Market Power, Fund Proliferation, and Asset Prices*

Marco Loseto[†] Federico Mainardi [‡]

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Abstract

We develop an equilibrium model of the passive mutual fund industry to analyze the welfare and asset pricing implications of fund proliferation. In the model, fund proliferation results from product entry decisions of oligopolistic, profit-maximizing asset management firms. Introducing a new fund increases competition but lowers the cost of launching additional funds in the future. These dynamic incentives lead asset management firms to smooth their product entry decisions over time, consistent with the fund proliferation patterns observed empirically. More efficient firms introduce more funds and grow larger. Despite the increase in market concentration, fund proliferation benefits households by lowering investment costs. We estimate the model by matching entry patterns observed in the data and find that the largest asset management firms enjoy substantial scale economies compared to the rest of the market. Removing the most efficient asset managers reduces household welfare, primarily due to reduced cost efficiencies rather than reduced competition. We close the model by deriving the equilibrium asset prices, which are jointly determined with the number of funds operating in the market. Our estimates indicate that fund proliferation can exacerbate the long-run price impact of passive institutional investors by as much as 40%.

KEYWORDS: Asset Management, Dynamic Oligopoly, Asset Pricing, Passive Investing

JEL Classification: G12, G23, G24, L13, L84

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[†]Bocconi University, marco.loseto@unibocconi.it

[‡]University of Chicago, Booth and Department of Economics, fmainard@chicagobooth.edu.

1 Introduction

The US mutual fund industry has witnessed a tremendous shift toward passive investing, with the share of assets under management (AUM) in passive equity funds more than doubling over the past two and a half decades. Unlike the active industry, the passive mutual fund industry is concentrated in a handful of large fund families, which together account for more than 80% of the market.[1] These largest families, not only manage more assets, but they also deploy many more funds relative to their competitors. This gap in the number of funds has been increasing over time, suggesting that fund proliferation might be a key mechanism through which these investment firms compete. To maintain their market shares, the largest families keep introducing new funds to capture investors demand (Figure 1).

While the proliferation of passive investment funds is a well-documented phenomenon, its implications for household welfare and asset prices are less well-known. To address this gap, this paper introduces a quantitative model of the passive mutual fund industry, in which the number of funds and asset prices are jointly determined in equilibrium. Fund proliferation results from product entry decisions of oligopolistic, profit-maximizing asset management firms. The most efficient firms introduce new funds earlier and at an higher rate, capturing more AUM relative to the rest of the market. Although these entry incentives lead to a concentrated market structure, investors benefit from lower investment costs. On the asset pricing side, these competitive dynamics exacerbate the price impact of passive institutional investors, consistent with the empirical observation that an increase in the growth rate of the number of passive funds predicts a significant reduction in equity market returns (Figure 2).

The distinction between individual mutual funds and asset management companies is key to rationalize the fund proliferation patterns observed in the data.[2] Our model accommodates the presence of both management companies and funds by introducing two layers of Cournot competition. In the inner layer, mutual funds compete by choosing quantities and make a profit from fees, determined by the investment service demand of a representative household investor. In the outer Cournot layer, an oligopoly of management companies compete with each other by deciding how many funds to operate. On the one hand, introducing a new fund reduces current profits because it increases competition between funds in the inner layer. On the other, introducing a new fund lowers the cost of launching additional funds in the future because of scale economies. These dynamic incentives lead asset management firms to smooth

[1] AUM in passive equity funds grew from \$500 billions in 2000 to \$5 trillions in 2020 (Figure B.1). While the average (asset-weighted) fee decreased from 25 basis points to 7 basis points (Figure B.2), fee-revenues increased by 2.25 billions over the same time horizon.

[2] While there exists an extensive literature that studies the mutual fund industry, most of it focuses on funds and disregards the role of fund families. Some exceptions are Massa (2003), Gaspar, Massa and Matos (2006), Bhattacharya, Lee and Pool (2013), Berk, Binsbergen and Liu (2017), Betermier, Schumacher and Shahrad (2022).

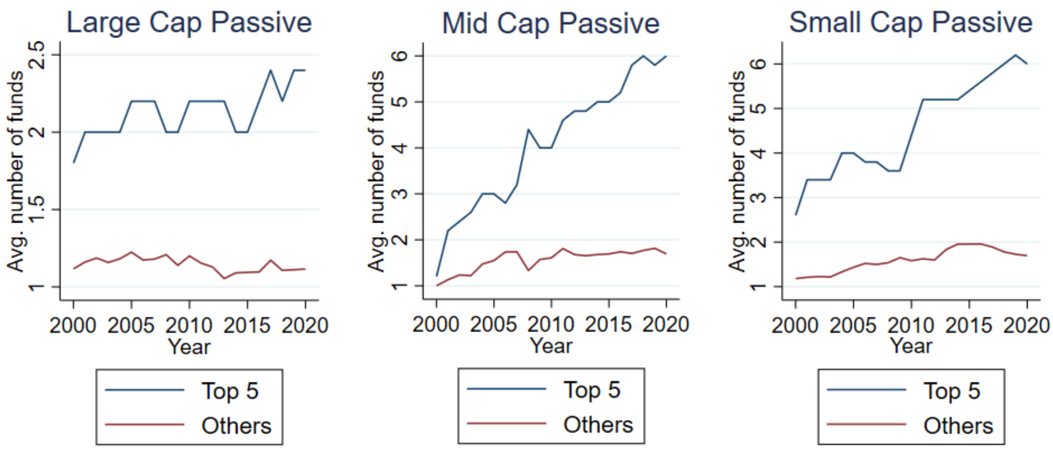

Figure 1: Average number of funds per management company. Funds with different share classes count as a single fund.

their product entry decisions over time, consistent with the entry patterns observed empirically.

On top of allowing the number of funds to emerge endogenously in equilibrium, we close the model and derive the equilibrium price that clears the asset market under the assumptions of strict mandates and a fixed supply of shares. At each point in time, the path for the number of funds created is a pure strategy Markov Perfect Nash equilibrium of the dynamic game between management companies, and the path for asset prices clears the asset market in every period. After setting up the model, in Proposition 1, we prove existence and uniqueness of a steady state equilibrium in which the number of funds and the equity index price are constant.

To the best of our knowledge, this is the first quantitative model that studies the asset pricing implications of fund proliferation by endogenizing the product entry decisions of profit maximizing intermediaries. Doing so allows us to link the mutual fund industry technology fundamentals to equilibrium asset prices: the price impact of large institutional investors is micro-founded from technology primitives such as fund initiation costs and scale economies.[3] A reduction in initiation costs pushes companies

[3]Several papers have emphasized the role of institutional investors in determining asset market movements. See for example, Petajisto (2009) Basak and Pavlova (2013), Koijen and Yogo (2019), Haddad, Huebner and Loualiche (2022) and Pavlova and Sikorskaya (2022).

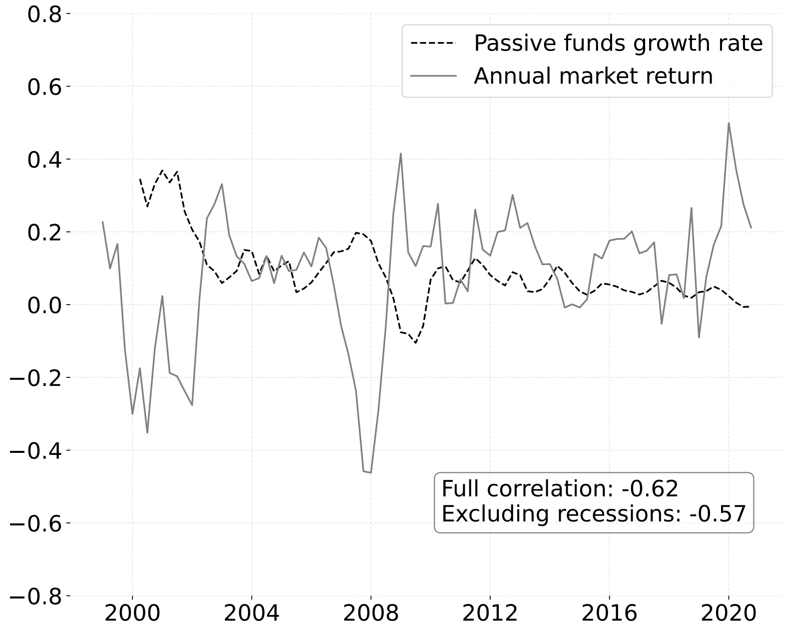

Figure 2: Growth rate in the number of passive US equity funds annualized over the previous four quarters together with the market return annualized over the following four quarters.

to introduce more products, which will lower the equilibrium fees and, in turn, attract more demand from households. Then, under fixed supply, asset prices will increase to clear the excess demand triggered by the initial reduction in initiation costs.[4]

In the second part of the paper, we estimate the model using data on US passive equity funds. We do so by matching the average curvature of the observed fund entry patterns. In our model, this moment informs a key parameter characterizing the cost of introducing new funds for management company j: the adjustment cost parameter δ_j. In the data, we compute this moment separately for each of the five largest management companies and the remaining companies pooled together.[5] For each of the five largest companies, we obtain an estimate of their fund initiation costs, and we show how our model can match the pattern of fund proliferation observed in the data. As a validation check, we also show how our dynamic model's time series of equilibrium fees closely follows the observed (and untargeted) time series of fund expense ratios.

An important contribution of the paper is to use the estimated model to quantify the welfare implications of alternative market structures through a series of conterfac-

[4] The presence of arbitrageurs could partially offset the price impact of these large passive investors. In practice, empirical evidence suggests that flows from large institutional investors tend to impact asset prices and, as we discuss later, even without arbitrageurs, our model is able to match the price impact estimates found in the recent empirical asset pricing literature.

[5] Our model only focuses on passive funds and, in estimation, we pool all the non-top five companies into one entity which we refer to as the outside company. Hence, the overall number of companies used in estimation will be 6. As shown in Figure B.3, more than 80% of the market is controlled by the five largest companies.

tual exercises. We begin by individually removing the five largest companies—BlackRock, Charles Schwab, Fidelity, State Street, and Vanguard—from the market. The welfare effects of removing any one of these companies are sizable and heterogeneous. For instance, we estimate that excluding BlackRock from the market would reduce household welfare by nearly $2 billions dollars. More importantly, we find that this welfare loss results primarily from BlackRock being the most efficient asset manager, rather than from reduced competition. To quantitatively demonstrate this, in a second counterfactual, we replace BlackRock with a different management company that has a cost structure similar to Charles Schwab, which we estimate to be less efficient. The welfare loss in this scenario is, in magnitude, only 25% lower. Overall, our analysis indicates that the high level of concentration observed in the US passive mutual fund industry is reflective of cost efficiencies rather than market power.

Because our model endogenizes asset prices, we are also able to quantify the asset pricing implications of fund proliferation. Our estimates imply that a 1% increase in household wealth increases the valuation of the equity index by nearly 1.4%, which is in line with what the recent asset pricing literature has found in different settings. In the context of our model, we can also quantify how much of this price impact is due to the product entry dynamics of the industry. We find that, in the long-run steady state, asset managers product entry decisions amplify the price impact of a shock to household asset demand by as much as 40%.

Related literature. Our paper contributes to the growing literature that studies theoretically and empirically the industrial organization of the asset management industry. Within this literature, a few papers highlight the importance of management companies in shaping the market structure and the proliferation of products in the asset management industry. Massa (2003) argues that fund families are incentivized to offer a broad menu of funds because investors value the possibility to switch across different funds belonging to the same family at no cost. Khorana and Servaes (1999) empirically analyze the determinants of mutual fund starts and show that scale and scope economies are among the factors that induce fund families to launch new funds. More recently, Betermier, Schumacher and Shahrad (2022) provide empirical evidence that incumbent families set up a large number of new funds in order to deter entry.[6] The role of fund families and product proliferation are also crucial elements in our dynamic model. In each period fund families decide how many new funds to introduce taking into account that operating more funds will generate scale economies next

[6] The importance of multi-product management companies is not limited to shaping the market structure of the industry. Gaspar, Massa and Matos (2006) provide empirical evidence of how fund families transfer performance across member funds to maximize family profits. Bhattacharya, Lee and Pool (2013) show that large families offer mutual funds that only invest in other funds in the family and how these type of funds provide insurance against liquidity shocks. Berk, Binsbergen and Liu (2017) argue that fund families exploit their private information about their managers skill and create value by reallocating capital efficiently among managers. Ørpetveit (2021) shows empirically that management companies improve the quality of their existing funds in response to higher competition.

period but will increase competition and reduce profits of existing funds. On top of this, we endogenize asset prices and examine the asset pricing implications of fund proliferation.

Our work is also related to the recent asset pricing literature that highlights the role of institutional investors in determining asset prices movements (see for example Petajisto (2009) Basak and Pavlova (2013), Koijen and Yogo (2019), Gabaix and Koijen (2021), Haddad, Huebner and Loualiche (2022) and Pavlova and Sikorskaya (2022)). Contrary to the traditional assumptions that investors are atomistic and that their demand shocks are uncorrelated, this literature documents how asset demand is far from perfectly elastic and how demand shocks affect equilibrium asset prices. The large size of these investors and the presence of specific investment mandates contribute to generating correlated demand shocks, which will inevitably impact asset prices. Our model further suggests that the competitive dynamics of the mutual fund industry may also contribute to and exacerbate the price impact of institutional investors. A shock to household asset demand not only increases asset prices on impact but also pushes companies to create more funds, which will in turn lead to lower investment fees and attract more flows from households.[7]

Motivated by the increasing regulatory scrutiny toward the growth of index investing,[8] Schmalz and Zame (2023) propose a static equilibrium model with heterogeneous investors and show that the presence of an index fund might hurt investors' welfare if one takes into account the general equilibrium effect on asset prices. When the index fund enters the market or lowers its fee, investors increase their stock holdings relative to their bond holdings, which leads to higher asset prices and, in turn, to lower asset returns. Although our model is different in several respects, we also look at how investors' welfare changes when the structure of the asset management industry changes, while taking into account the effects on asset prices. Our counterfactual analysis in Section 5.3 suggests that restricting the largest passive asset managers to favor competition might reduce investors' welfare. This happens because the largest

[7]The importance of large institutional investors has been shown to be relevant also for the efficiency of asset prices. In a recent paper, Kacperczyk, Nosal and Sundaresan (2022) consider an asset market with an oligopoly of large investors of exogenous sizes and study how market concentration affects price informativeness. Although we abstract from the role price informativeness, our model endogenizes flows and market concentration leaving heterogeneity in production technologies to be the fundamental model primitive. With the rise of passive investing the literature that studies how the presence of large passive investors affects the information embedded in asset prices is growing. See for instance: Bai, Philippon and Savov (2016), Baruch and Zhang (2022), Bond and García (2021), Farboodi, Matray, Veldkamp and Venkateswaran (2021), Coles, Heath and Ringgenberg (2022), Malikov (2021) and Sammon (2022).

