quintiles, 0 otherwise. $log(Fund\ Age)$ is the natural logarithm of the age of funds. All regressions include month-Morningstar category fixed effects and fund fixed effects. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

**Panel A: All Mgmt companies**

| | IsDead | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | 0.35*** | | 0.35*** | 0.45*** |
| | (0.05) | | (0.05) | (0.08) |
| HighTextUniq(30) | | 0.01 | -0.01 | 0.03 |
| | | (0.03) | (0.03) | (0.03) |
| Low Rating × HighTextUniq(30) | | | | -0.18* |
| | | | | (0.10) |
| log(Fund Age) | -0.25*** | -0.26*** | -0.25*** | -0.25*** |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,970 | 167,970 | 167,970 | 167,970 |
| $R^2$ | 0.02 | 0.02 | 0.02 | 0.02 |

**Panel B: Small Mgmt companies**

| | IsDead | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | 0.49*** | | 0.49*** | 0.68*** |
| | (0.09) | | (0.09) | (0.14) |
| HighTextUniq(30) | | -0.01 | -0.03 | 0.07 |
| | | (0.07) | (0.07) | (0.07) |
| Low Rating × HighTextUniq(30) | | | | -0.34* |
| | | | | (0.18) |
| log(Fund Age) | -0.18*** | -0.17*** | -0.18*** | -0.17*** |
| | (0.05) | (0.05) | (0.05) | (0.05) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 48,232 | 48,232 | 48,232 | 48,232 |
| $R^2$ | 0.04 | 0.04 | 0.04 | 0.04 |

**Panel C: Large Mgmt companies**

| | IsDead | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | 0.27*** | | 0.27*** | 0.32*** |
| | (0.06) | | (0.06) | (0.09) |
| HighTextUniq(30) | | 0.01 | -0.00 | 0.02 |
| | | (0.03) | (0.04) | (0.04) |
| Low Rating × HighTextUniq(30) | | | | -0.10 |
| | | | | (0.11) |
| log(Fund Age) | -0.28*** | -0.28*** | -0.28*** | -0.28*** |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 119,715 | 119,715 | 119,715 | 119,715 |
| $R^2$ | 0.02 | 0.02 | 0.02 | 0.02 |

Table 8: **The effect of rating and prospectus uniqueness on fund death**: This table reports results for regressions investigating how Morningstar ratings and prospectus uniqueness affect fund death. In all panels, the dependent variable is a dummy variable equal to one if the fund dies in that month (coefficients are multiplied by 100). In Panel A, the regressions are estimated on the full sample of funds (that eventually get a rating). In Panel B, the regressions are estimated on the restricted sample of funds that belong to small management companies (i.e., management companies whose size in 2009 belongs to the bottom three size quintiles). In Panel C, the regressions are estimated on the restricted sample of funds that belong to large management companies (i.e., management companies whose size in 2009 belongs to the top two size quintiles). $Low\ Rating$ is a dummy variable that is equal to 1 if a fund's initial rating is equal or less than 2 stars. $HighTextUniq$ is a dummy variable that is equal to 1 if the prospectus uniqueness of the fund is above the median of its Morningstar category in that month. $log(Fund\ Age)$ 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.

| | First Rating $\leq 2$ | First Rating $> 2$ |
|---|---|---|
| U statistic | -13.030 | -1.131 |
| P value | 0.000 | 0.258 |

Table 9: **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 lower than or equal to two stars, and second column focuses on the sample of funds whose initial rating is higher than two stars.

| | $R^2$ | $\beta\_Mkt-Rf$ | $\beta\_SMB$ | $\beta\_HML$ | $\beta\_MOM$ |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| TextUniq(30) | -0.73*** | -0.01*** | 0.00 | 0.01*** | 0.00 |
| | (0.22) | (0.00) | (0.00) | (0.00) | (0.00) |
| Time × Cat. FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 167,546 | 167,546 | 167,546 | 167,546 | 167,546 |
| $R^2$ | 0.24 | 0.26 | 0.77 | 0.52 | 0.22 |

Table 10: **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.

