# Why Do Index Funds Have Market Power?
# Quantifying Frictions in the Index Fund Market[*]

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## Abstract

Index funds are one of the most common ways investors access financial markets and are perceived to be a transparent and low-cost alternative to active investment management. Despite these purported virtues of index fund investing and the introduction of new products and competitors, many funds remain expensive and fund managers appear to exercise substantial market power. Why do index funds have market power? We develop a novel quantitative dynamic model of demand for and supply of index funds. In the model, investors are subject to inertia, search frictions, and have heterogeneous preferences. These frictions on the demand side create market power for index fund managers, which fund managers can further exploit by price discriminating and charging higher expense ratios to retail investors. Our results suggest that the average expense ratios paid by retail investors are roughly 45% higher as a result of search frictions and are 40% higher as a result of inertia compared to the friction-less baseline. In our counterfactuals, we find an interaction between search frictions and inertia—inertia imposes higher (lower) costs on investors when search frictions are low (high).

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# 1 Introduction

Index funds have been touted as a low-cost and transparent alternative to active investment management, particularly with the advent of exchange-traded funds (ETFs). While index fund fees have declined in recent years, there is still wide variation in the expense ratios of funds that track the same or similar benchmarks and many funds with expensive fees have non-trivial market share. The equal-weighted (asset-weighted) average index fund in 2020 still charged an expense ratio of nearly 63 (14) basis points, and the equal-weighted (asset-weighted) standard deviation of fund expense ratios within an investment class was 48 (19) basis points. One might have thought that with the growth of index fund investing and fund competition, market power would be minimal and the law of one price would start to take hold.

Why do index funds have market power? On the demand side, investor preference heterogeneity and various frictions such as inertia, search costs (e.g., Hortaçsu and Syverson (2004)), or lack of financial sophistication may cause some investors to choose expensive index funds and consequently soften price competition. The effects of these demand-side frictions may be further exacerbated by supply-side features of the market, such as price discrimination and conflicts of interest between brokers and investors. While a variety of frictions are potentially relevant, there is a lack of consensus on the relative importance and magnitude of each in shaping the index fund market. Understanding each friction and how they interact with each other is important not only for understanding household investment behavior, but also for informing policy.

If search frictions play an important role, this motivates transparency rules such as the SEC's recent proposal to address misleading or deceptive practices or tools such as the FINRA's Fund Analyzer to facilitate fund comparisons.[1] In contrast, if investors remain in expensive funds due to inertia, then policies such as investor nudges or changes in the tax treatment of capital gains could have a larger impact on market power.[2] The effectiveness of the regulation of price discrimination and broker commissions will also depend on the degree of frictions that investors face.[3] Finally, if most of the observed price dispersion is due to preference heterogeneity, there may be little room for policy intervention. Given that almost $10tn dollars were held in index funds as of 2020, understanding the frictions in this market has important implications for U.S. aggregate savings.[4]

In this paper, we develop and estimate a new model of index fund supply and demand where investors choose index funds in the presence of preference heterogeneity, search frictions,

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[1] See https://www.sec.gov/news/press-release/2022-91 and https://tools.finra.org/fund_analyzer/.

[2] Capital gains from selling assets that are held for less than a year are taxed at a higher rate, which generates incentives for investors to hold assets for longer periods.

[3] Regulations of price discrimination and broker commissions are already subject to Securities and Exchange Commission rule-making. For instance, some forms of price discrimination for mutual funds are already barred under SEC Rule 22d of the Investment Company Act of 1940.

[4] See https://www.ici.org/system/files/2021-05/2021_factbook.pdf.

inertia, price discrimination, and agency frictions. While previous work has focused on the role of certain frictions in isolation, separately identifying and quantifying the effects of each friction is challenging because these frictions operate simultaneously and interact with one another. We address this challenge using both new data and novel identification strategies. We then use our quantitative model to simulate counterfactuals that allow us to evaluate the relative importance of each mechanism, analyze how they interact with each other, and ultimately to better understand household investment behavior and the sources of market power.

We start by documenting potential determinants of price dispersion in the market for index funds. Given that index funds tracking the same index are relatively homogeneous, the presence of price dispersion provides initial evidence that fund managers may have substantial market power. We also provide initial evidence that suggests the presence of both inertia and search frictions.

Motivated by this evidence, we present a model of investor demand for index funds that introduces three mechanisms by which investors may not choose the lowest cost index fund. First, investors are subject to inertia and may not update their investment choices each period. Second, investors are subject to search frictions which diminish their capacity to select the optimal index fund even when they are making an active choice. Lastly, we allow investors to have heterogeneous preferences over index funds such that the product space is horizontally differentiated. Importantly, all of these mechanisms may give rise to market power.

There are two types of investors in the model: institutional and retail investors. We allow investor preferences, inertia, and search frictions to vary across investor types. For example, one might expect search frictions to pose a greater problem for retail investors than institutional investors. The set of index funds available to institutional investors is also different from the set of funds available for retail investors; for example, institutional index funds are only purchased by institutions while ETFs are purchased by both institutional and retail investors.

We model index fund demand as a discrete choice problem with the idea that an investor chooses an individual branded index fund within a specific investment class/category (e.g., Lipper Class), conditional on the investor's initial decision to invest in the specific investment class/category. Consequently, we abstract away from the investor's more general portfolio choice problem. Each period, with some probability, investors are either active or inert. If the investor is active, she chooses the index fund that maximizes her current utility, subject to search frictions.

Index fund managers compete for assets in a dynamic and differentiated Nash Bertrand price/expense-ratio setting game. Consistent with the data, index fund managers are multi-product issuers and potentially price discriminate across institutional and retail investors by separately offering funds that are only available to institutional investors. Index fund managers set expense ratios to maximize the present discounted value of future profits while accounting for investor inertia, preference heterogeneity, search frictions, and incentives to price discrimi-

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nate.

We show that these mechanisms have distinct implications for the optimal pricing behavior of index fund managers. Inertia has two potentially offsetting effects for how index fund managers set steady-state prices (e.g., Beggs and Klemperer, 1992). On the one hand, inertia increases the incentive to invest in new consumers, as demand from investors today will be more persistent into the future. On the other hand, an increase in inertia makes the demand curve more inelastic which incentivizes managers to charge a higher expense ratio and harvest existing investors. We derive a simple expression for steady state index fund pricing with inertia for our framework. We show that with efficient capital markets (e.g., expected returns equal required returns), the "invest" and "harvest" incentives perfectly offset such that inertia has no impact on the pricing behavior of managers; however, in practice we show that we would expect the presence of consumer inertia to increase steady state prices. In contrast, an increase in either search frictions or preference heterogeneity always incentivizes managers to increase their expense ratios.

We estimate the model using fund-level data from CRSP over the period 2000 to 2020. One empirical challenge in the economics literature generally is how one can separately identify inertia from preferences. For example, is demand highly persistent because investors suffer from inertia or is it because investors' preferences are persistent? We use a new strategy to identify inertia that is straightforward and flexible in incorporating heterogeneity. To measure the fraction of consumers who are inert and do not make an active investment decision in a period, we would ideally like to measure the causal effect of a one dollar increase in a fund's past assets under management (AUM) on its current AUM. We examine persistence of an exogenous shock to investors' past holdings using variation in past monthly fund returns. For example, if a fund experienced strong returns two months ago, this acts as a positive exogenous shock to lagged AUM. How these past return shocks translate into current AUM tells us the degree of investor inertia. One concern is that if investors chase returns, then past monthly returns could impact current demand for a fund. To account for this, we control for 1, 3, 6, and 12 month returns and year-to-date returns, with the idea that investors chase returns according to these horizons since they are the horizons reported in fund marketing documents. We separately estimate inertia for retail and institutional investors.

Our estimates suggest that roughly 99% (95%) of retail (institutional) investors are inert each month, which means that 13% of retail investors update their portfolio at least once each year. We also estimate inertia using a control function approach and using trading data and find similar estimates.

With our estimates of inertia in hand, we then turn to estimating the preferences of investors. We use our estimates of inertia to calculate active demand each period, and we recover the preferences of investors by estimating a standard Berry (1994) demand system for institutional and retail investors. We estimate the elasticity of demand to be 1.6 and 2.8 for retail

investors and institutional investors, respectively. It is important to note that the elasticity of demand we recover is a function of both search frictions and preference heterogeneity.

To separately identify search frictions from preference heterogeneity, we use additional data based on investors' choices in 401(k) plans. When making investment allocation decisions, 401(k) participants typically choose from a fixed investment menu of mutual funds that is determined by the plan sponsor (e.g., participant's employer). In addition, by law, 401(k) investors observe the full menu and receive expense- and performance-related summary disclosures (Kronlund et al., 2021). Since investors choose from a simplified menu with relative transparency, we assume that 401(k) investors do not face search frictions, which allows us to separately identify preference heterogeneity. To account for investor inertia, we restrict our attention to new 401(k) plans for which all participants are making an active decision. We find that the demand elasticity is 4.2 without search frictions. For retail investors, this suggests that search frictions are roughly 1.6 times more important than preference heterogeneity in the index fund market.

With our estimates of inertia, search frictions, and investor preferences, we turn to the supply-side of the model. We estimate the marginal cost of running an index fund by inverting each index fund manager's dynamic first order conditions. Given the presence of demand frictions, the estimates imply substantial market power. Estimated average (median) marginal cost is 14 (18) basis points, which implies an average (median) markup of 55 (26) basis points.

We use our model estimates to simulate counterfactuals where we both individually and simultaneously eliminate inertia, search frictions, and price discrimination. This allows us to quantify the relative importance of these frictions. For example, we find that eliminating search frictions would lower average expense ratios for retail investors by 45% and lower the standard deviation of expense ratios by 16%. Comprehending the significance and interplay of each friction is crucial for directing regulatory policy decisions, given that the policy instruments at the disposal of regulators are designed to address distinctive frictions.

Eliminating inertia also has a substantial effect and would lower average expense ratios for retail investors by 40% when the endogenous response of index fund managers is accounted for. However, the demand-side response is limited: the average expense ratios would fall by only 10% if the expense ratios were fixed at their observed values. This is somewhat surprising given that the vast majority of investors are inert each period (e.g., 99% of retail investors are inert each month). Part of the reason for the limited demand-side response is that investors suffer from fairly severe search frictions. In the presence of such severe search frictions, investors struggle to optimize their investment choices even when they make an active choice. Consequently, allowing investors to re-optimize more frequently (i.e., removing inertia) is not very valuable when investors are not optimizing in the first place. In contrast, removing both inertia and search frictions has a large impact on the prices retail investors pay. In this case, the average expense ratio retail investors pay falls by 78% and the standard deviation of prices

falls by 44%.

We also consider the counterfactual where we regulate market power by eliminating index fund managers' ability to price discriminate across institutional and retail investors. We find that eliminating price discrimination would lower the average expense ratio paid by retail investors by 30% (12 basis points) and would have a minimal impact on institutional investors. We also show that if retail investors did not suffer from search frictions and inertia, then eliminating price discrimination would have a negligible impact on retail investors. Price discrimination is effective in the current equilibrium because retail investors suffer from larger search frictions and inertia than institutional investors, which allows managers to charge retail investors higher expensive ratios for identical funds.

As an extension, we analyze the role of agency frictions in the index fund market using the framework in Robles-Garcia (2019). We find evidence that financial advisers distort demand; however, the conflicts of interest we estimate are smaller than have been found in other settings. This is intuitive given that the index fund market is more transparent than the other markets studied. Furthermore, we find that removing conflicts of interest has a limited impact on the expense ratios. This is because, especially in recent times, the incentives financial advisers face are relatively low-powered.[5]

**Related Literature**

The economic forces and frictions we measure in our analysis are motivated by much of the existing literature. It is well documented that even when financial products are similar, there is often a large degree of price dispersion and consumers often fail to choose the lowest price (see Campbell (2016) and Clark et al. (2021) for an overview).[6] One strand of the literature focuses on the role of search costs and other search frictions in explaining these facts. In their seminal paper, Hortaçsu and Syverson (2004) document price dispersion in relatively homogeneous S&P 500 index funds and explore the role of search costs. Using a novel empirical approach, the authors find that they can rationalize the observed dispersion in prices with modest search costs. Roussanov et al. (2021) extends the search model in Hortaçsu and Syverson (2004) to the market for active funds to study misallocation in the industry.[7] While these types of models are quite flexible, Hortaçsu and Syverson (2004) note that their measure of search costs potentially captures additional factors such as individual preference heterogeneity (e.g., horizontal differentiation) and switching costs, which cannot be separately identified from search costs in their setting. Our contribution is to further disentangle these frictions and account for other types of frictions such as inertia and agency frictions. While search costs are one explanation for

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[5]For example, no-load mutual funds without 12b-1 fees accounted for 89% of mutual fund sales in 2021. See https://www.ici.org/system/files/2022-03/per28-02_2.pdf.

[6]Grubb (2015) notes that the failure to choose the lowest price is often observed more generally when price is complicated and consumers have limited experience in the market.

[7]Honka et al. (2017) and Roussanov et al. (2021) show that search costs may also be affected by marketing.

why individuals choose expensive financial products, some have argued that search costs are unlikely to fully explain choice behavior in certain settings (Woodward and Hall, 2012; Grubb, 2015).

A related literature focuses on the role of consumer inertia and switching costs. A literature has explored investor inertia in retirement fund choice and the implications for pricing (Madrian and Shea, 2001; Illanes, 2016; Luco, 2019). A growing literature has also documented the importance of inertia and switching costs in mortgage choice (Allen and Li, 2020; Andersen et al., 2020; Zhang, 2022) and banking choice more generally (Kiser, 2002). While inertia is thought to be present in many settings, identifying inertia and switching costs can often be challenging.[8] We are not aware of work incorporating inertia in a model of the index fund market. We show how to estimate inertia in this setting using a new identification approach and examine the implications for pricing.

There is also literature pointing to agency frictions and other supply-side mechanisms that may lead to price dispersion in financial products. While brokers may help reduce search costs, evidence from Christoffersen et al. (2013), Hastings et al. (2017), Bhattacharya et al. (2019), and Robles-Garcia (2019) suggest that brokers distort demand and introduce agency frictions. Egan (2019) finds that brokers exploit search frictions in order to price discriminate across sophisticated and unsophisticated investors, selling high-commission products to less sophisticated investors and low-commission products to sophisticated investors.

Our paper also relates to the growing literature at the intersection of industrial organization and finance. In related work, An et al. (2021) develop a structural model of the ETF market that incorporates two-tiered competition of index and ETF managers. Baker et al. (2022) and Egan et al. (2022) use similar demand-side approaches to recover investor expectations in the index fund market. Gavazza (2011) shows how demand for product varieties and demand spillovers affect the market structure and the level of fees for mutual funds. While we focus on index fund choice, rather than the more general problem of portfolio choice, our framework relates to the growing literature using a demand system approach to asset pricing (Koijen and Yogo, 2019a).[9] Our work also relates to the growing literature using IO-type demand systems (e.g., Berry (1994), Berry et al. (1995), etc.) in other settings such as demand for banks (Dick, 2008; Egan et al., 2017; Xiao, 2020), mortgages (Allen et al., 2014; Benetton, 2021; Robles-Garcia, 2019) and insurance (Koijen and Yogo, 2016, 2022). We show how to extend these types of frameworks to quantify the role of various frictions. For example, we factor in managerial incentives within a dynamic environment characterized by investor inertia which is an important feature of many household financial markets.