[8]Regulators and antitrust legal scholars are investigating the consequences of the rise of passive investing on various economic outcomes. The trigger of many of the regulatory concerns has been a recent and growing literature that studies the anticompetitive effects of common ownership (Azar, Schmalz and Tecu (2018)), Posner, Scott Morton and Weyl (2017), Anton, Ederer, Gine and Schmalz (2017), Azar and Vives (2021), Backus, Conlon and Sinkinson (2021)). This literature asks whether product firms that share common owners, which in most cases are large passive asset managers, have less incentive to compete.

management companies are far more efficient than the rest of market and thus the efficiency loss that results from removing them hurts investors despite asset returns increase.

The rest of the paper proceeds as follows. Section 2 describes the model. Section 3 establishes uniqueness and existence of a steady-state equilibrium. Section 5 calibrates and estimates the model. Section 6 concludes.

2 Model

Time is discrete and indexed by $t \in \{1, 2, ...\}$. We consider an economy populated by three types of agents: a representative household, mutual funds and management companies. The representative household allocates wealth between the mutual fund sector and a risk-free asset to finance consumption and takes expected return, variance and fees as given. The mutual fund sector is populated by a discrete number of identical funds that internalize household demand and that optimally choose their size to maximize dollar revenues. Each fund invests in the same underlying index and takes the total number of operational funds as given. Finally, each management company is responsible for fund initiation. Specifically, at each time t, each management company controls a number of pre-existing funds that carries from previous periods and chooses the number of new funds to create. We close the model and derive equilibrium market prices by assuming that mutual funds have a strict mandate to invest in the underlying index and that the index is available in fixed supply. The model frames the competitive dynamics of the mutual fund industry assuming that not only mutual funds but also management companies simultaneously and dynamically compete with each other. Despite the complications created by the two layers of Cournot competition, we provide sufficient conditions under which the model admits a unique steady-state equilibrium.

We now proceed to describe in details the problem solved by each agent in the model.

2.1 Household

In each period, a representative household with log utility over consumption decides how much of its current wealth A_t to consume and how much to invest in the financial market. The investment opportunity set consists of two broad asset classes, namely a risk-free asset with return normalized to zero and a mutual fund sector. The mutual fund sector is populated by a discrete number of identical funds that invest in the same underlying index and that charge fee f_t at time t.[9] Because all mutual funds are identical, each household is indifferent between investing in any specific fund and it

[9]We will discuss this product homogeneity assumption in Section 2.5.

will only choose the fraction of wealth to invest in the aggregate mutual fund sector. The size of each individual fund will then be determined via Cournot competition.

We assume that the index tracked by each mutual fund pays a constant dollar dividend D and we denote by P_t the index price at time t. Next, we define the net of fee index return at time $t+1$ as

$$1 + R_{t+1} = \frac{P_{t+1} + D}{P_t} - f_t. \tag{1}$$

Our representative household knows D and f_t but is not able to foresee the equilibrium path of asset prices. In other words, the household is not able to anticipate the effect that actions of mutual funds and management companies have on equilibrium asset prices. Instead, he perceives the index log net returns to evolve as a Gaussian stationary process

$$r_{t+1} \equiv \log(1 + R_{t+1}) = \rho_t - f_t + \sigma_t \varepsilon_{t+1}$$

where $\varepsilon_{t+1} \sim \mathcal{N}(0,1)$.[10] Letting w_t denote the portfolio weight on the mutual fund sector, the problem solved by the representative household at time t is

$$V(A_t) = \max_{(C_s, w_s)_{s=0}^{\infty}} \mathbb{E}_t \left[\sum_{s=t}^{\infty} \beta^{s-t} \log(C_s) \right] \tag{2}$$

$$\text{s.t. } A_{t+1} = (1 + w_t R_{t+1})(A_t - C_t) \tag{3}$$

with associated Euler equation given by

$$1 = \mathbb{E}_t \left[\beta \left(\frac{C_{t+1}}{C_t} \right)^{-1} (1 + w_t R_{t+1}) \right]. \tag{4}$$

In every period our household optimally consumes a constant fraction of its wealth $C_t = (1-\beta)A_t$ and invests the rest βA_t in the financial market. Moreover, as we show in Appendix A, the household optimal portfolio allocation is given by

$$w_t = \frac{\mu_t - f_t}{\sigma_t^2}, \tag{5}$$

where $\mu_t \equiv \rho_t + \sigma_t^2/2$.

2.2 Mutual Funds

In any period t, each mutual fund takes the total number of funds in the market n_t as given and chooses its market share to maximize dollar profits. Given the optimal

[10] When net returns are sufficiently small $\log(1 + R_{t+1}) \approx R_{t+1} = \frac{P_{t+1}+D}{P_t} - f_t - 1$ so that ρ_t can be interpreted as the household subjective belief about the next period capital gain and dividend yield.

market share chosen by each fund, the equilibrium fee at time t is pinned down by the demand of the representative household in (5). In other words, we are assuming that, at each time t, mutual funds compete simultaneously and repeatedly a la Cournot. Each mutual fund internalizes that a higher individual market share leads to a higher market share of the aggregate mutual fund industry and to a lower fee that the household is willing to pay.

Let w_{it} denote the weight on mutual fund i in the portfolio of the representative household, and consider to rewrite household demand in (5) as

$$f_t = \mu_t - w_t \sigma_t^{2.} \tag{6}$$

Then fund i at time t solves

$$\max_{w_{it}} \; f_t w_{it} \beta A_t$$

subject to

$$f_t = \mu_t - w_t \sigma_t^2,$$
$$w_t = \sum_{i=1}^{n_t} w_{it}.$$

Taking the first-order condition with respect to w_{it} we obtain fund i's best response

$$w_{it} = \frac{\mu_t}{\sigma_t^2} - w_t. \tag{7}$$

Summing across funds yields the Cournot total quantity

$$w_t = \frac{\mu_t n_t}{\sigma_t^2 (n_t + 1)}. \tag{8}$$

By replacing (8) in (6) and (8) in (7) we recover the equilibrium fee and the symmetric equilibrium w_{it}:

$$f_t = \frac{\mu_t}{n_t + 1}; \quad w_{it} = \frac{\mu_t}{\sigma_t^2 (n_t + 1)}. \tag{9}$$

In equilibrium at time t and conditional on n_t, each mutual fund i realizes dollar profits

$$\Pi_t \equiv f_t w_{it} \beta A_t = \frac{\mu_t^2}{\sigma_t^2 (n_t + 1)^2} \beta A_t.$$

To save notation, we will rewrite dollar profits gained by each fund as

$$\Pi_t = \frac{\pi_t}{(n_t + 1)^2} \tag{10}$$

where $\pi_t \equiv \frac{\mu_t^2}{\sigma_t^2} \beta A_t$.

2.3 Management Companies

Consider an oligopoly of M multi-product management companies indexed by $j \in \{1, 2, \ldots, M\}$. Each management company j enters time t with n_{jt-1} pre-existing funds and chooses the number of funds n_{jt} to operate in the current period with the objective of maximizing the present discounted value of dollar profits. Equivalently, the decision of management company j to operate n_{jt} funds at time t requires the creation or deletion of $(n_{jt} - n_{jt-1})$ funds.

While pre-existing funds do not carry any cost for the controlling management company, opening a new fund is costly. We allow the initiation cost to depend on the size of management companies and we parameterize the cost of creating a new fund for management company j at time t as

$$C_j\left(n_{jt}, n_{jt-1}; c_j, \delta_j\right) = c_j n'_{jt} + \delta_j \left(\frac{n_{jt} - n_{jt-1}}{n_{jt-1}}\right)^2 n_{jt-1} \tag{11}$$

where $c_j > 0$ is the linear component of the initiation cost and $\delta_j > 0$ captures an additional cost of adjusting the menu of funds, which we assume decreasing in the size of the management company, i.e. in the number of pre-existing funds n_{jt-1}. The suggested functional form for $C_j(\cdot)$ implies that management companies with a higher number of pre-existing funds face a lower initiation cost and it is motivated by the newly documented evidence that largest management companies are responsible for most of fund creation. We interpret this evidence as suggesting that largest management companies face a lower cost of initiating a new fund and we incorporate this empirical fact in the model. Holding n_{jt-1} constant, the parameter δ_j captures how costly it s for company j to adjust its menu of funds. A lower δ_j and a higher n_{jt-1} both reduce j's cost of launching a new fund.

What is the trade-off that management companies face when initiating a new fund? First, in the current period, there is an ambiguous effect on profits. On one hand, profits increase because the company operates one additional fund thereby increasing its market share. On the other hand, creating one additional fund increases competition in the mutual fund sector, leading to a decrease in fee f_t and profit Π_t. Second, expanding the current menu of funds carries the additional benefit of reducing the initiation cost in future periods.

Overall, management company j at time t solves the following dynamic problem

$$V_j\left(n_{jt-1}\right) = \max_{n_{jt}} \; n_{jt}\frac{\pi_t}{(n_t+1)^2} - C_j\left(n_{jt}, n_{jt-1}; c_j, \delta_j\right) + \beta V_j\left(n_{jt}\right) \tag{12}$$

subject to

$$n_t = \sum_{j=1}^{M} n_{jt}.$$

Effectively, we are considering a dynamic game in which management companies compete simultaneously a la Cournot. For each management company j, the optimal strategies $n_{-jt} = (n_{j't})_{j' \neq j}$ chosen by the other management companies $j' \neq j$ enter the problem through the total number of funds $n_t = n_{jt} + \sum_{j' \neq j} n_{j't}$. Company j's value function V_j depends only on n_{jt-1} because, as we discuss in Section 3, we restrict our attention to Markov perfect equilibria where firms' strategies are only function of a company's stock of funds in the previous period.

2.4 Financial Market

The last aspect of the model that still has to be addressed is how the price of the index in which mutual funds are invested will be pinned down in equilibrium. To this end, we assume that mutual funds have a strict mandate to invest in the underlying index and that the index is available in fixed supply $\bar{Q}$. Letting Q_{it} denote the number of index shares demanded by mutual fund i at time t, then the assumption of strict mandate requires

$$Q_{it} P_t = w_{it} \beta A_t \qquad \forall i, t \tag{13}$$

Equation (13) simply states that, if mutual fund i has a strict mandate to invest in the index, then, at any time t, the dollar investment in the index (left-hand side) has to equal the total assets under management of mutual fund i (right-hand side). Summing (13) across funds and imposing market clearing yields

$$P_t = w_t \frac{\beta A_t}{\bar{Q}} = \frac{\mu_t n_t}{\sigma_t^2 (n_t + 1)} \frac{\beta A_t}{\bar{Q}} \tag{14}$$

where in the second equality we used equation (8). In equilibrium, the wealth A_t of the representative household will evolve according to the following law of motion:

$$A_{t+1} = \beta A_t \left[1 + w_t \left(\frac{P_{t+1} + D}{P_t} - f_t - 1 \right) \right] \tag{15}$$

$$= \beta A_t \left[1 + \left(\frac{\mu_t n_t}{\sigma_t^2 (n_t + 1)} \right) \left(\frac{P_{t+1} + D}{P_t} - f_t - 1 \right) \right] \tag{16}$$

$$= \beta A_t + \bar{Q} \left(D + \Delta P_{t+1} - f_t P_t \right) \tag{17}$$

where the second equality substitutes for the equilibrium portfolio weight w_t in (8) and the third equality uses expression (14). We stress that, because the household is not able to internalize the effect on asset prices coming from the actions of mutual funds and management companies, the law of motion of wealth derived in (17) will not in general be equivalent to the budget constraint used in (3).

2.5 Discussion of model assumptions

Before turning to the definition of equilibrium and proving existence and uniqueness of a steady state, we now discuss some of our modelling assumptions. All of the assumptions are needed to balance the model tractability and its ability to capture what we believe are the most relevant dynamics of the industry.

Myopic portfolio choice. In our model, the optimal portfolio choice is myopic because our representative household has logarithmic preferences over consumption. Unless the belief process is i.i.d over time, relaxing this assumption would preclude obtaining a closed-form solution for the portfolio weight w_t. With a time-varying belief process, the optimal portfolio choice would also depend on the incentives to hedge intertemporally, resulting in an asset demand function defined only implicitly. This complexity would hinder our ability to tractably set up the product entry game between management companies on the supply side.

Product homogeneity. In our model, we assume all funds are identical, although in reality, funds differ in holdings, management styles, fee structures, and tax benefits.[11] While incorporating all these dimensions of product differentiation would compromise the model's tractability,[12] our framework could accommodate for product differentiation by reinterpreting the product entry decisions of management companies. Rather than choosing the number of funds to operate, asset management companies could be modeled as choosing which investment sectors to enter. The choice variable n_{jt} would represent the number of investment segments in which company j is active. Under this reinterpretation, the dynamic trade-offs—where entering a market segment today is costly but reduces future entry costs—are preserved,[13] implying that the asset pricing implications would remain broadly consistent. Ultimately, this homogeneity assump-

[11] Product differentiation is a relevant dimension an important dimension through which investment firms compete to attract investors with heterogeneous preferences. For example, Kostovetsky and Warner (2020) develop a textual measure of product differentiation and show that more differentiated/unique funds are able to attract higher inflows at least the first few years upon introduction. Similarly, Abis and Lines (2022) use a k-means clustering algorithm based on a textual analysis of fund prospectuses and show that funds are differentiated in groups and that investors withdraw money if funds tend to diverge from their prospectus strategy. In the case of ETFs Ben-David, Franzoni, Kim and Moussawi (2022) provide evidence that specialized ETFs, tracking niche portfolios, are supplied to cater investors heterogeneous beliefs.

[12] To account for this type of product heterogeneity, extending the model would require adjustments in two directions: on the supply side, introducing some dimension of horizontal differentiation by characterizing a fund with a vector of both portfolio (e.g., type of holdings, factor exposures, etc.) and non-portfolio characteristics (e.g., management tenure, advertising, fund age, etc.). On the demand side, it would necessitate modifying household preferences in a way that makes all these product characteristics valuable.

[13] If the representative household substitutes across segments then entering a new investment segment today would also increase competition, reducing profits from other market segments.

tion allows us to examine the welfare and asset pricing implication of fund proliferation while maintaining model tractability.[14]

Investor learning. A large body of the literature on mutual funds has studied the so called flow-performance relationship.[15] According to the literature, past performance attracts new inflows regardless of whether performance persists or not. Building on this empirical finding, theoretical models studying the flow-performance relationship typically feature investors learning about unobserved managerial skills from past performance.[16] In our model we do not have investor learning because we are focusing on passive investment funds.