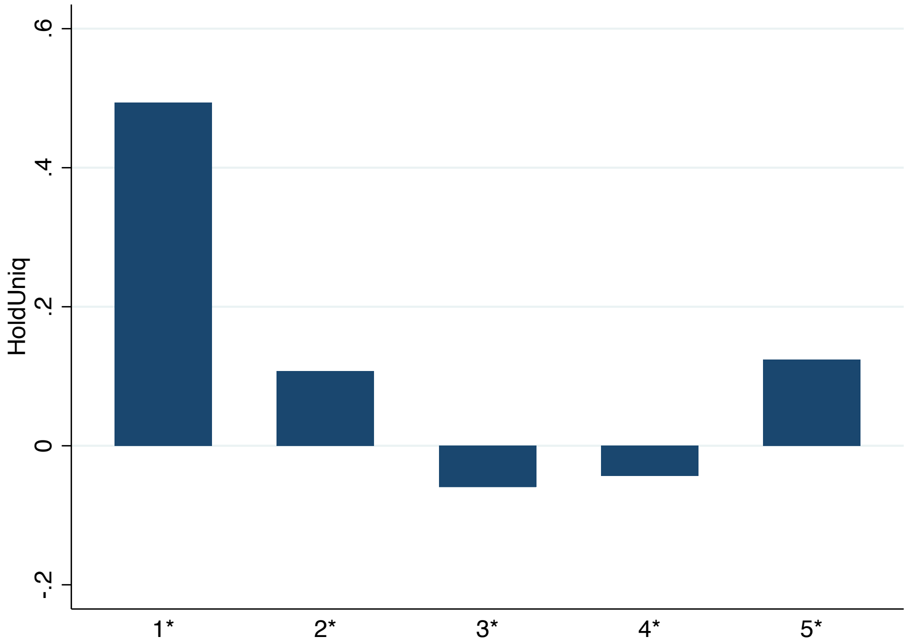
| | |
|---|---|
| **High Uniqueness** | Controversial, Activist, Climate, Coal, Nuclear, Workplace, ESG, Vote, Media, Retail |
| **Low Uniqueness** | Expense, Create, Lowest, Discount, Consider, Absolute, Effort, Accelerate, Model, Drive |

Table 11: **Deconstructing prospectus uniqueness.** Sample words which ranked very high on "uniqueness" (in the top 5% of the uniqueness measure, meaning they were found mostly in unique funds' prospectus) or very low on "uniqueness" (around 0, meaning they were found in almost all of the prospectuses).

