

# Marketing Mutual Funds

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Marketing and distribution expenses are responsible for about one-third of the cost of active management in the mutual fund industry. Estimating a structural model with costly investor search and learning about fund skill, we find that marketing is nearly as important as performance and fees in determining fund size. Eliminating marketing substantially improves welfare: capital shifts toward cheaper funds and competition decreases fees; active funds shrink and capital allocation becomes more closely aligned with skill. Declining investor search costs imply a reduction in marketing expenses and management fees as well as a shift toward passive investing, as observed empirically. (*JEL* G11, G28, D14, M31)

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In 2015, U.S. mutual fund industry managed a total of \$16 trillion of investor assets, generating fee revenue on the order of \$100 billion.<sup>1</sup> Historically, about

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<sup>1</sup> Berk and Green (2004), Chen et al. (2004), Pollet and Wilson (2008), Pástor and Stambaugh (2012), Berk and van Binsbergen (2015), and Pástor, Stambaugh, and Taylor (2015), among others, focus on the relationship between mutual fund size, performance, and fees. Understanding investor demand for (active) asset management is central to the broader debate about the size and value added of the finance industry as a whole (see, e.g., French 2008; Cochrane 2013; Greenwood and Scharfstein 2013; Malkiel 2013; Philippon and Reshef 2013; Gennaioli, Shleifer, and Vishny 2014; Philippon 2015).

one-third of this revenue has been designated as expenditures associated with marketing, largely consisting of sales loads and distribution costs (known as 12b-1 fees). Positive relationship between funds' marketing efforts and investor flows is well documented (e.g., Sirri and Tufano 1998; Barber, Odean, and Zheng 2005; Gallaher, Kaniel, and Starks 2006; Reuter and Zitzewitz 2006; Bergstresser, Chalmers, and Tufano 2009; Chalmers and Reuter 2012; Christofferson, Evans, and Musto 2013). Yet marketing expenses substantially contribute to total fund costs, thus reducing returns earned by investors for a given level of fund manager's skill. Is marketing a purely wasteful rat race, or does it help imperfectly informed investors find attractive investment opportunities more easily?<sup>2</sup> Does it enable capital to flow toward more skilled managers or, instead, distort allocation of assets by channeling them toward underperforming funds?

We start with a benchmark model based on Berk and Green (2004), which describes allocation of assets to mutual funds by rational investors in a frictionless market. By estimating the model, we document substantial differences between such an efficient allocation and the observed distribution of fund size. The vast majority of funds are "too big" relative to the model and deliver substantially negative abnormal returns to investors, while the top decile of funds, based on the Bayesian forecast of skill net of fees, are actually smaller than is "efficient," and thus are able to outperform.<sup>3</sup> To explain these differences, we introduce information frictions by generalizing the framework developed by Hortaçsu and Syverson (2004) in the context of index funds. We allow funds' marketing activities, as well as exogenous characteristics that capture funds' "brand value," to affect their inclusion in the investors' information sets. In our setting, both the expense ratios (fees paid by investors) and the marketing/distribution costs (components of these fees related to broker compensation) are endogenous choices of each fund. By estimating our structural model we find that marketing expenses are nearly as important as price (i.e., expense ratio) or performance (i.e., the Bayesian estimate of manager skill based on historical returns) for explaining the observed variation in fund size. Even though marketing in our model is informative, and indeed complementary with fund skill, counterfactual analysis indicates that it reduces welfare due to the positional arms race that it entails.

Following Hortaçsu and Syverson (2004), we model impediments to optimal allocation of capital to mutual funds as a search friction, whereby investors

<sup>2</sup> For example, Stigler (1961) argued that advertising serves to reduce information costs for consumers, thus helping reduce price dispersion. While commissions/kickbacks to financial intermediaries constitute a much larger portion of mutual fund marketing expenses than does advertising, it might seem reasonable to extend his classic logic to this more general notion of marketing, whereby it lowers effective search costs for imperfectly informed investors. In contrast, Mullainathan, Schwartzstein, and Shleifer (2008) interpret empirical patterns of mutual fund advertising using a model of marketing that is purely persuasive, rather than informative.

<sup>3</sup> Following Jensen (1968), the bulk of evidence of performance persistence among mutual funds indicates that consistent *underperformance* is much more prevalent than outperformance (see, e.g., Hendricks, Patel, and Zeckhauser 1993; Brown and Goetzmann 1995; Carhart 1997).

randomly sample and evaluate funds until deciding to invest in one of the funds drawn. Heterogeneity in search costs faced by investors captures the wide variation in financial sophistication (and perhaps even cognitive ability) required to consider and analyze the different investment alternatives. This approach is intuitive, at least when applied to retail investors: the task of choosing among thousands of funds can be daunting even for the most sophisticated individuals, and far more so for those lacking even basic financial literacy.<sup>4</sup> Mutual fund performance is determined by managerial skill as well as decreasing returns to scale. Investors care about funds' expected performance and expense ratios, but must learn about latent fund skill from past performance. Hence, our model nests Berk and Green (2004) as a limiting special case where search costs go to zero. Our key innovation is allowing mutual funds to influence the likelihood of being observed by investors through costly marketing (e.g., via broker commissions). Thus, mutual funds choose their expense ratios and marketing expenses, which increase a fund's probability of being sampled but decrease its profit margin.<sup>5</sup>

We estimate our structural model using data on well-diversified U.S. domestic equity mutual funds. Our estimation results reveal sizable information frictions in the mutual fund market. The average investor implicitly incurs a cost equivalent to foregoing 0.39% return on investment every time a fund is being sampled. This is roughly two-thirds of the average annual gross alpha in our sample. The large magnitude of the estimated search cost is a manifestation of the asset misallocation problem that we document. The intuition is simple: high search costs prevent investors from sampling more funds. Less intensive search leads to an inferior allocation, as many investors are forced to "settle" for high-cost, low-skill funds, since it is too costly for them to search further (in practice, this could mean investors who lack financial sophistication following a broker's recommendation without questioning it, consulting other sources, etc.). In comparison, Hortaçsu and Syverson (2004) estimate the mean search cost for an average investor of S&P 500 index fund between 11 and 20 basis points (bps). This difference should not be surprising since it is far easier for investors to evaluate index funds (which are essentially identical in terms of the returns they deliver, at least before fees) than actively managed funds. It is also possible that the index fund market is dominated by more sophisticated investors (i.e., those who know to look for relatively low-cost passive funds). Our higher estimated search cost indicates that asset misallocation problem is

<sup>4</sup> Indeed, Bronnenberg et al. (2015) find that informed retail consumers are less likely to pay the brand premium associated with heavily marketed products. In the mutual fund context, Choi, Laibson, and Madrian (2010) show experimentally that financial literacy helps investors avoid high-cost index funds.

<sup>5</sup> In this paper, we focus on marketing and distribution expenses, such as the 12b-1 fees, which can be observed at the level of individual funds. Advertising in the media, which is a particular form of marketing, is generally conducted (and measured) at the fund family level. The magnitude of advertising spending by fund families is about 5% of the total reported 12b-1 fees. As a robustness check, we include advertising spending at the family level as a variable that influences funds' sampling probabilities. Our main results are unchanged. See the Internet Appendix for details.

more severe in the mutual fund industry as a whole (including both active funds and passive index funds) than it is within the narrow confines of the S&P 500 index fund sector.

To verify that our estimates are not overly influenced by the assumption of vertical differentiation that we adopt from Berk and Green (2004), that is, the assumption that investors only care about the fund's (expected) abnormal return and expense ratio and there is no heterogeneity in investor preferences, we estimate an extended model that allows for horizontal differentiation. Specifically, we consider the possibility that different investors pursue funds that follow different investment "styles" or factors. Accordingly, in the model, we allow some investors to only sample funds from a particular Morningstar Style Box. We find that allowing for this important dimension of heterogeneity only slightly reduces the estimate of investors' search costs and slightly increases the estimate of investors' sensitivity to performance.

Our baseline estimates imply that marketing is relatively useful as a means of increasing fund size. On average, a 1-bp increase in marketing expenses leads to a roughly 1% increase in a fund's size. This effect is heterogeneous across funds. For high-skill funds, it amounts to a 0.99% increase in fund's size, while for low-skill funds it generates only a 0.83% increase. This result is intuitive: since, conditional on being included in an investor's information set, a high-skill fund is more likely to be chosen; such funds benefit more from a higher probability of being sampled than low-skill funds. The degree of this complementarity between skill and marketing depends on the effectiveness of marketing expenses in determining the likelihood that the fund will be sampled by investors, which is a key structural parameter that we estimate. Using the aggregate demand curves implied by our estimates we find that marketing expenses alone can explain close to 10% of the variation in mutual fund size; this explanatory power is comparable to either fund manager skill or fund price.

While our model suggests that it is optimal for more highly skilled funds to invest more in marketing, this does not imply that the resultant allocation of capital to funds is efficient. We quantify the importance of marketing expenses and search costs in shaping the equilibrium distribution of fund size as well as its impact on investor welfare via counterfactual experiments. Specifically, we simulate the impact of preventing funds from doing any marketing by solving for the new equilibrium size distribution and funds' fees choices using the estimated model parameters. We find that if the marketing is set to zero (instead of being capped at 1% of assets, as per current regulation), the mean expense ratio drops from 160 bps in the current equilibrium to 83 bps. Interestingly, funds lower their expense ratios by more than the original amount of marketing costs. The observed average marketing cost is 62 bps, but in the no-marketing equilibrium the average fund price drops by 77 bps. This result indicates that preventing funds from competing on nonprice attributes (such as marketing) significantly intensifies price competition. We also find the total share of active funds drops from 74% to 68%. This drop is accompanied by an increase in

average fund performance as measured by mean gross alpha. The increase in alpha is due to the effect of decreasing returns to scale on fund performance. In the no-marketing equilibrium, the “index fund” takes up the market share lost by active funds. Eliminating marketing creates two forces: (1) the index fund is known by more investors as active funds cannot use marketing to attract investors; (2) active funds become more attractive as the elimination of marketing expenses allows them to reduce prices. It turns out that the first force dominates the second, so we see an increase in the index fund’s market share.

Total investor welfare increases by 79.5 bps in the counterfactual equilibrium, where welfare is in the units of return on investment, given that we specify investor utility as a linear function of fund outperformance (alpha) and fees (expense ratios). Three factors contribute to this increase: in the no-marketing equilibrium, (1) active funds are cheaper, (2) more investors invest in the passive index fund, (3) active funds’ alpha is on average higher due to the decrease in fund size. The increase in investor welfare is substantially greater than the decline in aggregate mutual fund profits (or even total fee revenue). Thus, in the aggregate marketing reduces welfare. The reason for this inefficiency is that funds engage in a wasteful “arms race” as they compete for the same pool of investors via marketing. For the parameter values that we estimate this effect dominates the positive effect of complementarity between marketing and skill, even though in general this need not be true in our model.

To further understand the large increase in investor welfare, we examine the cross-section of investor search costs implied by our model. Naturally, high search cost investors search less and pay higher expense ratios than those with low search costs, while the funds they invest in have high marketing fees and lower alphas. Comparing investor welfare in the two equilibria, we show that the bulk of the welfare gain of eliminating marketing is driven by such high search cost investors. The intuition is simple: these are the investors who are “stuck” with the worst funds (unless they happen to be lucky to “find” the index fund or a high-skill active fund). In the no-marketing equilibrium, even the worst funds are much cheaper than in the current equilibrium. This leads to a significant welfare gain for the high-search-cost investors.<sup>6</sup>

In addition, we examine the impact of search costs on equilibrium market outcomes. With the advancement in information technology and the emergence of services enabling more transparent comparison between funds, we would expect the search frictions to decline over time. We conduct counterfactual experiments where we set the mean search cost to 35 bps and 20 bps

<sup>6</sup> A potential caveat is that a drastic reduction in marketing expenses could reduce access to financial advice, especially for small investors. If the role of financial advisors is in establishing investors’ trust, as argued by Gennaioli, Shleifer, and Vishny (2015), then investor welfare could be reduced, as would their allocation to the mutual fund sector and, potentially, the equity markets generally. However, empirical estimates by Linnainmaa, Melzer, and Previtero (forthcoming) suggest that net gains to financial advice that trade off certainty equivalent benefit of increased risky asset holdings against the cost of advice are likely to be small.

respectively. Given a new search cost distribution, funds reoptimize their prices and marketing expenses. We find that as the mean search cost decreases from 39 bps to 35 bps, marketing expenses drop from 61 bps to 44 bps, on average. However, when the mean search cost further drops to 20 bps, the equilibrium marketing expenses fall to zero, even though we maintain the regulatory cap at 100 bps. In the model funds invest aggressively in marketing so as to enter more of the high search cost investors' choice sets. Since high search cost investors will not search much, they are willing to invest with high fee funds, justifying these funds' marketing expenses. But when mean search cost drops to a sufficiently low level, this strategy is no longer effective, as more and more investors are willing to search for a "better" (in particular, cheaper) fund, intensifying price competition. Sufficiently low search costs render marketing unprofitable, since it becomes easy for most investors to find low-cost funds that don't expend resources on marketing themselves. Thus our model's mechanism is consistent with the observed decline in fees charged by active mutual funds along with the growth in passive index funds over the last two decades highlighted by Stambaugh (2014).

While we abstract from the specifics of the interaction between a mutual fund, its sales force (such as brokers and financial advisors), and individual investors, our model of marketing effort is motivated by a growing literature examining the role of retail financial advice. Bergstresser, Chalmers, and Tufano (2009) study broker-sold and direct-sold funds and find little tangible benefit of the former to fund investors, at least in terms of portfolio returns. Del Guercio and Reuter (2014) show that the relationship between fund flows and past performance is muted among funds that are sold through brokers, presumably because such funds are targeting investors with higher search costs. Chalmers and Reuter (2012) show that broker recommendations steer retirement savers toward higher-fee funds yielding lower investor returns; Mullainathan, Noeth, and Schoar (2012) provide similar evidence from an audit study of retail financial advisors. Christofferson, Evans, and Musto (2013) find that broker incentives affect investor flow to funds, especially for brokers not affiliated with the fund family. Egan, Matvos, and Seru (2019) exhibit the potentially severe conflict of interest between brokers/financial advisors and their retail investor clients, as exemplified by repeat incidence of misconduct in the industry (only about 5% of reported misconduct involves mutual funds, however). An alternative to the conflict of interest view is presented by Linnainmaa, Melzer, and Previtero (forthcoming), who show that financial advisors tend to commit common investment mistakes in their own portfolios. Choi and Robertson (2018) present survey-based evidence that the belief in the ability of active managers to deliver above-market returns and the recommendation of a financial advisor are by far the most important drivers of mutual fund investment decisions by individual investors.

More closely related to our work, Hastings, Hortaçsu, and Syverson (2017) study the role of marketing efforts on observed market outcomes in Mexico's privatized retirement savings system. In their model, a fund's sales force can both increase investors' awareness of the product and affect their price sensitivity. In our data, we cannot distinguish between these two effects. We thus assume that the observed marketing expenses are purely informative (rather than persuasive). Egan (2019) uses a search-based structural framework similar to ours to study the conflict of interest between brokers and retail investors in the market for structured convertible bonds. Jiang and Xiaolan (2018) show that a larger share of marketing/sales employees in a fund family labor force is associated with a faster growth of assets under management and a greater convexity of the flow-performance relationship (i.e., a higher sensitivity of fund size to outperformance than to poor performance).

Our paper is related to the literature that aims to understand the observed underperformance of active funds given investors' uncertainty about unobserved skill of asset managers. Baks, Metrick, and Wachter (2001) show that investors will find some active funds attractive even if they have skeptical prior beliefs about managerial ability. Pástor and Stambaugh (2012) develop a tractable model of the active management industry as a whole. They explain the popularity of active funds despite their poor past performance using two components: decreasing returns to scale and slow learning about the true skill level. In our model of the active management industry, we also include decreasing returns to scale and investor learning about unobserved skill (at the fund level). However, our model largely attributes the popularity of active funds to the information friction that prevents investors from easily finding out about index funds.<sup>7</sup>

This paper is also related to those studying the role of advertising and media attention in the mutual fund industry. Gallaher, Kaniel, and Starks (2006), Reuter and Zitzewitz (2006), and Kaniel and Parham (2016) study the impact of fund family-level advertising expenditures and the resultant media prominence of the funds on fund flows. In our model, we capture some of these effects parsimoniously by allowing fund family size to affect a fund's probability of being included in an investor's information set.<sup>8</sup>

<sup>7</sup> Huang, Wei, and Yan (2007) argue that differences in mutual fund prominence as well as heterogeneity in the degree of sophistication across investors help explain the observed asymmetry in the response of flows to fund performance. Garleanu and Pedersen (2018) incorporate search costs in their model of active management and market equilibrium, but assume that a passive index is freely available to all investors without the need to search.