3 Equilibrium

3.1 Equilibrium definition

We are now ready to define the equilibrium of our dynamic game. Following the industrial organization literature on dynamic oligopolies, we restrict our attention to Markovian strategies i.e., strategies that are a function of payoff-relevant state variables.[17] From problem (12), we can see that the payoff-relevant state variables for management company j are its menu of funds active in the previous period n_{jt-1}, as well as competitors' menus of funds active in the previous period $(n_{j't-1})_{j'\neq j}$. This is because any management company j' chooses a strategy $n_{j't}$ function of $(n_{j't-1})_{j'\neq j}$. Because $(n_{j't})_{j'\neq j}$ enter company j's problem through n_t, then the optimal strategy of each management company depends on its own menu of pre-existing funds as well as the menu of pre-existing funds of all its competitors. To preserve computational tractability, for each management company j, we restrict attention to strategies that are a function of company j's own state (in our case n_{jt-1}) and denote the policy function by $\alpha_j : [0,\infty) \to [0,\infty)$.[18]

Definition 1 *An equilibrium of our dynamic model consists in a profile of strategies $\alpha^* = (\alpha_j^*)_{j=1}^M$ with $\alpha_j^* : [0,\infty) \to [0,\infty)$, a path of asset prices $(P_t)_{t=1}^\infty$ and wealth*

[14] To further back up our homogeneity assumption, Tables C.3 and C.4, present some characteristics of the top 30 passive funds supplied in the Large Cap and Mid Cap sectors in 2018. The exposures to the 4 Carhart factors, the alphas and the gross-returns are similar across all funds especially within but also across the two sectors.

[15] See for instance the two seminal contributions Chevalier and Ellison (1997) and Sirri and Tufano (1998).

[16] The seminal contribution here is Berk and Green (2004) which rationalizes the flow-performance relationship in a model with rational investors who learn about managers' alphas. More recently, Roussanov, Ruan and Wei (2021) extends the Berk and Green (2004) to allow for search friction as in Hortaçsu and Syverson (2004).

[17] See for instance, Maskin and Tirole (1988), Ericson and Pakes (1995) and for a self-contained review Aguirregabiria, Collard-Wexler and Ryan (2021).

[18] Under this restriction, the solution concept is known as oblivious equilibrium which Weintraub, Benkard and Van Roy (2008) show to be a good (and computationally feasible) approximation of the unrestricted Markov perfect equilibrium.

$(A_t)_{t=1}^{\infty}$ such that:
(1) in any period t, $\alpha^* = (\alpha_j^*)_{j=1}^{M}$ is a pure strategy Markov perfect equilibrium such that for all j

$$\alpha_j^*(n_{jt-1}) = \arg\max_{n_{jt}} \left\{ n_{jt}\frac{\pi_t}{(1+n_t)^2} - c_j(n_{jt} - n_{jt-1}) - \delta_j \left(\frac{n_{jt} - n_{jt-1}}{n_{jt-1}} \right)^2 n_{jt-1} + \beta V(n_{jt}) \right\}$$

where n_{jt} denotes the number of company j's funds active in the current period, n_{jt-1} the the number of company j's funds active in the previous period, $n_t = n_{jt} + \sum_{j' \neq j} n_{j't}$ with $n_{j't} = \alpha_{j'}^*(n_{j't-1})$ and $\pi_t = \frac{\mu_t^2}{\sigma^2}\beta A_t$.
(2) in any period t the asset market clears,

$$P_t = \frac{\mu_t n_t}{\sigma_t^2(1+n_t)} \frac{\beta A_t}{\bar{Q}},$$

and the path of wealth solves,

$$A_{t+1} = \beta A_t + \bar{Q}\left(D + \Delta P_{t+1} - f_t P_t\right).$$

Before discussing existence and uniqueness of our equilibrium a few remarks are in order. First, our restricted Markovian strategies allow us to compute the envelope condition as in any single-agent dynamic programming framework. This greatly simplifies the derivation of the system of Euler equations characterizing the dynamic equilibrium. Second, we assume that, when adjusting their menu of funds, management companies do not internalize the price impact generated by their actions. Specifically, we assume that management companies take the term π_t in their profit function as given, although π_t is affected by n_{jt} through market clearing prices.

3.2 Steady state definition and existence

While the computational complexity of the model requires a numerical solution, we are able to characterize analytically a steady-state equilibrium where

- $n_{j,t} = n_j > 0$ for any management company j and time t;
- $P_t = P > 0$ for any time t;
- $A_t = A > 0$ for any time t.

In words, the steady-state features a constant index price, constant household wealth, and is such that the dynamic game between management companies resolves with each company maintaining the same number of funds over time.

We now turn to provide sufficient conditions for the existence and uniqueness of this type of steady state equilibrium. We start by assuming that household subjective beliefs are constant over time, that is $\mu_t = \mu$ and $\sigma_t^2 = \sigma$ for all t. We maintain this assumption from here throughout the paper. It follows that, in steady state, the term π_t in (12) is also constant over time and equal to

$$\pi_t \equiv \pi = \frac{\mu^2}{\sigma^2}\beta A.$$

Proposition (1) provides sufficient conditions under which such steady state exists and is unique.

Proposition 1 *Let* $\tilde{\pi} \equiv \frac{D}{1-\beta}\frac{\beta\mu^2}{\sigma^2}$, *assume* $M\tilde{\pi} > (1-\beta)c$ *with* $c = \sum_j c_j$ *and, without loss of generality, let* $\bar{Q} = 1$. *Then, there exists a unique steady-state* $\{(n_j)_{j=1}^M, P, A\}$ *such that:*

(1) for any management company j *and any period* t, $n_{jt} = n_j = \alpha_j^*(n_j)$ *satisfies*

$$n_j = \frac{1+n}{2} - \frac{(1-\beta)}{2\pi}c_j(1+n)^3 \tag{18}$$

where $n = \sum_{j=1}^M n_j$ *and* $\pi = \frac{\mu^2}{\sigma^2}\beta A$;

(2) the market clearing price $P_t = P$, *the wealth* $A_t = A$ *and the total number of funds* n *solve simultaneously*

$$A = \left(\frac{1}{1+\zeta(n)}\right)\frac{D}{1-\beta} \tag{19}$$

$$P = \frac{\mu}{\sigma^2}\frac{n}{1+n}\left(\frac{1}{1+\zeta(n)}\right)\frac{\beta}{1-\beta}D \tag{20}$$

$$\tilde{\pi}(M+n(M-2)) = (1-\beta)c(1+n)^3(1+\zeta(n)) \tag{21}$$

where

$$\zeta(n) \equiv \frac{\mu^2}{\sigma^2}\frac{\beta}{1-\beta}\frac{n}{(1+n)^2}. \tag{22}$$

Moreover, $n_j > 0$ *and company* j *remains active if* $\frac{\pi}{(1+n)^2} > (1-\beta)c_j$.

Proof: See Appendix A.

Equations (19) and (20) describe the equilibrium wealth and asset prices as functions of the equilibrium number of funds. Equation (19) suggests that the steady-state wealth A is proportional to the present discounted value of future dollar dividend D where the constant of proportionality depends on n, i.e. on the competitive outcome among management companies. In particular, it is easy to notice that $\zeta(n) > 0$ and $\zeta'(n) < 0$ for $n > 1$. Thus, when competitive forces push companies to initiate a higher number of funds n, $\zeta(n)$ declines and the steady-state wealth A increases. In the limit for $n \to \infty$, then $\zeta(n) = 0$ and $A = D/(1-\beta)$, i.e. the steady state wealth converges to the present discounted value of the dollar dividend D.

Similarly, according to equation (20), higher steady-state n leads to a higher index price P. In the limit for $n \to \infty$, we now have $P = \frac{\mu}{\sigma^2}\frac{\beta}{1-\beta}D$. More generally, equation (20) relates the equilibrium index price to the marginal cost of initiating new funds and thus microfounds the price impact of institutional investors in terms of the technological primitives of the asset management industry. In Section 5.4, we will use equations (19), (20) and (21) to characterize the steady-state index price multiplier with respect to household wealth and we will show that this suggested measure of price impact depends on the competitive outcome in the mutual fund sector. We will further perform a comparative static exercise to explore how the steady-state equilibrium, including the suggested measure of elasticity, vary with the dividend yield d and the total fund initiation cost c.

While the result in Proposition 1 guarantees existence and uniqueness of a steady state in which all companies have no incentives to create additional funds and the index asset price is constant, we know less about the path $\{(n_{jt})_{j=1}^{M}, P_t\}_{t=1}^{T}$ that leads to such steady state. In the next section we provide a numerical algorithm that, for a given initial condition on the number of active funds $(n_{j0})_{j=1}^{M}$ and a given terminal date T, finds the optimal path if such path exists. The algorithm can be used to solve the model numerically and derive the equilibrium path that, for given initial conditions, leads to the steady-state characterized in this section. For the purpose of this paper, we will use the algorithm to solve the model numerically and estimate the parameters of management companies' cost function.

3.3 Numerical solution for the equilibrium path

The ultimate goal of our model is quantitative. In the next sections, we will estimate the model using data on fund entry patterns and then use it to study how household welfare changes under different market structures. With such goal in mind, in this section we propose a numerical procedure that, given proper initial and terminal conditions, allows us to derive the equilibrium path if such path exists.

Our algorithm amounts to solving two fixed points, one nested into the other, that for a given set of initial conditions and parameter values, finds the optimal path of fund initiation, index price and household wealth. The numerical procedure can be summarized in the following steps:

Step 0. Set exogenous parameters to be kept constant throughout the algorithm:

- Fix exogenous parameters $\left\{\sigma,\ D,\ \mu,\ M,\ \ (\delta_j)_{j=1}^{M},\ \bar{Q},\ \beta\right\}$.
- Fix the initial household wealth A_0.
- Fix the initial number of funds managed by each company j, $(n_{j0})_{j=1}^{M}$.

- Fix a terminal date T at which the equilibrium enters the steady-state and the terminal number of funds managed by each company j, $(n_{jT})_{j=1}^{M}$.

Step 1. Solve the inner loop for a given path of asset prices $(P_t)_{t=1}^{T}$, household wealth $(A_t)_{t=1}^{T}$ and fund initiation costs $(c_j)_{j=1}^{M}$ as follows:

- Construct the path for $(\pi_t)_{t=1}^{T}$.

- Guess a path for the number of funds managed by each company j: $\left(\left(n_{jt}^{(k)}\right)_{t=1}^{T}\right)_{j=1}^{M}$.

- Use Euler equation defined in (35) to find a new path $\left(\left(\tilde{n}_{jt}^{(k)}\right)_{t=1}^{T}\right)_{j=1}^{M}$.

- Update the path of funds using

$$n_{jt}^{(k+1)} = n_{jt}^{(k)} + \chi_n \left(\tilde{n}_{jt}^{(k)} - n_{jt}^{(k)}\right) \quad \forall j, t. \tag{23}$$

- Repeat until convergence.

Step 2. Run the outer loop to find the equilibrium path of index price and household wealth:

- Guess a path of prices $\left(P_t^{(q)}\right)_{t=1}^{T}$, household wealth $\left(A_t^{(q)}\right)_{t=1}^{T}$ and fund initiation costs $\left(c_j^{(q)}\right)_{j=1}^{M}$

- Run inner loop as in Step 1 to obtain $\left(\left(n_{jt}^{(q)}\right)_{t=1}^{T}\right)_{j=1}^{M}$.

- Use market clearing in (14) and the law of motion of wealth in (17) to find new paths $\left(\tilde{P}_t^{(q)}\right)_{t=1}^{T}$ and $\left(\tilde{A}_t^{(q)}\right)_{t=1}^{T}$.

- Recover the new vector of costs $(\tilde{c}_j)_{j=1}^{M}$ by inverting the system of Euler equations in (35) assuming the system is in steady-state at $t = T$.

- Update price, wealth and costs using

$$P_t^{(q+1)} = P_t^{(q)} + \chi_p \left(\tilde{P}_t^{(q)} - P_t^{(q)}\right) \tag{24}$$
$$A_t^{(q+1)} = A_t^{(q)} + \chi_a \left(\tilde{A}_t^{(q)} - A_t^{(q)}\right) \tag{25}$$
$$c_j^{(q+1)} = c_j^{(q)} + \chi_c \left(\tilde{c}_j^{(q)} - c_j^{(q)}\right) \tag{26}$$

- Repeat until the maximum of $||P^{(q+1)} - P^{(q)}||_\infty$, $||A^{(q+1)} - A^{(q)}||_\infty$ and $||c^{(q+1)} - c^{(q)}||_\infty$ is below some tolerance

To sum up, for a given set of parameter values, the routine just described starts in Step 2 with a guess for the equilibrium index price and wealth. It then moves to the inner loop (Step 1) and solves for the equilibrium number of funds taking the path of index price and wealth as given. Finally, it returns to Step 2 to update the equilibrium price and wealth. This routine is repeated until convergence. It is a nested procedure because the fixed point that solves for the Markov perfect Nash equilibrium is solved within each iteration of the fixed point that solves for the market clearing price and wealth evolution.

4 Data

Before turning to the estimation of our model we overview our data sources and how we constructed our estimation dataset.

4.1 Data sources

We obtained data on US mutual funds from the Center for Research in Security Prices (CRSP) which we accessed through the Wharton Research Data Services (WRDS). The data provide detailed information on US mutual funds at monthly frequency starting from 1961 but we restrict the sample from year 2000 to 2020 for the reasons we describe in the following subsection.

The data is at the share class level but we collapse everything at the fund-by-year level. Moreover, we focus on US domestic equity funds that, according to the CRSP investment objective classification, belong to the Large Cap, Mid Cap and Small Cap sectors. Among those, we identify passive funds as either index funds or ETFs as classified by CRSP. The resulting sample contains around 16,500 fund-by-year observations of which around 3,700 are passive investment vehicles.

Table C.1 presents some summary statistics of our data. The average amount of asset under management at the end of year is around 2 billions but the distribution is quite skewed due to the presence of extremely large funds. The average monthly gross return in a given year is around 0.9%, with an average monthly alpha of 0.04% and an average market beta of 0.97. These latter are estimated for each year and each fund from a monthly regression of gross returns on the 3 Fama-French factors plus momentum including observations from the previous 3 years. Finally, the average market share at the management company level is around 1.7%, although also in this case the distribution is very skewed because, for most years, more than 50% of the market is captured by the five biggest management companies.