# Appendix

## A Additional stylized facts

**Panel A: Holding uniqueness across Morningstar ratings**




**Panel B: Holding uniqueness over management company size**

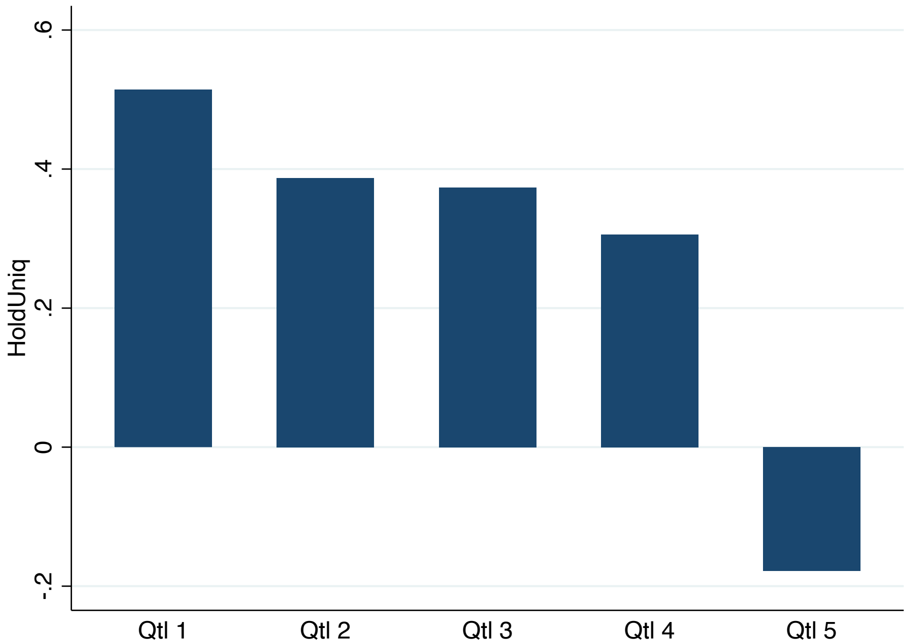



Figure A1: **Holding uniqueness over rating and Mgmt Company size:** This figure reports the average of portfolio holding uniqueness by rating and management company size quintiles, for rated funds. In Panel A, it shows the average of the holding uniqueness across Morningstar fund ratings. In Panel B, it shows the average holding uniqueness across the management company size quintiles.

## B Proofs of Propositions

### B.1 Proof of Proposition 1

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

$$p_B(V)\left[1 - F_B(U - V + p_B(V))\right] = p_N(V)\left[1 - F_N(U - V + p_N(V))\right]. \tag{17}$$

By definition of $p_B(v)$ and $p_N(v)$, which are the profit maximizing prices when the management company 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 (17), it follows that

$$1 - F_B(U - V + p_B(V)) \geq 1 - F_N(U - V + p_B(V)), \tag{18}$$

and

$$1 - F_N(U - V + p_N(V)) \geq 1 - F_B(U - V + p_N(V)). \tag{19}$$

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 (18). 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 (19). Therefore $p_N(V) > p_B(V)$ and from (17) we get

$$1 - F_B(U - V + p_B(V)) > 1 - F_N(U - V + p_N(V)). \tag{20}$$

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 (20), 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 firm chooses broad design. If $v < V$, $\Pi_{vB} < \Pi_{vN}$ and the firm chooses niche design.

### B.2 Proof of Proposition 2

We show that there exist management companies 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 $V$:

$$p_B(V + \delta) = p_B(V) + \delta \left.\frac{\partial p_B(v)}{\partial v}\right|_{v=V} + R_B(\delta), \tag{21}$$

and

$$p_N(V - \delta) = p_N(V) - \delta \left.\frac{\partial p_N(v)}{\partial v}\right|_{v=V} + R_N(\delta), \tag{22}$$

with $\delta > 0$ and $\lim_{\delta \to 0} R_s(\delta)/\delta = 0$, $s = B, N$. Taking the difference between (22) and (21), we get

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

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

# C Additional results on product differentiation in equilibrium

| | log(TNA) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | -1.49*** | | -1.20*** | -1.19*** |
| | (0.06) | | (0.06) | (0.07) |
| Small Mgmt Company | | -1.74*** | -1.51*** | -1.50*** |
| | | (0.09) | (0.08) | (0.09) |
| Small Mgmt Company × Low Rating | | | | -0.03 |
| | | | | (0.12) |
| log(Fund Age) | 1.11*** | 0.88*** | 0.87*** | 0.87*** |
| | (0.05) | (0.06) | (0.05) | (0.05) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,618 | 167,618 | 167,618 | 167,618 |
| $R^2$ | 0.26 | 0.30 | 0.36 | 0.36 |

Table A1: **Size and rating in the mutual fund industry**: This table reports results for regressions investigating how the performance of funds depends on the Morningstar ratings and management company size of funds. The dependent variables are the natural logarithm of the TNA of the funds. *Low Rating* is a dummy variable that is equal to 1 if a fund's rating is equal or less than 2 stars. *Small Mgmt Company* is a dummy variable that is equal to 1 if the TNA of the fund's management company in 2009 (before the beginning of our sample) belongs to the bottom three management size quintiles, 0 otherwise. $log(Fund\ Age)$ 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.