<sup>8</sup> We follow this simple approach to incorporating advertising since the latter constitutes a very small fraction of fund expenditure, compared to the distribution costs that we focus on. Advertising can be potentially quite important for steering consumers into financial products (e.g., Honka, Hortaçsu, and Vitorino 2017; Gurun, Matvos, and Seru 2016).

## 1. Model

Every period, heterogeneous investors conduct costly search to sample mutual funds to invest their (identical) endowments.<sup>9</sup> Investors care about expected fund performance and expense ratio (i.e., its price). Mutual fund performance is determined by managerial skill as well as the impact of decreasing returns to scale. Mutual funds choose their expense ratios and marketing expenses to maximize profits. Marketing expenditures can increase a fund's probability of being sampled, but decrease its profit margins.

We proceed by first describing how fund's performance is determined and then the investor's problem and lastly describe the funds' behavior.

### 1.1 Fund performance

In a time period  $t$ , the realized alpha  $r_{j,t}$  for an active fund  $j \in \{1, 2, \dots, N_t\}$  is determined by three factors: (1) the fund manager's skill to generate expected returns in excess of those provided by a passive benchmark in that period, denoted by  $a_{j,t}$ ; (2) the impact of decreasing returns to scale, given by  $D(M_t s_{j,t}; \eta)$  where  $M_t$  is the total size of the market and  $s_{j,t}$  is the market share of the fund  $j$ , and  $M_t s_{j,t}$  denoting fund size,  $\eta$  is a parameter measuring the degree of decreasing returns to scale; and (3) an idiosyncratic shock  $\varepsilon_{j,t} \sim \mathcal{N}(0, \delta^2)$ .

$$r_{j,t} = a_{j,t} - D(M_t s_{j,t}; \eta) + \varepsilon_{j,t}, \quad j = 1, \dots, N_t, \quad (1)$$

An important question in the mutual fund literature concerns the relative size of active funds vis-a-vis passive funds (e.g., Pástor and Stambaugh 2012). To be able to address this important extensive margin, we include a single index fund  $j=0$  into our model, and thus abstract from competition *between* index funds. We assume that the alpha of the index fund is zero, in that it neither has skill nor affected by the decreasing returns to scale. The total market size  $M_t$  includes both active funds and the index fund. We treat  $M_t$  as an exogenous variable in the model.

Our specification is very similar to Berk and Green (2004) with one exception: the manager's skill is allowed to vary over time. We assume manager's skill follows an AR(1) process:

$$a_{j,t} = (1 - \rho)\mu + \rho a_{j,t-1} + \sqrt{1 - \rho^2} \cdot v_{j,t}, \quad (2)$$

where  $v_{j,t} \sim \mathcal{N}(0, \kappa^2)$ . When a fund is born, its first period skill is drawn from the stationary distribution  $\mathcal{N}(\mu, \kappa^2)$ . Parameter  $\rho$  captures the persistence of the skill level. In the limiting case, when  $\rho = 1$ , skill is fixed over time, which is what Berk and Green (2004) assume.

<sup>9</sup> For tractability, we assume that all investors have the same amount to invest. In reality, a large investor likely incurs a smaller search cost as a fraction of her investment size. So, to some extent, the dispersion in search cost could be partly interpreted as heterogeneity in investment size. Without account-level data, we have no way to identify the two separately.



Following Berk and Green, we assume the manager's skill is not observable to either the investor or the fund manager herself: it is a hidden state. Let  $\tilde{a}_{j,t}$  be investors' (and manager's) belief about the manager's skill in that period. Since Equation (2) can be regarded as describing how the hidden state  $a_{j,t}$  evolves over time, and Equation (1) says that  $r_{j,t} + D(M_t s_{j,t}; \eta)$  is a signal on the hidden state, one can apply Kalman filter to obtain the following recursive formulas for the belief on manager's skill and the variance of that belief:

$$\begin{aligned}\tilde{a}_{j,t} &\equiv E(a_{j,t} | r_{j,t-1}, s_{j,t-1}, r_{j,t-2}, s_{j,t-2}, \dots) \\ &= \rho \left\{ \tilde{a}_{j,t-1} + \frac{\tilde{\sigma}_{j,t-1}^2}{\tilde{\sigma}_{j,t-1}^2 + \delta^2} [r_{j,t-1} + D(M_{t-1} s_{j,t-1}; \eta) - \tilde{a}_{j,t-1}] \right\} + (1 - \rho)\mu,\end{aligned}\quad (3)$$

$$\begin{aligned}\tilde{\sigma}_{j,t}^2 &\equiv \text{Var}(a_{j,t} | r_{j,t-1}, s_{j,t-1}, r_{j,t-2}, s_{j,t-2}, \dots) \\ &= \rho^2 \left( 1 - \frac{\tilde{\sigma}_{j,t-1}^2}{\tilde{\sigma}_{j,t-1}^2 + \delta^2} \right) \tilde{\sigma}_{j,t-1}^2 + (1 - \rho^2)\kappa^2.\end{aligned}\quad (4)$$

and  $\tilde{a}_{j,t} = \mu$ ,  $\tilde{\sigma}_{j,t}^2 = \kappa^2$  for the period  $t$  when  $j$  was born. In the special case of  $\rho = 1$  these coincide with the expressions derived by Berk and Green (2004) in their Proposition 1. The difference between our updating rule and theirs is that in the Berk and Green (2004) model, all the historical signals receive the same weight in determining the investor's belief, whereas in our case, when  $\rho$  is smaller than 1, the signals in the more recent periods receive greater weight. This allows us to capture the fact that fund managers and/or their strategies change over time, and that investors might therefore *rationally* place a larger weight on recent history.<sup>10</sup>

## 1.2 Investor search

Each investor allocates a unit of capital to a single mutual fund identified as a result of sequential search (conducted at the beginning of each period  $t$ ). Investors are short lived, in the sense that they derive utility from their investment in the fund of their choice, and the capital they invest in the funds dissipates at the end of the period. A new population of investors enters in the subsequent period  $t+1$  with new capital endowments that they allocate to the funds, and so on. Let  $p_{j,t}$  be the expense ratio charged by fund  $j$ . An investor's utility derived from investing in fund  $j$  is given by

$$u_{j,t} = \gamma \tilde{r}_{j,t} - p_{j,t}, \quad (5)$$

<sup>10</sup> Evidence suggests that investors "chase" recent performance, potentially more actively than would be justified from a purely Bayesian perspective. Our framework could be used in quantitatively assessing the degree to which this behavior is driven by irrational overextrapolation (e.g., Bailey, Kumar, and Ng 2011; Greenwood and Shleifer 2014; Bordalo et al. 2019). Some evidence in the literature indicates active managers' ability to deliver alpha varies over time, in particular with the state of the economy (e.g., Kacperczyk, Van Nieuwerburgh, and Veldkamp 2014).

where

$$\tilde{r}_{j,t} = \tilde{a}_{j,t} - \eta \log(M_t s_{j,t}).$$

Recall that  $\tilde{a}_{j,t}$  is the investors' belief on the manager's skill for fund  $j$  for this period  $t$  and  $\tilde{r}_{j,t}$  is the fund  $j$ 's expected alpha in period  $t$  implied by these updated beliefs as well as the size of the fund, given the decreasing returns to scale function parameterized as  $D(M_t s_{j,t}; \eta) = \eta \log(M_t s_{j,t})$ .<sup>11</sup> The coefficient in front of the expense ratio is normalized to 1. If  $\gamma = 1$  then investors simply care about the expected outperformance net of fees (net alpha), as assumed by Berk and Green (2004). We allow the more general formulation to account for the potential difference in salience of fees vs. performance as well as the investors' imperfect ability to estimate manager skill. The utility derived from investing in the index fund is given by  $u_{0,t} = -p_{0,t}$ , where  $p_{0,t}$  is the expense ratio charged by the index fund in period  $t$ ; the alpha of the index fund is set to be zero.

Investor  $i$  pays search cost  $c_i$  to sample one fund from the distribution of funds (this distribution is known to all investors, while specific fund identities are not). The search costs are different across the population of investors and follow a continuous distribution  $G$  (which we parameterize as exponential, with its mean given by  $\lambda$ ). As in Hortaçsu and Syverson (2004), we endow investors with one free search, so that every investor will invest in a fund (even if his search cost is very high). Fix a time period  $t$ . Let  $\Psi(u)$  be the probability of sampling a fund that delivers the investor an indirect utility smaller or equal to  $u$ . Standard Bellman equation arguments imply that it is optimal for the investor to follow a cutoff strategy (see the Internet Appendix for details). Let  $u^*$  be the highest indirect utility among the funds sampled thus far. The investor continues searching iff  $u^* \leq \bar{u}(c_i)$ , where the threshold  $\bar{u}$  is defined by

$$c_i = \int_{\bar{u}}^{+\infty} (u' - \bar{u}) d\Psi(u').$$

Since we have a finite number of funds, the above expression becomes

$$c_i = \sum_{j=0}^N \psi_j (u_j - \bar{u}) \cdot \mathbf{1}\{u_j > \bar{u}\},$$

where  $\psi_j$  is the probability of sampling fund  $j \in \{0, 1, \dots, N_t\}$ . Intuitively, the left-hand side is the cost for an additional search, and the right-hand side is the expected gain. Note that the right-hand side is strictly decreasing in  $\bar{u}$ . So  $\bar{u}(c_i)$  is strictly decreasing in  $c_i$ . Intuitively, the bigger  $c_i$  is, the smaller the cutoff  $\bar{u}(c_i)$  becomes, and the less persistent the investor is in searching. Following

<sup>11</sup> Alternatively, we can specify decreasing returns to scale as a function of market share,  $s_{j,t}$  rather than the actual dollar size,  $M_t s_{j,t}$ . However, in the Internet Appendix, we show that this alternative specification has a significantly lower likelihood than our benchmark specification above.

Hortaçsu and Syverson (2004), we can solve for the market share of each fund,  $s_{j,t}$ , explicitly as a function of the utilities  $\{u_{j,t}\}_{j=0}^{N_t}$ , sampling probabilities  $\{\psi_{j,t}\}_{j=1}^{N_t}$  and the distribution of search costs  $G(c_i)$  (see the detailed derivations in Appendix A). Note we have added back subscript  $t$  to indicate the dependence on time periods.

### 1.3 Marketing and equilibrium market shares

Fund sampling probabilities depend on fund characteristics and, crucially, on funds' marketing efforts. Let  $b_{j,t}$  denote marketing expenses of fund  $j$ ,  $\mathbf{x}_{j,t}$  denote a vector collecting the (observable) exogenous characteristics of the fund, and  $\xi_{j,t}$  represent the unobservable shock that affects the sampling probability of this fund. Vector  $\mathbf{x}_{j,t}$  includes year dummies, fund age, and the number of funds in the same family.<sup>12</sup> Then the probability that an investor randomly draws fund  $j$  in year  $t$  is specified as

$$\psi_{j,t} = \frac{e^{\theta b_{j,t} + \beta' \mathbf{x}_{j,t} + \xi_{j,t}}}{1 + \sum_{k=1}^N e^{\theta b_{k,t} + \beta' \mathbf{x}_{k,t} + \xi_{k,t}}}, \quad (6)$$

$$\psi_{0,t} = 1 - \sum_{k=1}^N \psi_{k,t}. \quad (7)$$

Thus,  $\theta$  is a key parameter that characterizes the effectiveness of marketing expenditure as a means of attracting investors. As long as  $\theta$  is positive, an increase in  $b_{j,t}$  increases the probability that the fund is sampled by investors, all else equal. We assume that the index fund does not engage in any marketing activities; thus, increasing marketing by all of the active funds automatically reduces its sampling probability.

Importantly, marketing expenditures are only incurred by the fund when it attracts investment. This is intuitive if we think of marketing as a commission paid to a broker or advisor - while a promise of a kickback might increase the probability the fund is recommended, if the client chooses not to invest in the fund, the commission is not paid. While we do not model this intermediated relationship between investors and funds in detail, our specification of the sampling probability function is meant to capture it in a somewhat reduced form.<sup>13</sup> In addition, it captures other aspects of marketing that are not directly tied to the marketing expenses that reported as a part of the fund expense ratio, such as "brand," which might be captured by both observed and unobserved characteristics of the fund. For example, older funds may be more prominent

<sup>12</sup> In addition to those variables, other factors that have been documented in the literature might affect a fund's sampling probability. In the Internet Appendix, we show that our main results are unchanged if we include in  $\mathbf{x}_{j,t}$  the advertising expenditures by fund families (Gallagher, Kaniel, and Starks 2006), Morningstar ratings (Reuter and Zitzewitz 2006), and appearances on the list of *Wall Street Journal* "Category Kings" (Kaniel and Parham 2016).

<sup>13</sup> Inderst and Ottaviani (2012) and Stoughton, Wu, and Zechner (2011) theoretically analyze the role of commissions/kickbacks in investment management.

and have better “name recognition” among investors, where as larger fund families may benefit from economies of scale in some forms of marketing, for example, because of fixed costs of advertising or availability of an in-house sales force.<sup>14</sup>

We use  $\mathbf{p}_t$  to denote the vector that collects  $p_{j,t}$  for  $j=1, \dots, N_t$ ; similar notation applies to other fund-specific variables in the model. With the specifications in (5), (6), and (7), the search model in Section 1.2 implies a mapping from  $\mathbf{p}_t$ ,  $\mathbf{b}_t$ ,  $\tilde{\mathbf{r}}_t$ ,  $\mathbf{x}_t$ ,  $\boldsymbol{\xi}_t$ , and  $p_{0,t}$  to a set of market shares. Let us write this mapping as

$$s_{j,t} = F_{j,t}(\mathbf{p}_t, \mathbf{b}_t, \tilde{\mathbf{r}}_t, \mathbf{x}_t, \boldsymbol{\xi}_t, p_{0,t}; \Theta), \quad j=1, \dots, N_t, \quad (8)$$

where  $\Theta$  collects the relevant parameters, which in this case include  $\gamma$ ,  $\boldsymbol{\beta}$ ,  $\theta$ , and the parameter  $\lambda$  for  $G$ . The share for the index fund is given by  $s_{0,t} = 1 - \sum_{j=1}^N s_{j,t}$ . We use vector  $\mathbf{s}_t$  to collect  $s_{j,t}$  for  $j=1, \dots, N_t$ .

Decreasing returns to scale imply that  $\tilde{\mathbf{r}}_t$  depends on the funds’ market shares:

$$\mathbf{s}_t = \mathbf{F}_t[\mathbf{p}_t, \mathbf{b}_t, \tilde{\mathbf{a}}_t - \eta \log(M_t \mathbf{s}_t), \mathbf{x}_t, \boldsymbol{\xi}_t, p_{0,t}; \Theta]. \quad (9)$$

As in Berk and Green (2004), investors understand that their returns depend on the size of the fund they invest in, and therefore the equilibrium vector of fund market shares  $\mathbf{s}_t$  is a fixed point of the above relation. We can write the fixed point as a function of the other inputs on the right-hand side of (9),

$$s_{j,t} = H_{j,t}(\mathbf{p}_t, \mathbf{b}_t, \tilde{\mathbf{a}}_t, \mathbf{x}_t, \boldsymbol{\xi}_t, p_{0,t}; \Theta), \quad j=1, \dots, N_t, \quad (10)$$

with  $\Theta$  now also including parameter  $\eta$ . In the Internet Appendix, we show that this fixed point is unique. Unlike  $F_{j,t}$ , we do not have a closed-form expression for  $H_{j,t}$  and so it requires fixed point iteration to compute.

Active funds maximize profits each period  $t$ , which are given by

$$\pi_{j,t} := M_t \cdot H_{j,t}(\mathbf{p}_t, \mathbf{b}_t, \tilde{\mathbf{a}}_t, \mathbf{x}_t, \boldsymbol{\xi}_t, p_{0,t}; \Theta) \cdot (p_{j,t} - b_{j,t}). \quad (11)$$

We assume a Nash equilibrium, where each fund chooses  $p_{j,t}$  and  $b_{j,t}$  to maximize  $\pi_{j,t}$ , given other funds’ choices  $p_{-j,t}$  and  $b_{-j,t}$  (as well as its own and other funds’ estimated skill levels and exogenous characteristics).<sup>15</sup> Passive fund expense ratio  $p_{0,t}$  is set exogenously. Because the SEC currently imposes a 1% upper bound on the 12b-1 fees, we restrict  $b_{j,t} \leq \bar{b} \equiv 0.01$  in equilibrium.

<sup>14</sup> This is consistent with evidence in Jiang and Xiaolan (2018) that larger fund families spend a higher fraction of their wage bill on employees in sales and marketing, despite charging lower expense ratios on their funds, on average.

<sup>15</sup> Our notion of profits most closely approximates management fees paid to the fund’s investment advisor. We can think of this either as profits accruing to the fund family or as compensation paid to the fund manager, although in reality the latter is a much more complicated object (e.g., see Ibert et al. 2018).