Table C.2 replicates Table C.1 restricting the sample to passive funds only. As expected passive funds tend to be cheaper with an average expense ratio of 0.5% and larger, managing an average of 5.7 billions of assets. On average passive funds also seem to deploy more funds with an average of 4.5 funds per management company.

4.2 Data construction

We now discuss in detail the way we constructed our final dataset which we will use for estimating the model in the next section.

Filling missing of fund and company identifiers. Information about US mutual funds collected by CRSP is provided at the share class level. Data on returns and asset under management are at the monthly frequency whereas information on fund characteristics are provided quarterly. The first thing we do is to aggregate all share classes of the same fund in one single observation so that the resulting dataset is at the fund level. To this end, we exploit a grouping variable constructed by CRSP (denoted by *crsp_cl_grp*) that contains a unique code for all share classes that belong to the same fund. This variable is available starting from 1999 which is the main reason for why we restrict our sample to start from 2000. To identify funds of the same share class when *crsp_cl_grp* is not available we rely on the WFICN identifiers and on fund names. Fund names in CRSP are useful because they contain three types of information: the name of the management company, followed by the name of the fund, followed by the type of share class. The former two are separated by a colon while the latter by a semicolon. Following this rule we parse each fund name in each month in three parts and then assign the same *crsp_cl_grp* to funds with the same fund name (i.e., the same second part of the name) in the same quarter. This procedure leaves us with 625 share class by quarter observations with a missing *crsp_cl_grp* out of more than 2 millions share class by quarter observations.

Key to our analysis is the role of management companies as fund initiators. In the data, we identify the management company that offers each fund using a unique management company identifier *mgmt_cd*, provided by CRSP, which is available starting from December 1999. Roughly 11% of share class by quarter observations have a missing *mgmt_cd* which we refill again exploiting the information available in the fund name. The first part of each fund name corresponds to the name of the management company; whenever missing we assign the same *mgmt_cd* to funds that feature the same management company name in the same quarter. This procedure fills around 60% of the missing *mgmt_cd*. Whenever this procedures fails because of mistakes in fund name spellings we refill *mgmt_cd* manually.[19] Overall, we were not able to iden-

[19] In some cases, mergers and acquisitions between companies create mismatches between fund names and the *mgmt_cd* code provided by CRSP which we manually correct whenever possible. For instance, after BlackRock acquired the iShare business from Barclays in June 2009 the *mgmt_cd* has not been updated accordingly. In this case there were two *mgmt_cd* codes "BZW" and "BLK" for BlackRock but we replaced "BZW" with "BLK" after 2009. Similarly, we replaced "PDR", the *mgmt_cd* for PDR services LLC owned by the American Stock Exchange, with "SSB" the *mgmt_cd* for State Street Bank which acquired the SPDR ETF license from PDR services LLC in 2005.

tify the controlling management company for less than 1% of share class by quarter observations.

Aggregation of share classes and further cleaning. After the refilling procedure, we merge the quarterly level data on funds' characteristics (which include the *crsp_cl_grp* and *mgmt_cd* identifiers) with the monthly data on returns and AUM. Then, for each month we aggregate share classes of the same fund into one observation based on the *crsp_cl_grp* identifier. To do so we sum the end of month AUM of all share classes and take averages of other relevant variables, such as monthly returns and expense ratios, weighting by the AUM at the end of the previous month. Finally we only keep domestic equity funds and, to remove incubation bias, we drop funds that we observe for less than 12 months and whose AUM are less than 15 millions.[20] The resulting dataset contains around 650,000 fund by month observations.

Dataset for model estimation. Our model focuses on homogenous passive investment vehicles that track an underlying index. In the data we identify passive funds using the variables *et_flag* and *index_fund_flag* and consider as passive both index funds and ETFs. Moreover, we restrict ourselves only to the Large Cap, Mid Cap and Small Cap sectors as identified by the *crsp_cl_grp* variable constructed by CRSP.[21] The reason is that more than half of pure index funds belong to these sectors and, as shown in Table C.4 these products seem to be sufficiently homogeneous in terms of the risk-return profile they offer. Finally, we collapse everything at the year level and we obtain a dataset of 16,500 fund by year observations of which 3,700 are passive.

5 Model estimation

Using the numerical algorithm discussed in Section 3, we now turn to estimate the model and discuss the results. In Section 5.1, we provide details of the estimation procedure. In Section 5.2, we comment on the results, including the ability of the model to match targeted as well as untargeted moments. We then turn in Section 5.3 to perform a series of counterfactuals devoted to assessing the contribution of each management companies to fund proliferation, fees and household welfare. Finally, Section 5.4 examines the asset pricing implication of fund proliferation.

5.1 Estimation procedure

The estimation procedure relies on calibrating a subset of the parameters while inferring a second subset of parameters from data. Because our model abstracts from

[20] To identify domestic equity funds we exploit the variable *crsp_obj_cd* which classifies funds based on their investment style. The variable is constructed by CRSP building on Strategic Insights, Wiesenberger, and Lipper objective codes

[21] Funds classified to belong to these sectors determine their holdings primarily on market capitalization considerations.

product differentiation, we estimate the model to match features of mutual funds classified as either Large Cap or Mid Cap in CRSP. In other words, we limit ourselves to passive funds that track reasonably mature firms and exclude instead mutual funds that track growing or developing companies. Table 1 summarizes the calibrated inputs.

Parameter	Description	Value
$\frac{D}{P_0}$	Dividend yield	2%
σ	Volatility	25%
μ	Expected return	6%
β	Discount factor	0.98
M	Number of management companies	6
A_0	Initial wealth	100
$\bar{Q}$	Supply of shares	1.00
T	Terminal date (years)	20

Table 1: Calibrated inputs

We first calibrate the dividend yield at 2% and then calibrate the dollar dividend D to match such yield at time $t = 0$. We set the household expected return μ to match an average return equity returns of 6% per year. Similarly, we set the return volatility σ to match the standard deviation of equity returns to 25%. We set the number of management companies equal to 6. This choice is motivated by the newly documented evidence that the five largest management companies behave differently compared to other management companies and are responsible for most of mutual fund proliferation. For this reason, we directly model competition among the five largest firms and classify all other management companies in one residual group (from here on, we will refer to this residual group as the outside management company, indexed by $j = 0$). We identify the top management companies as the five firms with the highest average annual market share throughout our sample.[22] We further normalize both the household initial wealth A_0 and the supply of index shares $\bar{Q}$ to one. Finally, we set the terminal date $T = 20$ to match the length of our dataset which ranges between 2000 and 2020. For the purpose of our solution algorithm, we then use as terminal condition $(n_{jT})_{j=0}^{5}$ the number of funds that we observe in our dataset for each management company in 2020.

While all the parameters discussed so far can be easily obtained from the data, the same is not true for the parameters $(c_j)_{j=0}^{5}$ and $(\delta_j)_{j=0}^{5}$ that characterize the cost

[22]The market share of a given management company in a given year is simply computed as the sum of net assets across all funds operated by the management company, rescaled by the sum of net assets across all funds that appear in our dataset in a given year.

function of the management companies in our model. For this reason, we estimate both set of parameters directly from data using the following estimation procedure.

Let $\theta = (c_j, \delta_j)_{j=0}^{5}$ denote the set of parameters to be estimated. We estimate θ by solving

$$\min_{\theta} \sum_{s=1}^{S} \sum_{j=0}^{5} \left(\Lambda_{sj}(\theta) - \bar{\Lambda}_{sj} \right)^2 . \tag{27}$$

where $\Lambda_{sj}(\theta)$ denotes the s^{th} moment for management company j implied by the model and expressed as a function of the unknown parameters in θ. On the other hand, we denote by $\bar{\Lambda}_{sj}$ the empirical analogue of $\Lambda_{sj}(\theta)$ observed in the data.

The parameter δ_j governs how costly it is, for management company j, to adjust its menu of funds. Specifically, given two management companies j and j' at time t with $n_{jt-1} = n_{j't-1}$, if $\delta_j < \delta_{j'}$ then adjusting the menu of funds is less costly for company j. In other words, management company j can more easily adapt its supply of funds without incurring in large adjustment costs. In mathematical terms, δ_j is directly related to the curvature of the path of the number of funds offered by company j over time, with lower δ_j translating into higher curvature in the equilibrium path.

The parameter c_j instead governs the linear trend in company j's fund proliferation path and is tightly linked to the average number of funds that management company j originates in each period. Our estimation algorithm pins down the vector of costs $(c_j)_{j=1}^{M}$ by inverting the steady-state Euler equations at the terminal date $t = T$, for a given guess of $(\delta_j)_{j=1}^{M}$. This allows us to limit the non-linear search for the point of minimum of (27) to the vector of adjustment cost parameters $(\delta_j)_{j=1}^{M}$.

Informed by the above discussion, we select the following set of moments to be matched in estimation:

$$\bar{\Lambda}_j = \sum_{t=1}^{T} \frac{\Delta\left(\Delta n_{jt}\right)}{T} \quad \forall j. \tag{28}$$

In words, $\bar{\Lambda}_j$ captures the concavity of management company j creation rate over time, and it allows to pin down δ_j. For each of the five largest management companies, this moment is computed from the time-series of the number of funds operated by the management company between 2000 and 2020. For the outside management company, this moment is computed from the time-series of the average number of funds operated by non-top five management companies over the same time interval. Finally, observe that the estimation problem involves 6 moments and 6 unknowns i.e., we are exactly identified.

Concretely, we employ the following steps to obtain an estimate of θ:

- At the end of each iteration in the nested fixed loop described in Section 3.3, we compute $\Lambda_j(\theta)$ for each management company j.

- Given $\bar{\Lambda}_j$ from the data, we form the objective function in equation (27).

- We iterate over θ until the objective is minimized.

Table 2 reports summary statistics for the six management companies used in our estimation procedure. In reporting the last row, we first construct the outside management company by averaging in each year across all non-top five management companies and by subsequently averaging in the time-series.[23]

Management company	Share	Num. of funds	n_{j0}	n_{jT}	$\bar{\Lambda}_j$
Vanguard	46.73%	6.95	4	9	0.00
State Street	17.25%	6.24	1	10	-0.05
Blackrock	9.89%	11.90	2	13	-0.36
Fidelity	9.61%	3.10	2	8	0.05
Charles Schwab	2.28%	2.62	2	4	0.00
Outside MC	0.17%	1.78	1.33	1.97	-0.01

Table 2: Summary statistics and estimated inputs

The five largest management companies have, on average, a cumulative market share of 85.76%. A second feature of the data is the positive relation between the average market share and the average number of controlled funds. This pattern is consistent with the mechanisms in our model where, given the absence of fund differentiation, a management company can increase its market share by increasing the number of funds it operates. The last three columns in Table 2 further provide three set of parameters that directly enter the estimation procedure. Columns four and five report the number of funds that each management company used to operate in year 2000 and 2020 respectively, which we employ as initial and terminal conditions in the model estimation. Columns six provides the empirical analogue of the moments we use to estimate the model. BlackRock and State Street are characterized by the most concave transition pattern, pointing toward a low adjustment cost δ_j compared to the others. The concavity of the transition pattern are lower for Vanguard, Fidelity, Charles Schwab and the outside management company, although the average number of funds operated is substantially higher for the former three. Interestingly, Fidelity is the only management company with positive $\bar{\Lambda}_j$, determined by the fact that Fidelity started engaging in fund creation only in recent years, after 2015. These features of data are confirmed by Figure 3, which reports the time-series of the number of funds controlled by the five largest management companies.

[23]This practice has the shortcoming that average market shares do not generally sum to one, but it has the advantage that the outside management company can be interpreted as a representative "small" management company.

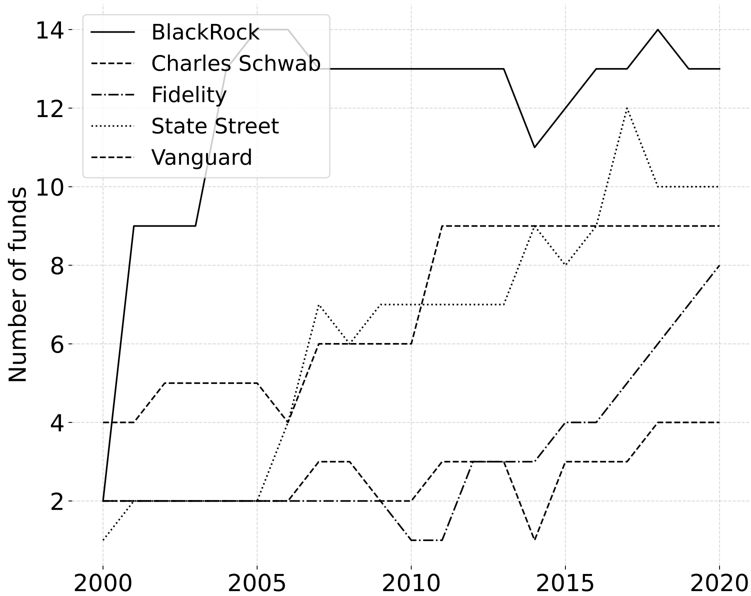

Figure 3: Number of funds operated by each of the top five management companies over time.

5.2 Results

We use the procedure as well as the moments discussed in Section 3 to estimate the model. In Table 3 we report the estimated vector of parameters θ across the six management companies considered. For a direct comparison between the estimated parameters and target moments, we also include the initial number of funds n_{j0}, the terminal number of funds n_{jT} and the targeted moments $\bar{\Lambda}_j$.

	n_{j0}	n_{jT}	$\bar{\Lambda}_j$	c_j	δ_j	Avg. number of funds	
						Model	Data
Vanguard	4	9	0.00	0.0697	0.4030	6.46	6.95
State Street	1	10	-0.05	0.0649	0.0224	7.74	6.24
Blackrock	2	13	-0.36	0.0505	0.0003	12.66	11.90
Fidelity	2	8	0.05	0.0745	0.1858	4.98	3.10
Charles Schwab	2	4	0.00	0.0938	0.6303	2.98	2.62
Outside MC	1.33	1.97	-0.01	0.1036	1.6168	1.65	1.90

Table 3: Estimated fund initiation costs for each asset management company. The average number of funds is untargeted in estimation.

With the lowest linear cost c_j and the highest speed of adjustment δ_j, BlackRock is the most efficient management company.[24] Such efficiency allowed BlackRock to

[24] In the estimation we considered BlackRock and Barclays an unique entity even before their merger

increase massively the number of controlled funds from 2 to 13 throughout the sample, with an average of nearly 12 fund per year. Compared to the beginning of our sample, BlackRock managed to become an industry leader by 2020. The second most efficient firm is State Street. While in 2000 State Street was controlling only one fund (less than the average number of funds controlled by the outside management companies), it managed to conclude the 2020 with 10 funds, second only to BlackRock. In 2000, Vanguard controlled more funds than any other management companies. The rate of fund creation, however, has been lower for Vanguard than for BlackRock and State Street. Finally, Fidelity and Charles Schwab appear as the least efficient firms among the top five management companies, although Fidelity experienced a significant bounce up that started in 2015.