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[8] Inertia has been shown to be important for competition in many other settings including electricity (Hortaçsu et al., 2017), retail gasoline (MacKay and Remer, 2022), cloud computing (Jin et al., 2022) and health insurance markets (e.g. Handel, 2013; Ho et al., 2017).

[9] Other examples include Koijen and Yogo (2019b); Bretscher et al. (2020); Benetton and Compiani (2021) and Haddad et al. (2021).

The remainder of the paper is structured as follows. In Section 2 we describe our data and present motivating evidence for the frictions incorporated in our model. In Section 3 we develop our structural model, and we present the corresponding estimates in Section 4. We present our counterfactual analysis in Section 5. Lastly, Section 6 concludes.

## 2 Data and Motivating Evidence

### 2.1 Data

Our base index fund data set comes from CRSP mutual fund and covers the period 2000 to 2020. We restrict our attention to funds classified in CRSP as index funds, including both mutual funds and ETFs.[10] We observe monthly data on total net assets and returns and quarterly information on other fund characteristics such as expense ratios and Lipper classification. Index funds in the data are defined at the share class level, which implies many of the funds in our data share common investment portfolios with other funds in our data. While some of the mutual fund literature aggregates share classes to the fund level, we keep the unit of observation at the share class level because we are interested in how share classes, in particular retail and institutional share classes, contribute to the observed price dispersion in the index fund market.

Table 1 displays the summary statistics corresponding to our base data set. We have roughly 500,000 month-by-fund observations, which covers 5,266 index funds across 150 different Lipper Classes. On average, we have roughly 8 years of monthly AUM data for each fund in our sample and 35 funds per Lipper Class. Consistent with the previous literature, we find a large degree of price dispersion. The average expense ratio is 77 basis points with a standard deviation of 65. Following Hortaçsu and Syverson (2004) we construct load-adjusted expense ratios. We add 1/3rd of all loads to the expense ratio because, given our estimates of inertia, investors update their portfolios roughly once every three years on average. This adjustment has a very minor impact on expense ratios because most funds do not have front or rear loads, especially in more recent years.[11] For example, 90% of index funds in our sample did not have any loads in 2020.

One dimension we are particularly interested in is understanding the behavior of institutional versus retail investors. For index funds structured as mutual funds, we can observe in CRSP whether the fund is an institutional fund or retail mutual fund. In contrast, exchange traded funds may be purchased by either institutional or retail investors. We use quarterly in-

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[10]We restrict our data set to all funds defined in CRSP as index funds (i.e., $index\_fund\_flag$ is equal to "B", "D" or "E"). We focus on index funds given that these products are relatively homogeneous and form an important part of the market. Because CRSP only started reporting whether a fund is an index fund in 2003, we define a fund as an index fund if it is ever classified by CRSP as an index fund in the data. We find quantitatively similar results if we restrict our attention to those funds classified as "pure" index funds as per CRSP (i.e., $index\_fund\_flag$ is equal to "D").

[11]We use load adjusted expense ratios in our analysis but note that our findings are quantitatively similar if we do not adjust expense ratios for loads or if we drop all funds with loads.

stitutional holdings data (13F) to determine the share of ETF assets held by institutional versus retail investors. Roughly 35% of the funds in our sample are classified as retail mutual funds, 26% are classified as institutional mutual funds, and the remaining 38% are classified as ETFs.

Employer-sponsored investment accounts provide a simplified menu of fund offerings due to disclosure requirements, providing a setting with minimal search frictions. We supplement our analysis with data on the menu and allocation of funds within 401(k) plans from 2009 to 2019 from BrightScope Beacon. The data cover 85 percent of employer-sponsored investment accounts subject to ERISA. Additional detail on the data can be found in Egan et al. (2021).[12]

## 2.2 Motivating Evidence

### 2.2.1 Price Dispersion

We start by documenting that there is substantial price dispersion in index funds. For index funds that are relatively homogeneous, the presence of price dispersion provides initial evidence consistent with market power.

Despite the fact that the number of index funds increased 5-fold during our sample period, price dispersion remained relatively constant over time. Figure 1 displays the distribution of fund expense ratios over time. Panels (a) and (b) display the equal-weighted and asset-weighted distribution of expense ratios for our full sample. Panel (a) indicates that the average index fund expense ratios have fallen from 90 basis points in 2000 to roughly 65 basis points in 2020. The 10th percentile and 90th percentile of expense ratios have experienced similar declines, which indicates that the decline in average expense ratios has been driven by a general level shift in the distribution of fund expense ratios. However, the interdecile range has remained relatively constant at 150-160 basis points over the bulk of our sample.

Comparing the equal-weighted distribution of expense ratios (Panel a) with the asset-weighted distribution of expense ratios (Panel b) provides prima facie evidence about investors' elasticity of demand. The asset-weighted distribution is shifted downwards relative to the equal-weighted distribution of expense ratios, which suggests investors are price sensitive. However, there is still substantial dispersion in expense ratios even when we weight by assets, which suggests that a large fraction of investors still purchase expensive index funds.

Dispersion in expense ratios could be driven in part by product differentiation related to the underlying types of index funds/asset classes. For example, it could be the case that index funds classified in Lipper as commodities based metals funds are more expensive than funds classified in Lipper as S&P 500 index funds. Thus, some of the observed dispersion in expense ratios in Panels (a) and (b) is potentially attributable to these types of observable fund differences. To account for these differences we residualize expense ratios by regressing them on Lipper Class-by-month fixed effects. Figure 1 Panels (c) and (d) plot the residualized expense ratios.

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[12]Bhattacharya and Illanes (2022) use these data to study the design of defined contribution plans.

These fixed effects explain 35% of the variation in fund expense ratios and 79% of the variation in fund returns. Thus, even after accounting for differences across Lipper Classes, there is still a substantial amount of variation in expense ratios. The results indicate that over the whole sample funds in the 90th percentile were on average 1 percentage point more expensive than funds in the 10th percentile. Overall, the results show there has been substantial price dispersion for seemingly homogeneous products that has persisted over the past 20 years.

### 2.2.2 Potential Drivers of Price Dispersion

We wish to provide insight into the drivers of index fund market power and observed dispersion in prices. Here, we provide initial motivating evidence for three mechanisms that appear to be important: inertia, search frictions, and price discrimination.

**Investor Inertia:** It is well documented that investors exhibit inertia. Recent survey evidence indicates that roughly 12-18% of defined contribution plan investors update their portfolio each year.[13] Given the secular decline in average expense ratios, inertia could be quite costly for those 82-88% of investors that do not update their portfolios each year and could help explain the persistent dispersion in expense ratios.

We provide initial evidence on the role of investor inertia in index funds by examining how fund flows respond to the introduction of new low-cost funds. Since inertia prevents investors from switching to cheaper new funds, the sluggishness of outflows into these funds provides a preliminary test of whether inertia plays an important role in this market.

Figure 3 shows how the aggregate market share of newly launched low-cost funds within a Lipper Class evolves over time. We compute the aggregate market share as the sum of shares of funds in the bottom quartile of the expense ratio distribution at the time of launch by time since introduction. We focus on funds that survive 5 or more years to avoid selection issues. Consistent with there being a large degree of inertia, demand for inexpensive funds is initially low and it takes multiple years for investors to switch. After four years, the market share of funds in the bottom quartile of the price distribution is only 15%. The fact that demand for low cost funds is not higher in the long run when most investors have made an active choice may be a result of search frictions or preference heterogeneity.

**Search Frictions:** Given that the expense ratios of 401(k) plans are more transparent, investors may be more price sensitive. We examine price dispersion for 401(k) plans in Figure 2. There is a large difference between the equal-weighted distribution of expense ratios (Panel a) and the asset-weighted distribution of expense ratios (Panel b), suggesting that investors in 401(k) plans are quite price sensitive. While the interdecile range of asset-weighted expense

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[13]See `https://www.ici.org/system/files/2021-09/21_rpt_recsurveyq2.pdf`. ICI reports rebalancing activity for the first half of the year, which we annualize by multiplying by two.

ratios is about 40 basis points for index funds, the interdecile range is only 8 basis points at the end of the sample for 401(k) plans. Given that preference heterogeneity is likely similar, lower price dispersion in 401(k) plans relative to the broader index fund market provides initial evidence that search frictions play an important role in the index fund market.

**Price Discrimination:**  Index fund managers will often create multiple funds and ETFs that share the same index/underlying portfolio. In particular, mutual funds often have a class structure which allows intermediaries to explicitly price discriminate across investor types. The fund manager will then typically offer a less expensive version of the mutual fund to institutions, who are more price sensitive, and a more expensive version of the mutual fund to retail investors, who are less price sensitive. For a given underlying portfolio (identified in the data as crsp_portno) and moment in time, we calculate the difference between the average expense ratio of retail mutual funds and that of institutional mutual funds. Figure 4 displays the distribution of this difference for those portfolios that are held by at least one retail and one institutional fund. The results indicate that, on average, an institutional fund charges an expense ratio that is 94 basis point lower than the retail fund within the same portfolio. These results suggest that part of the observed dispersion in expense ratios is driven by the ability of index managers to segment the market and further exercise their market power.

## 3   Framework

We develop a dynamic quantitative model of supply and demand for index funds. Our objective is to use the model to provide new insight into the mechanisms driving the price dispersion we observe in the data. The baseline version of the model includes two types of agents: heterogeneous investors who possess demand for index funds and index fund managers who create a suite of available index funds. We also consider an extension of the model in Appendix B where we introduce financial advisers who potentially distort the investment decisions of investors due to conflicts of interest.

Motivated by the evidence in Section 2.2, we focus on four mechanisms that may explain why investors buy expensive index funds and why funds have market power in our baseline framework. First, investors have heterogeneous preferences over index funds such that that index funds are horizontally differentiated. Second, investors face search frictions and have imperfect information about fund characteristics when choosing a fund. Third, investors exhibit inertia and do not actively update their portfolios every period. Fourth, index fund managers are able to price discriminate across institutional and retail investors.

### 3.1 Investors: Demand for Index Funds

We model an investor's demand for index funds as a discrete choice problem. We consider an investor's index fund choice conditional on her decision to invest in a specific investment category/asset class (e.g., small-cap value, mid-cap growth, etc.), which allows us to abstract away from the investor's portfolio choice problem. For example, we model an investor's decision to invest in a particular Vanguard S&P 500 Index fund over a similar BlackRock S&P 500 Index fund, but do not model the investor's initial decision of whether and how much to invest in S&P 500 Index Funds. In our counterfactuals, we assume that changes in expense ratios affect demand for funds within a category/asset class but do not cause investors to switch category/asset classes.

There are two types of investors: retail and institutional. We denote investor type by $(T)$ such that $T \in \{R, I\}$ where $R$ denotes retail investors and $I$ denotes institutional investors. Investor-types differ with respect to their preference parameters, frictions (e.g., inertia and search frictions), and ability to purchase certain types of funds. For example, the set of index funds available to retail investors is potentially different from the set of index funds available to institutional investors.

#### 3.1.1 Investor Preferences

Investor $i$'s indirect utility from choosing fund $j$ at time $t$ is given by:

$$u_{i,j,t} = \underbrace{-p_{j,t} + X'_{j,t}\theta_{T(i)} + \xi_{T(i),j,t}}_{\bar{u}_{T(i),j,t}} + \sigma_{\epsilon,T(i)}\epsilon_{i,j,t}.$$

The term $-p_{j,t}$ reflects the dis-utility investors get from paying expense ratio $p_{j,t}$ where, without any loss in generality, we normalize the coefficient to one. The term $X'_{j,t}\theta_{T(i)}$ measures the utility generated by other fund characteristics $X_{j,t}$ where $\theta_{T(i)}$ captures investor preferences over those characteristics.

The indirect utility function includes two latent terms. The term $\xi_{T(i),j,t}$ measures unobserved product characteristics that are commonly valued among investors of type $T$. The term $\epsilon_{i,j,t}$ captures preference heterogeneity which varies across investors. This implies that index funds are horizontally differentiated such that any two investors may disagree on which index fund is the best. The degree of product differentiation also varies across type $T$ which is captured by the term $\sigma_{\epsilon,T(i)}$. The horizontal differentiation is also captured by $\theta_{T(i)}$ as different types of investors disagree on the relative importance of the expense ratio and other fund characteristics.[14]

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[14]It is straightforward to incorporate additional taste differences by allowing random coefficients on the expense ratio, for example.

### 3.1.2 Search Frictions

Investors may not research all funds and may not fully understand fund characteristics such as the expense ratio. We assume that each investor potentially faces search frictions such that the investor's subjective utility when selecting a fund may differ from the realized utility from owning a fund. Investors choose index funds based on their subjective utility $\tilde{u}_{ij}$, which is a noisy signal of their indirect utility function:

$$\tilde{u}_{i,j,t} = u_{i,j,t} + \nu_{i,j,t} \tag{1}$$
$$= \bar{u}_{T(i),j,t} + \sigma_{\epsilon,T(i)}\epsilon_{i,j,t} + \nu_{i,j,t}.$$

The term $\nu_{i,j,t}$ reflects idiosyncratic choice/search frictions that cause individuals to not always choose their preferred index fund. Let $Var[\nu_{i,j,t}] = \frac{\pi^2}{6}\sigma^2_{\nu,T(i)}$, where $\sigma_{\nu,T(i)}$ reflects the degree of search frictions. This approach can also be considered a stylized approach to modeling a cost to learn about each fund. An increase in search frictions (larger $\sigma_{\nu,T(i)}$) makes individuals less likely to choose the lowest cost fund. In the second line of Eq. (1), we write subjective utility in terms of the common component of utility, $\bar{u}_{T(i),j,t}$.

Following the literature we assume that $\nu_{i,j,t}$ is distributed according to Cardell (1997); i.e., $\nu_{i,j,t} \sim C(\frac{\sigma_{\epsilon,T(i)}}{\sigma_{\eta,T(i)}}, \sigma_{\epsilon,T(i)})$ such that the composite error term $\eta_{i,j,t} = \sigma_{\epsilon,T(i)}\epsilon_{i,j,t} + \nu_{i,j,t}$ is distributed Type 1 Extreme Value with scale parameter $\sigma_{\eta,T(i)} = \left(\sigma^2_{\nu,T(i)} + \sigma^2_{\epsilon,T(i)}\right)^{1/2}$. We can then write investor $i$'s subjective utility as:

$$\tilde{u}_{i,j,t} = \bar{u}_{T(i),j,t} + \sigma_{\eta,T(i)}\eta_{i,j,t}. \tag{2}$$

### 3.1.3 Fund Choice

When individuals make an active choice (and are not subject to inertia as described below), they maximize subjective utility given by Eq. (2). The market share of fund $j$ among active type $T$ investors at time $t$ is given by:

$$s_{T,j,t} = \frac{\exp\left(\frac{-p_{j,t}+X'_{j,t}\theta_{T(i)}+\xi_{j,T(i),t}}{\sigma_{\eta,T(i)}}\right)}{\sum_{l \in \mathcal{J}_{T(i),m(j),t}} \exp\left(\frac{-p_{l,t}+X'_{l,t}\theta_{T(i)}+\xi_{l,T(i),t}}{\sigma_{\eta,T(i)}}\right)}. \tag{3}$$

The set $\mathcal{J}_{T(i),m(j),t}$ denotes the investors consideration set: the set of index funds available to a type $T(i)$ investor in market $m(j)$ at time $t$. Recall that our model is a model of index fund choice, conditional on an investors' choice to buy a fund in a given market. The above equation is a core part of our estimation strategy below, where we separately identify investors' preferences ($\theta_{T(i)}$) as well as decompose the error term into two components: one due to search frictions ($\sigma_{\nu,T(i)}$) and the other due to product differentiation ($\sigma_{\epsilon,T(i)}$).