## 2. Data

The data come from CRSP and Morningstar. Our sample contains 2,285 well-diversified actively managed domestic equity mutual funds from the United States between 1964 and 2015. Our data set has 27,621 fund-year observations. In the Internet Appendix, we provide the details about how we construct our sample. We closely follow data-cleaning procedures in Berk and van Binsbergen (2015) and Pástor, Stambaugh, and Taylor (2015).

To compute the annual realized alpha  $r_{j,t}$ , we start with monthly return data. We first augment each fund's monthly net return with the fund's monthly expense ratio to get the monthly gross return  $r_{j,t}^{Gross}$ . Then we regress the excess gross return (over the 1-month U.S. Treasury-bill rate) on the risk factors throughout the life of the fund to get the betas for each fund. We multiply betas with factor returns to get the benchmark returns for each fund at each point in time. We subtract the benchmark return from the excess gross return to get the monthly gross alpha. Last, we aggregate the monthly gross alpha to the annual realized alpha  $r_{j,t}$ . We use four different benchmark models: CAPM, Fama-French three-factor model, Fama-French and Carhart four-factor model and Fama-French five-factor model. For our main results, we use the Fama-French five-factor model as the benchmark, but our results are robust to other risk adjustments. In our sample, the average annual realized alpha for Fama-French five-factor model is 54 bps. This result is very close to Pástor, Stambaugh, and Taylor's (2015) estimates, where they find the monthly alpha is 5 bps, which translates to 60 bps of annual alpha.

Since our focus is on the efficient allocation of assets across active funds, we choose to minimize the details related to modeling index funds.<sup>16</sup> We aggregate all index funds from Vanguard to build a single index fund. We choose Vanguard because, as argued by Berk and van Binsbergen (2015), Vanguard index funds have been the most accessible index funds for retail investors historically.<sup>17</sup> Specifically, we compute its assets under management (hereafter AUM) by summing AUM across all funds; we compute the combined fund's expense ratio by asset-weighting across all included index funds. We count the combined index fund's age from the inception year of Vanguard, which is 1975.

We define the total mutual fund market  $M_t$  as the sum of AUMs of all the active funds and the combined index fund in year  $t$  (the units are millions of 2015 dollars). We define market share  $s_{j,t}$  as the ratio between fund  $j$ 's AUM and the total fund market.  $M_t s_{j,t}$  gives the fund  $j$ 's AUM in millions of dollars in year  $t$ . We exclude fund-year observations with fund's AUM below \$15

<sup>16</sup> For a detailed study of search frictions *within* the index fund market, see Hortaçsu and Syverson (2004).

<sup>17</sup> Other fund families, such as Fidelity and Blackrock, offer similar products. We show in the Internet Appendix that our results are robust to alternative definitions of aggregate index fund that include all passive equity funds not charging 12b-1 fees; the same is true if we include some popular equity index tracking exchange-traded funds (ETFs).

million in 2015 dollars. Elton, Gruber, and Blake (2001), Chen et al. (2004), Yan (2008), and Pástor, Stambaugh, and Taylor (2015) also use a \$15 million minimum. In our data set, there is a huge skewness in fund's AUM. From the summary statistics (see the Internet Appendix for details), we can see the mean of funds' AUM is much larger than the median. The funds at the 99th percentile is over 1,100 times larger than the funds at the 1st percentile. This skewness could potentially affect our estimates. Following Chen et al. (2004), we use the logarithm of a fund's AUM as our measure of fund size.

In taking our model to the data, we use the reported distribution costs (sales loads and 12b-1 fees, which are typically used to compensate brokers for directing client investment to funds) as our combined proxies for marketing costs (rather than using, e.g., advertising expenditures). The reason is that according to ICI (2005), in the United States, more than 80% of investors purchase mutual funds through intermediaries, such as brokers or financial advisors. Among all the expenses that mutual fund companies categorized as marketing, advertising expenses constitute about 2% of the expenses (according to ICI 2005). The bulk of the marketing costs is compensation paid to brokers and financial advisors, albeit we do not observe this compensation directly.

In the mutual fund industry, a single mutual fund may provide several share classes to investors that differ in their fees structures (typically, the difference is in the combination of front loads and 12b-1 fees). Following much of the literature (with some exceptions, e.g., Bergstresser, Chalmers, and Tufano 2009), we conduct our analysis at the fund level instead of the share class level. To be able to do so, we need to aggregate the share class level expense ratios, 12b-1 fees and front loads up to the fund level. We define the marketing expense  $b_{j,t}$  as the "effective" 12b-1 fees that includes amortized loads (see the Internet Appendix for details).

### 3. Structural Estimation

Our estimation proceeds in two steps. We first estimate the set of parameters governing mutual fund investment performance:  $\mu$ ,  $\kappa$ ,  $\delta$ ,  $\rho$ , and  $\eta$ , using the observed panel of fund returns and market shares:  $\{r_{j,t}, s_{j,t} | j=1, \dots, N_t, t=1, \dots, T\}$  using maximum likelihood estimation (MLE). This also gives us the posterior beliefs on the funds' skills in every period. Then we estimate the other parameters (which are related to the search model) using generalized method of moments (GMM) by relating the observed  $s_{j,t}$  to the fund characteristics, as well as making inferences from the equilibrium restrictions on the fee-setting behavior of funds, taking the Bayesian posterior beliefs about funds' skills as given. An alternative approach to using equilibrium restrictions for estimation of the effect of marketing expenses is to use an instrumental variable (IV). We present the results of using the IV approach in the Internet Appendix as a robustness check. IV estimation produces very similar estimate for the effect of marketing.

### 3.1 Fund performance

From expression (1), we can write down the probability of observing  $r_{j,t}$  conditional on observed market shares and realized outperformances up to  $t$ :

$$\Pr\left(r_{j,t} \mid s_{j,t}, r_{j,t-1}, s_{j,t-1}, r_{j,t-2}, s_{j,t-2}, \dots\right) \sim \mathcal{N}[\tilde{a}_{j,t} - \eta \log(M_t s_{j,t}), \tilde{\sigma}_{j,t}^2 + \delta^2].$$

In writing down the above conditional likelihood, note that the current market share  $s_{j,t}$  does not provide further information about the skill  $a_{j,t}$  beyond  $\{r_{j,t-1}, s_{j,t-1}, r_{j,t-2}, s_{j,t-2}, \dots\}$ , because it is a function of  $\tilde{a}_{j,t}$ , but not  $a_{j,t}$ .  $s_{j,t}$  does not provide any information on  $\varepsilon_{j,t}$  for the same reason.

We can use the above conditional probability to construct a partial log likelihood function (see Wooldridge 2010, § 13.8):

$$\sum_{j=1}^{N_t} \sum_t \log \Pr\left(r_{j,t} \mid s_{j,t}, r_{j,t-1}, s_{j,t-1}, r_{j,t-2}, s_{j,t-2}, \dots\right).$$

The first summation is across all funds. The second summation is across all periods in which fund  $j$  exists. We maximize this likelihood with respect to  $\mu$ ,  $\kappa$ ,  $\delta$ ,  $\rho$ , and  $\eta$  to obtain the estimates.

Our MLE estimation does not rely on the assumptions and structure of our search model - only on the specification of the exogenous skill process. Therefore, our estimates of skill and decreasing returns to scale parameters are valid even if fund market shares are determined by some other model, for example, Berk and Green (2004). Technically, this means that the likelihood at this step (purposely) chooses not to make use of a model for fund sizes but only tries to fit the dynamics of returns *conditional on* the observed fund sizes. This partial MLE is agnostic about how the observed market shares are determined (as long as they are some functions of historical returns and shares). This allows us to conduct our estimation in two steps, first estimating the parameters driving fund performance and then the parameters of the search model as described below in Section 3.2. Alternatively, we could write down the full likelihood by including market shares implied by our search model. However, this would require us to (a) make a distributional assumption on  $\xi$  in the search model, and (b) subject the skill estimates to possible misspecification of the search model. Our sequential approach does not share these shortcomings and is therefore more robust.

### 3.2 Search model

The parameters in the search model are estimated using (a) a set of moment conditions constructed with  $\xi_{j,t}$  and (b) the optimality of the funds' behaviors. For (a), we first need to back out the  $\xi_{j,t}$ 's from the data given any set of parameter values. This amounts to finding the  $\xi_t$  that equates the model-predicted market shares  $\mathbf{H}_t(\mathbf{p}_t, \mathbf{b}_t, \tilde{\mathbf{a}}_t, \mathbf{x}_t, \xi_t, p_{0,t}; \Theta)$  to the observed shares  $\mathbf{s}_t$  for each period  $t$ . Since the fixed point of  $\mathbf{H}_t$  is observed as  $\mathbf{s}_t$  in the data we can

achieve this by solving  $F_t[p_t, b_t, \tilde{a}_t - \eta \log(M_t s_t), x_t, \xi_t, p_{0,t}; \Theta] = s_t$  (which is described in Equation (9)) for  $\xi_t$  (given a set of parameter values and observed fund choices).<sup>18</sup>

The definition of  $\xi_t$  gives us our first set of moment conditions:  $E(\xi_{j,t} | x_t, \tilde{a}_{j,t}) = 0$ . This condition states that  $\xi_{j,t}$  is mean independent of the  $x_{j,t}$ , the exogenous variables that affect fund's sampling probability in addition to marketing expenses, and  $\tilde{a}_{j,t}$ , the posterior belief about the fund skill at the beginning of period  $t$ . Let  $j \in t$  denote any active fund  $j$  that is alive in period  $t$ . The sample version of the moment conditions is

$$\sum_{t=1}^T \sum_{j \in t} \xi_{j,t} \begin{pmatrix} x_{j,t} \\ \tilde{a}_{j,t} \end{pmatrix} = 0. \quad (12)$$

Following Hortaçsu and Syverson (2004) and Chen et al. (2004), we include in  $x_{j,t}$  both log age and the number of funds in the same fund family to capture the fund-level social learning effects. Importantly, we do not include lagged fund size into  $x_{j,t}$ . In the data, fund size is persistent over time, so including lagged fund size creates an overfitting problem, where  $s_{j,t}$  is almost mechanically explained by  $s_{j,t-1}$ . From the point of view of the moment conditions, this problem is due to potential serial correlation within the residuals  $\xi_{j,t}$ . Because lagged size  $s_{j,t-1}$  depends on  $\xi_{j,t-1}$ , autocorrelation in the residuals will imply correlation between the lagged size and  $\xi_{j,t}$ . As a result, if we include the lagged size in  $x_{j,t}$ , its coefficient will be overestimated, though this will make the model appear to fit  $s_{j,t}$  better due to the persistence in fund size.

In contrast to this first set of moment conditions, we do *not* require  $E(\xi_{j,t} | p_{j,t}, b_{j,t}) = 0$  because  $p_{j,t}$  and  $b_{j,t}$  are endogenous outcomes of the model and thus depend on  $\xi_{j,t}$ . One typical approach that the literature explores to deal with such endogeneity is using instruments for firms' pricing or marketing choices, for instance, Berry, Levinsohn, and Pakes (1995) (hereafter BLP). The BLP price instruments that are based on competitiveness measures of a particular market (e.g., the number of products competing in the market) rely on the assumption that the product characteristics of the other firms are exogenous to the unobserved characteristic  $\xi_{j,t}$ . But in our mutual fund industry setting this assumption is unlikely to hold, since introduction and closure of funds by fund families can respond swiftly to shifts in investor demand for mutual funds, thus using, for example, the number of funds in the market as an instrument would violate the exclusion restriction. Another common approach, which we follow here, is to rely on the optimality of the observed firm choices. Intuitively, the levels of fees and marketing expenses that are optimal for different funds will depend on the elasticities of demand. Therefore, as long as the observed choices are optimal, they help to identify the demand function.<sup>19</sup>

<sup>18</sup> The solution to this equation can be found by iteration similar to the contraction mapping approach in Berry, Levinsohn, and Pakes (1995).

<sup>19</sup> We can illustrate the identification with a simpler "toy version" of the model. Let investors' demand function be  $s_j = \alpha_j + \beta p_j + \theta_j b_j + \xi_j$ , where the demand for fund  $j$ ,  $s_j$ , is affected by the skill  $\alpha_j$ , price  $p_j$ , marketing



The first-order condition for the price for fund  $j$  at period  $t$  is

$$s_{j,t} + \partial H_{j,t} / \partial p_{j,t} \cdot (p_{j,t} - b_{j,t}) = 0.$$

To exactly align the behaviors predicted by a model with the observed behaviors of each individual fund in the data, one must either introduce unobserved heterogeneity in costs or allow for the first-order conditions to be satisfied with error.<sup>20</sup> In our estimation, we implicitly allow decision errors as each fund chooses its price and marketing expense. Specifically, we allow the first-order condition above to be satisfied up to an error:

$$s_{j,t} + \left( \frac{\partial H_{j,t}}{\partial p_{j,t}} \cdot e^{\zeta_{j,t}} \right) (p_{j,t} - b_{j,t}) = 0, \quad (13)$$

where  $\zeta_{j,t}$  represents the fund's "error" in setting its price (e.g., because of a misassessment of the slope of the demand curve). The error term enters the slope of the demand curve with respect to price, rather than as a separate additive term in the first-order condition. Under this specification, we will assume that  $\zeta_{j,t}$  has a mean of zero across all periods and funds. In other words, while discrepancies are allowed at the individual fund level, we still ask the average behavior to be consistent with the model.

The first-order condition for the marketing expenses is similar but slightly more involved because of the corner restrictions  $0 \leq b_{j,t} \leq \bar{b}$ . We let

$$-s_{j,t} + \left( \frac{\partial H_{j,t}}{\partial b_{j,t}} \cdot e^{\omega_{j,t}} \right) (p_{j,t} - b_{j,t}) \begin{cases} \leq 0, & \text{if } b_{j,t} = 0; \\ \geq 0, & \text{if } b_{j,t} = \bar{b}; \\ = 0, & \text{otherwise.} \end{cases} \quad (14)$$

Here, we again allow a mean-zero error  $\omega_{j,t}$ , which affects the slope of the demand curve with respect to marketing. One interpretation of these decision errors is inertia: if it is costly for funds to change the fees that they charge, including the component that covers marketing costs, these will be sticky over time, typically deviating from the level that is optimal at a particular point in time (we abstract from modeling the dynamic fee-setting behavior here). Indeed, unlike expense ratios, marketing expenses observed in the data tend to cluster at "round" numbers, such as 75 bps. Some of these values are salient due

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expense  $b_j$  and an unobserved component  $\xi_j$ . We assume that the funds set marketing optimally, on average. Maximizing the fund's profit,  $(p_j - b_j)s_j$  leads to the first-order condition  $-s_j + \theta_j(p_j - b_j) = 0$ . We specify  $\theta_j = \theta \cdot e^{\omega_j}$  where  $\omega_j$  is a mean-zero error term. Then,  $\theta_j$  is always positive and centered on  $\theta$ . Taking log of the first-order condition implies  $\log(\theta) + \omega_j = \log\left(\frac{s_j}{p_j - b_j}\right)$ . We can estimate  $\log(\theta)$  as the mean of the  $\log\left(\frac{s_j}{p_j - b_j}\right)$  across  $j$  because  $\omega_j$  is a mean-zero error term. Note, particularly, here we do not require orthogonality between  $b_j$  and  $\xi_j$ .

<sup>20</sup> See Baye and Morgan (2004), who show that allowing only a small amount of bounded rationality in players' optimization behaviors can be of great use in reconciling the Nash hypothesis with the commonly observed price patterns in the data.

to regulation (e.g., only funds with zero sales loads and 12b-1 fees that do not exceed 25 bps can be designated as “no load”). Clearly, there is no reason that such clustering would be optimal given the objective in (11). Another source of errors would come from fund-family-related constraints (e.g., some families have financial advisory arms and might choose to cross-subsidize those by channeling marketing fees to the advisors they employ, even if it is suboptimal from the standpoint of maximizing profits on some of the funds they manage, while other families might eschew marketing altogether even if some of their funds might benefit from it).