We next turn to validate our estimated parameters. Using the estimated vector of parameters θ, we reconstruct the time-series of n_{jt} for each management company $j \in \{0, ..., 5\}$ as implied by the model solution. As a first validation check, we compute the average number of funds introduced in each period and compare it with the corresponding moment in the data. We do this for each asset management company and report the results in the last two columns of Table 3. Our model does a good job in matching the average number of funds created in each period by each of the companies, despite being untargeted in estimation.

In Figure 4 we perform a similar validation exercise, this time comparing the entire model-implied path of fund creation with the one observed in the data. As before, we perform this comparison, separately for each management company. Although we only target the average curvature and the initial and final values of each fund creation path, the model fits closely the observed creation paths for all management companies, perhaps with the exception of Fidelity. The reason why the model finds difficulties in matching Fidelity's fund creation pattern is the convex nature of the observed path. To see this, observe that a low δ generates a concave path where a company introduces more funds earlier without needing to wait for the stock of funds to build up. A large δ instead pushes companies to slowly build up their stock of funds over time, generating a more linear creation path. A convex fund creation path is not consistent with the optimal path in a model with a time-constant single-parameter adjustment cost function. Matching a convex fund creation path is more challenging because it requires more degree of freedom, like for example allowing Fidelity to have a time-varying δ.

The model is also able to closely match the observed average fee charged by Mid and Large Cap passive funds, both in terms of levels and secular decline. Figure 5

in 2009, when BlackRock acquired the Barclays' iShare business. Before the acquisition BlackRock market share was small whereas Barclays was one of the five largest. Another way to interpret this is considering the iShare to be itself a multi-product company and according to our estimate the most efficient one. In practice, although the owner of the iShare business changed, iShare has always been one of the market leaders since the early 2000.

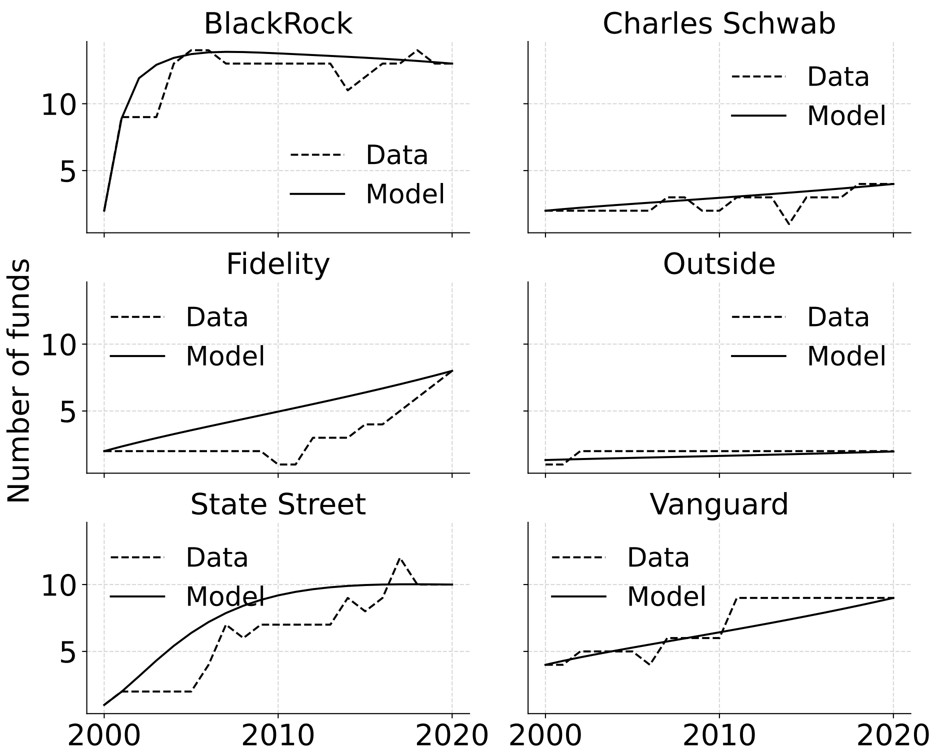

Figure 4: Time-series of the average number of funds operated by the five largest management companies as well as the number of funds operated by the outside management company in model vs data.

compares the asset-weighted fee observed in data against the equilibrium fee implied by the model and estimated using equation (9).

5.3 Counterfactuals and welfare analysis

We now turn to examine the welfare implications of the fund proliferation competitive dynamics. Using the estimated model, we perform a series of counterfactuals to understand how changing the market structure of the passive mutual fund industry impacts household welfare.

For each management company $j \in \{0, .., 5\}$ we fix the initial number of funds n_{j0} at the level observed in 2000, the beginning of our sample. We further fix c_j and δ_j to the estimates obtained and discussed in Section 5.2. Using the calibrated parameters in Table 1, we solve for the model equilibrium assuming it enters the long-run steady state after 20 years of simulations. The model solution allows us to derive the equilibrium path for the number of funds n_{jt} held by each management company, the total number of funds n_t and the fee f_t earned by each management company j.

We construct our baseline welfare measure as

$$W = \sum_{t=0}^{T} \beta^t \log(C_t) + \beta^T \frac{\log(C_T)}{1-\beta} \tag{29}$$

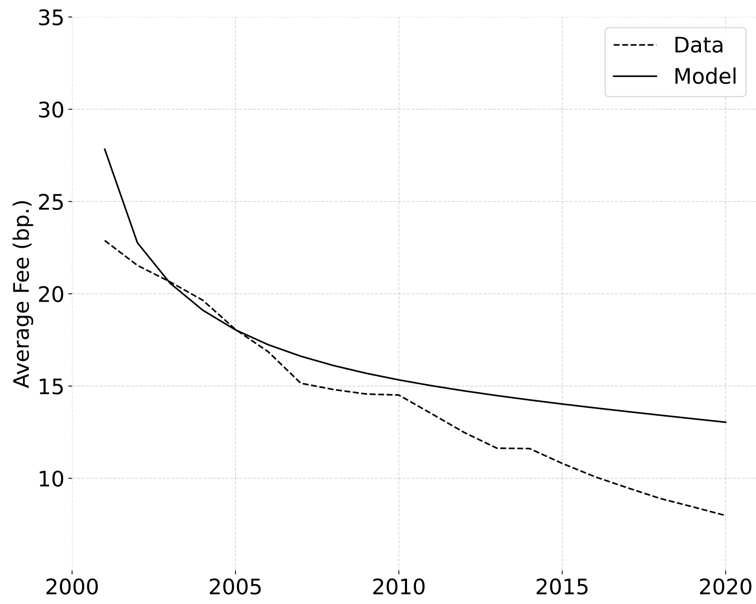

Figure 5: Time-series of the observed value-weighted average fee versus the model implied fee. The asset-weighted fee from data is estimated, for each year, by averaging the expense ratio reported by CRSP for each fund, with weights proportional to lagged total net assets.

where we assume that the equilibrium enters the long-run steady-state at T, with our representative household consuming C_T for $t \geq T$. To obtain a dollar measure of welfare, we scale W by the marginal utility of wealth at $t = 0$, $V'(A_0)$, assuming an initial wealth of \$500 billions of dollars, consistent with the AUM held by the passive industry in 2000.

Given the model solution, we perform a series of counterfactuals to quantify the welfare consequences of removing each management company from the market. To do so, we solve the model after removing each company j, one at a time. For each of the remaining management companies $j' \neq j$, we keep the same initial condition $n_{j'0}$, the same estimates $c_{j'}$ and $\delta_{j'}$, and we compute the terminal condition $n_{j'T}$ implied by the system Euler equations in a steady-state without company j. This procedure allows us to construct the counterfactual equilibrium path for number of funds, the fees, and household welfare that would have prevailed if management company j had not been operational.

Figure 6 presents the results of our counterfactual analysis, with each bar labeled after the management company excluded in the respective counterfactual of interest.

The top two panels depict the change in household welfare relative to the status quo, measured in billions of dollars. Generally, excluding any of the companies results in reduced welfare because the counterfactual scenarios feature higher fees and fewer operating funds. The extent of these losses varies due to differences in production costs among firms, and different responses from competitors when different companies

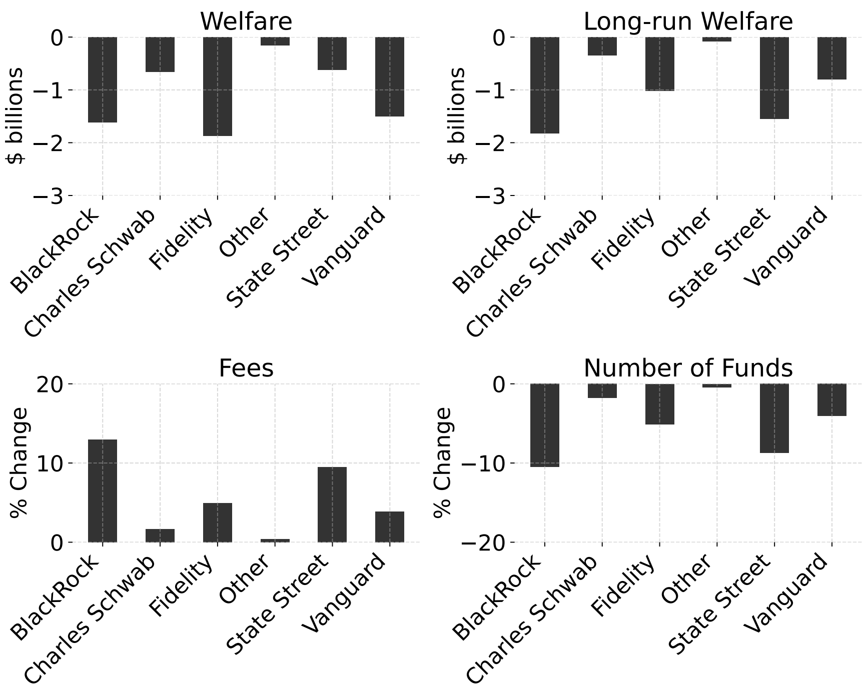

Figure 6: Change in welfare, fees and number of funds in each counterfactual compared to the status quo. Welfare changes are measured in billions of dollars. For the number of funds, we report the percentage change in the average number of funds, where the average is computed over 100 years. For the fees, we report the percentage change in the average fee, where the average is computed over 100 years.

are removed. For example, in the absence of BlackRock, other companies initiate new funds earlier to capture a larger share of household AUM. Despite this incentive, the total number of funds remains lower, in part because the remaining companies cannot match the efficiency of BlackRock's fund creation, and in part because these companies strategically restrict quantities to increase their fee-cost margins. Overall, the resulting welfare loss amounts to 1.6 billions.

Similarly, when State Street, the second most efficient company, is removed, analogous dynamics occur. The remaining competitors create additional funds to capture the AUM previously held by State Street while also increasing their fee-cost margins. The relatively modest welfare loss initially suggests that these companies can match State Street's fund creation pace. However, the more substantial long-run welfare loss indicates that their ability to keep pace is limited to the earlier years, when the number of funds operated by State Street in the status quo is relatively low.[25]

The exclusion of Fidelity or Vanguard also results in considerable welfare losses, ranging between 1.5 and 2 billions. In these scenarios, the long-run losses are notably smaller. Unlike the cases involving BlackRock or State Street, the removal of Fidelity

[25]The welfare in the long-run steady state is computed as $\log(C_T)/(1-\beta)$. To obtain a comparable the dollar measure we divide it by $V'(A_0)$ rather than by $V'(A_T)$. This leads to welfare losses that are conservative because the marginal utility of wealth in the long-run steady state is lower.

or Vanguard prompts a slower response in fund creation from the remaining companies. Compared to the status quo, this results in fewer funds and higher fees, particularly in the earlier years, which carry more weight in the welfare calculations. Conversely, only the steady state number of funds matters for welfare in the long-run. In this case, the welfare loss from removing Fidelity or Vanguard is smaller compared to when BlackRock or State Street are removed because the former two operate fewer funds in the status quo steady state.

The two bottom panels present the percentage changes in fees and the number of funds. In all counterfactual scenarios, fees are higher and the number of operating funds is lower, which is expected given the reduced competition from fewer companies. The magnitudes of these changes reflect the cost efficiency of the company removed from the market, with the counterfactual scenarios involving the removal of BlackRock or State Street leading to the largest increases in fees and the most significant decreases in the number of operating funds. Both the average fee and the average number of operating funds are computed over an horizon of 100 years. Since the model enters the steady state after 20 years of simulations, the steady state levels of fees and number of funds account for 80% of observations in their respective counterfactual time series. This implies that counterfactual scenarios with larger increases in fees and greater reductions in the number of funds lead to larger long-run welfare losses.

Overall, the results so far suggest that removing any asset management company from the market reduces household welfare. On the one hand, part of this decline in welfare can be attributed to reduced competition. An oligopolist facing less competitive pressure optimally restricts the quantity produced to capture more consumer surplus. On the other hand, the heterogeneity in welfare losses suggests that these may also depend on the cost efficiency of the company removed from the market. When an efficient firm is removed, it may be too costly for the remaining competitors to replicate the production levels of the efficient company, which further lowers consumer surplus.