### 3.1.4 Inertia

We consider the possibility that investors suffer from inertia. In each period, there is some probability an investor will be active and some probability the investor will be inactive, similar to the setup in Beggs and Klemperer (1992). Inactive investors simply maintain their investments from the previous period, while active investors update their portfolios to maximize their objective function. We assume that the probability an investor is inactive in a given period is heterogeneous across investor types but is constant across investors conditional on their type. The probability a type $T$ investor is inactive in a given period is $\phi_T$ and the probability she is active is $1 - \phi_T$. This model of inertia is consistent with the idea that investors may only check their portfolio at specific intervals, such as when they file taxes or receive annual reports (e.g., Benartzi and Thaler, 1995). Alternatively, it is possible that the $\phi_T$ is endogenous and responds to market conditions, a situation we consider in Section 4.1.

We assume that when active investors choose a fund, market shares are given by Eq. (3). Thus, investors are either myopic or they assume that their preferences and the product space will be constant over time. Given that $\phi_T$ of investors of type $T$ are inactive each period, the total assets under management of fund $j$ held by type $T$ investors at time $t$, denoted $AUM_{T,j,t}$ is given by:

$$AUM_{T,j,t} = \underbrace{\phi_T AUM_{T,j,t-1}(1 + r_{m(j),t-1})}_{AUM_{T,j,t}^{Inactive}} + \underbrace{(1 - \phi_T)M_{T,m(j),t}s_{T,j,t}}_{AUM_{T,j,t}^{Active}}. \tag{4}$$

The term $AUM_{T,j,t}^{Inactive} \equiv \phi_T AUM_{T,j,t-1}(1 + r_{m(j),t-1})$ captures demand from inactive investors who simply maintain their holdings from the previous period, which grow based on the return of fund $j$ over the period $t-1$ to $t$, denoted $r_{m(j),t-1}$. We assume, in part for ease of exposition, that fund returns are constant across all index funds in a given market such that $r_{j,t} = r_{m(j),t}$. The term $AUM_{T,j,t}^{Active} \equiv (1 - \phi_T)M_{T,m(j),t}s_{T,j,t}$ measures demand from active investors, where $M_{T,m(j),t}$ denotes the total assets invested in market $m(j)$ held by investors of type $T$ at time $t$.

## 3.2 Index Fund Managers: Supply of Index Funds

Index funds are created and managed by a set of differentiated index fund managers $k$. Index fund managers create three different types of products, retail mutual funds, institutional mutual funds, and ETFs. The products are functionally equivalent except that retail mutual funds are only purchased by retail investors and institutional mutual funds are only purchased by institutional investors. Both retail and institutional investors can purchase ETFs.

Index fund managers' per-period profits in a market $m$ are given by

$$\Pi_{k,m,t} = \sum_{j \in \mathcal{J}_{k,m}} (AUM_{R,j,t} + AUM_{I,j,t})(p_{j,t} - c_j),$$

13

where $\mathcal{J}_{k,m}$ denotes the set of index funds sold by index fund manager $k$ in market $m$. The terms $AUM_{R,j,t}$ and $AUM_{I,j,t}$ denote demand for fund $j$ from retail and institutional and retail investors, and funds earn a markup of $p_{j,t} - c_j$ for each dollar of assets collected, where $c_j$ is the marginal cost of operating the fund.

We assume that index fund managers play a differentiated, multi-product, dynamic, Nash-Bertrand, expense ratio setting game. Let $\mathbf{p}_{k,t}$ be the vector of prices for funds managed by $k$ in period $t$. An index fund manager's problem is to set the sequence of prices/expense ratios $\mathbf{p}_{k,t}$, $\mathbf{p}_{k,t+1}, \ldots$ to maximize the presented discounted value of future profits discounted by $\beta$.

$$\max_{\mathbf{p}_{k,t},\mathbf{p}_{k,t+1}\cdots|\mathbf{P}_{-k,t},\mathbf{P}_{-k,t+1}\cdots} \sum_{\tau=t}^{\infty} \beta^{\tau-t} \sum_{j\in\mathcal{J}_{k,m}} (AUM_{R,j,\tau} + AUM_{I,j,\tau})(p_{j,\tau} - c_j). \qquad (5)$$

For tractability, we assume that fund managers observe and condition on the full sequence of competitors' prices when setting their own prices. This assumption simplifies the suppliers' problem because it rules out strategic pricing interactions where a firm may change its price today to influence the future prices of its competitors. We believe this assumption is reasonable in the index fund setting for two reasons. First, approximately 70% of funds have a market share smaller than 1%. Given the many funds with very small market share, it is unlikely that fund managers internalize their future strategies. Second, prices appear quite sticky. As of 2020, only 3.5% funds (weighted by assets) charged an expense ratio that was more than 10 basis points lower than what the fund charged five years previously in 2015. It is important to note that even with this assumption, firms set prices while fully accounting for how current demand impacts future demand and profitability due to inertia.

To develop intuition for how firms set prices with consumer inertia, we first consider the simple case where an index fund manager operates a single retail mutual fund. We then extend our model to the multi-product and multi-investor-type setting.

### 3.2.1 Single Product Retail Mutual Fund Manager

Consider a fund manager's profit maximization problem for retail mutual fund $j$. The corresponding first order condition for price $p_{j,t}$ is:

$$0 = \frac{\partial AUM_{R,j,t}}{\partial p_{j,t}} \left[ \underbrace{p_{j,t} - c_j}_{\text{Static Profits}} + \underbrace{\sum_{\tau=t+1}^{\infty} \left(\beta(1 + \tilde{r}_{m(j),\tau})\phi_R\right)^{\tau-t} (p_{j,\tau} - c_j)}_{\text{Present Value of Future Profits}} \right] + AUM_{R,j,t}.$$

The first order condition is fairly standard except for the term $\sum_{\tau=t+1}^{\infty} \left(\beta(1 + \tilde{r}_{m(j),\tau})\phi_R\right)^{\tau-t}(p_{j,\tau} - c_j)$, which captures the effects of inertia. For every investor the fund attracts today, there is a

$\phi_R$ chance the investor will remain in the subsequent period, a $\phi_R^2$ chance the investor remains for at least two periods, and so on. Furthermore, inactive investors' assets are expected to grow based on fund expected returns, $\tilde{r}_{m(j),\tau}$.[15]

In the static problem (e.g. no inertia), a firm's assets today do not impact its assets tomorrow such that $\frac{\partial AUM_{R,j,\tau}}{\partial AUM_{R,j,t}} = 0, \forall \tau \neq t$. As a result of investor inertia, $\frac{\partial AUM_{R,j,\tau}}{\partial AUM_{R,j,t}} = ((1 + \tilde{r}_{j,t})\phi_R)^{\tau-t}$. Thus, when setting prices, firms account for how changing prices impacts both current and future demand. In order to attract new investors who will be inert in the future, firms may want to set lower prices the more inertia is present. This is often referred to as the incentive to "invest" in new customers. However, inertia also makes demand less elastic. To see this, note that:

$$\frac{\partial AUM_{R,j,t}}{\partial p_{j,t}} = (1 - \phi_R)M_{R,m(j),t}\frac{\partial s_{R,j,t}}{\partial p_{j,t}}.$$

Consequently, an increase in inertia will make a fund's current assets less sensitive to expense ratios, which, all else equal, will cause firms to want to set higher prices. This is often referred to as the incentive to "harvest" current consumers.

We study a steady-state equilibrium where firms' market shares are constant over time such that $p_{j,t} = p_j$ and $s_{j,t} = s_j$ $\forall j$ and $M_{R,m(j),t} = M_{R,m(j),t-1}(1 + r_{m(j),t-1})$. Thus, dropping the $t$ subscripts and noting that $p_{j,t} - c_j + \sum_{\tau=t+1}^{\infty}(\beta(1 + \tilde{r}_{m(j)})\phi_R)^{\tau-t}(p_{j,\tau} - c_j) = \frac{p_j - c_j}{1 - \beta\phi_R(1 + \tilde{r}_{m(j)})}$, the manager's first order condition simplifies to:

$$\frac{p_j - c_j}{p_j} = \frac{1 - \beta(1 + \tilde{r}_{m(j)})\phi_R}{1 - \phi_R} \times \frac{1}{-\varepsilon_j^D}, \tag{6}$$

where $\varepsilon_j^D$ denotes the elasticity of demand of product $j$ for active investors given prices for all other funds.

A couple of features of this first order condition are worth noting. First, if inertia is equal to zero (i.e., $\phi_R = 0$), the first order condition simplifies to a standard static first order condition. Second, given a growth-adjusted discount factor of 1 (i.e. $\beta(1 + \tilde{r}_{m(j)}) = 1$ such that the growth-adjusted discount rate is zero), the dynamic pricing condition simplifies to the standard static first order condition even if inertia is greater than zero, and the share of inactive investors does not affect steady-state prices. Note that this result would hold for any generic demand system given how inertia works in our model. While the incentive to invest in new consumers can lower prices and the incentive to harvest existing customers can raise prices, our model implies that these forces perfectly offset when the growth-adjusted discount factor is equal to 1. The CAPM model would imply that we would expect the growth-adjusted discount factor to be close to 1 because, if expected returns are equal to required returns, it should be the case that $\beta_{m(j)}$ varies at the market level such that $\beta_m = \frac{1}{1+\tilde{r}_m}$.

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[15]For ease of exposition, we assume that fund expected returns is constant over time and constant across index funds in a given market (i.e. $\tilde{r}_{j,t} = \tilde{r}_{m(j)}$).

In practice, we would expect the growth-adjusted discount rate to be positive such that the discount factor is slightly less than one.[16] Given a growth-adjusted discount factor less than one, the first order condition implies that with inertia, the index fund manager will set a higher markup than in the static model without inertia. As the growth-adjusted discount factor decreases (i.e., the discount rate increases), managers will place more value on extracting profits from current investors than on profits from future demand.

### 3.2.2   Multi-product Managers

In the data, index fund managers often issue multiple retail funds, institutional funds, and ETFs in a single market. Consider the profit maximization problem of an index manager $k$ who issues set of index funds $\mathcal{J}_{k,T,m}$ available to type $T$ investors in market $m$. The corresponding first order condition with respect to $p_{j,t}$, given our demand system, in steady state is given by

$$
\begin{aligned}
0 =& \mathbf{1}(j \in \mathcal{J}_{k,R,m}) \frac{M_{R,m(j)}}{M_{I,m(j)}} s_{R,j} \left[ 1 - \frac{\frac{1}{\sigma_{\eta,R}}(1-\phi_R)}{1 - \beta(1+\tilde{r}_{m(j)})\phi_R} \left( p_j - c_j - \sum_{l \in \mathcal{J}_{k,R,m(j)}} s_{R,l}(p_l - c_l) \right) \right] \\
&+ \mathbf{1}(j \in \mathcal{J}_{k,I,m}) s_{I,j} \left[ 1 - \frac{\frac{1}{\sigma_{\eta,I}}(1-\phi_I)}{1 - \beta(1+\tilde{r}_{m(j)})\phi_I} \left( p_j - c_j - \sum_{l \in \mathcal{J}_{k,I,m(j)}} s_{I,l}(p_l - c_l) \right) \right],
\end{aligned} \tag{7}
$$

where $\frac{M_{I,m(j)}}{M_{R,m(j)}}$ denotes the relative size of the institutional and retail markets which are constant in steady state. Again notice that if either $\phi_I = \phi_R = 0$ or $\beta(1+\tilde{r}_{m(j)}) = 1$, then firm's first order condition for setting prices in the dynamic model simplifies to the standard first order condition for the static model.

## 4   Estimation and Results

We estimate our structural model of demand and supply for index funds using the mutual fund data set described in Section 2.2. On the investor demand side, we first estimate inertia using an instrumental variable strategy. Once investors' inertia is pinned down, we estimate their preference parameters, and then, we use additional data on choices in 401(k) plans to estimate search frictions. Finally, with the demand parameters in hand, we estimate the index fund managers' marginal costs of operating index funds on the supply side.

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[16]For example, due to fund expense ratios the expected fee-adjusted growth rate will be less than the required return.

## 4.1 Investor Demand

### 4.1.1 Inertia

Demand for an index fund is comprised of new demand from active investors and past demand from inactive investors. Following Eq. (4), the total assets under management held by investors of type $T$ of fund $j$ at time $t$ is equal to:

$$AUM_{T,j,t} = \phi_T AUM_{T,j,t-1}(1 + r_{j,t}) + AUM_{T,j,t}^{Active}. \tag{8}$$

In principle, one could estimate the fraction of inactive consumers ($\phi_T$) by simply regressing current assets under management on lagged assets under management scaled by returns.

One challenge in estimating Eq. (8) is that lagged assets under management $AUM_{T,j,t-1}$ are potentially endogenous and correlated with $AUM_{T,j,t}^{Active}$, which is unobserved. For example, if investor preferences for funds are correlated over time, then we would expect lagged assets to be positively correlated with the assets held by active consumers. This endogeneity bias would cause us to overestimate the fraction of inactive investors. To address the endogeneity issue, we need an instrument that is correlated with lagged assets but that is uncorrelated with contemporaneous demand by active consumers.

One potential instrument we consider is past returns. The instrument will be relevant provided at least some investors are inactive each period and do not re-balance their portfolios. The instrument will be exogenous provided that past returns are uncorrelated with current demand from active investors. In other words, the instrument will be valid as long as active investors do not chase returns. While in a rational benchmark model we might not expect investors to chase returns, there is a long literature suggesting that at least some investors chase returns. To allow for return chasing, we assume that investors that chase returns do so based on 1-month, 3-month, 6-month, 12-month, and year-to-date cumulative returns, which are the returns that are typically reported by index funds. We then instrument for lagged assets using the past twelve monthly returns. The idea is that conditional reported returns, the choice of active investors is not affected by past monthly returns. We also consider additional specifications where we include market-by-time fixed effects to help control for return chasing with the idea that investors primarily chase returns at the index/Lipper Class level rather than the fund level.[17]

We estimate the fraction of inactive consumers using the following empirical analog of Eq. (8):

$$\ln AUM_{T,j,t} = \phi_T(i) \ln AUM_{T,j,t-1}(1 + r_{j,t}) + X'_{j,t-1}\Gamma + \iota_{T,j,t}, \tag{9}$$

where observations are at the fund-by-month-by-investor type level.[18] The key independent

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[17]In our specifications where we include market-by-time fixed effects, we control for 1-month and year-to-date cumulative returns because the market-by-time fixed effects capture much of the variation in returns.

[18]Note that we estimate our empirical specification in logs rather than levels. This is because we implicitly assume

variable of interest is $\ln AUM_{T,j,t-1}$. Importantly, we instrument for lagged assets using the past twelve monthly returns while simultaneously controlling for 1-,3-,6-, 12-month, and year-to-date cumulative returns. In all our specifications, we also control for the log number of funds offered by the management company, the standard deviation of daily fund returns over the past 12 months, and whether the fund is an ETF, has a front load, or has a rear load. The estimate $\phi_T$ measures the causal impact of an exogenous change in lagged AUM on current AUM, which we attribute to inertia. For example, a 1% exogenous increase AUM last period leads to a $\phi_T$ percent increase in AUM this period.[19]

We report the corresponding estimates in Table 2. Panel (a) and (b) present the results for retail investors and institutional investors, respectively, and the baseline results are in column (2). For retail investors, a 1% increase in lagged assets under management causes a 0.988% increase in assets under management today in the baseline. In other words, we estimate that 98.8% of retail investors are inactive each month. Put differently, our estimates imply that roughly 13% ($= 1 - 0.988^{12}$) of retail investors update their portfolios at least once a year. We include year-month fixed effects in our baseline specification; however, columns (3) show that estimated inertia is quite similar when including year-month-market fixed effects.