Thus, we assume that fund choices of prices and marketing expenses are optimal *on average*, so that the first-order conditions are satisfied up to a fund-period-specific errors. Given (13) and (14), this amounts to  $E(\zeta_{j,t})=0$  and  $E(\omega_{j,t})=0$ . Notice that these moments do not impose any distributional or correlational assumptions on  $\zeta_{j,t}$  or  $\omega_{j,t}$ . In sample versions,

$$\sum_{t=1}^T \sum_{j \in t} \zeta_{j,t} = 0, \quad (15)$$

$$\sum_{t=1}^T \sum_{j \in t} \omega_{j,t} = 0. \quad (16)$$

The first error,  $\zeta_{j,t}$ , can be directly backed out from the first-order condition given any set of parameter values:

$$\zeta_{j,t} = -\log\left(\frac{-\partial H_{j,t}/\partial p_{j,t}}{s_{j,t}}\right) - \log(p_{j,t} - b_{j,t}).$$

The second error,  $\omega_{j,t}$ , can be computed exactly for  $j$  with  $0 < b_{j,t} < \bar{b}$ , but unfortunately not for the boundary cases:

$$\omega_{j,t} \begin{cases} \leq \bar{\omega}_{j,t}, & \text{if } b_{j,t} = 0; \\ \geq \bar{\omega}_{j,t}, & \text{if } b_{j,t} = \bar{b}; \\ = \bar{\omega}_{j,t}, & \text{otherwise,} \end{cases}$$

where

$$\bar{\omega}_{j,t} \equiv -\log\left(\frac{\partial H_{j,t}/\partial b_{j,t}}{s_{j,t}}\right) - \log(p_{j,t} - b_{j,t}).$$

In principle, we cannot simply use the average of  $\bar{\omega}_{j,t}$  as an estimate of  $E(\omega_{j,t})$ . A conventional way to deal with this kind of truncation problem is to make an additional distributional assumption and apply an MLE estimator. However, a key issue here is that the truncation interval is not fixed but varies across funds endogenously, and thus it may be correlated with  $\omega_{j,t}$ .

We take a simpler approach of comparing the estimates based on several subsample versions of (16):

$$(i) \sum_{0 < b_{j,t} < \bar{b}} \omega_{j,t} = 0; (ii) \sum_{b_{j,t}=0} \bar{\omega}_{j,t} = 0; (iii) \sum_{b_{j,t}=\bar{b}} \bar{\omega}_{j,t} = 0; (iv) \sum_{\text{all } j,t} \bar{\omega}_{j,t} = 0.$$

The first version (i) assumes that on average, the funds that choose an interior level of marketing expenditure are right about the effect of marketing on market

share. These are the funds for which we can exactly calculate the  $\omega_{j,t}$ . We acknowledge that these funds are a selected subsample of all funds; their average does not necessarily reflect the average across all funds. However, these are the funds that choose the less extreme marketing expenses. In addition, they make up a substantial portion (about 30%) of the funds in the data, so it is reasonable to believe that their average assessment is not far from the population average. The second version (ii) uses the truncated values (lower bounds) of the  $\omega_{j,t}$  of the funds that choose zero marketing expenses. The third version (iii) uses the truncated values (upper bounds) of the  $\omega_{j,t}$  of the funds that choose the highest possible marketing expenses,  $\bar{b}$ , which has been 1% imposed by the SEC. The last version (iv) uses all the values for  $\omega_{j,t}$ . We use these three latter cases as robustness checks. If the estimates based on these four different assumptions are similar, then we can be confident that estimates based on the full sample moment (16) are not too severely affected by the truncation.<sup>21</sup>

Our GMM estimation is just identified, since there are five unknown parameters (not counting the year fixed effects) and five moment conditions. The parameters are the average search cost  $\lambda$ , the utility weight of outperformance  $\gamma$ , the sensitivity of sampling probability to marketing  $\theta$ , and a two-dimensional vector of sensitivities  $\beta$  (for number of funds in the fund family and fund age). There are three moment conditions for the sampling probability residual  $\xi$  and two more moment conditions based on the first-order necessary conditions for the optimality of funds' pricing and marketing behavior in Equations (15) and (16), respectively. We conduct this second-stage estimation in one step using the identity weighting matrix. Standard errors are estimated via parametric bootstrap (described in the Internet Appendix), which allows for arbitrary correlation between error terms, in particular  $\zeta_{j,t}$  and  $\omega_{j,t}$ .

## 4. Results

### 4.1 Fund performance

Table 1 reports estimates of the fund performance-related parameters using our full sample.<sup>22</sup> The magnitude of decreasing returns to scale parameter  $\eta$  is 0.0048, and it is statistically significant. Since the standard deviation of log fund size is 1.628, a one-standard-deviation *increase* in log fund size is associated

<sup>21</sup> We analyze how sensitive our parameter estimates are to the violations of these two key moment conditions using the method proposed by Andrews, Gentzkow, and Shapiro (2017) in the Internet Appendix. We show the parameter estimates are insensitive to reasonable deviations from the assumption that these moment conditions hold with equality.

<sup>22</sup> In our data set, the first period with nonmissing data is the year 1964, so our full sample estimates use the data from 1964 to 2015. It is important to use all the available information to estimate the learning model that is the core of Berk and Green (2004). In the model, when a fund is born, it draws an initial skill level from the prior skill distribution. Then investors use the *entire* history of subsequent realized performance to update their beliefs about each fund's skill level. If we were to start the sample at a later date, for example, year 1995, we would lose the performance information for a lot of funds that were in operation well before 1995. One way to circumvent the above truncation problem is to pick a starting year and keep only the funds that are founded after this year. But this approach would bias the estimates toward newer funds.

**Table 1**  
**Investor beliefs and manager skill parameters**

Parameters	Description	1964–2015
$\eta$	Decreasing returns to scale (%)	0.48 (0.04)
$\mu$	Mean of prior (%)	3.05 (0.25)
$\kappa$	SD of prior (%)	2.41 (0.12)
$\delta$	SD of realized alpha (%)	7.62 (0.05)
$\rho$	Skill persistence	0.94 (0.02)
Num of obs		27,621

This table presents the estimates of the fund performance-related parameters. The decreasing returns to scale parameter,  $\eta$ , the mean of manager's ex ante skill distribution,  $\mu$ , the standard deviation of this distribution,  $\kappa$ , the standard deviation of the idiosyncratic noise in the realized alpha,  $\delta$ , and the persistence of the manager's skill,  $\rho$ . Standard errors are in the parentheses.

with approximately a 78 bps *decrease* in mean annual alpha. This result is close to Chen et al. (2004). This magnitude is economically significant, in particular as compared to the mean gross alpha of 54 bps. For robustness, we also estimate the model using linear (rather than logarithmic) specification that is similar to Pástor, Stambaugh, and Taylor (2015) and obtain estimates broadly consistent with theirs.<sup>23</sup>

Existence of stock-picking skill among mutual fund managers is one of the oldest queries in empirical finance. Early literature used persistence of fund-level performance as an indicator of skill in active fund management, an approach that is called into question by Berk and Green (2004), who argue that the lack of performance persistence does not imply absence of fund manager skill, as long as capital flows to outperforming funds and if the resultant increase fund size erodes performance. Here, we take a different approach by estimating a version of the Berk and Green (2004) model directly. We find that the mean of the prior distribution of managerial skill is 3.05% (per annum). This number is positive and statistically significant, which means that an average active mutual fund manager is skilled. Over 71% of the funds have fundamental skill levels that are higher than the mean expense ratio, at least when applied to the first dollar of assets under management (i.e., before any of the effects of decreasing returns to scale).

Another parameter of interest is  $\rho$ , the persistence of fund manager's skill. Our empirically estimated persistence is 0.94, which means past beliefs are quite useful in predicting future performance. Our skill persistence result is

<sup>23</sup> Some disagreement appears in the literature about the role of fund size in eroding performance due to decreasing returns to scale, since estimates of the latter can potentially suffer from omitted variable bias, since both fund size and observed performance are correlated with underlying fund skill, which is unobservable (see, e.g., the discussion in Pástor, Stambaugh, and Taylor 2015 and Reuter and Zitzewitz 2015). Our estimation approach is not subject to this concern, however, since it does not rely on the correlation between fund size and performance across funds to identify  $\eta$ . Indeed, we verify that our estimator is able to recover the true value of this parameter, which controls the strength of decreasing returns, via Monte Carlo simulation.

consistent with Berk and van Binsbergen (2015), who find that the cross-sectional differences in value added persist for as long as 10 years. One of the reasons that skill persistence is not perfect as assumed in the Berk and Green model is managerial turnover. To the extent that the skill of a mutual fund is partially due to the fund's manager, a change in the management team might affect the skill level of the fund. Fidelity Magellan's Peter Lynch is a case in point: during his tenure at the helm of the fund from 1977 to 1990 Magellan achieved 14 consecutive years of positive alpha according to our measure of performance. After Peter Lynch's departure, the fund's performance becomes less impressive, consistent with reversion toward the mean.

Finally, we want to note that the posteriors of skills, filtered under the above parameter estimates, do predict realized performance. We present this result and more details in the Internet Appendix.

## 4.2 Asset misallocation

Equipped with estimated parameters of the fund skill distribution, we compute the implied investor beliefs about each fund's skill level at each point in time. We can then derive corresponding fund size implied by a benchmark frictionless model following Berk and Green (2004) (henceforth BG). By comparing BG-implied fund size with the data, we can assess the degree of asset misallocation in the mutual fund industry.

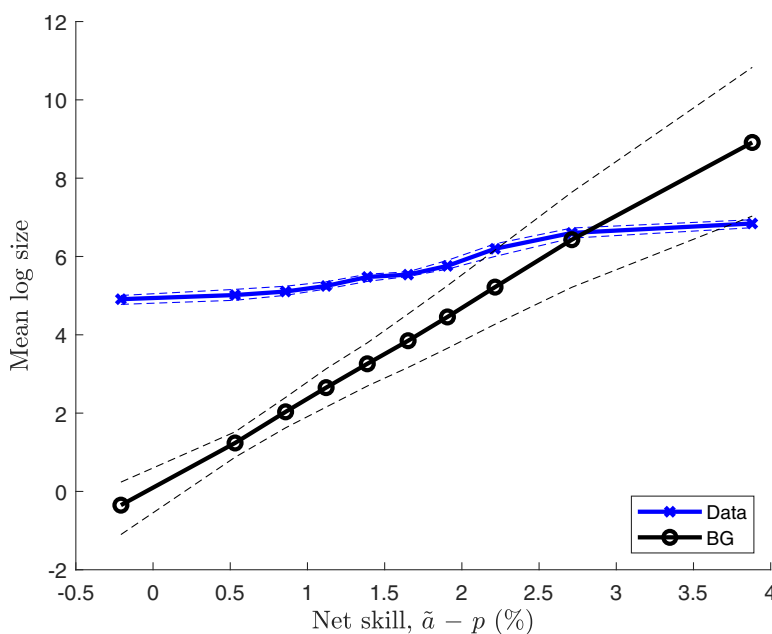
First, we compute the investor beliefs about each fund's skill level  $\tilde{a}_{j,t}$  using the recursive expression derived in Section 1.1. As an example, consider a fund  $j$  that was born in period  $t=1$ . At the fund's birth, we assign the fund an expected skill level of  $\mu$ , then we use realized return  $r_{j,1}$  and fund size  $M_{1s_{j,1}}$  to get the updated belief,  $\tilde{a}_{j,1}$ . By iterating forward, we can generate the whole series of fund's expected skill levels. Next, we compute the BG-implied fund size. Berk and Green's model predicts that fund's size (i.e., total assets under management), which we denote by  $s_{j,t}^{BG}$ , should be such that the decreasing returns to scale exactly offsets the investor belief less fund expense ratio, denoted as "net skill":  $D(s_{j,t}^{BG}; \eta) = \tilde{a}_{j,t} - p_{j,t}$ . So, with a log specification for  $D(\cdot)$ , we have

$$\log(s_{j,t}^{BG}) = \frac{\tilde{a}_{j,t} - p_{j,t}}{\eta}. \quad (17)$$

This expression is intuitive: the higher the net skill of a fund, the larger is the efficient fund size; the stronger the effect of decreasing returns to scale, the smaller the fund's size will be.

To compare BG-implied fund size with the data, we construct ten portfolios of mutual funds sorted on net skill. We then compute the mean of log size in the data and in the BG model for each portfolio.<sup>24</sup> Figure 1 presents the result. First, we can see that in the data, the mean fund size monotonically increases with net

<sup>24</sup> We winsorize the belief  $\tilde{a}$  at the 1% and 99% levels because of outliers in the estimated beliefs.



**Figure 1**  
**Capital (mis)allocation in mutual funds: size versus net skill**

This figure plots the mean of log fund size (measured in millions of dollars) for portfolios of funds formed on net skill (defined as posterior belief about the skill level  $\tilde{a}$  minus expense ratio  $p$ ). We compute fund size according to the generalized version of the Berk and Green (2004) model that we estimate:  $\log(s_{j,t}^{BG}) = \frac{\tilde{a}_{j,t} - p_{j,t}}{\eta}$ , where  $\eta$  captures decreasing returns to scale. The black line represents the mean of the Berk and Green model-implied fund sizes for each portfolio (BG). The blue line represents the mean of log fund size in the data for each portfolio. There are 10 portfolios; portfolio 1 has the lowest net skill, and portfolio 10 has the highest net skill. Dashed lines represent 95% confidence bounds.

skill. This result is consistent with the Berk and Green model's prediction. But we also witness a discrepancy between the data and the model. On the higher end, BG predicts the mean size of funds in portfolio 10 to be \$7.3 billion. In the data, the mean fund size in portfolio 10 is \$936 million. On the lower end, according to BG, the mean fund size in portfolio 1 is \$0.7 million. And in the data, it is \$134 million. These differences are statistically significant, as indicated by the 95% confidence intervals. From this figure, we can draw the conclusion that asset misallocation exists in both bad funds and good funds in the data.

The key prediction of Berk and Green (2004) is that asset inflows into funds that are estimated to be skilled based on their past returns will erode their subsequent performance due to decreasing returns to scale. In addition, fund managers who have been revealed as skilled can raise their fees and thus extract the rents associated with their ability. As a result, net alpha of these funds should be zero in the future, on average. We can test this prediction of the model by looking at abnormal returns on the portfolios of mutual funds formed on their

net skill discussed above. Thus, using the updated belief about fund skill as well as its fees in year  $t$ , funds are placed into portfolios, and we track equal-weighted returns on these portfolios over the subsequent 12 months, until the portfolios are re-sorted based on the updated information from  $t+1$ . Figure 2 displays estimated five-factor alphas on these portfolios along with their 95% confidence intervals. Consistent with much of the mutual fund literature, the vast majority of alphas are negative (i.e., for all but the top-two deciles of net skill). Perhaps more surprisingly, funds in the top decile of estimated net skill actually do display statistically significant outperformance. Overall, realized alpha is monotonically increasing with the estimated net skill, ranging from close to  $-3\%$  per annum for the funds in the bottom decile, to about  $0.7\%$  for those in the top decile. This result indicates a stark rejection of the key prediction of the BG model. Assets don't seem to flow out of unskilled and/or expensive funds toward the relatively more skilled ones, as suggested by evidence in Figure 1 above, and even the "best" funds that are "too small" relative to the BG model don't raise their prices sufficiently to fully capture their outperformance. Thus the observed allocation of capital across equity mutual funds, combined with their price setting behavior, present a quantitative puzzle for the frictionless BG model.

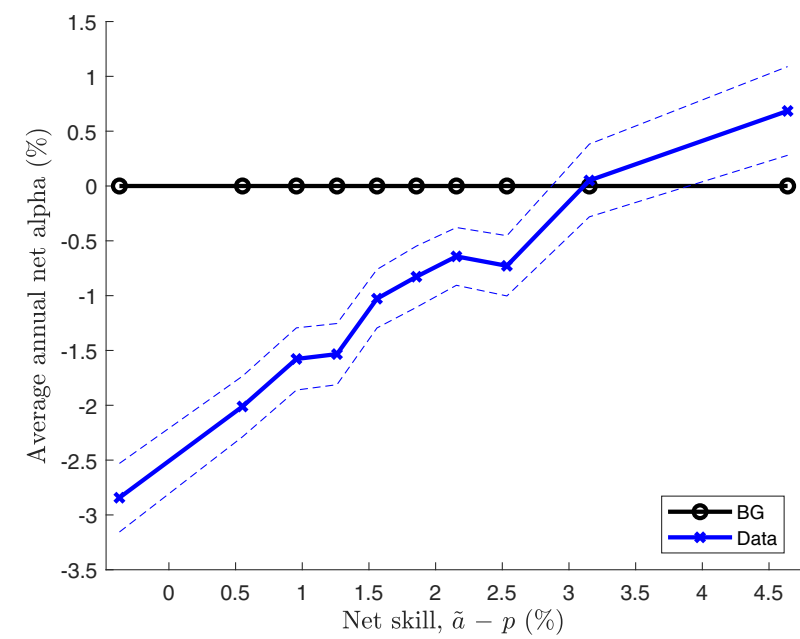
### 4.3 Search model parameters

Our search model is meant to bridge the gap between the efficient capital allocation described by the Berk and Green model and the actual allocation of assets across mutual funds observed in the U.S. data. Table 2 reports the estimated parameters of the structural search model. With the view toward conducting counterfactual analysis, we rely on the more recent sample of the data for this part of the estimation, choosing 2001 as our starting point (our estimation results are robust to various starting points, however). As described in the estimation section, we estimate the model using four versions of the moment conditions in (16). All the parameters other than  $\theta$  are quite stable across the four sets of estimates. This assures us that even though our identification of  $\theta$  relies on one subsample, it does not affect other parameters drastically.