To quantify the importance of these two channels, we consider a counterfactual scenario where BlackRock is removed from the market and replaced with a management company whose cost structure is identical to Charles Schwab's. Since we estimate Charles Schwab to be less efficient than BlackRock, household welfare in this counterfactual is expected to be lower than in the status quo. However, the presence of a "second" Charles Schwab increases the competitive pressure, implying that the welfare loss should be less severe compared to a scenario where BlackRock is removed without replacement. The relevant question is: how much lower? Figure 7 shows that the welfare loss when BlackRock is replaced by Schwab amounts to more than half of the loss when BlackRock is not replaced. According to our baseline welfare measure, the loss amounts to 75% of the loss when BlackRock is not replaced, whereas in terms of long-run welfare, the loss amounts to about 60% of the loss when BlackRock is not

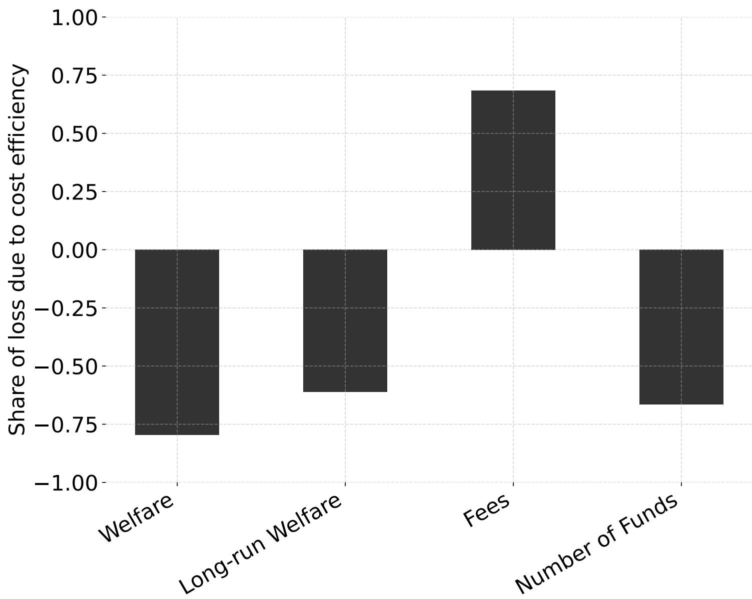

Figure 7: Welfare, long-run welfare, fees and number of funds in a counterfactual where BlackRock is replaced by a firm identical to Charles Schwab. The change of each variable is scaled by the magnitude of the corresponding change in a counterfactual where BlackRock is removed.

replaced. Overall, this exercise suggests that cost efficiencies play a major role in determining market and welfare outcomes, implying that the high level of concentration observed in the US passive mutual fund industry is likely reflective of cost efficiencies rather than market power.

5.4 Asset pricing implications

We now go back to the steady-state equilibrium that we are able to characterize analytically and, within this equilibrium, we use the estimates from Section 5.2 to characterize the asset pricing implications of fund proliferation. In particular, we estimate that a 1% increase in the steady-state wealth A, increases the valuation of the equity index by 1.4%. We refer to it as the long-run (or steady-state) multiplier of household wealth on the equity index price and denote it by ξ.

We start with the following proposition that provides a closed-form expression for the multiplier ξ in the steady-state of the model.

Proposition 2 *Under the conditions detailed in Section 3.2, the steady-state multiplier ξ is given by*

$$\xi \equiv \frac{dP}{dA}\frac{A}{P} = \left(1 - \frac{1}{n(1+n)}\frac{1+\zeta(n)}{\zeta'(n)}\right) \tag{30}$$

with $\zeta(n) > 0$ and $\zeta'(n) < 0$ for $n > 1$.

Parameter	Description	Value
c	Estimated initiation cost	0.410
P	Steady-state index price	78.98
A	Steady-state financial wealth	83.93
$\frac{D}{P}$	Steady-state dividend yield	0.022
n	Steady-state total number of funds	48.32
ξ	Steady-state multiplier	1.383

Table 4: Estimated multiplier

Proof: See Appendix A.

We use the estimates for $\{c_j\}_{j=0}^{5}$ derived and discussed in Section 5.2 to compute $c = \sum_{j=0}^{5} c_j$. Moreover, we use equations (19), (20) and (21) to solve for the steady-state wealth A, index price P and number of funds n. Thus, we have all the inputs needed to produce an estimate for the steady-state multiplier ξ using equation (30). Details about the inputs used to estimate ξ are provided in Table 4. For completeness and to ease comparison, we also report parameter values that have been already introduced but enter the expression of ξ.

Our estimated steady-state multiplier of 1.4 was untargeted, yet close to the range of estimates reported in the literature. Among others, Gabaix and Koijen (2021) show that previous estimates range approximately between 1.5 and 6.5. Our model generates a multiplier larger than one because management companies product entry decisions amplify the impact of any shock that shifts household asset demand. This amplification effect increases the baseline multiplier by 40%. To see this, observe that, if asset management firms were to keep their number of funds constant, a 1% increase in household wealth A would increase P by 1%, implying a baseline long-run multiplier of 1. Allowing firms to adjust their number of funds, increases the multiplier to 1.4. This happens because firms increase their number of funds, which increases competition, reduces fees, and in turn attracts more asset demand from our representative household.

Although we defined the multiplier directly in terms of changes to household wealth A, in our model wealth is endogenous and depends on model primitives. Therefore, we perform a comparative static exercise, where we vary two primitives, the dividend yield d and fund initiation costs c, and study how wealth, price, multiplier and fees vary in the steady-state.

We start from varying c in Figure 8 and we mark with a circle the estimates we obtain in our model. The top left panel shows the steady state fee as function of c. Not surprisingly, the equilibrium fee increases with the initiation costs. From the

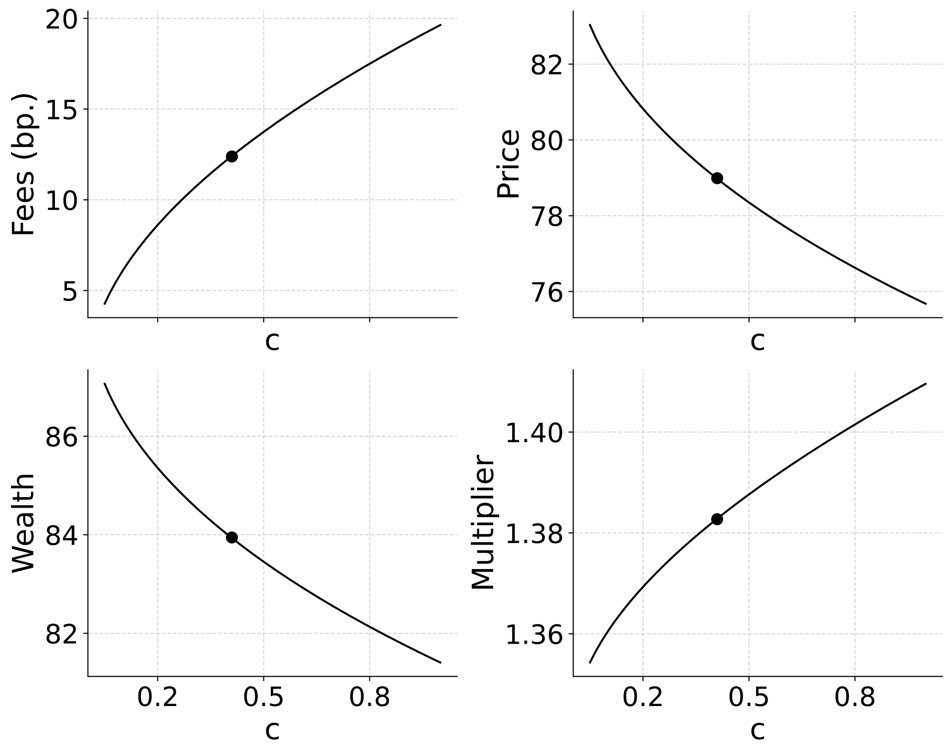

Figure 8: Equilibrium comparative static with respect to initiation costs c.

perspective of our model, higher costs will push management companies to supply less funds. Lower competition in the mutual fund sector would then endogenously lead to higher fees. The top right panel looks at the equilibrium index price P and shows that as initiation costs rise, the equilibrium index price decreases. From the top left panel we know that higher initiation costs are passed-through investors via higher fees which in turn reduce household demand for the equity index. Finally, via market-clearing, lower demand for the equity index leads to a lower equilibrium price. Higher initiation costs also lead to lower equilibrium wealth A as shown in the bottom left panel. Once again, the mechanism for this outcome is driven by the competitive incentives in the mutual fund sector. Higher costs lead to lower fund creation and higher fees resulting in redistribution of wealth from household to mutual funds and management companies.

Lastly, the bottom right panel shows how the multiplier ξ varies with initiation costs. As initiation costs rise, the steady-state multiplier also increases. When introducing a new fund becomes more expensive, fewer funds compete for household assets, thereby raising the marginal benefit of introducing new funds to absorb shocks in household asset demand. Fund proliferation incentives decline as the number of competing funds increases, since revenues from fees diminish with more funds in the market. Consequently, the price-impact amplification, driven by management companies' decisions on product entry, is more pronounced when the costs of introducing new funds are higher.

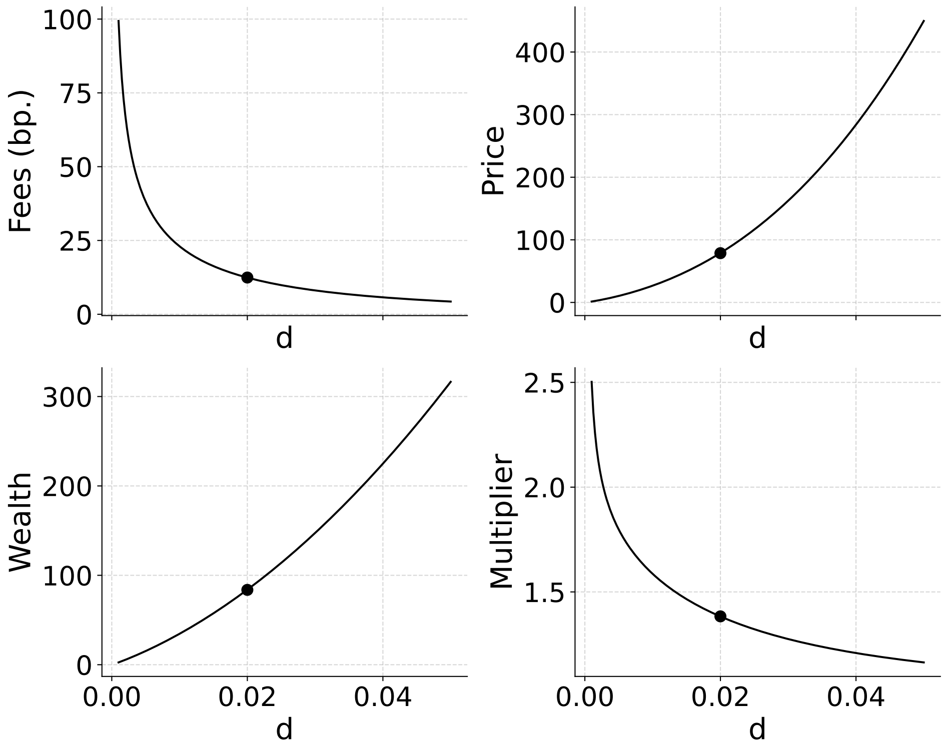

Figure 9: Equilibrium comparative static with respect to dividend yield d.

Next, in Figure 9 we consider the comparative static of the same variables with respect to the dividend yield d. As before, the top left panel shows the comparative static for the equilibrium fees. In this case, a higher dividend leads to a decline in fees because a higher d increases the rate at which wealth accumulates. To accommodate the increase in asset demand, management companies create more funds. The stronger competition in the mutual fund sector ultimately leads to lower fees. Turning to the comparative static for P (top right panel) and A (bottom left), we notice that, differently from initiation costs, d affects the equilibrium price and wealth both directly and indirectly through the equilibrium number of funds n. Starting from the top right panel, we see that the index price increases with d. Indeed, a higher dividend increases the rate at which household wealth accumulates which in turn increases household demand for the equity index. Moreover, management companies accommodate the increase in demand by creating additional funds, leading to a decrease in fees and to a further increase in household demand. Both the direct effect on wealth as well as the indirect effect through n contribute to increasing household demand, ultimately leading to an increase in the index price through market clearing.

Turning to the bottom left panel, we can see that the equilibrium wealth increases with d. The dividend affects the equilibrium wealth directly because it mechanically increases the rate at which wealth accumulates and indirectly through fund initiation. In other words, higher d directly increases wealth accumulation rate and indirectly prompts management companies to increase the number of funds, given the increase in demand. Stronger competition in the mutual fund sector leads to a decline in fees which further accelerates wealth accumulation. This indirect effect is summarized by the term $\frac{1}{1+\zeta(n)}$ in equation (19). Because $\frac{1}{1+\zeta(n)}$ is an increasing function of n, it contributes to amplify direct increase in d.

Finally, the bottom right panel describes how the steady-state multiplier varies with d. Notice that the steady-state multiplier depends on d only indirectly, through n. Consider first the case of small d. In this case, household demand for the equity index is relatively low with the consequence that management companies are constrained to manage a relatively limited menu of funds. It follows however that any increase in household wealth is particularly attractive for management companies and they respond to an increase in A by creating a larger number of funds compared to the case of high d. The larger response of management companies in turn leads to a larger decline in fee, a larger increase in household demand and, ultimately, to a larger increase in the equity index price via market clearing.

6 Conclusions

This paper develops an equilibrium model of the passive mutual fund industry to study the welfare and asset pricing implications of fund proliferation. We find that fund proliferation patterns among large asset managers are driven by scale economies that allow them to introduce new funds at lower costs. While these dynamics contribute to increasing market concentration, they also benefit household investors by reducing investment costs. Through counterfactual simulations, we show that the exclusion of the most efficient asset managers would lead to sizable welfare losses for investors, driven primarily by the reduction in cost efficiencies rather than reduced market competition.

Our analysis further indicates that the observed market structure, characterized by high concentration among a few dominant players, reflects these firms' cost advantages rather than market power distortions. By estimating the model on data from passive equity funds, we capture the entry patterns of new funds among the industry's largest players and quantify their welfare implications. For instance, the removal of an efficient market leader from the industry leads to welfare losses of nearly $2 billions dollars, highlighting the efficiency benefits that large asset managers provide in this market.

Beyond investor welfare, fund proliferation has implications for asset prices. By endogenizing asset prices within the model, we demonstrate that the dynamic entry patterns of asset managers can amplify the price impact of passive investors, with our estimates suggesting a potential 40% increase in price impact in the long-run steady state. This finding connects product entry dynamics within the passive mutual fund industry to broader market effects, revealing the extent to which industry growth and investor demand influence equity valuations.

References

Abis, S. and Lines, A. (2022), 'Do mutual funds keep their promises?', SSRN working paper.

Aguirregabiria, V., Collard-Wexler, A. and Ryan, S. (2021), 'Dynamic games in empirical industrial organization', NBER working paper.

Anton, M., Ederer, F., Gine, M. and Schmalz, M. (2017), 'Common ownership, competition, and top management incentives', *Journal of Political Economy* 81(3), 669–728.

Azar, J., Schmalz, M. and Tecu, I. (2018), 'Anticompetitive effects of common ownership', *Journal of Finance* 73(4), 1513–1565.

Azar, J. and Vives, X. (2021), 'General equilibrium oligopoly and ownership structure', *Econometrica* 89(3), 999–1048.

Backus, M., Conlon, C. and Sinkinson, M. (2021), 'Common ownership and competition in the ready-to-eat cereal industry', NBER working paper.