We find somewhat lower rates of inertia for institutional index fund investors. Roughly 49% ($= 1 - 0.946^{12}$) of institutional investors update their portfolios at least once a year in the baseline. It is also useful to compare our OLS estimates versus our IV estimates (column 1 versus 2). As expected, we estimate a smaller fraction of inactive investors once we account for the endogeneity of lagged assets under management.

In the Appendix, we use new data and alternative specifications to explore the robustness of our estimates. First, we use data on mutual fund sales and redemptions from the SEC's NPORT filings, made available starting in 2019, to assess the active share of investors.[20] We use these data to calculate the active share of investors at the market level as the total value of new sales (redemptions) divided by total AUM. We find that for the median market, the total number of new shares purchased (shares redeemed) relative to total AUM is 2.1% (1.8%), which are broadly in line with our estimates of investor inertia (see Appendix Figure A1). In Appendix Table A2 we estimate inertia using a control function approach and find similar results. We examine heterogeneity in inertia over time and across funds and find no clear evidence of trends in inertia over time and only modest evidence of heterogeneity in inertia by

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that inactive investors may passively allocate money to their account each period based on their previous holdings. For example, even if inactive investors do not actively choose index funds each period they may passively allocate their savings to their existing holdings each period. Modeling AUM in terms of logs also has the additional benefit for tractability that the implied active assets under management will always be positive. In Appendix Table A1 we estimate the corresponding regression in levels and find quantitatively similar estimates of inertia.

[19]We attribute this effect to inertia, thereby implicitly assuming that conditional on the expected returns and quality of the fund, investors do not care about lag fund size.

[20]Since 2019, funds are required to report the total net asset value of new shares purchased (excluding reinvestments of dividends and distributions) and of shares redeemed each month.

fund characteristics.[21] These results motivate our assumption that inertia is exogenous in our context.

### 4.1.2 Active Investor Demand

These estimates of inertia help us separately determine the choices of active and inactive investors. Then, we estimate both retail and institutional investor demand using the revealed choices of active investors following our framework in Section 3.1. It is important to focus on the choices of active investors because these choices reflect investors' current preferences and search frictions with respect to available index funds. In contrast, because investors suffer from inertia, total assets are driven in part by the past choices of inactive investors, which depend on past preferences and product characteristics.

Given our framework (Eq. 3) and following Berry (1994), the market share of fund $j$ in market $m$ among active type $T$ investors can be written in logs as:

$$\ln s_{T,j,t} = \frac{1}{\sigma_{\eta,T}}\left(-p_{j,t} + X'_{j,t}\theta_T + \xi_{T,j,t}\right) - \ln\left(\sum_{l\in\mathcal{J}_{T,m(j),t}}\exp\left(\frac{-p_{l,t} + X'_{l,t}\theta_T + \xi_{T,l,t}}{\sigma_{\eta,T}}\right)\right). \quad (10)$$

We estimate the corresponding regression specification:

$$\ln s_{T,j,t} = -\underbrace{\alpha_T}_{\frac{1}{\sigma_{\eta,T}}} p_{jt} - X'_{j,t}\underbrace{\Gamma_T}_{\frac{\theta_{T(i)}}{\sigma_{\eta,T}}} + \underbrace{\mu_{T,m(j),t}}_{\ln\left(\sum_{l\in\mathcal{J}_{T,m(j),t}}\exp\left(\frac{-p_{l,t} + X'_{l,t}\theta_T + \xi_{T,l,t}}{\sigma_{\eta,T}}\right)\right)} + \underbrace{\zeta_{T,j,t}}_{\frac{\xi_{T,j,t}}{\sigma_{\eta,T}}}. \quad (11)$$

Observations are at the fund-by-month level. Importantly, we include market-by-time fixed effects $\mu_{T,m(j),t}$, which absorb the non-linear term in Eq. (10). Consequently, we can estimate Eq. (11) using linear methods to recover investors' demand parameters. We also control for 1-, 3-, 6-, 12-month, and year-to-date cumulative returns; the log number of funds offered by the management company; the standard deviation of daily fund returns over the past 12 months; and whether the fund is an ETF, has a front load, or has a rear load.

As described above, to estimate the model we first need to calculate market shares among active investors. We use our estimates of inertia to calculate total assets held of fund $j$ by active

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[21]Inertia for retail investors may have been lower at the beginning of the period, however inertia for retail investors is very similar from 2006 to the end of the sample (see Appendix Table A3). We also allow inertia to vary with whether a fund has a front-, a rear-, or no-load since one might expect investors that purchase funds with loads suffer from greater inertia. As seen in Appendix Table A4, retail investors that purchase funds with rear-loads are slightly more likely to be inert than investors that purchase funds without rear loads. Lastly, we examine whether inertia varies with past returns. One might expect that investors in funds that experienced positive returns to have stickier demand as a result of potential tax consequences. We find some modest evidence that retail investor inertia increases after a fund has experienced positive returns, but its economic magnitudes are quite small.

investors of type $T$ at time $t$ as

$$AUM_{T,j,t}^{Active} = \exp\left(\frac{\ln AUM_{T,j,t} - \hat{\phi}_T(i)\ln(AUM_{T,j,t-1}(1+r_{j,t}))}{1-\hat{\phi}_T}\right).$$

We then compute the market share among active type $T$ investors for each fund $j$ at time $t$ in market $m$ as:

$$s_{T,j,t} = \frac{AUM_{T,j,t}^{Active}}{\sum_{l \in \mathcal{J}_{T,m(j),t}} AUM_{T,l,t}^{Active}}.$$

This provides us with an estimate of active market shares, which is the dependent variable in our main demand specifications.

One additional challenge in estimating Eq. (11) using ordinary least squares (OLS) is that fund expense ratios ($p_{j,t}$) are potentially endogenous. For example, if an index fund manager anticipates high latent demand for their fund (e.g., high $\xi_{T,j,t}$), they may find it optimal to charge a higher expense ratio. This type of behavior would cause our OLS estimates of investors' sensitivity to prices $\alpha_T$ to be biased downwards such that investors appear less sensitive to prices than they actually are. To account for the potential endogeneity of expense ratios, we instrument for expense ratios with Hausman (1996) instruments. Specifically, we instrument for the expense ratio that an index fund manager $k$ charges on its fund $j$ at time $t$ using the average expense ratio that fund manager $k$ charges on all of its funds in other markets at time $t$ (i.e., excluding market $m(j)$). For example, we instrument for the fee that BlackRock charges on its large-cap value funds using the average fees it charges on its non-large-cap value funds, such as BlackRock's high-yield bond funds. The idea is that the instrument is relevant because BlackRock's costs of managing its large-cap equity funds are correlated with its costs of managing its high-yield bond funds. The instrument is exogenous provided that the fee that BlackRock charges on its high-yield bond fund is uncorrelated with demand shocks for BlackRock's large-cap value fund.

Table 3 displays our baseline demand estimates. We report the estimated perceived utility parameters for our retail investor sample in columns (1)-(2) and the estimates for our institutional investor sample in columns (3)-(4). In each specification, as expected, we estimate a negative and significant relationship between expense ratios and demand. In the bottom row of the table, we report the corresponding elasticity of demand. We estimate an elasticity of demand ranging from 1.3-2.8, depending on the exact specification. Consistent with intuition, we find that institutional investor demand is substantially more elastic than retail investor demand; institutional investors demand is roughly 75% more elastic than retail investor demand (column 2 vs 4). As described above, part of this could be due to the fact that retail investors have more search frictions (or less information) such that $\sigma_{\eta,R} > \sigma_{\eta,I}$.[22]

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[22]In Appendix Table A5 we estimate our demand specification where we use data on new mutual fund sales. Since 2019, funds are required to report the total net asset value of new shares purchased (excluding reinvestments of

We examine the robustness of the demand estimates to including a cost shifter as an instrument, which further addresses potential endogeneity of expense ratios. In particular, we include asset-weighted average trading cost as measured by the bid-ask spreads of securities held by each index fund as an additional instrument. We find very similar elasticity of demand for both retail and institutional investors (see Appendix Table A6). In addition, we explore preferences for top fund managers by including an indicator for whether the fund manager is among the top three firms measured by total assets (BlackRock, State Street Bank, and Vanguard), and also find similar elasticity of demand (see Appendix Table A7).

### 4.1.3 Search Frictions

A challenge in the literature is that it can be difficult, if not impossible, to separately identify search frictions/search costs from preference heterogeneity. To address this, we estimate our demand system in the unique 401(k) setting where search frictions are likely to be close to zero. Investors choose 401(k) investments from a fixed menu of roughly 10 to 30 options. And within each broad asset class (e.g., large cap US equities), an average plan typically offers two index funds.[23] For the funds in the 401(k) menu, employers are also required to provide expense ratio- and performance-related disclosures, which are designed to be transparent for investors and shown to be effective in reducing search frictions (Kronlund et al., 2021). Therefore, we argue that investors have information on the full menu of 401(k) funds. Comparing demand by active investors in the 401(k) setting and in the broader index fund market provides insight into the magnitude of search frictions.

Given that 401(k) investors do not face search frictions, ($\nu_{i,j,t} = 0$), investors select the fund that maximizes their indirect utility ($u_{i,j,t}$) rather than their selecting the fund that maximizes their perceived utility ($\tilde{u}_{i,j,t}$). Therefore, following Eq. (3), the market share of fund $j$ in 401(k) plan $l$ is given by:

$$S_{j,l,t} = \frac{\exp\left(\frac{-p_{j,t}+X'_{j,t}\beta+\xi_{j,t}}{\sigma_\epsilon}\right)}{\sum_{n\in\mathcal{J}_{l,m(j),t}} \exp\left(\frac{-p_{n,t}+X'_{n,t}\beta+\xi_{n,t}}{\sigma_\epsilon}\right)}, \tag{12}$$

where $\mathcal{J}_{l,m,t}$ corresponds to the index funds in market $m$ that are available in 401(k) menu for plan $l$ at time $t$. As described in the previous section, we can then directly estimate Eq. (12) following Berry (1994) using our 401(k) plan data. Here, we recover the term $\sigma_\epsilon$ which measures the importance of product heterogeneity. In contrast, we previously recovered the term $\sigma_\eta$, which is a function of both search frictions and product heterogeneity. This allows us to separately identify search frictions and product heterogeneity.

Similar to the previous section, we include 401(k)-plan-by-market-by-time fixed effects, and

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dividends and distributions). We find qualitatively similar estimates using these alternative data.

[23]Broad asset classes are defined as per Brightscope and include: allocation funds, alternatives, bonds, cash, international equities, large cap equities, mid cap equities, and small cap equities.

use both OLS and instruments for expense ratios.[24] Due to concerns about investor inertia, we restrict our attention to newly created 401(k) plans in the first year they were introduced, when all investors were active and there was no inertia.

Table 4 displays the estimates. Column (1) displays our OLS estimates and column (2) displays our IV estimates. In both specifications, we find a negative relationship between demand and fund expense ratios. The elasticity of demand in our preferred specification (column 2) is 4.2, which is substantially higher than the retail investors' elasticity of demand in our main sample but closer to the institutional investors' elasticity of demand (Table 3). Given that search frictions are likely negligible in the 401(k) plan setting, this difference in demand elasticity implies significant search frictions for retail investors. Also, given that unobserved product heterogeneity is likely similar for institutional and retail funds[25], these results suggest that search frictions help explain why retail investors have a lower elasticity of demand than institutional investors in Section 4.1.2.

We separately identify search frictions and preference heterogeneity by exploiting exogenous variation in search frictions in the 401(k) setting. One might be worried that the sample of index funds available in 401(k) may be different from the sample of index fund available more generally, so there is less unobserved heterogeneity in our sample of 401(k) funds. To address this concern, we re-estimate our baseline specification from Section 4.1.2, restricting our data set to fund-year observations that correspond to our 401(k) sample (Appendix Table A8). The results suggest that unobserved heterogeneity is not smaller in our 401(k) sample. An additional concern is that investors may still face some search frictions choosing from a transparent menu of 401(k) funds. To this end, our estimates may be a lower bound on search frictions. We discuss the implications for our counterfactual exercises in Section 5.

## 4.2 Index Fund Managers: Supply

We estimate the supply side of the model by inverting the index fund manager's first order condition to solve for the marginal cost that rationalizes the manager's chosen expense ratio. Given our demand specifications, we rewrite the first order condition in Eq. (7) in matrix form as

$$M_{R,t}\mathbf{s}_{R,t} + M_{I,t}\mathbf{s}_{I,t} = (M_{R,t}\Omega_{R,t} + M_{I,t}\Omega_{I,t}) \times (\mathbf{p}_t - \mathbf{c}_t)$$

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[24] Given the nature of the 401(k) data, we construct our Hausman instruments following Egan et al. (2021) where we construct the instrument for fund $j$ in plan $l$ as the average expense ratio of all other funds offered by manager $k(j)$ that do not appear on the plan $l$'s 401(k) menu.

[25] For example, roughly 80% of retail index funds are available to institutional investors through alternative share classes

where elements of matrix $\Omega_{T,t}(\mathbf{p})$ are given by

$$\Omega_{(l,m)}(\mathbf{p}) = \begin{cases} -\frac{1-\phi_T}{1-\beta(1+\tilde{r}_{m(l)})\phi_T}\frac{\partial s_l}{\partial p_m}(\mathbf{p}_t) & \text{if } l, m \in \mathcal{J}_{k,m} \\ 0 & \text{else} \end{cases}$$

In the data we directly observe the scalars $M_{R,t}$ and $M_{I,t}$ and the vectors $\mathbf{s}_R$ $\mathbf{s}_I$, and $\mathbf{p}$. Given $\beta \times (1 + \tilde{r})$, we can then use our inertia and demand estimates to compute the matrices $\Omega_{R,t}$ and $\Omega_{I,t}$. We assume managers' annualized growth-adjusted discount rate is 5%, which implies that, on a monthly basis, $\beta \times (1 + \tilde{r}) = 0.996$. For each period $t$, we then directly solve for implied costs as:

$$\mathbf{c}_t = \mathbf{p}_t - (M_{R,t}\hat{\Omega}_{R,t} + M_{I,t}\hat{\Omega}_{I,t})^{-1}(M_{R,t}\mathbf{s}_{R,t} + M_{I,t}\mathbf{s}_{I,t}).$$

We report the estimated distribution of marginal costs and markups in the Appendix.[26] To account for outliers, we report the winsorized distribution of marginal costs where we winsorize costs at the 5% level.[27] The mean (median) marginal cost is 14 (18) basis points, and the mean (median) markup is 55 (26) basis points.

# 5    Counterfactuals

Regulatory authorities, such as the SEC, have deployed an array of rules and regulations in pursuit of fostering a just, steady, and inclusive financial environment. Using these different policy tools, the SEC aims to improve financial markets by effectively targeting different underlying frictions in the market. For example, the SEC's recently proposed "Names Rule" aims to foster improved market transparency and mitigate informational frictions due to deceptive or misleading fund names.

To understand the potential impact of various financial regulations, we use our model and corresponding parameter estimates to quantitatively assess the impact of inertia, search frictions, and price discrimination on the expense ratios paid by investors. Specifically, we conduct counterfactual analyses where we separately and then simultaneously remove each friction. A critical insight gleaned from these analyses is the need to account for the interplay among these frictions; understanding this dynamic interaction becomes an essential step in crafting effective regulatory policies.