**Panel A**

| | Gross Ret. | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | -0.34*** (0.01) | | -0.34*** (0.01) | -0.30*** (0.01) |
| Young Mgmt Company | | -0.06*** (0.01) | -0.01 (0.01) | 0.01 (0.01) |
| Young Mgmt Company × Low Rating | | | | -0.08*** (0.02) |
| log(Fund Age) | 0.01 (0.01) | 0.00 (0.01) | 0.00 (0.01) | 0.00 (0.01) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,393 | 167,393 | 167,393 | 167,393 |
| $R^2$ | 0.91 | 0.90 | 0.91 | 0.91 |

**Panel B**

| | Net Ret. | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | -0.36*** (0.01) | | -0.36*** (0.01) | -0.32*** (0.01) |
| Young Mgmt Company | | -0.07*** (0.01) | -0.02** (0.01) | 0.01 (0.01) |
| Young Mgmt Company × Low Rating | | | | -0.09*** (0.02) |
| log(Fund Age) | 0.01 (0.01) | 0.00 (0.01) | 0.00 (0.01) | 0.00 (0.01) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,618 | 167,618 | 167,618 | 167,618 |
| $R^2$ | 0.91 | 0.90 | 0.91 | 0.91 |

**Panel C**

| | Alpha | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | -0.26*** (0.01) | | -0.26*** (0.01) | -0.25*** (0.01) |
| Young Mgmt Company | | -0.05*** (0.01) | -0.01 (0.01) | -0.00 (0.01) |
| Young Mgmt Company × Low Rating | | | | -0.03** (0.02) |
| log(Fund Age) | -0.01*** (0.00) | -0.02*** (0.01) | -0.02*** (0.00) | -0.02*** (0.00) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,546 | 167,546 | 167,546 | 167,546 |
| $R^2$ | 0.25 | 0.13 | 0.25 | 0.25 |

Table A2: **Performance and rating in the mutual fund industry**: This table reports results for regressions investigating how the performance of funds depends on the Morningstar ratings and age of management companies. In Panel A, the dependent variables are the gross (before-fee) return (in pp) of funds. In Panel B, the dependent variables are the net (after-fee) return (in pp) of funds. In Panel C, the dependent variables are the net alpha of funds, estimated from a 4-factor model (FF 3 factors + momentum factor) using a rolling window of 24 months. $Low\ Rating$ is a dummy variable that is equal to 1 if a fund's initial rating is equal or less than 2 stars. $Young\ Mgmt\ Company$ is a dummy variable that is equal to 1 if the management firm's age belongs to the bottom three size quintiles, 0 otherwise. $log(Fund\ Age)$ is the natural logarithm of the age of funds. All regressions include month-Morningstar category fixed e□ects. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

**Panel A**

| | TextUniq(10) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | 0.08*** | | 0.08** | 0.05 |
| | (0.03) | | (0.03) | (0.04) |
| Young Mgmt Company | | 0.04 | 0.03 | 0.01 |
| | | (0.04) | (0.04) | (0.04) |
| Young Mgmt Company × Low Rating | | | | 0.07 |
| | | | | (0.06) |
| log(Fund Age) | -0.02 | -0.01 | -0.01 | -0.01 |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,618 | 167,618 | 167,618 | 167,618 |
| $R^2$ | 0.22 | 0.22 | 0.22 | 0.22 |

**Panel B**

| | TextUniq(20) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | 0.08** | | 0.07** | 0.05 |
| | (0.03) | | (0.03) | (0.04) |
| Young Mgmt Company | | 0.05 | 0.04 | 0.03 |
| | | (0.04) | (0.04) | (0.04) |
| Young Mgmt Company × Low Rating | | | | 0.06 |
| | | | | (0.06) |
| log(Fund Age) | -0.01 | -0.00 | -0.00 | -0.00 |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,618 | 167,618 | 167,618 | 167,618 |
| $R^2$ | 0.22 | 0.22 | 0.22 | 0.22 |

**Panel C**

| | TextUniq(30) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | 0.08*** | | 0.08** | 0.05 |
| | (0.03) | | (0.03) | (0.04) |
| Young Mgmt Company | | 0.05 | 0.04 | 0.03 |
| | | (0.04) | (0.04) | (0.04) |
| Young Mgmt Company × Low Rating | | | | 0.05 |
| | | | | (0.06) |
| log(Fund Age) | -0.01 | -0.00 | 0.00 | -0.00 |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,618 | 167,618 | 167,618 | 167,618 |
| $R^2$ | 0.22 | 0.22 | 0.22 | 0.22 |