Bai, J., Philippon, T. and Savov, A. (2016), 'Have financial markets become more informative', *Journal of Financial Economics* 122, 625–654.

Baruch, S. and Zhang, X. (2022), 'The distortion in prices due to passive investing', *Management Science* forthcoming.

Basak, S. and Pavlova, A. (2013), 'Asset prices and institutional investors', *American Economic Review* 103(5), 1728–1758.

Ben-David, I., Franzoni, F., Kim, B. and Moussawi, R. (2022), 'Competition for attention in the etf space', *Review of Finacial Studies* forthcoming.

Berk, J., Binsbergen, J. and Liu, B. (2017), 'Matching capital and labor', *Journal of Finance* 72(6), 500–523.

Berk, J. and Green, R. (2004), 'Mutual fund flows and performance in rational markets', *Journal of Political Economy* 112(6), 1269–1295.

Betermier, S., Schumacher, D. and Shahrad, A. (2022), 'Menu proliferation and entry deterrence', *Review of Asset Pricing Studies* forthcoming.

Bhattacharya, U., Lee, J. and Pool, V. (2013), 'Conflicting family values in mutual fund families', *Journal of Finance* 68(1), 173–200.

Bond, P. and García, D. (2021), 'The equilibrium consequences of indexing', *The Review of Financial Studies* 35(7), 3175–3230.

Campbell, J. and Viceira, L. (2002), ‘Strategic asset allocation: Portfolio choice for long-term investors’, Oxford University Press.

Chevalier, J. and Ellison, G. (1997), ‘Risk taking by mutual funds as a response to incentives’, *Journal of Political Economy* 105(6), 1167–1200.

Coles, J., Heath, D. and Ringgenberg, M. (2022), ‘On index investing’, *Journal of Financial Economics* .

Ericson, R. and Pakes, A. (1995), ‘Markov-perfect industry dynamics: A framework for empirical work’, *Review of Economics Studies* 62(1), 53–82.

Farboodi, M., Matray, A., Veldkamp, L. and Venkateswaran, V. (2021), ‘Where has all the data gone?’, *Review of Financial Studies* 35(7), 3101–3138.

Gabaix, X. and Koijen, R. (2021), ‘In search of the origins of financial fluctuations: the inelastic markets hypothesis’, NBER working paper.

Gaspar, J., Massa, M. and Matos, P. (2006), ‘Favoritism in mutual fund families? evidence on strategic cross-fund subsidization’, *Journal of Finance* 61(1), 73–104.

Haddad, V., Huebner, P. and Loualiche, E. (2022), ‘How competitive is the stock market? theory, evidence from portfolios, and implications for the rise of passive investing’.

Hortaçsu, A. and Syverson, C. (2004), ‘Product differentiation, search costs, and competition in the mutual fund industry: A case study of s&p 500 index funds.’, *Quarterly Journal of Economics* 119(2), 403–456.

Kacperczyk, M., Nosal, J. and Sundaresan, S. (2022), ‘Market power and price informativeness’, *Review of Economic Studies* .

Khorana, A. and Servaes, H. (1999), ‘The determinants of mutual fund starts’, *The Review of Financial Studies* 12(5), 1043–1074.

Koijen, R. and Yogo, M. (2019), ‘A demand system approach to asset pricing’, *Journal of Political Economy* 127(4), 1475–1515.

Kostovetsky, L. and Warner, J. (2020), ‘Measuring innovation and product differentiation: Evidence from mutual funds’, *Journal of Finance* 75(2), 779–823.

Malikov, G. (2021), ‘Information, partecipation and passive investing’, working paper.

Maskin, E. and Tirole, J. (1988), ‘A theory of dynamic oligopoly, i: Overview and quantity competition with large fixed costs’, *Econometrica* 56(3), 549–599.

Massa, M. (2003), ‘How do family strategies affect fund performance? when performance-maximization is not the only game in town’, *Journal of Financial Economics* 67, 249–304.

Pavlova, A. and Sikorskaya, T. (2022), ‘Benchmarking intensity’, *Review of Financial Studies* .

Petajisto, A. (2009), ‘Why do demand curves for stocks slope down?’, *Journal of Financial and Quantitative Analysis* 44(5), 1013–1044.

Posner, E., Scott Morton, F. and Weyl, G. (2017), ‘A proposal to limit the anticompetitive power of institutional investors’, *Antitrust Law Journal* 81(3), 669–728.

Roussanov, N., Ruan, H. and Wei, Y. (2021), ‘Marketing mutual funds’, *Review of Financial Studies* 34, 3045–3094.

Sammon, M. (2022), ‘Passive ownership and price informativeness’, SSRN working paper.

Schmalz, M. and Zame, W. (2023), ‘Index funds, asset prices, and the welfare of investors’, SSRN working paper.

Sirri, E. and Tufano, P. (1998), ‘Costly search and mutual fund flows’, *Journal of Finance* 53(5), 1589–1622.

Weintraub, G., Benkard, L. and Van Roy, B. (2008), ‘Markov perfect industry dynamics with many firms’, *Econometrica* 76(6), 1375–1411.

Ørpetveit, A. (2021), ‘Competition and fund family product development’, SSRN working paper.

A Derivations and Proofs

Derivation of HH portfolio allocation. Under the assumption of log utility, it is easy to verify that consuming a constant fraction of wealth is optimal for HH. In particular, from the Euler equation (4) and the budget constraint, one can verify that $C_t = (1-\beta)A_t$ is the optimal consumption in each period.

To derive the optimal portfolio allocation w_t, denote the log consumption and log wealth by $c_t \equiv \log(C_t)$ and $a_t \equiv \log(A_t)$ respectively so that $c_t = \log(1-\beta) + a_t$. The budget constraint in logs is then

$$\begin{aligned}\Delta a_{t+1} &= \log(1 + w_t R_{t+1}) + \log(\beta) &(31)\\ &\approx w_t r_{t+1} + \frac{1}{2} w_t(1-w_t)\sigma_t^2 + \log(\beta) &(32)\end{aligned}$$

where $\Delta a_{t+1} \equiv a_{t+1} - a_t$, $r_{t+1} \equiv \log(1+R_{t+1})$ and the second line follows the log-linear approximation of log portfolio returns in Campbell and Viceira (2002). Next, note that under the assumption that r_{t+1} is a Gaussian stationary process, we can take logs on both sides of (4) to obtain

$$\mathbb{E}_t[\Delta c_{t+1}] = \log(\beta) + \rho_t - f_t + \frac{1}{2}\sigma_t^2 + \frac{1}{2}\mathbb{V}_t[\Delta c_{t+1}] - Cov_t[\Delta c_{t+1}, r_{t+1}].$$

Moreover, because we normalized the return on the risk-free to zero, the above expression boils down to

$$\rho_t - f_t + \frac{1}{2}\sigma_t^2 = Cov_t[\Delta c_{t+1}, r_{t+1}]. \tag{33}$$

Lastly, approximation (32) and the constant consumption-wealth ratio imply that we can solve for w_t in (33) to obtain

$$w_t = \frac{\rho_t + \sigma_t^2/2 - f_t}{\sigma_t^2}. \tag{34}$$

Proof of Proposition 1. For given π_t, company j's Euler equation implied by problem (12) is given by

$$\begin{aligned}&\frac{\pi_t}{(1+n_t)^2} + \delta_j \beta \left(\frac{n_{jt+1} - n_{jt}}{n_{jt}}\right)\left[\frac{n_{jt+1}}{n_{jt}} + 1\right] = \\ &\frac{2\pi_t n_{jt}}{(1+n_t)^3} + (1-\beta)c_j + 2\delta_j \left(\frac{n_{jt} - n_{jt-1}}{n_{jt-1}}\right). &(35)\end{aligned}$$

If a steady-state $\{(n_j)_{j=1}^M, P, A\}$ exists, then for given P and A, n_j must satisfy

(35) which boils down to

$$n_j = \frac{1+n}{2} - \frac{(1-\beta)}{2\pi} c_j (1+n)^3 \tag{36}$$

where $\pi = \beta A \frac{\mu^2}{\sigma^2}$. Summing across j, the steady state total number of funds n in the market solves

$$\beta \frac{\mu^2}{\sigma^2} A(M + n(M-2)) = (1-\beta)(1+n)^3 c. \tag{37}$$

Moreover, given the steady state fee

$$f = \frac{\mu}{n+1} \tag{38}$$

we can rewrite the equations that pin down the steady state P and A as

$$P = \frac{\mu n}{\sigma^2(1+n)} \beta A \tag{39}$$

$$A = \beta A + D - \frac{\mu}{1+n} P \tag{40}$$

where without loss of generality we normalized $\bar{Q} = 1$. From (39) and (40) we can solve for A and P as function of n and other parameters

$$P = \left(\frac{\frac{\mu}{\sigma^2} \frac{\beta}{1-\beta} \frac{n}{1+n}}{1 + \zeta(n)} \right) D \tag{41}$$

$$A = \left(\frac{1}{1+\zeta(n)} \right) \frac{D}{1-\beta} \tag{42}$$

where

$$\zeta(n) \equiv \frac{\mu^2}{\sigma^2} \frac{\beta}{1-\beta} \frac{n}{(1+n)^2}. \tag{43}$$

The steady-state n can then be found by substituting (42) into (37)

$$\tilde{\pi} \left(\frac{1}{1+\zeta(n)} \right) (M + n(M-2)) = (1-\beta)(1+n)^3 c \tag{44}$$

which can be rearranged more conveniently as

$$\tilde{\pi} \left(M + n(M-2)\right) = (1-\beta)c \left[(1+n)^3 + \frac{\mu^2}{\sigma^2} \frac{\beta}{1-\beta} n(1+n) \right] \tag{45}$$

with $\tilde{\pi} \equiv \frac{D}{1-\beta} \frac{\beta \mu^2}{\sigma^2}$.

To show existence and uniqueness, note that at $n = 0$, the LHS of (45) is greater than its RHS provided $\tilde{\pi}M > (1-\beta)c$. Next, note that the LHS increases in n at a constant rate, whereas the RHS increases in n at an increasing rate. Thus, there will be one and only one $n > 0$ at which (45) is satisfied ■

Proof of Proposition 2. Consider an increase in fund initiation costs c and note that the only way this change in costs affects the equilibrium wealth A and asset prices P is through the effect on n. Differentiating (41) and (39) with respect to n gives

$$\frac{dA}{dn} = -\frac{\zeta'(n)}{(1+\zeta(n))^2}\frac{D}{1-\beta}$$

$$\frac{dP}{dn} = \frac{\mu}{\sigma^2}\frac{n}{1+n}\beta\frac{dA}{dn} + \frac{1}{(1+n)^2}\frac{\mu}{\sigma^2}\left(\frac{1}{1+\zeta(n)}\right)\frac{\beta}{1-\beta}D.$$

Next, take the ratio of the two expressions above and note that

$$\frac{P}{A} = \frac{\mu}{\sigma^2}\beta\frac{n}{1+n} \tag{46}$$

we obtain

$$\frac{dP}{dA} = \frac{P}{A}\left(1 - \frac{1}{n(1+n)}\frac{1+\zeta(n)}{\zeta'(n)}\right) \tag{47}$$

with

$$\zeta'(n) = \frac{\mu^2}{\sigma^2}\frac{\beta}{1-\beta}\frac{1-n}{(1+n)^3} \tag{48}$$

which is negative for $n > 1$ ■

B Figures

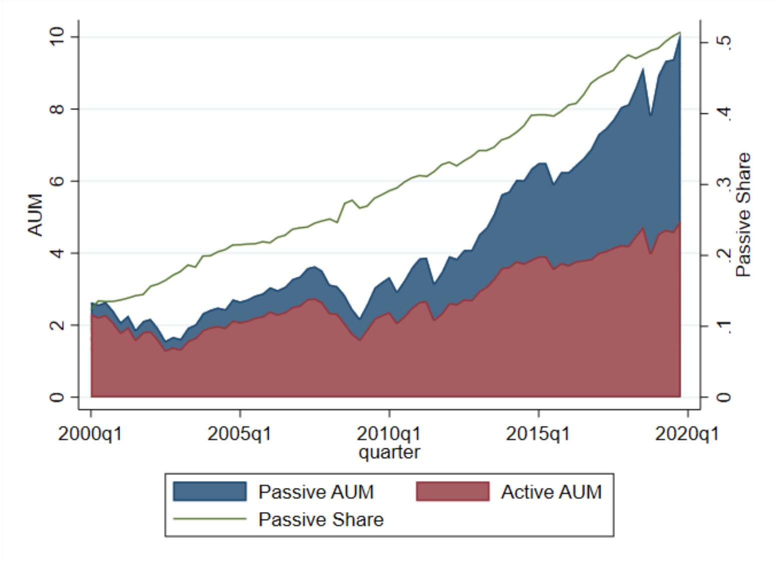

Figure B.1: Left Axis: AUM in trillions of $ for both passive and active equity industry. Right Axis: Share of AUM held in the passive industry.

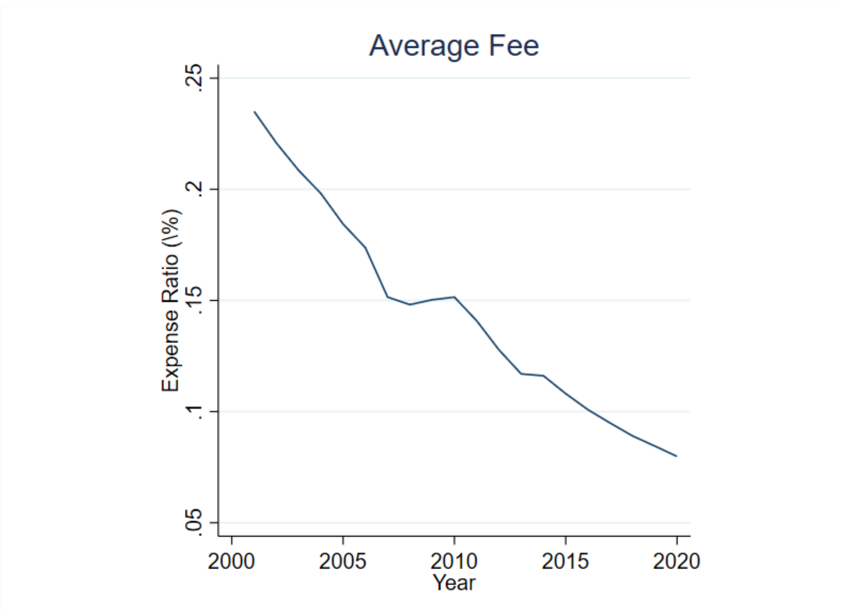

Figure B.2: Average asset-weighted fee across passive funds. Funds with different share classes count as a single fund.