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[26] See Appendix Figure A2. For computational ease, we restrict our attention to those index funds with a market share such that $s_{R,j,t} + s_{I,j,t} \geq 1e - 6$.

[27] Our estimates imply that some funds have negative marginal costs. One explanation for this is that mutual funds generate revenue by lending the shares that they own for a fee, which offsets the costs of running the fund. For example, State Street estimates that securities lending increases the yield of SPY by 7.5 bps per year (`https://www.ssga.com/us/en/individual/etfs/insights/unlocking-the-securities-lending-potential-of-spy`). The large fund families return these fees to investors: see for example `https://www.vanguard.ca/documents/securities-lending-considerations.pdf`.

For each counterfactual, we first consider a partial equilibrium analysis where we keep fund expense ratios fixed thereby ignoring the potential supply-side response. We then consider a general equilibrium analysis where we allow managers to optimally update their expense ratios, and we solve for a new equilibrium. Separating the demand and supply-side response is useful for understanding the full implications of each friction.

We also separately focus on the implications for retail and institutional investors, paying particular attention to retail investors. Our estimation results indicate that, relative to institutional investors, retail investors face greater search frictions and inertia. Retail investors are also more likely to be adversely impacted by price discrimination.

In our counterfactual analyses, we focus on how the distribution of expense ratios changes as a function of inertia, search frictions, and price discrimination. We compute the distribution of expense ratios in each counterfactual where we weight fund expense ratios by the predicted market share multiplied by market size. We compute the predicted market share of fund $j$ at time $t$ among type $T$ investors as a function of inertia, expense ratios and search frictions:

$$\mathcal{S}_{T,j,t}(\phi, \mathbf{p}, \sigma_\nu) = \sum_{\tau=0}^{\infty} (1-\phi)\phi^\tau s_{T,j,t-\tau}(\mathbf{p}_{t-\tau}, \sigma_\nu). \tag{13}$$

The term $(1-\phi)\phi^\tau$ reflects the share of investors that were last active at time $t-\tau$ and $s_{T,j,t-\tau}(\mathbf{p}_{t-\tau}, \sigma_\nu)$ denotes the share of active investors that would purchase fund $j$ at time $t-\tau$ given the vector of expense ratios $\mathbf{p}_{t-\tau}$ and search frictions $\sigma_\nu$.[28] Note that to make the underlying economic mechanisms in our counterfactuals more transparent, we compute predicted market shares under the assumption that the market size is constant over time. For each counterfactual we consider, we then compute the equilibrium vector of expense ratios and predicted market shares.

## 5.1 Eliminating Inertia

We first consider the counterfactual where we eliminate inertia in the model such that $\phi_R = \phi_I = 0$. Each period, all investors are active and select the fund that maximizes subjective utility. Panel (a) of Figure 5 displays the counterfactual distribution of expense ratios paid by retail investors under three different scenarios (with the corresponding mean and standard deviation summarized in Panel A of Table 5). First, the solid black line displays the distribution of expense ratios in our baseline scenario where investors suffer from inertia. The average (median) expense ratio in our baseline counterfactual is 40 (25) basis points.

Second, the gray solid line displays the distribution of expense ratios retail investors pay in the scenario where investors no longer suffer from inertia and we keep the expense ratios

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[28]When computing Eq. (13) we assume that all investors were active in the first month of our sample (i.e. January 2000). A fund's active market share is zero in all months prior to the introduction of the fund.

managers charge fixed at their observed values. This scenario reflects a partial equilibrium counterfactual where we allow the demand-side to respond but not the supply-side. The results indicate, somewhat surprisingly, that eliminating inertia has a modest effect on the distribution of expense ratios and would lower the average expense ratio by 4 basis points. As discussed further below, part of the reason eliminating inertia is not very valuable is because, as a result of search frictions, retail investors are not very good at optimally selecting index funds in the first place. Thus, allowing them to select funds more frequently (i.e., removing inertia) does not have a big impact on the funds investors choose.

Third, the dashed-gray line displays the distribution of expense ratios retail investors pay in the scenario where investors no longer suffer from inertia and we allow index fund managers to endogenously update their expense ratios. The results indicate that the average expense ratio falls by roughly 16 basis points from 40 basis points to 24 basis points. Recall from Section 3, that if index fund managers use a growth-adjusted discount factor of 1 (i.e., $(1 + \tilde{r}_{m(j)})\beta = 1$), inertia would have no impact on the price setting behavior of managers. However, because we calibrate the model using a growth-adjusted annual discount factor of 0.95, the optimal price index fund managers charge will be increasing in investor inertia. Overall, our results imply that removing investor inertia will lower the average expense ratio by 40%, but most of the effect comes from supply-side response rather than the demand-side response. Interestingly, there is little effect on price dispersion, as measured by the standard deviation of prices. This is consistent with the idea that some investors are still choosing expensive funds even when they are making an active choice.

While we focus on retail investors reported in Figure 5 and Panel A of Table 5, we also report the corresponding findings for institutional investors in Figure 6 and Panel B of Table 5. We find similar results for institutional investors. Overall, we find that eliminating inertia would also lower the average expense ratios that institutional investors pay by 15%, from 27 basis points to 23 basis points.

## 5.2 Eliminating Search Frictions

We next consider the counterfactual where we eliminate search frictions. We implement this counterfactual by computing market shares and solving for equilibrium expense ratios where we re-scale the price coefficient to be equal to the case without search frictions. In other words, we compute counterfactuals where for both institutional and retail investors we set $\alpha_T$ to the value we recover from our estimates using the 401(k) data (Table 4).[29]

We argue that the 401(k) setting provides a setting with minimal search frictions, providing a benchmark for demand without search frictions. To the extent that search frictions are still present in the 401(k) setting, this counterfactual can be interpreted as the effect of making the

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[29]Alternatively, we can eliminate search frictions by re-scaling the unobserved component of the utility such that its variance is equal to our estimates from the 401(k) setting, i.e., $\sigma_{\nu,T} = 0$, and we get qualitatively similar results.

index fund market as transparent as the 401(k) setting. In this case, counterfactual estimates would be a lower bound of the effect of completely removing search frictions.

We report the counterfactual distribution of retail expense ratios in Panel (b) of Figure 5 and we summarize the results in Panel A of Table 5. The solid black line again displays the baseline distribution of expense ratios. Keeping the expense ratios fixed, the solid gray dashed line indicates that the average expense ratio retail investors pay would fall by 18% from 40 basis points to 33 basis points. In equilibrium, reducing search frictions would effectively reduce the market power held by index fund managers and would put further downward pressure on expense ratios. The gray dashed line indicates that after accounting for the supply-side response, average expense ratios would fall by 45% to 22 basis points. The standard deviation of expense ratios falls by 16% to 36 basis points.

We find similar effects for institutional investors (Figure 6 and Panel B of Table 5). The results indicate that reducing search frictions would ultimately lower the average expense ratio institutional investors pay by 11 basis points to 16 basis points. Not surprisingly, the effect of removing search frictions is slightly more muted for institutional investors than for retail investors. This is because institutional investors were less burdened by search frictions in the first place.

## 5.3 Eliminating Both Inertia and Information Frictions

Panels (c) of Figures 5 and 6 display the counterfactual distributions of expenses that retail and institutional investors would pay if both inertia and search frictions are simultaneously eliminated. Here, eliminating inertia has a much larger effect on the expense ratios investors pay after search frictions are eliminated. For example, consider the partial equilibrium setting where the supply-side remain fixed. The solid gray line in Panel (a) of Figure 5 indicates that if we just eliminate inertia, the average expense ratio retail investors pay falls by a negligible amount from 40 basis to 36 basis points. In contrast, the gray line in Panel (c) of Figure 5 shows that eliminating inertia has a much larger effect when investors do not face search frictions. The average expense ratio retail investors pay falls by 9 basis points, from 33 basis points to 24 basis points. This result is intuitive; removing inertia and allowing investors to shop for index funds more frequently is more valuable when investors are good at shopping for index funds. This is also reflected in the standard deviation of prices which falls by 26%.

## 5.4 Eliminating Price Discrimination

In terms of supply-side regulations, we consider the effects of eliminating price discrimination. As illustrated in Section 2.2, managers' ability to price discriminate contributes meaningfully to the dispersion in fund expense ratios. We implement this counterfactual by requiring index fund managers to charge the same expense ratio for all funds that share the same underlying

portfolio defined by portfolio identifier reported by CRSP and then by solving for a new equilibrium. In practice this means that index fund managers must charge the same expense ratio for both their institutional and retail investors.

Panels (d) of Figures 5 and 6 display the counterfactual distributions of expenses that retail and institutional investors would pay if managers were unable to price discriminate across investor types. The dashed gray line in Panel (d) of Figure 5 (summarized in Panel A of Table 5) indicates that eliminating price discrimination would lower the expenses retail investors pay by 30%, to 28 basis points. In contrast, eliminating price discrimination has effectively very little impact on the expense ratios that institutional investors pay (Figure 6 and Panel B of Table 5).

These results highlight that price discrimination in this setting differs from many other non-financial settings in which price discrimination benefits retail consumers relative to institutional buyers. In many other non-financial settings, retail consumer demand is more elastic, leading to lower prices when firms can price discriminate. Given retail investors' higher search frictions in the market for index funds, the situation is reversed. This speaks to the importance of the interaction between search frictions and price discrimination.

Figure 8 summarizes the counterfactual effect of removing inertia, search frictions, and price discrimination sequentially. While removing inertia decreases average retail expense ratios by 39%, removing search frictions decreases average expense ratios by another 37%. The effect of eliminating price discrimination has minimal effect on the expenses retail investors pay once we have already eliminated search frictions and inertia.[30] The reason for this is that price discrimination is not very effective when investors are good at shopping for index funds (i.e., investors do not face search frictions and never inert). Investors will simply search until they find the best available fund.

## 5.5 Accounting for Financial Advisers and Eliminating Conflicts of Interest

Lastly, we explore the role of financial advisers and the potential conflicts of interest that arise from their involvement. Specifically, we consider an extension of the model where we follow the setup developed in Robles-Garcia (2019) and further used in Egan et al. (2022). In this extension, we assume that financial advisers, rather than investors, select index funds for their investors. Financial advisers select the fund that maximizes the weighted average of the financial adviser's financial incentives and the consumer's utility. Full details of the model extension and estimation are in Appendix B.

We find evidence of modest conflicts of interest. We measure the financial incentives of

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[30]We find that the average retail expense ratio actually increases by 3 basis points once we eliminate price discrimination. The reason the price increases on average is because some fund managers own multiple retail funds with the same portfolio but charge different prices for them. Forcing them to charge the same price leads to some price increases.

advisers using data on 12b-1 fees, of which 92% is used to compensate financial advisers.[31] Our estimates suggest that brokers are willing to trade off a 1 percentage point increase in 12b-1 fees with a 0.56 increase in expense ratios. While still relevant, the conflicts of interest in the index fund market we estimate are smaller than what has been estimated in other markets such as the structured product and variable annuity markets (Egan, 2019; Egan et al., 2022). This is intuitive because the index fund market is more transparent than each of those markets.

We consider how conflicts of interest impact the expense ratios that both institutional and retail investors pay in equilibrium. We implement this counterfactual by setting 12b-1 fees equal to zero and decreasing marginal costs by the corresponding amount. The results indicate that the effects of conflicts of interest are modest in the index fund market (see Appendix Figure A3). Keeping the product space fixed, eliminating conflicts of interest would reduce the expense ratios that retail investors pay by two basis points. Similarly, eliminating conflicts of interest would reduce the institutional expense ratios by one basis point. The effects are relatively modest because roughly 75% of the index funds in our sample do not pay 12b-1 fees.

## 6 Conclusion

We quantify the underlying demand- and supply-side frictions in the index fund market and show how they support an equilibrium with substantial market power. We develop a model in which investors have inertia, are subject to search frictions, and have heterogeneous preferences. The model provides sharp insights into how each friction impacts both demand for and the supply of index funds. Using a novel instrumental variables strategy based on historical returns, we show how we can separately identify inertia from investor preferences and show how data from 401(k) choices can be used to separately identify preference heterogeneity from search frictions.

Our estimates imply that both inertia and search frictions give firms significant market power and play a major role in explaining the observed price dispersion in the index fund market. Search frictions are particularly important and increase the average expense ratios paid by retail investors by roughly 45%. These search frictions have distinct implications from preference heterogeneity given that the presence of search frictions implies that investors are not obtaining welfare gains from variety. This suggests that disclosure policies, rule-making that reduces misleading practices, or further development of comparison tools such as FINRA's Fund Analyzer, could lead to a meaningful reduction in market power and increase welfare. Inertia is also important for explaining demand, potentially driven in part by taxation of capital gains. We estimate that average expense ratios are 40% higher as a result of inertia, slightly smaller than the effect of search frictions. Interestingly the effects of these frictions are interrelated. For example, inertia becomes much more costly for investors when search frictions are reduced,

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[31]See https://www.ici.org/system/files/attachments/fm-v14n2.pdf.

suggesting that it may be beneficial for policy makers to focus on search frictions first. These results highlight why it is important to consider multiple frictions and their interaction. In the presence of search frictions and inertia, price discrimination is quite costly for retail investors; however, its effect is negligible without these other frictions.

Overall, our results provide new detailed insight into why investors purchase expensive index funds. Many markets likely present similar issues and the results highlight the importance of identifying how frictions interact and the underlying sources of market power.