Table A3: **Text Uniqueness and rating in the mutual fund industry**: This table reports results for regressions investigating how the text uniqueness of funds depends on the Morningstar ratings and the age of management companies. In Panel A, Panel B and Panel C, the dependent variables are the text uniqueness of funds (normalized negative cosine similarity of text, adjusted by number of words) after removing 10, 20, and 30 common words of text respectively. $Low\ Rating$ is a dummy variable that is equal to 1 if a fund's initial rating is equal or less than 2 stars. $Young\ Mgmt\ Company$ is a dummy variable that is equal to 1 if the management firm's age belongs to the bottom three size quintiles, 0 otherwise. $log(Fund\ Age)$ 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.

**Panel A**

| | HoldUniq | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | 0.29*** | | 0.26*** | 0.27*** |
| | (0.02) | | (0.02) | (0.03) |
| Young Mgmt Company | | 0.22*** | 0.19*** | 0.19*** |
| | | (0.03) | (0.03) | (0.03) |
| Young Mgmt Company × Low Rating | | | | -0.02 |
| | | | | (0.04) |
| log(Fund Age) | -0.09*** | -0.05*** | -0.05*** | -0.05*** |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,102 | 167,102 | 167,102 | 167,102 |
| $R^2$ | 0.66 | 0.66 | 0.67 | 0.67 |

**Panel B**

| | SimIdx | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | -0.08*** | | -0.07*** | -0.08*** |
| | (0.01) | | (0.01) | (0.01) |
| Young Mgmt Company | | -0.06*** | -0.05*** | -0.05*** |
| | | (0.01) | (0.01) | (0.01) |
| Young Mgmt Company × Low Rating | | | | 0.01 |
| | | | | (0.01) |
| log(Fund Age) | 0.02*** | 0.01** | 0.01** | 0.01** |
| | (0.00) | (0.01) | (0.01) | (0.01) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 162,637 | 162,637 | 162,637 | 162,637 |
| $R^2$ | 0.43 | 0.42 | 0.44 | 0.44 |

Table A4: **Holding Uniqueness and rating in the mutual fund industry**: This table reports results for regressions investigating how the holding uniqueness of funds depends on the Morningstar ratings and management company size of funds. In Panel A the dependent variables are the holding uniqueness of funds (normalized negative cosine similarity of portfolio holdings). In Panel B, the dependent variables are the similarity to index (cosine similarity with respect to the index of the corresponding category). $Low\ Rating$ is a dummy variable that is equal to 1 if a fund's initial rating is equal or less than 2 stars. $Young\ Mgmt\ Company$ is a dummy variable that is equal to 1 if the management firm's age belongs to the bottom three size quintiles, 0 otherwise. $log(Fund\ Age)$ is the natural logarithm of the age of funds. All regressions include month-Morningstar category fixed e￿ects. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

| | Exp. Ratio | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | 0.27*** | | 0.26*** | 0.23*** |
| | (0.02) | | (0.02) | (0.03) |
| Young Mgmt Company | | 0.15*** | 0.12*** | 0.10*** |
| | | (0.02) | (0.02) | (0.02) |
| Young Mgmt Company × Low Rating | | | | 0.06 |
| | | | | (0.05) |
| log(Fund Age) | -0.01 | 0.02 | 0.02 | 0.02 |
| | (0.01) | (0.02) | (0.01) | (0.01) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,393 | 167,393 | 167,393 | 167,393 |
| $R^2$ | 0.17 | 0.13 | 0.19 | 0.19 |

Table A5: **Performance and rating in the mutual fund industry**: This table reports results for regressions investigating how the fees of funds depends on the Morningstar ratings and the age of management companies. The dependent variables are the expense ratio (in pp) of the funds. *Low Rating* is a dummy variable that is equal to 1 if a fund's initial rating is equal or less than 2 stars. *Young Mgmt Company* is a dummy variable that is equal to 1 if the management firm's age belongs to the bottom three size quintiles, 0 otherwise. *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.