Our estimate of  $\lambda$ , the mean of search cost, is 39 bps.<sup>25</sup> Hortaçsu and Syverson (2004) find that the mean search cost for the S&P 500 index fund market is from 11 bps to 20 bps across different specifications.<sup>26</sup> Our estimated average search cost is somewhat higher than theirs since, presumably, investors in their sample have higher than average level of financial sophistication (implying a

<sup>25</sup> We also estimate our model using three subsamples: 2001-2005, 2006-2010, 2011-2015. The results are in the Internet Appendix. The decreasing pattern of mean search costs is consistent with the observed growth in passive index funds over the last two decades highlighted by Stambaugh (2014).

<sup>26</sup> Hortaçsu and Syverson (2004) estimated two variants of their search model: one in which sampling probabilities are different across funds, and another one where they are identical. We view our model as being closer to the former. The estimation results for that version of the model are reported in table III of their paper. The log mean search cost is around  $-6.17$  to  $-6.78$ , which implies mean search costs ranging from 11 bps to 20 bps.



**Figure 2**  
**Capital (mis)allocation in mutual funds: Net alpha versus net skill**

This figure plots the average annual net alpha for portfolios of funds formed on net skill (defined as posterior belief about the skill level  $\tilde{a}$  minus expense ratio  $p$ ). The black line represents the Berk and Green (2004) model-implied net alpha for each portfolio (BG). The blue line represents the mean of net alpha in the data for each portfolio. There are 10 portfolios; portfolio 1 has the lowest net skill, and portfolio 10 has the highest net skill. The horizontal axis indicates the average net skill of each portfolio. Dashed lines represent 95% confidence bounds.

**Table 2**  
**Search model parameters**

Parameters	Description	(1) Interior	(2) Lower	(3) Upper	(4) All
$\lambda$	Mean search cost (%)	0.39 (0.04)	0.39 (0.04)	0.39 (0.04)	0.39 (0.04)
$\gamma$	Alpha weight	0.41 (0.03)	0.41 (0.03)	0.41 (0.03)	0.41 (0.03)
$\theta$	Marketing effectiveness	113.11 (7.33)	111.22 (7.29)	133.18 (8.79)	122.56 (7.39)
$\beta_1$	Family size effect	0.40 (0.03)	0.40 (0.03)	0.38 (0.03)	0.39 (0.03)
$\beta_2$	Fund age effect	1.03 (0.04)	1.03 (0.04)	1.03 (0.04)	1.03 (0.04)
Year FE		Yes	Yes	Yes	Yes

This table presents the estimates of the structural search model. We use the data from 2001 to 2015. The four columns correspond to four sets of moment conditions as described in Section 3. In column 1, we use the funds that are not constrained in their marketing expenses to estimate the model. In column 2, we use only funds with zero marketing expenses to estimate the model. In column 3, we use the funds whose marketing expenses are 100 bps to estimate the model. In column 4, we use all of the funds to estimate the model.



lower level of search costs). This is because they focus on investment in S&P 500 index funds in the late 1990s, when these funds were not as prominent as they are today. Alternatively, it may be the case that it is difficult to evaluate actively managed mutual funds (compared to index funds, which are relatively simple products), and hence implied barriers to information acquisition that are implied by the observed distribution of fund size are greater.

The magnitude of the mean search cost is quite significant. For the average investor, the cost of drawing another sample fund is 39 bps, which is comparable to the mean alpha in our sample. The large magnitude of estimated search cost is a reflection of the active fund underperformance puzzle. In the mutual fund literature, numerous papers documented the (persistent) underperformance of (at least a large subset of) active funds (e.g., Carhart 1997). Since many underperforming funds enjoy sizable market shares, our model requires a high search cost to rationalize those facts. In our model, high search cost investors will find it suboptimal to continue searching for a better fund than those drawn in the first couple of attempts. In the counterfactual case, if the search costs were low then index funds would be much larger than observed in the data, and underperforming active funds would be substantially smaller.

Our key parameter of interest is  $\theta$ , the coefficient in front of marketing expenses in the sampling probability function. First, we notice that the estimated  $\theta$  is the smallest when we use the moment conditions of the funds that choose to do no marketing, and the largest for the funds that choose the upper bound of 1%. For the funds that choose the interior levels,  $\theta$  is in the middle. This is intuitive because  $\theta$  measures the effectiveness of marketing. The funds that are at the upper bound are more likely to be constrained in their ability to increase their marketing in an effort to increase investors' awareness. Consequently, the first-order condition (16) is likely to be satisfied with an inequality, and forcing it to be zero in estimation biases the estimate upward. Similarly, the funds at the lower bound are likely to find it optimal to receive a "rebate" on marketing in order to increase their profits, but since such rebates are not available their first-order condition is also likely not to be satisfied, biasing the estimate of  $\theta$  downward. In what follows, we rely on the estimates obtained with funds in the interior of the marketing expenditures as our benchmark.

In the sampling probability function, besides marketing expenses, we include fund family size, log fund age, and year fixed effect. The coefficient of family size is positive and significant, confirming the idea that larger fund families are better at informing investors about their products. The fund age coefficient is positive and significant, which is intuitive, as older funds also have more visibility than younger funds. This result is also consistent with Hortaçsu and Syverson (2004) evidence from the S&P 500 index fund market.

To put these estimates into perspective, we conduct the following experiments. We compute the percentage changes in fund size for various groups of funds when marketing expense increases by 1 bp. Table 3 provides the results. Each column corresponds to results computed using different

**Table 3**  
**Change in size when marketing expenses increase by 1 bp**

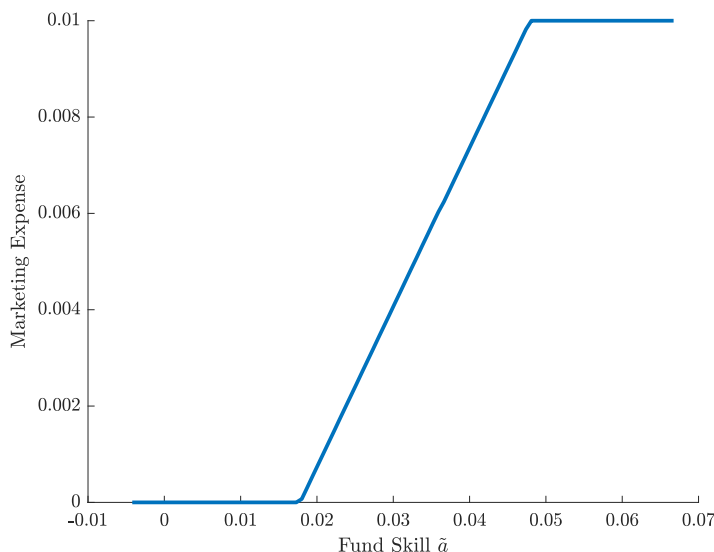
	$\theta = 113.11$	111.22	133.18
<i>A. Sort by size</i>			
Big funds	0.8904	0.8735	1.043
Intermediate size funds	0.8965	0.8794	1.050
Small funds	0.9261	0.9085	1.085
<i>B. Sort by skill</i>			
High skill funds	0.9858	0.9670	1.155
Intermediate skill funds	0.9161	0.8987	1.073
Low skill funds	0.8311	0.8154	0.973
<i>C. Sort by original marketing expense</i>			
Binding at lower bound	0.9739	0.9554	1.141
Nonbinding	0.9165	0.8990	1.073
Binding at upper bound	0.8575	0.8413	1.004

This table provides the percentage changes in fund size resulting from a 1-bp increase in marketing expenses for various groups of funds using parameters from Table 2, column 1 except  $\theta$ . For  $\theta$ , we use the estimated value of  $\theta$  from columns 1, 2 and 3, respectively, in Table 2. In panel A, we sort funds by size. “Big funds” are funds in the top decile. “Small funds” are funds in the bottom decile. “Intermediate size funds” are the rest. In panel B, we sort funds by skill level. “High skill funds” are funds in the top decile. “Low skill funds” are funds in the bottom decile. “Intermediate skill funds” are the rest. In panel C, we sort funds by marketing expenses. “Binding at lower bound” are funds with no marketing expenses. “Binding at upper bound” are funds whose marketing expenses are at the upper bound of 1%. “Nonbinding” refers to the rest.

values of the  $\theta$  parameter - those obtained with the funds on the upper bound ( $\theta = 133.18$ ), lower bound ( $\theta = 111.22$ ), and in the interior ( $\theta = 113.11$ ) of marketing expenditures, as described above. All the other parameters are fixed at the benchmark levels (estimates from the “interior” funds). When we change fund  $j$ ’s marketing, we fix all the other funds’ prices and marketing expenses and fund  $j$ ’s price (i.e., this is a comparative static, not counterfactual analysis). Thus, holding total fees fixed, a 1 bp increase in marketing implies an equivalent reduction in profit margins.

Overall, a 1 bp increase in marketing expenses leads to a roughly 1 % increase in fund’s size, but there is substantial variation across different types of funds, and this elasticity naturally increases with  $\theta$ . In panel A, we sort funds by their size. We find that as fund size decreases, the sensitivity of size to a 1 bp increase in marketing rises. Using the benchmark estimates ( $\theta = 113.11$ ) it goes from approximately 0.89% for large funds to 0.93% for small funds. This is intuitive because as a prior, marketing investment should be much more effective for smaller funds because they have smaller probabilities of being known (e.g., typically, they are younger). Investing in marketing is a good way for small funds to attract greater investor attention. Interestingly, this sensitivity is higher both at the upper and at the lower estimates of  $\theta$ .

In panel B, we sort funds by their skill level  $\tilde{a}$ . We find that marketing is much more useful for highly skilled funds. If high-skill funds can get into the consideration sets of more investors they will be picked by more investors. But for the low-skill funds, even if they are known to more investors, their size will not increase sufficiently to justify the extra expense. In fact,



**Figure 3**  
**Marketing and skill**

This figure plots the relationship between fund's skill  $\bar{a}$  and model-implied fund's marketing expense, for a fund in year 2015 that has average characteristics,  $\xi=0$ ,  $\zeta=0$ , and  $\omega=0$ . We vary the posterior belief about its skill  $\bar{a}$  and calculate the associated optimal marketing expense, given the choices of the other funds observed in the data.

Figure 3 shows that, for a fund of average age and belonging to a fund family of average size, with fund-year shock  $\xi=0$ , the optimal level of marketing is increasing in the posterior belief about its skill. This result indicates that marketing is complementary to skill, yet it does not mean that it helps improve welfare in the presence of the search friction, since high-skill funds may be forced to spend “too much” on marketing, leading to a wasteful “arms race.”

Lastly, in panel C, we sort funds by their original marketing expenses levels. Lower bound funds are funds that originally choose zero marketing expenses. Upper bound funds are funds that originally chose 1% marketing expenses. Nonbinding funds are the rest of funds, which choose interior marketing levels. We find that an additional 1 bp increase in marketing is not very useful to funds at the upper bound (suggesting that many of these funds are at suboptimally high levels of marketing, perhaps due to inertia). Similarly, for funds at the lower bound extra marketing appears more worthwhile. Some of these funds might belong to fund families that choose to sell their funds directly rather than through brokers, for example, and as a consequence do not charge any 12b-1 fees, even though doing so might be beneficial for some of their funds.

Next, we analyze the impact of marketing on fund profits. Table 4 displays the results. In panel A, we sort funds by size; we find that for the small funds extra marketing increases profits, if all the other funds' strategies in pricing and marketing stay the same (since we are not recomputing their best responses

**Table 4**  
**Change in profits when marketing expenses increase by 1 bp**

	$\theta = 113.11$	111.22	133.18
<i>A. Sort by size</i>			
Big funds	-0.4150	-0.4317	-0.2645
Intermediate size funds	-0.0143	-0.0311	0.1381
Small funds	0.1024	0.0850	0.2602
<i>B. Sort by skill</i>			
High skill funds	-0.1081	-0.1267	0.0597
Intermediate skill funds	-0.3186	-0.3358	-0.1634
Low skill funds	-0.1972	-0.2128	-0.0567
<i>C. Sort by original marketing expense</i>			
Binding at lower bound	-0.1917	-0.2100	-0.0263
Nonbinding	-0.1550	-0.1722	0.0006
Binding at upper bound	-0.4019	-0.4180	-0.2569

This table provides the percentage changes in fund profits resulting from a 1-bp increase in marketing expenses for various groups of funds using parameters from Table 2, column 1 except  $\theta$ . For  $\theta$ , we use the estimated value of  $\theta$  from columns 1, 2 and 3, respectively, in Table 2. In panel A, we sort funds by size. “Big funds” are funds in the top decile. “Small funds” are funds in the bottom decile. “Intermediate size funds” are the rest. In panel B, we sort funds by skill level. “High skill funds” are funds in the top decile. “Low skill funds” are funds in the bottom decile. “Intermediate skill funds” are the rest. In panel C, we sort funds by marketing expenses. “Binding at lower bound” are funds with no marketing expenses. “Binding at upper bound” are funds whose marketing expenses are at the upper bound of 1%. “Nonbinding” refers to the rest.

in this exercise). In panel B, we show that when  $\theta$  is at the higher level of estimates, it is profitable for high-skill funds to do more marketing. In panel C, we find that essentially all of the funds are worse off if they increase their marketing, which is not surprising given that the estimation procedure assumes that funds are at their optimal levels of marketing (on average).

**4.4 Accounting for variation in fund size**

In this section, we quantify the role of individual ingredients of our search model in explaining the empirical size distribution of mutual funds. Our method is as follows: we first set a particular component in the investor utility function (5) or in the sampling probability function (6) to a constant. For example, by setting all funds’ marketing expenses  $b$  to zero, we are effectively removing all the explanatory power of marketing expenses from the model. We then compute synthetic market shares using investor demand curves implied by our estimated model, as summarized in Equation (9), and compare them with actual market shares. Specifically, let

$$s_t^* = F_t[p_t^*, b_t^*, \tilde{a}_t^* - \eta \log(M_t s_t), x_t^*, \xi_t^*, p_{0,t}; \Theta], \tag{18}$$

where the arguments with the asterisks are equal to their empirical values if the variable is “included” in the specification, and otherwise set to zero (for fund skill  $\tilde{a}_j$  and expense ratio  $p_j$  we use sample means when the variables are “not included” in the specification.<sup>27</sup>). Importantly, in this exercise we are not

<sup>27</sup> An explicit recursive expression for the market share function  $F$  is provided in the Appendix A.

Table 5  
Quantifying the importance of search model components

Specification	$\xi$	Age	Num of family funds	Marketing	Skill	Price	$R^2$	Correlation between $s^{BG}$ and $s^{Model}$
(1)		Y	Y	Y	Y	Y	0.5169	0.2988
(2)			Y	Y	Y	Y	0.2122	0.4988
(3)				Y	Y	Y	0.1614	0.5698
(4)					Y	Y	0.1152	0.5947
(5)	Y	Y	Y		Y	Y	0.9157	0.1456
(6)	Y	Y	Y	Y		Y	0.9008	0.0301
(7)	Y	Y	Y	Y	Y		0.9005	0.0776
Data							1	0.0901

This table presents results regarding quantifying the importance of various components of the search model in explaining the size distribution of funds. Our method is as follows: we first set a particular component in the utility function (5) or the sampling probability Equation (6) equal to zero. Then we compute synthetic market shares of all funds using Equation (9). Notice that here we are not recomputing the whole equilibrium. We fix all other variables and parameters. Lastly, we regress the log of market share of funds in the data onto synthetic log market shares and report the  $R$ -squared. We also report the correlation between the synthetic fund size and the generalized Berk and Green model-implied fund size. “Y” indicates that we include this component in the sampling probability. A blank entry means that we remove this component. The data period is from 2001 to 2015.

recomputing the whole equilibrium, since we keep other variables fixed (rather than solving for every fund’s best response).

We regress the log of market share in the data  $s_{j,t}$  on these synthetic log market shares  $s_{j,t}^*$  and report the  $R$ -squared of these regressions in Table 5. The lower the  $R$ -squared, the more important that argument is for explaining the size distribution in the data. Among all of them, the unobserved characteristics of the fund  $\xi$  constitute the most important component (responsible for almost half of the  $R$ -squared). This is intuitive since we only include a limited number of variables in our estimation; any other variables that could potentially affect fund size would be subsumed by  $\xi$ . The second-most important variable is fund age. After controlling for fund’s age and other variables, the family size doesn’t add much explanatory power.