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# Tables and Figures

Figure 1: Distribution of Fund Expense Ratios over Time
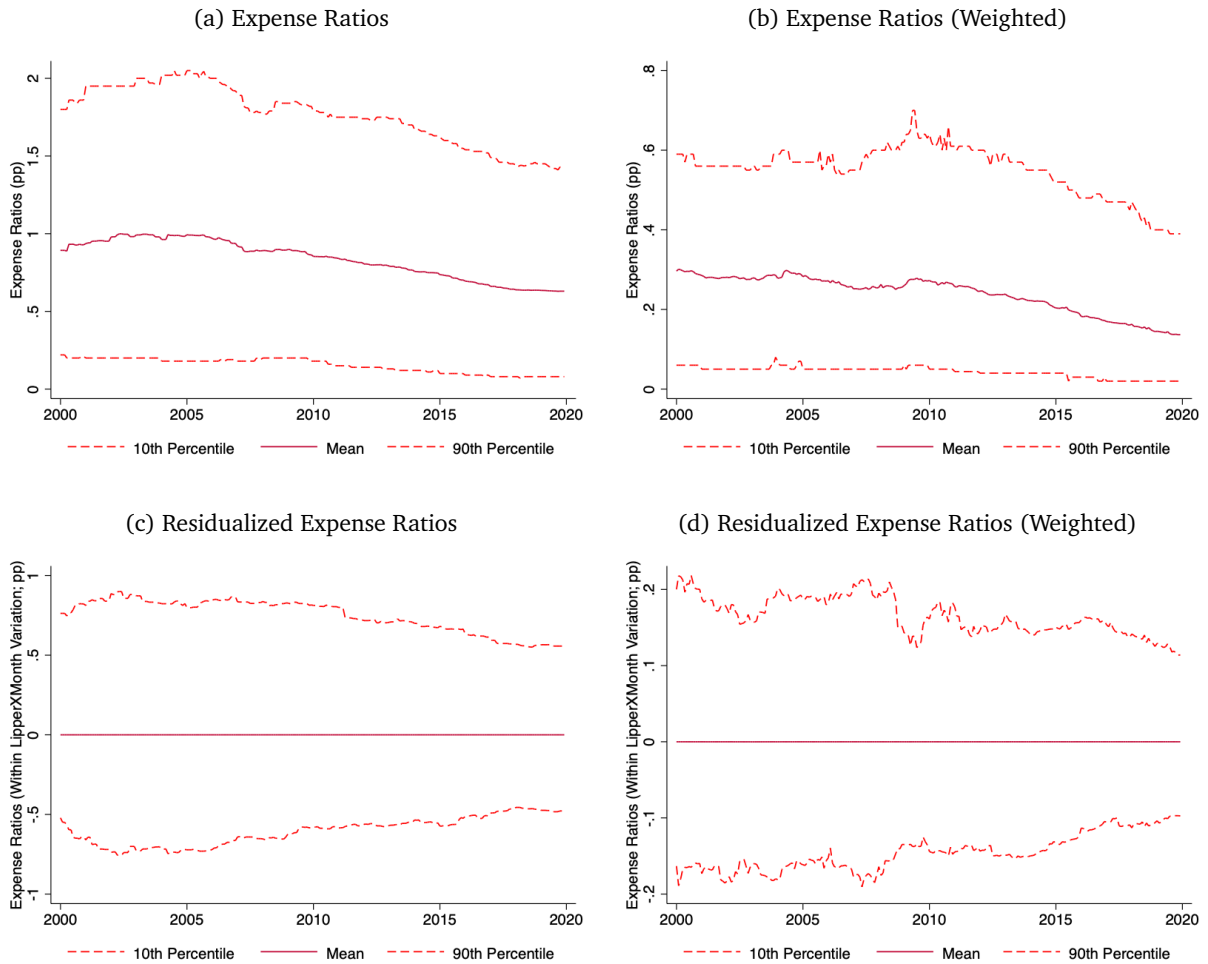
(a) Expense Ratios

(b) Expense Ratios (Weighted)

(c) Residualized Expense Ratios

(d) Residualized Expense Ratios (Weighted)

Figure 1 displays the distribution of index fund expense ratios over time. Panels (a) and (b) display the equal weighted and asset-weighted distribution of expense ratios. Panels (c) and (d) display the equal weighted and asset-weighted distribution of residualized expense ratios, where we residualize expense ratios by regressing them on Lipper Class × Month fixed effects. Panels (c) and (d) therefore display the within Lipper Class × Month variation in expense ratios.

Figure 2: Distribution of Expense Ratios for 401(k) Plans over Time

(a) Expense Ratios



(b) Expense Ratios (Weighted)



(c) Residualized Expense Ratios



(d) Residualized Expense Ratios (Weighted)
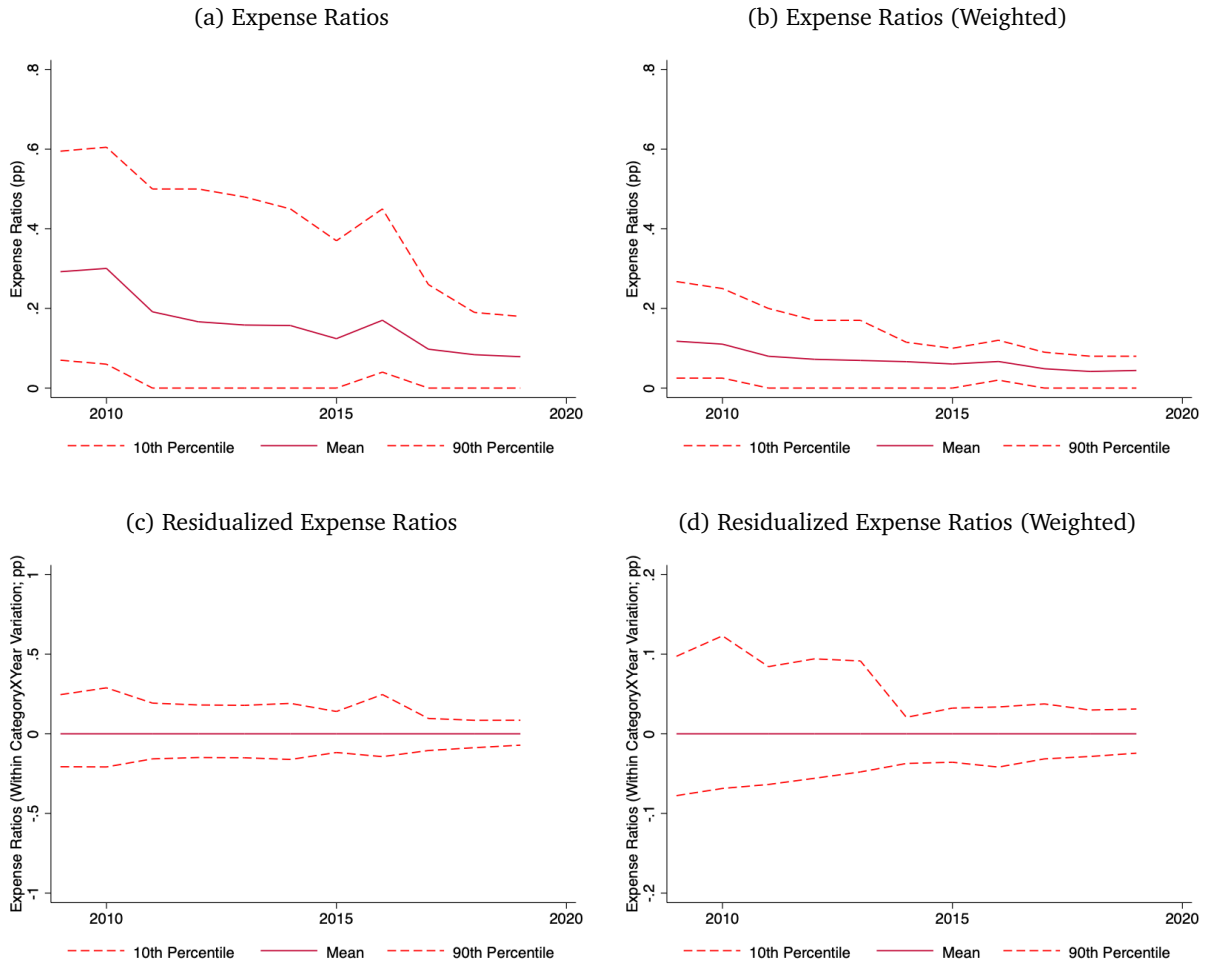


Figure 2 displays the distribution of index fund expense ratios in 401(k) plans over time. Panels (a) and (b) display the equal weighted and asset-weighted distribution of expense ratios. Panels (c) and (d) display the equal weighted and asset-weighted distribution of residualized expense ratios, where we residualize expense ratios by regressing them on Category $\times$ Year fixed effects. Panels (c) and (d) therefore display the within Category $\times$ Year variation in expense ratios.

## Figure 3: Market Share of Newly Launched Low Cost Funds
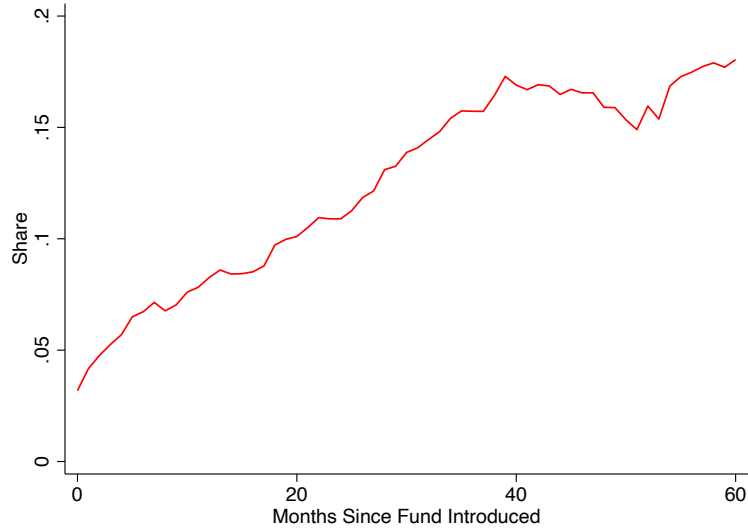


Figure 3 displays the aggregate market share of newly launched low-cost funds that survive at least 5 years by month since introduction. Low-cost funds are defined as those in the bottom quartile of the price distribution in their lipper class at the time of launch.

## Figure 4: Within Portfolio Variation in Expense Ratios
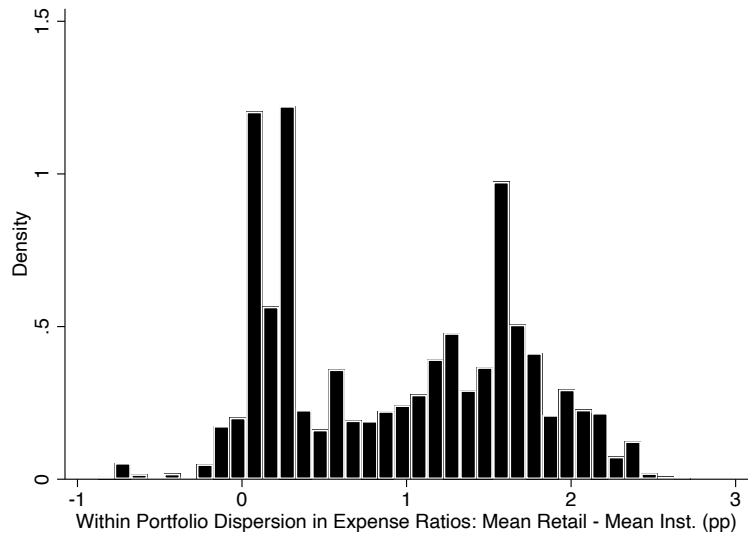


Figure 4 displays the within portfolio dispersion in expense ratios across retail and institutional funds. We focus on differences between retail and institutional funds. For a given underlying portfolio (identified in the data as $crsp\_portno$) and moment in time, we calculate the difference in the average expense ratio of retail funds and that of institutional funds for those portfolios that are held by at least one retail and one institutional fund. Observations are at the fund portfolio-by-year level.

Figure 5: Counterfactuals: Retail Investors

(a) Eliminating Inertia



(b) Eliminating Search



(c) Eliminating Inertia and Search



(d) Eliminating Price Discrimination
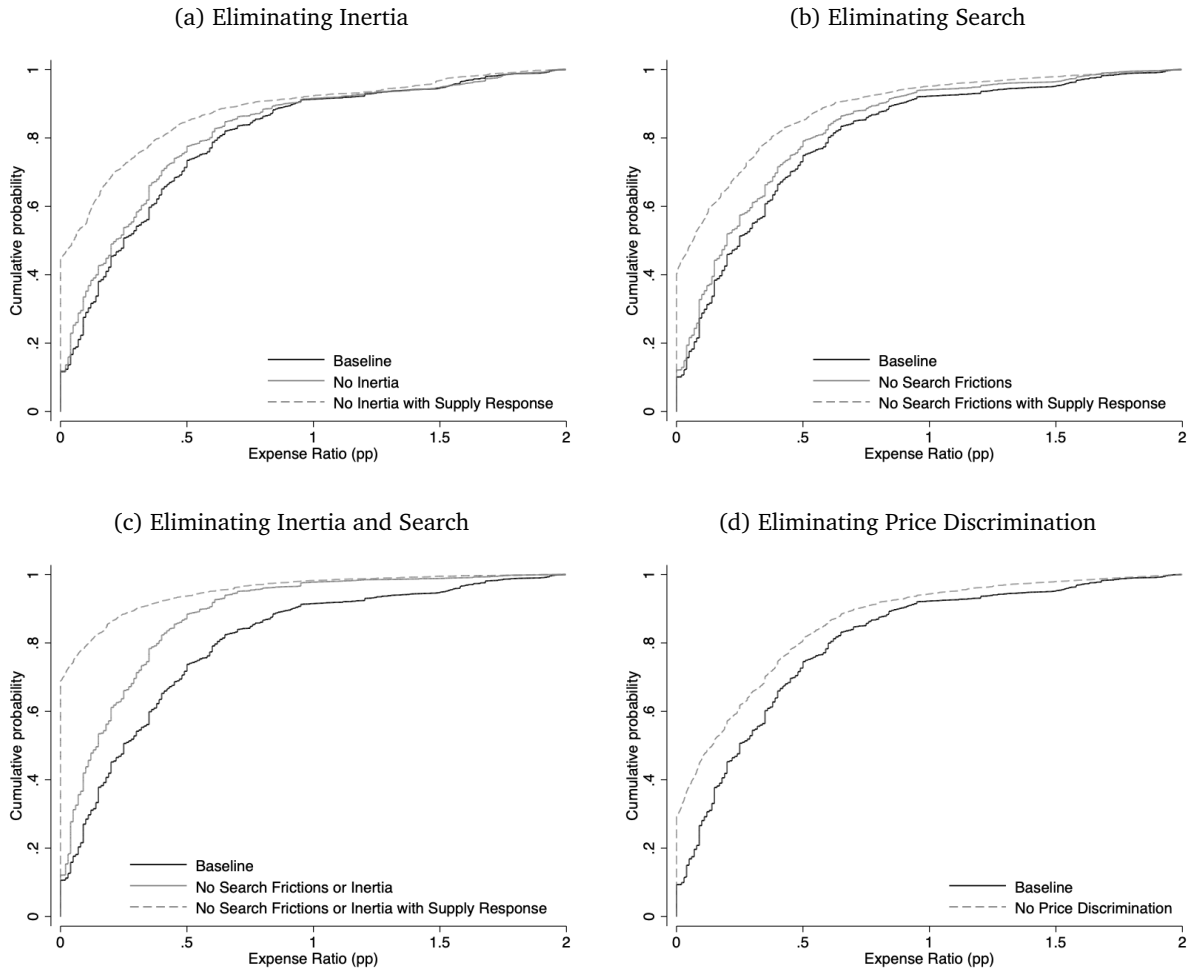


Figure 5 displays the estimated distribution of expense ratios in counterfactual analysis where we eliminate inertia, search frictions and price discrimination.