| | log(TNA) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Rating | -1.49*** | | -1.33*** | -1.35*** |
| | (0.06) | | (0.06) | (0.08) |
| Young Mgmt Company | | -1.18*** | -0.99*** | -1.01*** |
| | | (0.09) | (0.08) | (0.09) |
| Young Mgmt Company × Low Rating | | | | 0.05 |
| | | | | (0.12) |
| log(Fund Age) | 1.11*** | 0.89*** | 0.88*** | 0.88*** |
| | (0.05) | (0.06) | (0.06) | (0.06) |
| Time × Cat. FE | Yes | Yes | Yes | Yes |
| Observations | 167,618 | 167,618 | 167,618 | 167,618 |
| $R^2$ | 0.26 | 0.23 | 0.31 | 0.31 |

Table A6: **Size and rating in the mutual fund industry**: This table reports results for regressions investigating how the performance of funds depends on the Morningstar ratings and the age of management companies. The dependent variables are the natural logarithm of the TNA of the funds. *Low Rating* is a dummy variable that is equal to 1 if a fund's initial rating is equal or less than 2 stars. *Young Mgmt Company* is a dummy variable that is equal to 1 if the management firm's age belongs to the bottom three size quintiles, 0 otherwise. *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.

# D Additional results on the differences in differences analysis

| | TextUniq(10) | TextUniq(20) | TextUniq(30) | HoldUniq | SimIdx |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Post × Low Rating × Young Mgmt Company | 0.070** | 0.073** | 0.072** | 0.039* | -0.014** |
| | (0.032) | (0.032) | (0.031) | (0.022) | (0.007) |
| Post × Low Rating × Old Mgmt Company | 0.032 | 0.031 | 0.026 | 0.025 | -0.006 |
| | (0.046) | (0.046) | (0.047) | (0.035) | (0.012) |
| Post × Med-High Rating | 0.008 | 0.008 | 0.006 | 0.004 | 0.001 |
| | (0.018) | (0.018) | (0.018) | (0.013) | (0.004) |
| log(Fund Age) | -0.017 | -0.015 | -0.015 | -0.012 | 0.002 |
| | (0.016) | (0.015) | (0.015) | (0.010) | (0.003) |
| Time × Cat. FE | Yes | Yes | Yes | Yes | Yes |
| Fund FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 187,969 | 187,969 | 187,969 | 187,247 | 179,951 |
| $R^2$ | 0.92 | 0.93 | 0.93 | 0.95 | 0.92 |

Table A7: **Low Rating and Uniqueness of funds**: This table reports results for the diff-in-diff regressions investigating how the uniqueness of funds change after receiving Morningstar Ratings. In Column (1) - Column (3), the dependent variables are the text uniqueness of funds (normalized negative cosine similarity of text, adjusted by number of words) after removing 10, 20, and 30 common words of text respectively. In Column (4), the dependent variable is the holding uniqueness of funds (normalized negative cosine similarity of portfolio holdings). In Column (5), the dependent variable is the similarity to index (cosine similarity with respect to the index of the corresponding category). $Post$ is a dummy variable that is equal to 1 if a fund is rated. $Low\ Rating$ is a dummy variable that is equal to 1 if a fund's initial rating is equal to or less than 2 stars. $Med - High\ Rating$ is a dummy variable that is equal to 1 if a fund's initial rating is more than 2 stars. $Young\ Mgmt\ Company$ is a dummy variable that is equal to 1 if the management firm's age belongs to the bottom three size quintiles, 0 otherwise. $Old\ Mgmt\ Company$ is a dummy variable that is equal to 1 if the management firm's age belongs to the top two size quintiles, 0 otherwise. $log(Fund\ Age)$ is the natural logarithm of the age of funds. All regressions include month-Morningstar category fixed effects and fund fixed effects. Standard errors in parentheses are clustered at the fund level. * p<.10; ** p<.05; *** p<.01.

# E 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 A8: **ETFs 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.

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