What about the key features of mutual funds that have been the main focus of the literature, namely, skill and costs? Removing variation in either posterior skill or the fund price (expense ratio) reduces the  $R$ -squared to about 90% in each case. Importantly, removing the marketing variable yields a very similar  $R$ -squared of 92%. This indicates that marketing is nearly as important in terms of explaining the size distribution of mutual funds as price or skill.

We are also interested in understanding how do various components of our model contribute to the observed misallocation of capital to funds. We compute the correlation between the synthetic fund size  $s_{j,t}^*$  and the BG-implied fund size  $s_{j,t}^{BG}$ , as defined in Equation (17). We can see that in the data (or, equivalently, our unrestricted model, which matches the data by construction) the correlation is positive but small, at 0.09. If changing one of the components of the model increases this correlation, that means that this change makes capital allocation more efficient (in the sense of BG). This correlation is at its highest level of 0.59 if we only include fund skill and price. Conversely, removing price or skill but

including other (search model) ingredients reduces this correlation, since these are the key elements of the Berk and Green model. At the same time, removing marketing increases the correlation. This result suggests that marketing could potentially account for at least some of the misallocation that we observe in the data. However, it is possible that if funds were not able to market they would respond in other ways that might either improve or further harm allocational efficiency. In Section 5 below we describe counterfactual experiments that fully take into account the equilibrium behavior of both investors and funds.

## 5. Counterfactual Analysis

Section 4.2 documents substantial capital misallocation in the mutual fund industry. In this section, we use our model to quantitatively study the importance of marketing expenses and search costs in shaping the equilibrium fund size and expense ratios. We also investigate how they affect allocational efficiency and investor welfare. First, we explore a counterfactual equilibrium with no marketing.<sup>28</sup> We then investigate the impact of changing search costs on equilibrium marketing expenses. We focus on the most recent year in our sample (2015) for these experiments and abstract from horizontal differentiation between funds, relying on the parameter estimates for the baseline model.

### 5.1 Welfare measures

To analyze the welfare impact of marketing, we need to define welfare for all the agents in the model. Fix a year  $t$  (the time subscript  $t$  will be suppressed in this section). In our model, investors' utility consists of two parts, the expected indirect utility provided by the fund that investor chooses and the expected total search costs the investor incurs in order to find this fund. The welfare of investor  $i$  with search cost  $c_i$  is given by

$$V(c_i) = \frac{\int_{\bar{u}(c_i)}^{+\infty} u d\Psi(u)}{1 - \Psi[\bar{u}(c_i)]} - c_i \frac{\Psi[\bar{u}(c_i)]}{1 - \Psi[\bar{u}(c_i)]}, \quad (19)$$

where  $\bar{u}$  is the reservation level of indirect utility (a detailed derivation of investors' welfare is provided in Appendix B). For a higher level of reservation utility, the investor needs to search more in order to find the desired fund. We see that the expected total search cost  $c_i \frac{\Psi[\bar{u}(c_i)]}{1 - \Psi[\bar{u}(c_i)]}$  is increasing in  $\bar{u}$ . In the first term of Equation (19), the numerator is the expected indirect utility for the funds with higher than  $\bar{u}$  utility level. The denominator adjusts for the fact that the investor will only pick the funds from this part of the distribution. The

<sup>28</sup> Recently, the SEC considered a proposal to improve the regulation of mutual fund distribution fees, in particular, by limiting fund sales charges as a way of protecting retail consumers from unnecessarily high costs. Our counterfactual analysis can be viewed as analyzing welfare consequences of a policy that sets the marketing cap at zero.

aggregate measure of investor welfare in this model is derived by integrating across the search cost distribution:

$$U = \int_0^{+\infty} V(c_i) dG(c_i). \quad (20)$$

Fund profits are also part of the total welfare. These include the profits for both active funds and index funds (even though the latter are not maximizing agents in our model):

$$P = \sum_{j=1}^N (p_j - b_j) s_j + s_0 p_0. \quad (21)$$

Here the first part is the total profits for the active funds, the second part is the total profits for the passive funds. In the counterfactual analysis, we assume index fund price is fixed and we resolve the equilibrium for the active funds' prices and marketing expenses. In our counterfactual we assume the total size of the mutual fund market  $M$  stays the same.

If marketing expenses constitute payments to labor (e.g., broker commissions) or profits accruing to advisory and marketing firms, rather than dead weight costs, they should also be considered in the welfare analysis:

$$B = \sum_{j=1}^N b_j s_j. \quad (22)$$

Our measure of total welfare is the sum of the three components above:  $U + P + B$ .

## 5.2 Equilibrium with no marketing

In this simulation, we restrict marketing expenses to zero. We use year 2015's data and the benchmark parameters from column 1 in Table 2. Table 6 provides the comparison between the currently observed equilibrium and the no-marketing equilibrium on some of the key measures. First, the mean expense ratio drops by almost 77 bps in the counterfactual relative to the current equilibrium. This drop is larger than the decrease in the average marketing expenditure. It indicates fiercer price competition between funds when they cannot attract investors through marketing. To further understand the price changes across funds, we split the funds into four groups based on their marketing expenses in the current equilibrium: (1) funds whose marketing is at the upper bound of 100 bps, (2) funds whose marketing is at the lower bound of 0, (3) funds whose marketing is between 1 bp to 49 bps and (4) funds whose marketing is between 50 bps and 99 bps. We plot the price differences for all funds between the current equilibrium and the no-marketing equilibrium in Figure 4, panel A. We find that all the funds lower their prices in the no-marketing equilibrium, but the magnitude of change varies substantially across

**Table 6**  
**Summary of outcomes for current equilibrium and no-marketing equilibrium**

	Current	No-marketing
Mean price (bps)	160.27	82.96
Mean marketing (bps)	61.29	0
Mean alpha (bps)	37.24	41.07
Total share of active funds (%)	74	68
Mean sampling prob (%)	0.085	0.078
Mean sampling prob for low price funds (%)	0.042	0.14
Mean sampling prob for index fund (%)	5.91	13.66
Investor welfare (bps)	-140.72	-61.25
Active fund profits (bps)	57.51	42.19
Index fund profits (bps)	2.32	2.86
Total welfare (bps)	-37.37	-16.20
Aggregate investor search cost (bps)	29.09	12.15

This table provides various measures of the mutual fund industry under current and no-marketing equilibrium. Mean price, mean marketing, and mean alpha are the arithmetic average of price, marketing expenses and alpha for all active funds, respectively. Total share of active funds is the market share of all active funds. Mean sampling prob for low price funds is the mean sampling probability for funds with below-average prices. Investor welfare is defined in Equation (20). Active fund profits are defined as  $\sum_{j=1}^N (p_j - b_j)s_j$ , which are the total profits for all active funds. Index fund profits are defined similarly. Total welfare is the sum of investor welfare, funds' total profits and total marketing expenses. Aggregate investor search cost is described in Equation (23).

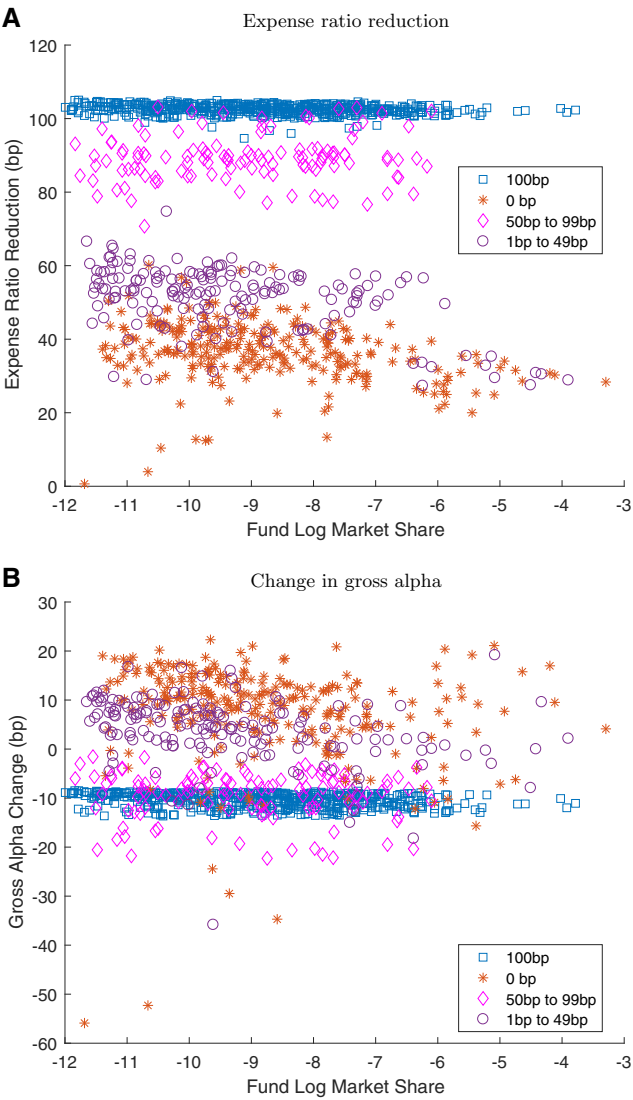
the four groups. Group (1) funds lower their prices by around 100 bps (i.e., roughly their original marketing costs). The most interesting finding is that the group (2) funds in the no-marketing equilibrium also lower their prices by around 30 bps, which necessarily has to come from a reduction in profit margins since these funds do not have any marketing expenses in the current equilibrium. This is mainly due to the effect of competition between funds. A similar but weaker effect is present for most of the funds in groups (2) and (3).

Second, we find that the total market share of active funds drops from 74% to 68%. This indicates that marketing is useful for steering investors toward active funds. When funds cannot do marketing, they lose market share since they are less likely to enter investors' information sets. The sampling probability of index funds increases. This is due to the assumption that all the sampling probabilities sum to 1. When active funds cannot do marketing, the index funds are more likely to be "found." In the no-marketing equilibrium, active funds' profits drop by 15 bps on average. This is the result of both the total market share shrinking and the profit margins falling.

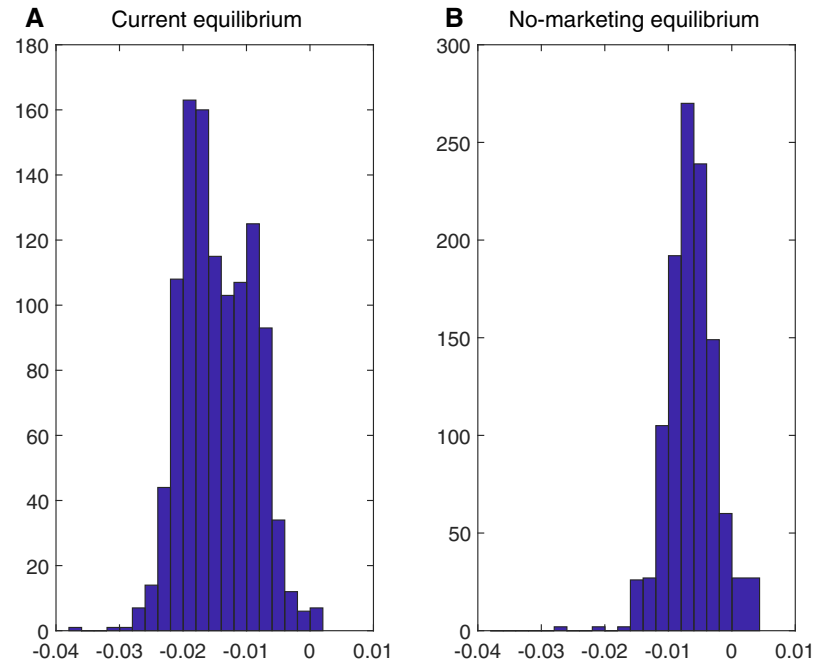
Investor welfare in the no-marketing equilibrium increases by around 79.5 bps.<sup>29</sup> Three main factors contribute: lower prices, higher alphas, and lower search costs. As assets under management decline, the average alpha of the industry increases from 37 bps to 41 bps, due to the effect of decreasing returns to scale. Figure 4, panel B, plots the difference in fund alphas between the no-marketing equilibrium and current equilibrium for different groups of funds. We find that for funds in group (1) alpha increases consistently. This is mainly

<sup>29</sup> In our model, all the welfare calculations are in the unit of alpha (rather than consumption or wealth), since this is the unit that the utility function is defined in.





**Figure 4**  
**Price and performance: Current equilibrium versus no-marketing equilibrium**  
Panel A plots the expense ratio reduction as a result of moving from the current equilibrium (which allows marketing) to the counterfactual no-marketing equilibrium. The  $x$  axis is fund size (here we use log market share). The  $y$  axis is the current equilibrium price minus the no-marketing equilibrium price.  
Panel B plots the differences in gross alpha between the current equilibrium and the no-marketing equilibrium. The  $x$  axis is fund size (here we use log market share). The  $y$  axis is the gross alpha changes.  
We split funds into four groups based on their current marketing expenses. Group 1, indicated by squares, marketing expenses of 100 bps. Group 2, indicated by asterisk, marketing expenses of 0 bp. Group 3, indicated by diamond, marketing expenses between 1 and 49 bps. Group 4, indicated by circle, marketing expenses between 50 and 99 bps.



**Figure 5**  
**Indirect utilities: Current equilibrium versus no-marketing equilibrium**  
Panel A shows the histogram of indirect utilities associated with funds in the current equilibrium (which allows marketing). Panel B shows the histogram of indirect utilities associated with funds in the no-marketing equilibrium. The x axis is utility level. The y axis is frequency. Indirect utility is defined in Equation (5).

because in the no-marketing equilibrium their assets under management fall and so, due to decreasing returns to scale, their alphas increase. For other groups of funds, some of the alphas increase, while others decrease.

We can compute the aggregate search cost incurred by the investors in the two equilibrium. The aggregate search cost is given by:

$$\int_0^{+\infty} c_i \frac{\Psi[\bar{u}(c_i)]}{1 - \Psi[\bar{u}(c_i)]} dG(c_i). \tag{23}$$

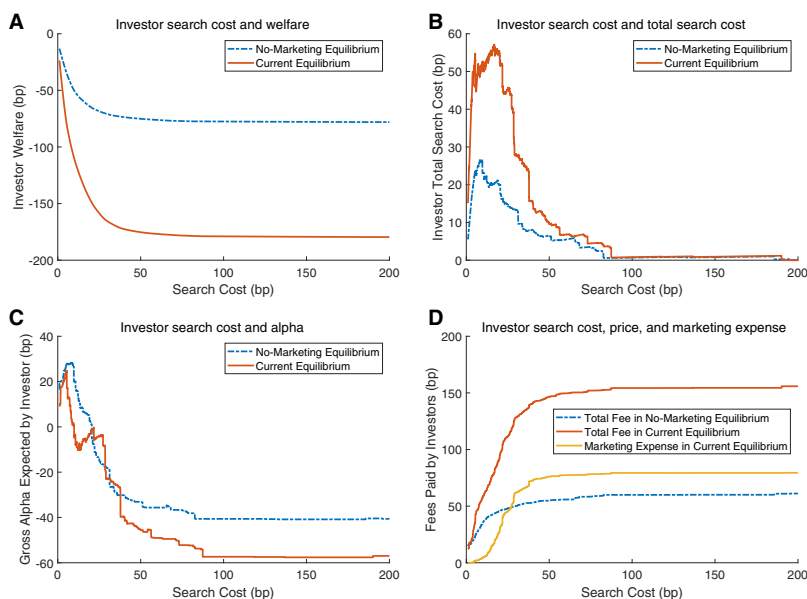
We find aggregate search costs are lower in the no-marketing equilibrium. In the model, investors search until the expected benefit of finding better funds is smaller than the unit search cost. If investor  $i$  has already found fund  $j$  with utility  $u_j$ , then her incentive to search hinges on both her search cost  $c_i$  and the expected possible gain from continuing the search. Without better funds available, an investor's incentive to search is weaker. To show that this is indeed the reason investors search less in the no-marketing equilibrium, Figure 5 plots the histogram of indirect utilities associated with individual funds in the two equilibria. We find the standard deviation of utility levels in the no-marketing equilibrium is substantially lower than in the current equilibrium.

Since the dispersion in available utilities is reduced, so are the expected benefits of searching and, consequently, investors search less. Through the resultant reduction in search costs, investor welfare increases by 17 bps on average.

When marketing is eliminated the size of active funds doesn't drop drastically for two reasons. First, exogenous fund characteristics in the sampling probability function ensure that all active funds sampling probabilities are positive. Second, reducing the size of active funds improves their expected performance. This effect makes active funds more attractive.