Figure 6: Counterfactuals: Institutional Investors

(a) Eliminating Inertia



(b) Eliminating Search Frictions



(c) Eliminating Inertia and Search Frictions



(d) Eliminating Price Discrimination
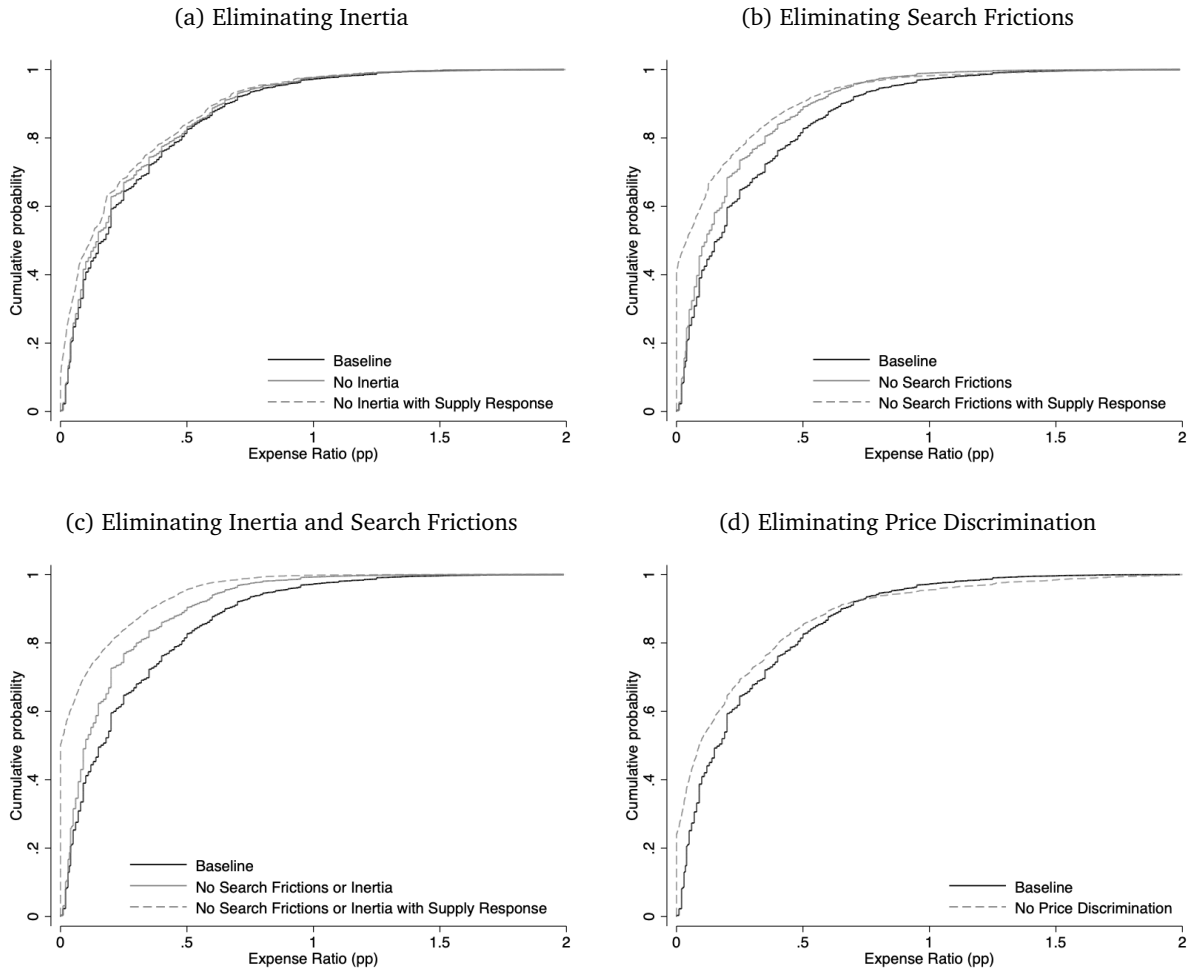


Figure 6 displays the estimated distribution of expense ratios in counterfactual analysis where we eliminate inertia, search frictions and price discrimination.

## Figure 7: Counterfactuals: Remove All Frictions

(a) Retail Investors                    (b) Institutional Investors
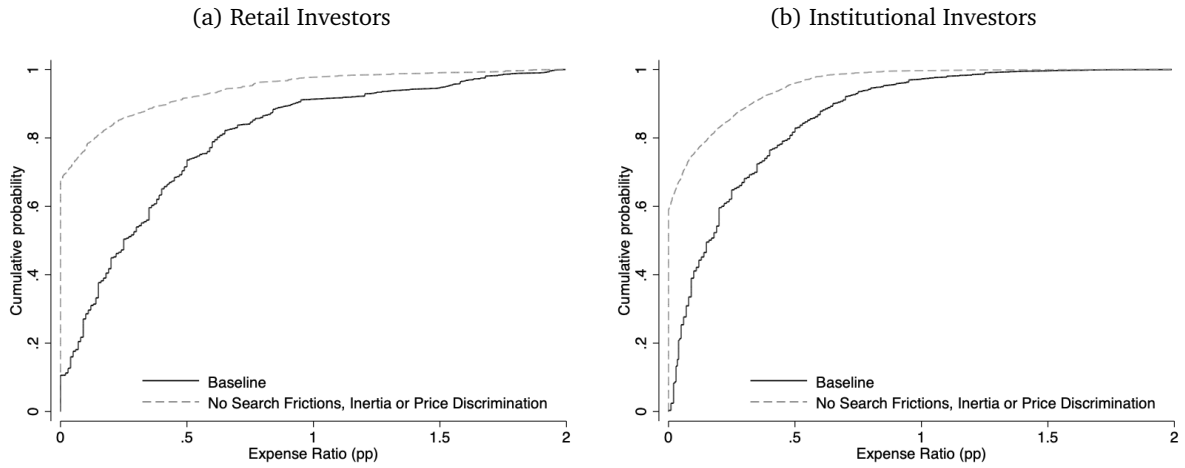


Figure 7 displays the estimated distribution of expense ratios in counterfactual analysis where we eliminate inertia, search frictions and price discrimination.

## Figure 8: Sequential Decomposition by Mechanism

(a) Retail Investors                    (b) Institutional Investors
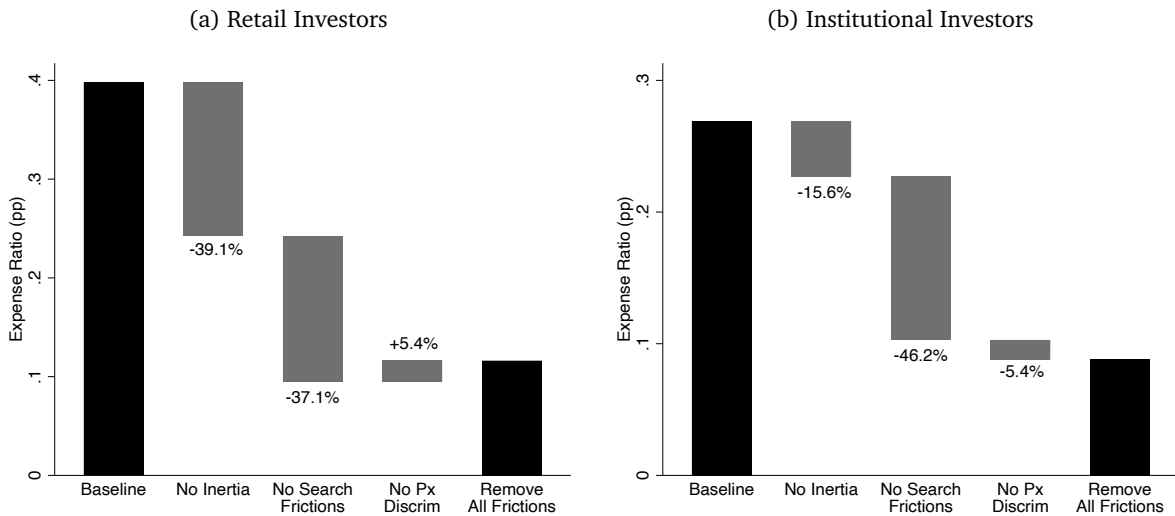


Figure 8 displays the mean asset-weighted expense rations investors pay after sequentially removing inertia, search frictions, and price discrimination. All counterfactuals account for supply response.

Table 1: Summary Statistics

|  | Count | Mean | Std. Dev. | Median |
|---|---|---|---|---|
| Total Net Assets ($mm) | 564,272 | 1,371.95 | 7,886.88 | 61.60 |
| Expense Ratio (bp) | 564,272 | 96.27 | 91.72 | 63.00 |
| Exp Ratio (Unadj. for Loads; bp) | 564,272 | 76.53 | 64.63 | 60.00 |
| Annual Returns (%) | 507,135 | 5.54 | 23.05 | 6.13 |
| Retail Mutual Fund | 564,272 | 0.35 | 0.48 | 0.00 |
| Institutional Mutual Fund | 564,272 | 0.26 | 0.44 | 0.00 |
| ETF | 564,272 | 0.38 | 0.49 | 0.00 |
| ln(# of Funds in Same Mgmt. Company) | 564,272 | 4.04 | 1.41 | 4.34 |
| 12b-1 Fees (bp) | 564,272 | 13.74 | 28.94 | 0.00 |
| Has Front Load | 564,272 | 0.07 | 0.26 | 0.00 |
| Has Rear Load | 564,272 | 0.13 | 0.34 | 0.00 |
| Std. of Daily Returns (pp, annualized) | 559,611 | 18.56 | 13.79 | 15.06 |
| Number of Index Funds | 5,266 | | | |
| Number of Lipper Classes | 150 | | | |

Note: Table 1 displays summary statistics corresponding to our main sample. Observations are at the fund-by-month level. The variables *Retail Mutual Fund*, *Institutional Mutual Fund*, and *ETF* are all indicator variables.

## Table 2: Investor Inertia

### (a) Retail Investors

| VARIABLES | (1) | (2) | (3) |
|---|---|---|---|
| Lag AUM | 0.990*** | 0.988*** | 0.979*** |
| | (0.000) | (0.018) | (0.013) |
| | | | |
| Observations | 331,040 | 327,866 | 325,758 |
| R-squared | 0.984 | 0.984 | 0.982 |
| IV | | X | X |
| Year-Month FE | X | X | |
| Year-Month-Mkt FE | | | X |

### (b) Institutional Investors

| VARIABLES | (1) | (2) | (3) |
|---|---|---|---|
| Lag AUM | 0.991*** | 0.946*** | 0.973*** |
| | (0.000) | (0.013) | (0.012) |
| | | | |
| Observations | 324,144 | 320,364 | 318,544 |
| R-squared | 0.986 | 0.984 | 0.984 |
| IV | | X | X |
| Year-Month FE | X | X | |
| Year-Month-Mkt FE | | | X |

Note: Table 2 displays the estimates corresponding to a linear regression model (Eq. 9). Observations are at the index fund-by-month level. The dependent variable is log assets under management. In Panel (a) we restrict our attention to retail investors/AUM and in Panel (b) we restrict our attention to institutional investors/AUM. As described in the text, we address the endogeneity of *Lag AUM* using an instrumental variables approach in columns (2)-(4). In all specifications we control for the log number of funds offered by the management company, the standard deviation of daily fund returns over the past 12 months, and whether the fund is an ETF, has a front load, or has a rear load. In columns (1)-(3) we control for 1-, 3-, 6-, 12-month, and year-to-date cumulative returns. In columns (4), where we include year-by-month-by-market fixed effects, we control for 1-month and year-to-date cumulative returns because the year-by-month-by-market fixed effects capture much of the variation in returns. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.10.

Table 3: Investor Preferences when Actively Demanding Index Funds

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Expense Ratio | -233.977*** | -283.468*** | -296.658*** | -490.951*** |
| | (5.164) | (19.293) | (2.386) | (9.509) |
| Observations | 332,165 | 122,593 | 322,146 | 133,535 |
| R-squared | 0.118 | 0.023 | 0.266 | 0.135 |
| Year-Month-Mkt FE | X | X | X | X |
| IV | | X | | X |
| Retail Sample | X | X | | |
| Inst. Sample | | | X | X |
| Elasticity of Demand | 1.3 | 1.6 | 1.7 | 2.8 |

Note: Table 3 displays the estimates corresponding to a linear regression model (Eq. 11). Observations are at the index fund-by-month-by-investor type (i.e., retail vs. institutional) level. In all specifications we control for: the log number of funds offered by the management company; the standard deviation of daily fund returns over the past 12 months; 1-, 3-, 6-, 12-month, and year-to-date cumulative returns; and whether the fund is an ETF, has a front load, or has a rear load. Robust standard errors are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 4: Demand for Index Funds In 401(k) Plans

| VARIABLES | (1) | (2) |
|---|---|---|
| Expense Ratio | -616.101*** | -743.290*** |
| | (52.096) | (110.898) |
| Observations | 2,020 | 2,016 |
| R-squared | 0.552 | 0.099 |
| PlanxMarketxYear FE | X | X |
| IV | | X |
| Elasticity of Demand | 3.5 | 4.2 |

Note: Table 4 displays the estimates corresponding to a linear regression model. Observations are at the index fund-by-year-by-401(k) plan level. Robust standard errors are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 5: Counterfactuals: Mean and Standard Deviation of Expense Ratios

| Panel A: Retail Investors | | | | |
|---|---|---|---|---|
| | Mean | Std Dev. | Mean | Std Dev. |
| Baseline | 0.40 | 0.43 | | |
| Counterfactuals | Without Supply Response | | With Supply Response | |
| No Inertia | 0.36 | 0.43 | 0.24 | 0.41 |
| No Search Frictions | 0.33 | 0.38 | 0.22 | 0.36 |
| No Inertia or Search Frictions | 0.24 | 0.28 | 0.09 | 0.24 |
| No Px Discrimination | | | 0.28 | 0.37 |
| No Inertia, Search Frictions, or Px Discrimination | | | 0.12 | 0.28 |
| No Conflicts of Interest | 0.38 | 0.41 | 0.40 | 0.38 |

| Panel B: Institutional Investors | | | | |
|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std Dev. |
| Baseline | 0.27 | 0.29 | | |
| Counterfactuals | Without Supply Response | | With Supply Response | |
| No Inertia | 0.25 | 0.28 | 0.23 | 0.28 |
| No Search Frictions | 0.21 | 0.23 | 0.16 | 0.26 |
| No Inertia or Search Frictions | 0.19 | 0.21 | 0.10 | 0.18 |
| No Px Discrimination | | | 0.23 | 0.34 |
| No Inertia, Search Frictions, or Px Discrimination | | | 0.09 | 0.17 |
| No Conflicts of Interest | 0.26 | 0.28 | 0.25 | 0.27 |

Note: Table 5 displays the mean and standard deviation of asset-weighted expense ratios investors pay in each counterfactual.