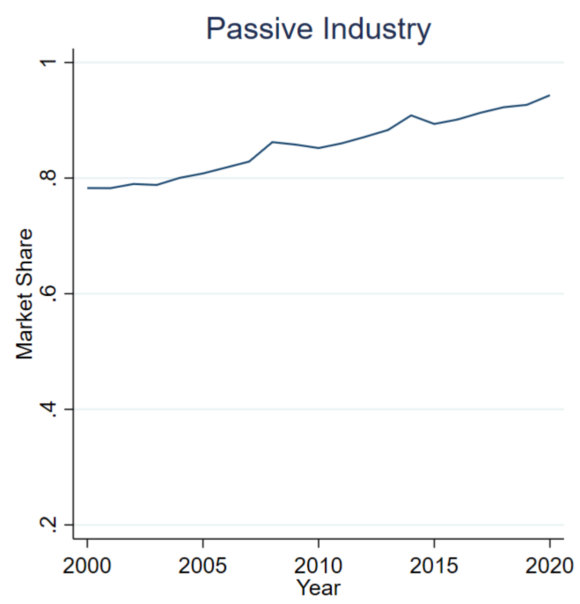

Figure B.3: Market share of the five biggest investment companies in the passive industry. Market shares are in terms of end-of-year assets under management (AUM).

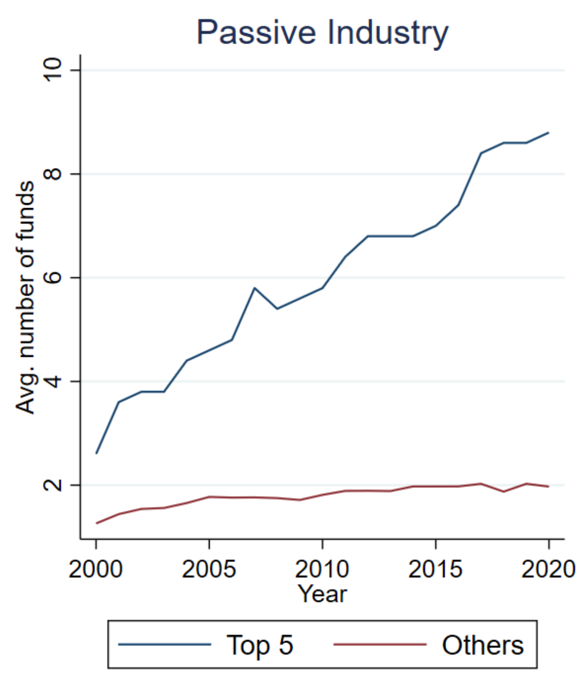

Figure B.4: Average number of passive funds per management company. Funds with different share classes count as a single fund.

C Tables

	Obs.	Mean	Std. Dev	p5	p25	p50	p75	p95
AUM (bln.)	16552	2.00	13.41	0.02	0.08	0.28	0.96	5.76
Gross return (%)	16159	0.89	1.79	-2.52	-0.07	1.09	2.04	3.27
Expense Ratio (%)	16160	1.06	0.48	0.19	0.83	1.11	1.35	1.83
Passive	16552	0.22	0.42	0.00	0.00	0.00	0.00	1.00
Alpha (%)	13552	0.04	0.59	-0.47	-0.12	0.02	0.19	0.54
Market beta	13552	0.97	0.21	0.77	0.91	0.98	1.03	1.18
Market share (%)	16552	1.80	4.45	0.01	0.08	0.33	1.07	10.28
# of funds per company	16552	3.79	3.31	1.00	1.00	3.00	5.00	11.00

Table C.1: Summary statistics of the full sample. All variables are winsorized at 1% and 99% levels. Returns and alpha are monthly. The expense ratio is annual.

	Obs.	Mean	Std. dev.	p5	p25	p50	p75	p95
AUM (bln.)	3697	5.70	27.72	0.02	0.09	0.42	1.89	18.10
Gross return (%)	3620	0.94	1.75	-2.12	-0.02	1.11	2.04	3.12
Expense Ratio	3621	0.48	0.42	0.08	0.20	0.35	0.60	1.57
Alpha (%)	3112	0.04	0.51	-0.31	-0.07	0.00	0.09	0.37
Market beta	3112	0.97	0.15	0.83	0.94	0.98	1.01	1.09
Market share (%)	3697	3.88	7.59	0.01	0.10	0.47	3.29	20.11
# of funds per company	3697	4.48	3.95	1.00	1.00	3.00	6.00	13.00

Table C.2: Summary statistics for the passive sample. All variables are winsorized at 1% and 99% levels. Returns, alpha and expense ratios are monthly. The expense ratio is annual.

Company Code	Ticker	Fund Name	Beta	SMB	HML	MOM	Alpha	Gross Monthly Returns	Expense Ratio
VAN	VFIAX	Vanguard 500 Index Fund	0.9841	-0.1190	-0.0083	0.0002	-0.0001	-0.0028	0.0006
VAN	VINIX	Vanguard Institutional Index Fund	0.9864	-0.1196	-0.0082	0.0001	-0.0001	-0.0028	0.0005
SSB	SPY	SPDR S&P 500 ETF Trust	0.9863	-0.1222	-0.0057	0.0029	0.0000	-0.0028	0.0009
SSB	SSEYX	State Street Equity 500 Index II Portfolio	0.9830	-0.1251	-0.0141	0.0018	0.0003	-0.0028	0.0005
SSB	SVSPX	State Street S&P 500 Index Fund	0.9866	-0.1215	-0.0072	-0.0001	-0.0001	-0.0029	0.0016
SSB	SSSYX	State Street Equity 500 Index Fund	0.9889	-0.1157	-0.0066	0.0028	-0.0001	-0.0028	0.0013
BLK	IVV	iShares Core S&P 500 ETF	0.9864	-0.1200	-0.0081	0.0003	-0.0001	-0.0028	0.0005
BLK	WFSPX	iShares S&P 500 Index Fund	0.9858	-0.1191	-0.0079	-0.0003	-0.0001	-0.0028	0.0012
FID	FXAIX	Fidelity 500 Index Fund	0.9864	-0.1199	-0.0086	-0.0001	-0.0001	-0.0028	0.0005
CSW	SWPPX	Schwab S&P 500 Index Fund	0.9845	-0.1193	-0.0095	0.0003	-0.0001	-0.0028	0.0005
PRI	PREIX	T Rowe Price Equity Index 500 Fund	0.9855	-0.1194	-0.0083	-0.0002	-0.0001	-0.0028	0.0019
DFA	DFUSX	US Large Company Portfolio	0.9864	-0.1173	-0.0109	0.0000	-0.0001	-0.0028	0.0008
NTC	NOSIX	Stock Index Fund	0.9858	-0.1177	-0.0089	-0.0009	-0.0001	-0.0028	0.0010
USA	USPRX	S&P 500 Index Fund	0.9860	-0.1181	-0.0085	0.0000	-0.0001	-0.0028	0.0020
PGI	PLFIX	LargeCap S&P 500 Index Fund	0.9845	-0.1187	-0.0091	-0.0002	-0.0001	-0.0028	0.0027
DRY	DSPIX	Dreyfus Institutional S&P 500 Stock Index Fund	0.9857	-0.1206	-0.0063	0.0013	-0.0001	-0.0028	0.0028
DRY	PEOPX	Dreyfus S&P 500 Index Fund	0.9873	-0.1200	-0.0075	0.0009	-0.0001	-0.0028	0.0050
TIA	TISPX	S&P 500 Index Fund	0.9854	-0.1202	-0.0072	-0.0004	-0.0001	-0.0028	0.0011
SEI	SPINX	S&P 500 Index Fund	0.9853	-0.1167	-0.0055	0.0023	-0.0001	-0.0028	0.0005
SEI	SSPIX	S&P 500 Index Fund	0.9856	-0.1192	-0.0085	0.0003	-0.0001	-0.0028	0.0028
JPM	OGFAX	JPMorgan Equity Index Fund	0.9862	-0.1202	-0.0085	0.0005	-0.0001	-0.0028	0.0017
LBR	NINDX	Columbia Large Cap Index Fund	0.9887	-0.1206	-0.0081	0.0006	-0.0001	-0.0029	0.0026
GWC	MXVIX	Great-West S&P 500 Index Fund	1.0046	0.3668	0.2179	0.0117	0.0031	-0.0033	0.0040
MAS	MMIZX	MM S&P 500 Index Fund	0.9880	-0.1200	-0.0083	0.0001	-0.0001	-0.0028	0.0039
NFS	GRMIX	Nationwide S&P 500 Index Fund	0.9863	-0.1219	-0.0089	-0.0013	-0.0001	-0.0028	0.0030
DWS	SCPIX	DWS S&P 500 Index Fund	0.9792	-0.1191	-0.0122	-0.0001	0.0000	-0.0025	0.0045
DWS	BTIEX	DWS Equity 500 Index Fund	0.9790	-0.1204	-0.0109	0.0000	0.0000	-0.0025	0.0027
WFB	WFILX	Wells Fargo Index Fund	0.9864	-0.1196	-0.0085	0.0003	-0.0001	-0.0028	0.0038
AIM	SPIAX	Invesco S&P 500 Index Fund	0.9851	-0.1187	-0.0071	0.0008	-0.0001	-0.0028	0.0072
ABF	GEQYX	Equity Index Fund	0.9904	-0.1039	-0.0027	-0.0020	0.0000	-0.0026	0.0012

Table C.3: Top 30 passive funds in the Large Cap sector.

Company Code	Ticker	Fund Name	Beta	SMB	HML	MOM	Alpha	Gross Monthly Returns	Expense Ratio
VAN	VIMAX	Vanguard Mid-Cap Index Fund	0.9266	0.1544	-0.1520	-0.0888	-0.0016	-0.0070	0.0005
VAN	VEXAX	Vanguard Extended Market Index Fund	0.9793	0.5387	-0.0685	0.0017	-0.0010	-0.0068	0.0006
VAN	VOE	Vanguard Mid-Cap Value Index Fund	0.9127	0.0971	0.0370	-0.1222	-0.0015	-0.0100	0.0007
VAN	VMGMX	Vanguard Mid-Cap Growth Index Fund	0.9390	0.2126	-0.3615	-0.0567	-0.0017	-0.0036	0.0007
VAN	VSPMX	Vanguard S&P Mid-Cap 400 Index Fund	0.9550	0.4006	0.0800	0.0367	-0.0006	-0.0085	0.0010
VAN	IVOG	Vanguard S&P Mid-Cap 400 Growth Index Fund	0.9667	0.3504	-0.0314	0.1663	-0.0008	-0.0077	0.0015
VAN	IVOV	Vanguard S&P Mid-Cap 400 Value Index Fund	0.9408	0.4493	0.1865	-0.1036	-0.0005	-0.0093	0.0015
BLK	IJH	iShares Core S&P Mid-Cap ETF	0.9623	0.3957	0.0776	0.0412	-0.0005	-0.0084	0.0008
BLK	IWR	iShares Russell Mid-Cap ETF	0.9243	0.1976	-0.0896	-0.0579	-0.0014	-0.0068	0.0019
BLK	IWS	iShares Russell Mid-Cap Value ETF	0.8752	0.1899	0.0787	-0.0871	-0.0016	-0.0099	0.0024
BLK	IWP	iShares Russell Mid-Cap Growth ETF	0.9805	0.2031	-0.2968	-0.0121	-0.0009	-0.0028	0.0024
BLK	IJK	iShares S&P Mid-Cap 400 Growth ETF	0.9685	0.3477	-0.0329	0.1651	-0.0010	-0.0079	0.0024
BLK	IJJ	iShares S&P Mid-Cap 400 Value ETF	0.9413	0.4490	0.1859	-0.1039	-0.0005	-0.0093	0.0025
BLK	BRMKX	iShares Russell Mid-Cap Index Fund	0.9267	0.1785	-0.0932	-0.1354	-0.0017	-0.0068	0.0015
BLK	JKG	iShares Morningstar Mid-Cap ETF	0.9659	0.1216	-0.0766	-0.0828	-0.0026	-0.0099	0.0025
BLK	JKI	iShares Morningstar Mid-Cap Value ETF	0.8690	0.1603	0.2226	-0.1096	-0.0012	-0.0101	0.0030
BLK	JKH	iShares Morningstar Mid-Cap Growth ETF	0.9811	0.2746	-0.3795	-0.0104	-0.0012	-0.0015	0.0030
BLK	BSMKX	iShares Russell Small/Mid-Cap Index Fund	1.0170	0.5240	0.0045	-0.0239	-0.0015	-0.0075	0.0013
BLK	SMMD	iShares Russell 2500 ETF	1.1511	0.0000	0.0000	0.0000	-0.0018	-0.0452	0.0006
FID	FSMAX	Fidelity Extended Market Index Fund	0.9792	0.5365	-0.0687	0.0034	-0.0010	-0.0069	0.0005
FID	FSMDX	Fidelity Mid Cap Index Fund	0.9233	0.1932	-0.0919	-0.0591	-0.0013	-0.0069	0.0005
FID	FZFLX	Fidelity SAI Small-Mid Cap 500 Index Fund	0.9554	0.3259	-0.0766	-0.0718	-0.0017	-0.0067	0.0014
SSB	MDY	SPDR S&P MidCap 400 ETF	0.9527	0.3999	0.0794	0.0363	-0.0006	-0.0085	0.0024
SSB	MDYG	SPDR S&P 400 Mid Cap Growth ETF	1.0514	0.4881	0.1740	0.0753	0.0000	-0.0077	0.0015
SSB	SPMD	SPDR Portfolio S&P 400 Mid Cap ETF	1.0051	0.5495	0.0771	0.0314	-0.0012	-0.0076	0.0006
SSB	MDYV	SPDR S&P 400 Mid Cap Value ETF	0.9637	0.6339	0.2154	-0.2250	0.0013	-0.0093	0.0015
SSB	SSMHX	State Street Small/Mid Cap Equity Index Portfolio	1.0035	0.5111	-0.0461	-0.0204	-0.0011	-0.0066	0.0005
SSB	SSMKX	State Street Small/Mid Cap Equity Index Fund	0.9645	0.5212	-0.0466	0.0150	-0.0012	-0.0066	0.0008
DFA	DFFVX	US Targeted Value Portfolio	1.0049	0.7027	0.3546	-0.0201	-0.0013	-0.0125	0.0037
CSW	SCHM	Schwab US Mid-Cap ETF	0.9576	0.3030	-0.0782	-0.0053	-0.0005	-0.0064	0.0005

Table C.4: Top 30 passive funds in the Mid Cap sector.