The increase in investor welfare in the counterfactual equilibrium exceeds both the decline in fund profits  $P$  and the loss of marketing "revenue"  $B$ , resulting in a total welfare increase. Thus, even though marketing in our model is purely informative, it can still be excessive from the social standpoint. To some extent, this is due to the fact that the low cost index fund is not on an equal footing with the active funds since it does not engage in marketing. But, even in the absence of the low cost index fund alternative, competition on marketing (rather than just price) generates overinvestment in marketing and, as a result, excessive fees borne by investors. This is due to the positional externality induced by the inelastic aggregate demand for funds. As an example, fund  $i$ 's marketing investment could decrease fund  $j$ 's probability of being known by increasing its own sampling probability. In a Nash equilibrium, funds do not take the externality into consideration when choosing their individual marketing investment levels. All of the funds might be better off if they could agree on a lower level of marketing investment. Of course, such an agreement would be fragile, since a deviation from it by any individual fund is potentially highly profitable. Hence, all fund engage in too much marketing as they compete for market share. This arms race externality is at the root of the welfare results documented above.

**5.2.1 Heterogeneous effect across investors.** In our model investors are heterogeneous in their ability to sample and screen mutual funds, which we model as exogenous variation in their search costs. In this section, we study the impact of eliminating marketing across investors with different levels of search costs. We focus on the following dimensions for each investor: individual investor welfare, total incurred search cost, gross alpha expected by investors, total expense ratios investors pay, and marketing expenses that investors implicitly pay for as part of their chosen funds' expense ratios (in expectation). Figure 6, panel A, shows that for all the search cost levels investors achieve a higher level of welfare in the no-marketing equilibrium. But the biggest improvements come from the high search cost investors. Their welfare increases roughly by 100 bps. For the low search cost investors the increase is not very large. This is because the low search cost investors always find the "best" funds available in the market. Figure 6, panel B, shows a somewhat nonmonotonic relationship between unit search cost and total search costs incurred. For the low search cost investors the total search cost is not very high



**Figure 6**  
**Investor heterogeneity**

Panel A plots investor welfare as a function of unit search cost levels. The  $x$  axis is investors' unit search cost,  $c_i$  in basis points. The investor welfare is in unit of bp. The  $y$  axis is investor welfare defined as indirect utility provided by chosen fund minus total incurred search cost. For the expression of investor welfare as a function of search cost, please refer to Equation (19).

Panel B plots investors' expected total search cost as a function of unit search cost levels. Expected total search cost is defined as  $c_i \frac{\Psi[\bar{u}(c_i)]}{1 - \Psi[\bar{u}(c_i)]}$ , where  $c_i$  is the search cost level,  $\Psi[\bar{u}(c_i)]$  is the probability of sampling a fund that delivers the investor an indirect utility smaller or equal to  $\bar{u}(c_i)$  (a detailed derivation is in Appendix B.)

Panel C plots the gross alpha expected by investors as a function of unit search cost levels.

Panel D plots the expense ratios and marketing expenses investors incur as a function of the unit search cost levels.

The solid line represents the current equilibrium, and the dashed line represents no-marketing equilibrium.

even though they search a lot since their unit search costs are low. The high search cost investors find it too costly to conduct any search, so they search infrequently, many stopping after the first (free) search. Consequently, high search cost investors' total search cost is also low. The intermediate search cost investors search relatively aggressively and their search costs are non-trivial. So in total they incur the largest total search costs. Comparing the two equilibria, we find that in the no-marketing equilibrium, the intermediate search cost investors incur lower total search costs. This is due to the fact that in the no-marketing equilibrium, average fund quality improves, so that it is easier for investors to find funds that satisfy their reservation levels.

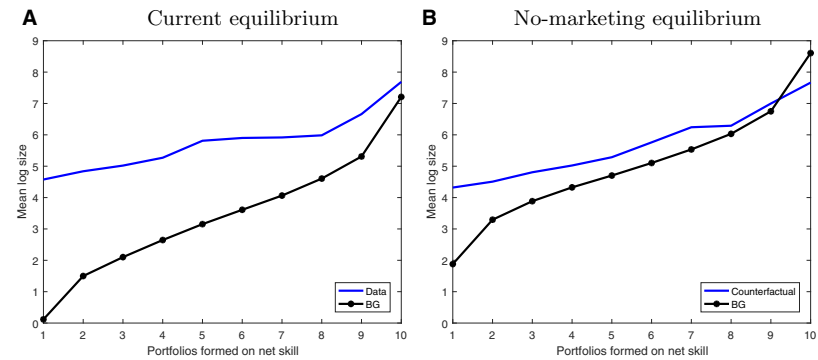
Focusing on Figure 6, panels C and D, we find that, in general, high search cost investors invest in lower alpha funds, pay high prices and, implicitly, incur high marketing expenses. This is simply because high search cost investors don't search very much. In contrast, investors who have very low search costs

invest in funds that have positive net alphas. In Berk and Green's model, since all investors have zero search costs, in equilibrium, all the funds have zero net alphas. But in our model, since all investors incur a positive search cost, only the low search investors are able to find funds that are both skilled and cheap, but not found by enough other investors, so that their performance is not fully eroded by decreasing returns to scale. At the same time, these high-skill funds do not find it optimal to increase their expense ratios (and thus drive net alphas toward zero) because that would make these funds less attractive to the more discerning (low search cost) investors, whose choices are very sensitive to fees.

**5.2.2 Allocational efficiency.** It is also interesting to consider the consequences of restricting marketing on capital allocation within the mutual fund sector. On the one hand, we see that average (gross) fund alpha increases in the no-marketing equilibrium, suggesting that some highly skilled funds might be "too small," operating below their efficient scale. Indeed, since we show that in the current equilibrium highly skilled funds benefit more from marketing, *ceteris paribus*, it is reasonable to expect that without the ability to do any marketing these funds might be disproportionately hurt by the imposed constraint. On the other hand, marketing is an important driver of costs, which are in turn a major determinant of net alphas (and indirect utilities) enjoyed by investors.

In keeping with our initial approach, we compare fund size distribution implied by the frictionless benchmark in the style of Berk and Green (2004) and that generated by our search model counterfactual. Figure 7 provides the comparison for the year 2015. Panel A displays the direct analog of Figure 1 restricted to the data for 2015: the BG-implied values are computed using the posterior beliefs about fund alphas as well as their observed expense ratios and the estimated decreasing returns to scale parameter (the fund size in the data is consistent with the search model by construction). Panel B presents the analog of these values in the counterfactual equilibrium with no marketing. That is, the "counterfactual" plot uses the fund size computed under the counterfactual equilibrium, where as the "BG-implied" values are recomputed using the expense ratios in the counterfactual equilibrium.

We observe that in the no-marketing case the two lines are much closer to each other than in the current equilibrium. This is true only in small part due to the steepening in the relationship between log size and net skill, visible mostly in the middle of the skill distribution. The changing BG-implied distribution plays a noticeably more important effect. This is due to the fact that funds are charging substantially lower fees to their investors in the no-marketing equilibrium. Thus, the solid black line in the graph shifts upward, closer to the blue line. The shift appears especially pronounced for the lowest-skill funds, even though they are still "too big" in the counterfactual relative to the frictionless model, where as for the highest-skill funds there is not much difference between the two measures. Thus, the overall effect of eliminating marketing expenditures is to



**Figure 7**  
**Capital (mis)allocation: Counterfactual**

Panel A plots the mean of log fund size (measured in millions of dollars) for portfolios of funds formed on net skill (defined as posterior belief about the skill level  $\tilde{a}$  minus expense ratio  $p$ ) for the current equilibrium, using data on mutual funds in the year 2015.

Panel B plots the mean of log fund size (measured in millions of dollars) for portfolios of funds formed on net skill for the no-marketing equilibrium.

We compute fund size according to the generalized version of the Berk and Green (2004) model that we estimate:

$$\log(s_{j,t}^{BG}) = \frac{\tilde{a}_{j,t} - p_{j,t}}{\eta}, \text{ where } \eta \text{ captures decreasing returns to scale.}$$

The black line represents the mean of log fund size for each portfolio implied by the Berk and Green (2004) model. The blue line represents the mean of log fund size in the data or in the counterfactual for each portfolio. We construct ten portfolios based on the deciles of net skill. Portfolio 1 has the lowest net skill, and portfolio 10 has the highest net skill.

improve the efficiency of capital allocation in the active fund industry, at least from the standpoint of net abnormal returns to investors as emphasized in Berk and Green (2004).

### 5.3 Reducing search costs

Last, we examine the impact of search costs on equilibrium market outcomes with special attention to marketing expenses. Because of search costs, competing on marketing could be a potential profitable strategy for some funds, since they essentially just need to be sampled by the least-discerning high-cost investors frequently enough. But with the emergence of the internet, advancement in search technologies (e.g., Google), more transparent comparison (e.g., services like Morningstar and Lipper), and better investor education, we would expect the search frictions to decline over time. To analyze the potential impact of new technologies, we consider a counterfactual equilibrium where we set the mean search cost to 35 bps or 20 bps. Given the new search cost, funds reoptimize their prices and marketing expenses. Table 7 provides the results. We find that as the average search cost decreases from 39 bps to 35 bps, mean marketing expenses drop from 61 bps to 44 bps. But when the mean search cost further drops to 20 bps, the equilibrium marketing expenses become zero. Notice that the regulatory cap is still held at 100 bps. The intuition is as follows: low search costs render marketing less profitable. In the model with high mean search cost, there exists a large fraction

**Table 7**  
**Summary of outcomes for different search costs**

	Low $\lambda$ 20 bps	Mid $\lambda$ 35 bps	High $\lambda$ 39 bps
Mean price (bps)	58.52	136.24	160.27
Mean marketing (bps)	0	44.78	61.29
Mean alpha (bps)	38.94	39.00	37.24
Total share of active funds (%)	64	71	74
Mean sampling prob (%)	0.07	0.08	0.08
Mean sampling prob for low price funds (%)	0.15	0.04	0.04
Mean sampling prob for index fund (%)	13.66	7.16	5.91
Investor welfare (bps)	-48.42	-118.41	-140.72
Active fund profits (bps)	31.97	51.46	57.51
Index fund profits (bps)	3.15	2.58	2.32
Total welfare (bps)	-13.98	-33.04	-37.37
Aggregate investor search cost (bps)	9.18	25.75	29.09

This table presents various measures of the mutual fund industry under different search costs distributions. In the top row, there are three levels of mean search costs: 20bps, 35bps, and 39bps. Thirty-nine basis points is our estimated value from the data. Mean price, mean marketing and mean alpha are the arithmetic average of price, marketing expenses, and alpha for all active funds, respectively. Total share of active funds is the market share of all active funds. Mean sampling prob for low price funds is the mean sampling probability for funds with below-average prices. Investor welfare is defined in Equation (20). Active fund profits are defined as  $\sum_{j=1}^N (p_j - b_j) s_j$ , which are the total profits for all active funds. Index fund profits are defined similarly. Total welfare is the sum of investor welfare, funds' total profits and total marketing expenses. Aggregate investor search cost is described in Equation (23).

of investors with very high search costs. A subset of funds specifically exploit these “unsophisticated” investors. Those funds invest aggressively in marketing so as to enter more of the high search cost investors’ choice sets. Since such investors will not search much, they do end up investing with those funds even if they are not very skilled and quite expensive. But when mean search cost drops to a sufficiently low level, this strategy is no longer profitable, since the model presumes there are fewer investors who find it too costly to continue searching for a better fund. Therefore, when search costs are not very high, funds will not invest in marketing and instead compete on price.

Thus our model provides a new perspective on the recent evolution of the asset management industry documented by Stambaugh (2014): declining fees charged by active funds coincident with the growth in passive index funds. From the standpoint of our model, both trends can be seen as resulting from falling search costs, due to a combination of information technology and growing investor sophistication. Indeed, we show in the Internet Appendix that if we estimate our model over subsamples representing different time periods, average search costs decline from 49 bps in 2001–2005, to 39 bps in 2006–2010, and to 20 bps in 2011–2015.

## 6. Extension: Horizontal Differentiation

We have so far assumed that mutual funds in our sample are vertically differentiated. That is, in a given year, all funds can be ranked by the utility they deliver to investors, which is based on the combination of their expected performance and fees, and any two funds with identical skills and fees are

viewed by all investors as perfect substitutes. This is consistent with the assumptions of the BG model, where investors only care about expected (abnormal) returns net of fees. However, in reality funds differ on a variety of attributes that investors may not be indifferent about, other than performance and fees. Importantly, investors may have a preference for funds that provide exposure to particular risk factors (e.g., as suggested by Cochrane 1999) or funds that pursue certain investment styles (e.g., as in Barberis and Shleifer 2003).<sup>30</sup> Indeed, even within the diversified equity mutual fund sector most funds specialize in a certain subset of stocks defined by key characteristics (e.g., large value, small growth, mid-cap blend) This type of heterogeneity matters because it can influence our estimates of the search cost distribution; some funds that are “too large” (or “too small”) relative to their observed skill might be so because they pursue a popular (or shunned) investment style, rather than due to high investor search costs.

To address this concern, we extend our model by treating funds in different Morningstar “style box” categories (e.g., Large Cap Blend, Large Cap Growth, Large Cap Value, Mid Cap Blend, Mid Cap Growth, Mid Cap Value, Small Cap Blend, Small Cap Growth, and Small Cap Value) as different goods. Estimating an arbitrary elasticity between these goods is not feasible in our setting, as it would not be separately identified from the search cost parameter. Instead, we consider the polar opposite to the case of perfect vertical differentiation, whereby certain subsets of investors only consider funds within a particular style box. Specifically, we assume  $K$  categories of funds and a certain proportion of investors  $\Upsilon_k$ , where  $k \in \{1 \dots K\}$ , only consider funds in category  $k$ . We also assume that there potentially exist some investors who consider all the funds; we denote their proportion as  $\Upsilon_0$ ; and we have

$$\sum_{k=0}^K \Upsilon_k = 1. \quad (24)$$

Type-0 investors behave exactly like the investors in Section 1.2. For type- $k$  investors, all their decision rules are the same as type 0 investors. The only difference is that they consider funds from category  $k$  exclusively, in addition to the index fund. Funds in sector  $k$  offer indirect utility

$$u_{j,t} = \gamma \tilde{r}_{j,t} - p_{j,t},$$

where

$$\tilde{r}_{j,t} = \tilde{a}_{j,t} - \eta \log(M_t s_{j,t}).$$

Type- $k$  investors conduct sequential costly search to decide in which fund they want to invest, in the same fashion as described in Section 1.2, except that their

<sup>30</sup> A growing literature analyzes the role of active funds in allowing investors to hedge against particular states of the world (see, e.g., Glode 2011; Savov 2014; Kacperczyk, Van Nieuwerburgh, and Veldkamp 2014; Polkovnichenko, Wei, and Zhao 2019).



search is “directed” toward funds in sector  $k$ . Thus, we can solve for the market share of each fund within category  $k$ ,  $s_{j,t}^k$  as a function of the utilities  $\{u_{j,t}\}_{j \in k,t}$ , sampling probabilities  $\{\psi_{j,t}\}_{j \in k,t}$ , and the distribution of search costs  $G(\cdot)$ , where  $j \in k, t$  indicates the fund belonging to category  $k$  during time period  $t$ . Within sector  $k$ , we have  $\sum_{j \in k,t} s_{j,t}^k = 1$  where  $j=0$  denotes the index fund; we also have  $\sum_{j \in k,t} \psi_{j,t} = 1$ . The index fund’s market share in sector  $k$  is computed as the residual of all the other funds in that sector,

$$s_{0,t}^k = 1 - \sum_{j \in k,t} s_{j,t}^k. \quad (25)$$

To convert the above category-specific market share into the total market share we defined in Section 1.3, we can use the following relationships. For active funds,

$$s_{j,t} = s_{j,t}^k \cdot \Upsilon_k + s_{j,t}^0 \cdot \Upsilon_0; \quad (26)$$

where  $s_{j,t}^0$  denotes the market share of fund  $j$  among funds chosen by type-0 investors. For the index fund,

$$s_{0,t} = \sum_{k=0}^K s_{0,t}^k \cdot \Upsilon_k. \quad (27)$$

## 6.1 Estimation

In addition to the parameters in the search model described in Section 3.2, we now have  $K$  additional parameters  $\{\Upsilon_1, \dots, \Upsilon_K\}$  to estimate.<sup>31</sup> The additional moment conditions are that  $\xi$  is mean-zero within each sector. Let  $j \in k, t$  denote any active fund  $j$  in category  $k$  that is alive in period  $t$ , as indicated above. The sample version of the moment conditions (for all  $k$ ) is

$$\sum_{t=1}^T \sum_{j \in k,t} \xi_{j,t} = 0. \quad (28)$$

The intuition for these additional moment conditions is as follows: in the benchmark model, taking funds’ utilities and sampling probabilities as given,  $\xi$  works as the residual to make model-predicted market shares equal their data counterparts. When we group funds into different sectors, as  $\Upsilon_k$  increases, the  $\{\xi_j\}_{j \in k}$  would need to decrease to match model-predicted shares with observed shares. So we can pin down  $\Upsilon$  by imposing that  $\xi$  is mean zero within each sector. In terms of identification,  $\Upsilon$  works like sector fixed effects or sector-specific dummies. The differences in the total market shares across sectors (beyond what observed fund characteristics can capture) are attributed to  $\Upsilon$ . For example, if the market share of, say, large-value funds exceeds what the model predicts using observed fund characteristics, then we attribute this to a

<sup>31</sup> Since  $\{\Upsilon_0, \dots, \Upsilon_K\}$  sums to one, we only need to estimate  $K$  out of  $K+1$  parameters.

**Table 8**  
Search model parameters for different subsamples with investor heterogeneity

Parameters	Description	$\Upsilon_0=0.4$			$\Upsilon_0=0.2$		
		2001–2005	2006–2010	2011–2015	2001–2005	2006–2010	2011–2015
$\lambda$	Mean search cost (%)	0.45 (0.07)	0.35 (0.07)	0.17 (0.07)	0.43 (0.07)	0.37 (0.07)	0.18 (0.07)
$\gamma$	Alpha weight	0.42 (0.05)	0.47 (0.05)	0.56 (0.54)	0.44 (0.05)	0.47 (0.05)	0.56 (0.54)
$\theta$	Marketing effectiveness	112.24 (12.66)	125.16 (12.48)	143.14 (13.21)	113.25 (12.55)	125.10 (12.88)	143.01 (13.11)
$\beta_1$	Family size effect	0.44 (0.04)	0.36 (0.04)	0.39 (0.04)	0.44 (0.04)	0.36 (0.04)	0.39 (0.04)
$\beta_2$	Fund age effect	1.08 (0.06)	1.07 (0.06)	1.10 (0.06)	1.08 (0.06)	1.07 (0.06)	1.10 (0.06)
Year FE		Yes	Yes	Yes	Yes	Yes	Yes

This table presents the estimates of the structural search model for different subsamples with investor heterogeneity. In this table, we choose  $\Upsilon_0$ , the proportion of investors who consider all the funds to be 0.4 and 0.2. The moment conditions are described in Section 6.1.

larger size of the group of large-value-sector investors. Of course, in terms of the modeling, this is different than simply adding dummies for sector  $k$  in the baseline model as estimated in Section 3.2, since the specifications of market shares differ, implying different price elasticities. With heterogeneous sectors, each fund competes for investors more intensely with funds that belong to the same style box than with other funds. In the extreme case  $\Upsilon_0=0$ , a fund effectively does not compete with funds outside its style category.

Since  $\xi$  is mean-zero across all funds and now we also require  $\xi$  to be mean-zero in each sector, one of the new moment conditions is redundant. If (28) is satisfied in  $K-1$  sectors, then it will automatically satisfy for sector  $K$ . We address this underidentification problem by setting  $\Upsilon_0$ , the proportion of investors who consider all funds exogenously. In the estimation results reported below, we set  $\Upsilon_0=0.4$ , and, as a robustness check, we also consider  $\Upsilon_0=0.2$ .

6.2 Results

To accommodate the potentially changing importance of investment styles over time, we estimate the extended model over three subperiods: 2001–2005, 2006–2010, and 2010–2015. Table 8 reports parameter estimates. Estimates of our baseline model parameters for the three corresponding subperiods are provided in the Internet Appendix. After allowing for heterogeneity, the search costs are somewhat lower in each than under the baseline model estimates over the same subsamples. This result is intuitive: both search cost and preference for particular categories of funds can help explain the fact that some “bad” (low alpha) funds have sizable market shares, either because some investors have very high search costs so that they settle with “bad” funds or because some investors just want to invest in certain types of funds even though these funds might underperform factor-based benchmarks. However, the differences between the two sets of search cost estimates are small: for example, for

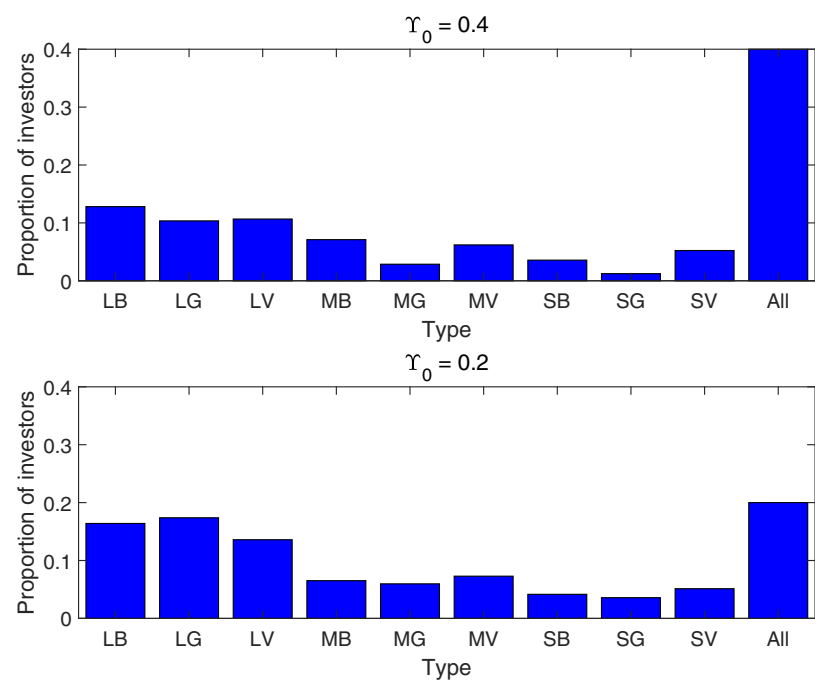
the 2001-2005 period, it falls from 49 bps to 43 bps when we introduce heterogeneity in (preference toward) fund styles. This suggests that this (most natural) source of horizontal differentiation introduces at most a mild upward bias to the estimate of the average search cost under our baseline model.

Another interesting finding is that  $\gamma$ , the coefficient in front of performance in the investor's utility function is generally larger in the model allowing for heterogeneity. This result is also reasonable: for instance, some investors might have a preference for, say, large-cap funds, despite the fact that they might (hypothetically) exhibit lower alpha than small-cap funds, which, in turn, might have higher expense ratios, on average. Our baseline model does not account for this effect and will instead attribute the larger size of such "disproportionately expensive" funds to investors' insensitivity to performance (relative to fees). Here, too, however, the effect is relative small: when allowing for heterogeneity  $\gamma$  increases from 0.41 to 0.47 in the 2006-2010 subperiod (and by even less in the other subperiods).

All of the other parameter estimates remain essentially the same as in the baseline model, which is intuitive. All our results are quantitatively similar for the two exogenously set values of the residual share of investors considering all funds,  $\Upsilon_0=0.4$  and  $\Upsilon_0=0.2$ . This fact gives us confidence that assuming vertical differentiation in our baseline model does not substantially bias our parameter estimates in the baseline model, thus allowing us to conduct meaningful counterfactual experiments. That is not to say that horizontal differentiation in itself is not interesting or important. In fact, there is quite a bit of heterogeneity in fund size along the style dimension, as evidenced by our estimates of  $\Upsilon_k$  parameters that capture the fraction of investors considering only funds pursuing a particular style. Figure 8 displays these estimates for the nine Morningstar style box categories, as well as for the fraction considering all funds, for the two possible values that we consider. There is a consistent, monotonically declining pattern of  $\Upsilon_k$  as stock size that the funds invest in declines, indicating that investors generally prefer large-cap funds, with small-cap funds being least popular. The preference for value versus growth funds is less consistent, however, although the latter are the least "popular" categories within mid-cap and small-cap stocks.

## 7. Concluding Remarks

The question whether actively managed mutual funds exhibit skill, that is, persistent outperformance, has a long history in financial economics, since it is central to the debate about informational efficiency of securities markets in the sense of Fama. Although the ability of an "average" fund manager to generate abnormal returns (before or after fees are taken into account) is still substantially debated, perhaps one of the most robust findings in the literature is that investors' flows are much less sensitive to past bad performance than to outperformance (Ippolito 1992; Carhart 1997; Chevalier and Ellison 1997;



**Figure 8**  
**Investor preferences for fund styles**

The figure plots the histogram of different types of investors for the period of 2011–2015 for  $\gamma_0=0.4$  and  $\gamma_0=0.2$ , respectively. LB stands for Large Blend; LG stands for Large Growth; LV stands for Large Value; MB stands for Mid-Cap Blend; MG stands for Mid-Cap Growth; MV stands for Mid-Cap Value; SB stands for Small Blend; SG stands for Small Growth; and SV stands for Small Value. All indicates the type-0 investors who consider all types of funds.

Sirri and Tufano 1998, among others). This evidence hints that the market for mutual funds may not be efficient at allocating capital across funds because bad funds aren’t punished sufficiently for poor performance, and therefore underperforming managers control more assets than justified by their level of skill. Capital misallocation in the mutual fund industry could potentially lead to inefficiencies in capital allocation across firms, distorting real investment (van Binsbergen and Opp 2019). It is therefore important to understand quantitatively how much capital is misallocated in the mutual fund industry. By estimating the Berk and Green model, we find that in the U.S. equity mutual funds data, from 1964 to 2015, all but the best-performing decile of mutual funds are “too large” relative to the optimal scale predicted by the BG model. These results indicate that there exist substantial frictions in the market for mutual funds.

Our model could be extended to analyze the impact of financial regulation. While we do not model the market for retail financial advice, much of the marketing expenditure by mutual funds that we capture involves commissions to brokers and financial advisors who channel investors’ search effort in

the direction of particular funds. Recent policy proposals aimed at requiring advisors to act in the “best interest” of their clients might reduce, if not completely eliminate, such kickbacks, getting closer to our “no-marketing” equilibrium. However, since we do not model the advisors’ problem explicitly (e.g., the cost of providing financial advice to investors), our model cannot speak to the effect of such a policy without additional modifications. Similarly, the model could be modified to analyze the effect of encouraging advisors to “nudge” investors (e.g., Choi, Laibson, Madrian, and Metrick 2003; Thaler and Sunstein 2009) by presenting them with the lowest-cost options (typically, index funds) first. Since the high-cost investors do not go beyond the “free search” in our model, “nudging” would imply that index funds would become a de facto default option. Such a policy could completely reshape the mutual fund industry, potentially intensifying competition and driving expense ratios even further down, while virtually eliminating underperforming funds. However, it would also dramatically change the incentives of brokers and financial advisors, including their willingness to provide any (not directly compensated) advice at all on selecting among active funds. Again, such policy analysis would require extending our model to explicitly account for advisors’ optimal behavior.

An additional important caveat cautions the interpretation of the welfare implications of our analysis, even if we take the role of marketing as given. While the more intense competitive pressure driven by the elimination of marketing or introduction of default options may improve immediate investor welfare, the reduction in the amount of active management in the aggregate might, in turn, cause underprovision of effort by investment managers, making the underlying capital markets less informationally efficient (e.g., as discussed by Stambaugh 2014), potentially with further negative consequences for the real economy.

In our paper, we view mutual fund marketing expenses as purely informative (e.g., Butters 1977). It is possible that a portion of these expenses serves a persuasive function in ways highlighted in the theoretical literature: for example, firms may find it profitable to steer investors toward nonprice attributes (Mullainathan, Schwartzstein, and Shleifer 2008; Gabaix and Laibson 2006; Carlin 2009; Ellison and Ellison 2009). Separating the informative effect from the persuasive effect of marketing one would require information on investors’ actual choice sets. By making the assumption that all marketing is informative, our welfare analysis results provide an upper bound on the social value of mutual fund marketing. Relaxing this assumption in order to understand the possible welfare loss from “persuasive” marketing is a fruitful venue for future research.

## Appendix A. Market Shares

To facilitate subsequent derivations, here we define a fund-specific cutoff  $f_j$ ,  $j=0, 1, \dots, N$ , where

$$f_j = \sum_{k=0}^N \psi_k(u_k - u_j) \cdot \mathbf{1}\{u_k > u_j\}.$$

Notice that  $u_j = \bar{u}(f_j)$ . So, if  $c_i > f_j$ , then  $u_j > \bar{u}(c_i)$ . In other words, if an investor's search cost is larger  $f_j$ , he will stop searching once he finds fund  $j$ . With these funds' specific cutoffs, we can derive closed-form expressions for market shares: first, for the fund with the lowest utility, then, for the fund with the second lowest utility, etc. Let  $\tau$  be a permutation on  $\{0, 1, \dots, N\}$  such that  $u_{\tau(0)} \leq u_{\tau(1)} \leq \dots \leq u_{\tau(N)}$ . As a result,  $f_{\tau(0)} \geq f_{\tau(1)} \geq \dots \geq f_{\tau(N)}$ .

Any investor who has a search cost that is higher than  $f_{\tau(0)}$  will not make a second search beyond the free search. Then, among all of these investors, with  $\psi_{\tau(0)}$  probability, they will find fund  $\tau(0)$  (the "worst" fund). Nevertheless, they will invest in fund  $\tau(0)$ . No one else will invest with fund  $\tau(0)$ . So the market share for fund  $\tau(0)$  is

$$s_{\tau(0)} = \psi_{\tau(0)} [1 - G(f_{\tau(0)})],$$

where  $G$  is the cumulative distribution function for the distribution of  $c_i$  in the population.

Two kinds of investors will buy fund  $\tau(1)$ . The first kind is the investors with  $c_i > f_{\tau(0)}$  that find fund  $\tau(1)$  in the free search. They have no choice but to invest. The second kind is investors with  $f_{\tau(0)} \geq c_i > f_{\tau(1)}$ . For these investors to invest in fund  $\tau(1)$ , they could have found it in the free search, or have found  $\tau(0)$  in the free search and  $\tau(1)$  in the second search, or have found  $\tau(0)$  in the first two searches and  $\tau(1)$  in the third search, and so forth. The total probability of these events is  $\psi_{\tau(1)} + \psi_{\tau(0)}\psi_{\tau(1)} + \psi_{\tau(0)}^2\psi_{\tau(1)} + \dots = \frac{\psi_{\tau(1)}}{1 - \psi_{\tau(0)}}$ . So the market share for fund  $\tau(1)$  is

$$\begin{aligned} s_{\tau(1)} &= \psi_{\tau(1)} [1 - G(f_{\tau(0)})] + \frac{\psi_{\tau(1)}}{1 - \psi_{\tau(0)}} [G(f_{\tau(0)}) - G(f_{\tau(1)})] \\ &= \psi_{\tau(1)} \left[ 1 + \frac{\psi_{\tau(0)} G(f_{\tau(0)})}{1 - \psi_{\tau(0)}} - \frac{G(f_{\tau(1)})}{1 - \psi_{\tau(0)}} \right]. \end{aligned}$$

We can follow this line of deduction to obtain closed-form expressions for the market shares of all funds. For  $j \geq 2$ ,

$$s_{\tau(j)} = \psi_{\tau(j)} \left[ 1 + \sum_{k=0}^{j-1} \frac{\psi_{\tau(k)} G(f_{\tau(k)})}{(1 - \psi_{\tau(0)} - \dots - \psi_{\tau(k-1)}) (1 - \psi_{\tau(0)} - \dots - \psi_{\tau(k)})} - \frac{G(f_{\tau(j)})}{1 - \psi_{\tau(0)} - \dots - \psi_{\tau(j-1)}} \right].$$

## Appendix B. Investor Welfare

In this section we compute investor  $i$ 's welfare for a given search cost  $c_i$ . First, we denote  $\bar{u}(c_i)$  as the reservation level of utility for the investor  $i$ . Investor  $i$  will only accept the funds which provide utilities higher or equal to  $\bar{u}(c_i)$ , so the expected utility for the potentially accepted funds is

$$\frac{\int_{\bar{u}(c_i)}^{+\infty} u d\Psi(u)}{1 - \Psi[\bar{u}(c_i)]}.$$

As to the search cost, the probability that the investor will conduct  $t$  searches beyond the free search is  $(1 - \Phi)\Phi^t$ , so the expected total search cost is

$$\begin{aligned} c[1 - \Psi(\bar{u})] \sum_{t=0}^{+\infty} \Psi(\bar{u})^t &= c[1 - \Psi(\bar{u})] \left\{ \left[ \Psi(\bar{u}) + \Psi(\bar{u})^2 + \Psi(\bar{u})^3 + \dots \right] + \right. \\ &\quad \left. \left[ \Psi(\bar{u})^2 + \Psi(\bar{u})^3 + \dots \right] + \dots \right\} \\ &= c[1 - \Psi(\bar{u})] \left\{ \frac{1}{1 - \Psi(\bar{u})} + \frac{\Psi(\bar{u})}{1 - \Psi(\bar{u})} + \dots \right\} \\ &= c \frac{\Psi(\bar{u})}{1 - \Psi(\bar{u})}, \end{aligned}$$

where  $\bar{u}$  is  $\bar{u}(c_i)$ . Combining the two parts together, we have the expression for investors' expected welfare.

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