# A  Additional Figures and Tables

Figure A1: Mutual Fund Sales and Redemptions

(a) New Shares/AUM (Retail Investors)

(b) New Shares/AUM (Institutional Investors)

(c) Redemptions/AUM (Retail Investors)

(d) Redemptions/AUM (Institutional Investors)
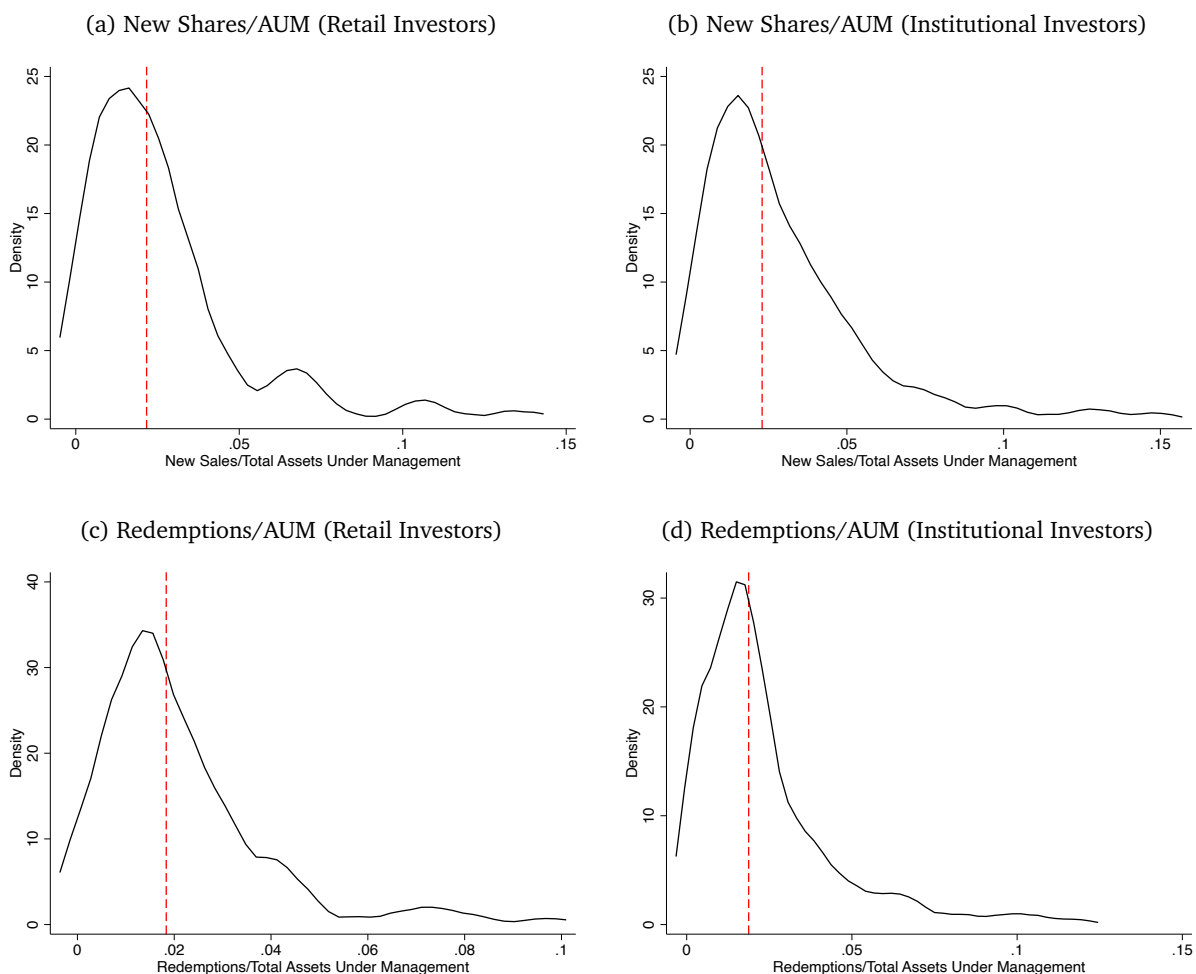


Figure A1a and Figure A1b display the distribution of the total net asset value of new shares purchased relative to total AUM calculated at the market-by-month level over the period 2019-2020 for retail and institutional investors. To account for outliers we restrict the data set to those observations with positive sales, and we censor the distribution at the 95% level. Figure A1c and Figure A1d display the distribution of the total net asset value of shares redeemed relative to total AUM calculated at the market-by-month level over the period 2019-2020. To account for outliers we restrict the data set to those observations with positive redemptions, and we censor the distribution at the 95% level. Data are from Morningstar. The red dashed lined in each figure corresponds to the median observation.

## Figure A2: Estimated Marginal Costs and Markups

(a) Distribution of Marginal Costs

(b) Distribution of Markups
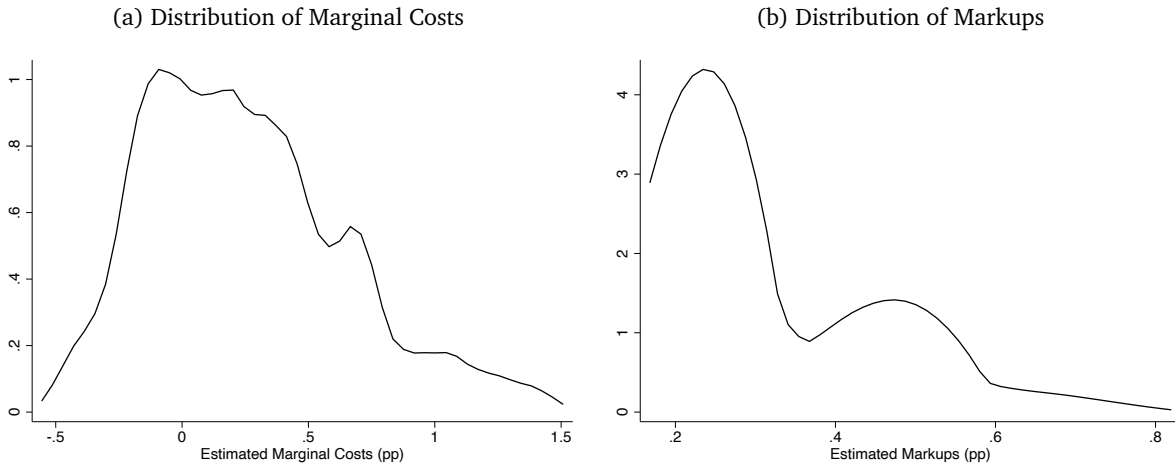


Figure A2 displays the estimated equal-weighted distributions of marginal costs and markups. To account for outliers, both distributions are censored at the 5% and 95% level. Panel (a) displays the density of marginal costs, and panel (b) displays the density of markups.

## Figure A3: Counterfactuals: Eliminating Conflicts of Interest

### (a) Retail Investors



### (b) Institutional Investors



Figure A3 displays the estimated distribution of expense ratios in counterfactual analysis where we eliminate conflicts of interest.

Table A1: Investor Inertia - Estimation in Levels

(a) Retail Investors

| VARIABLES | (1) | (2) | (3) |
|---|---|---|---|
| | | | |
| Lag AUM | 0.973*** | 0.981*** | 0.981*** |
| | (0.002) | (0.003) | (0.003) |
| | | | |
| Observations | 371,710 | 357,178 | 355,160 |
| R-squared | 0.998 | 0.998 | 0.998 |
| IV | | X | X |
| Year-Month FE | X | X | |
| Year-Month-Mkt FE | | | X |

(b) Institutional Investors

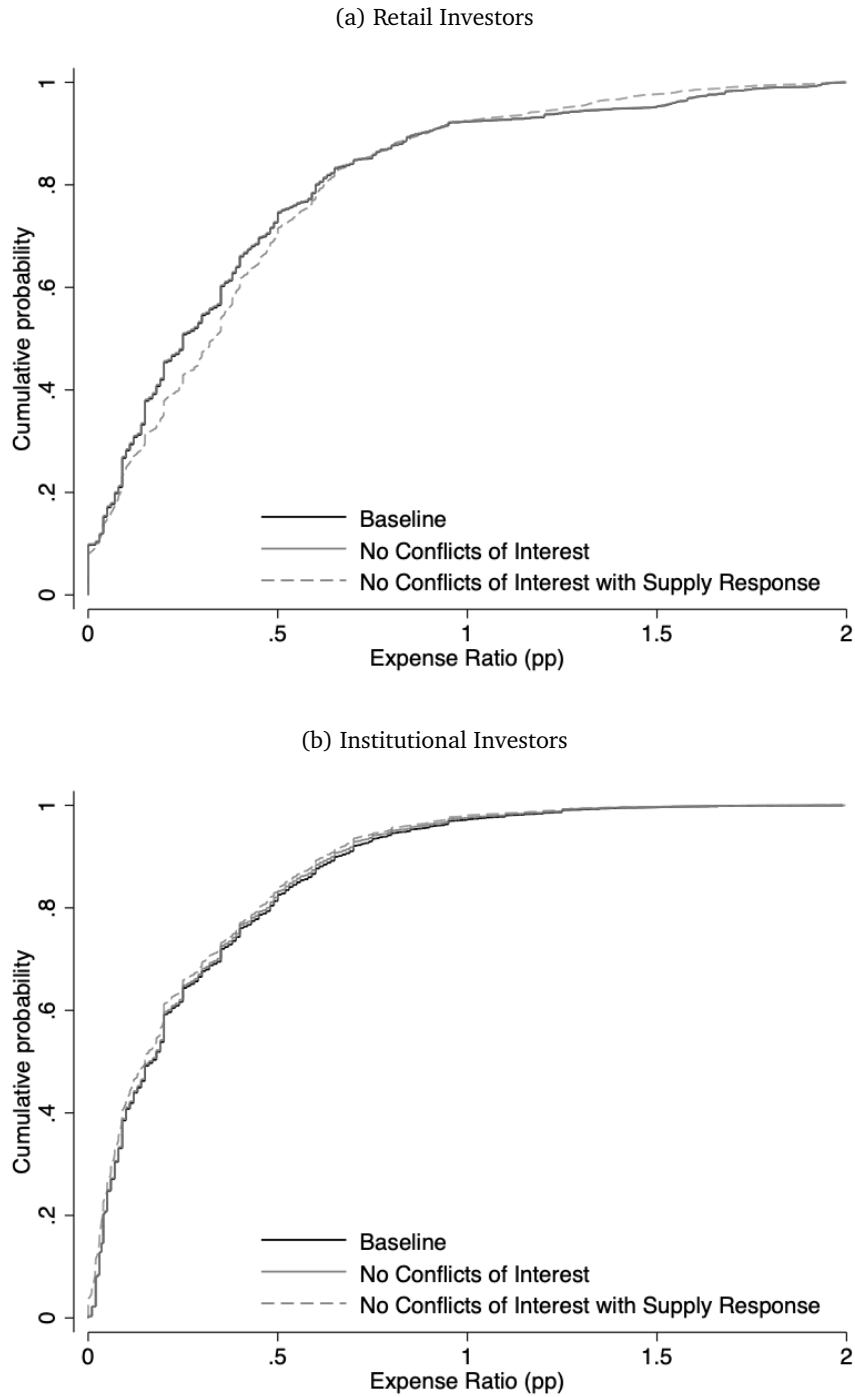| VARIABLES | (1) | (2) | (3) |
|---|---|---|---|
| | | | |
| Lag AUM | 0.991*** | 0.988*** | 0.988*** |
| | (0.002) | (0.002) | (0.002) |
| | | | |
| Observations | 324,158 | 313,471 | 311,654 |
| R-squared | 0.996 | 0.996 | 0.996 |
| IV | | X | X |
| Year-Month FE | X | X | |
| Year-Month-Mkt FE | | | X |

Note: Table A1 displays the estimates corresponding to a linear regression model (Eq. 9) that we estimate in levels rather than logs. Observations are at the index fund-by-month level. The dependent variable is assets under management. The independent variable of interest is $AUM_{j,T,t-1}(1+r_{j,t})(1+g)$, where $r_{j,t}$ reflects the monthly return of the fund and $g$ is the average monthly growth rate of AUM held in index funds. In Panel (a) we restrict our attention to retail investors/AUM and in Panel (b) we restrict our attention to institutional investors/AUM. We address the endogeneity of *Lag AUM* using an instrumental variables approach in columns (2)-(4) using the past 12 monthly dollar returns of the fund. In all specifications we control for the log number of funds offered by the management company, the standard deviation of daily fund returns over the past 12 months, and whether the fund is an ETF, has a front load, or has a rear load. In columns (1)-(3) we control for 1-, 3-, 6-, 12-month, and year-to-date cumulative returns. In columns (4), where we include year-by-month-by-market fixed effects, we control for 1-month and year-to-date cumulative returns because the year-by-month-by-market fixed effects capture much of the variation in returns. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.10.

Table A2: Investor Inertia - Control Function

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Lag AUM | 0.939*** | 0.934*** | 0.968*** | 0.965*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| | | | | |
| Observations | 150,198 | 147,819 | 150,198 | 147,819 |
| R-squared | 0.978 | 0.980 | 0.983 | 0.985 |
| Retail Sample | X | X | | |
| Inst. Sample | | | X | X |
| Control Function | X | X | X | X |
| Year-Month FE | X | | X | |
| Year-Month-Mkt FE | | X | | X |

Note: Table A2 displays the estimates corresponding to a linear regression model (Eq. 9). Observations are at the index fund-by-month level, where we restrict our attention to ETFs. The dependent variable is log assets under management. As described in the text, we address the endogeneity of *Lag AUM* using a control function approach. Specifically, when estimating inertia for retail investors, we form a control function by controlling for current and lagged demand from institutional investors, which helps control for product/investment quality. Similarly, when estimating inertia for institutional investors, we form a control function by controlling for current and lagged demand from retail investors, which helps control for product/investment quality. In all specifications we control for: the log number of funds offered by the management company; the standard deviation of daily fund returns over the past 12 months; whether the fund is an ETF, has a front load, or has a rear load; and 1-, 3-, 6-, 12-month, and year-to-date cumulative returns. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.10.

Table A3: Investor Inertia Heterogeneity by Period

(a) Retail Investors

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Lag AUM | 0.649*** | 1.166*** | 0.947*** | 0.955*** |
|  | (0.097) | (0.053) | (0.018) | (0.020) |
| Observations | 32,699 | 60,413 | 110,812 | 123,942 |
| R-squared | 0.871 | 0.958 | 0.982 | 0.984 |
| IV | X | X | X | X |
| Year-Month FE | X | X | X | X |
| Period | 2001-2005 | 2006-2010 | 2011-2015 | 2016-2020 |

(b) Institutional Investors

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Lag AUM | 0.999*** | 0.968*** | 0.928*** | 0.937*** |
|  | (0.014) | (0.023) | (0.022) | (0.020) |
| Observations | 21,838 | 50,095 | 102,414 | 146,017 |
| R-squared | 0.994 | 0.987 | 0.981 | 0.983 |
| IV | X | X | X | X |
| Year-Month FE | X | X | X | X |
| Period | 2001-2005 | 2006-2010 | 2011-2015 | 2016-2020 |

Note: Table A3 displays the estimates corresponding to a linear regression model (Eq. 9) by time period. Observations are at the index fund-by-month level. The dependent variable is log assets under management. As described in the text, we address the endogeneity of *Lag AUM* using an instrumental variable approach. In all specifications we control for: the log number of funds offered by the management company; the standard deviation of daily fund returns over the past 12 months; whether the fund is an ETF, has a front load, or has a rear load; and 1-, 3-, 6-, 12-month, and year-to-date cumulative returns. Robust standard errors are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A4: Investor Inertia Heterogeneity by Load Type

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Lag AUM | 0.987*** | 0.981*** | 1.045*** | 0.946*** | 0.945*** | 0.994*** |
| | (0.018) | (0.019) | (0.017) | (0.013) | (0.013) | (0.008) |
| Lag AUM x Has Front Load | 0.005 | | | -0.049 | | |
| | (0.010) | | | (0.092) | | |
| Lag AUM x Has Rear Load | | 0.017** | | | 0.010 | |
| | | (0.008) | | | (0.009) | |
| Lag AUM x 1 Year Return | | | 0.040*** | | | 0.008 |
| | | | (0.015) | | | (0.010) |
| | | | | | | |
| Observations | 327,866 | 327,866 | 327,866 | 320,364 | 320,364 | 320,364 |
| R-squared | 0.984 | 0.984 | 0.981 | 0.984 | 0.984 | 0.986 |
| Retail Sample | X | X | X | | | |
| Inst. Sample | | | | X | X | X |
| IV | X | X | X | X | X | X |
| Year-Month FE | X | X | X | X | X | X |

Note: Table A4 displays the estimates corresponding to a linear regression model (Eq. 9). Observations are at the index fund-by-month level. The dependent variable is log assets under management. As described in the text, we address the endogeneity of *Lag AUM* using an instrumental variable approach. In all specifications we control for: the log number of funds offered by the management company; the standard deviation of daily fund returns over the past 12 months; whether the fund is an ETF, has a front load, or has a rear load; and 1-, 3-, 6-, 12-month, and year-to-date cumulative returns. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.10.

Table A5: Estimated Investor Preferences Using New Sales Data

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Expense Ratio | -255.330*** | -460.981*** | -433.080*** | -1,007.447*** |
| | (4.374) | (38.051) | (9.411) | (83.890) |
| | | | | |
| Observations | 8,141 | 3,841 | 8,317 | 6,253 |
| R-squared | 0.552 | 0.449 | 0.402 | 0.034 |
| Year-Month-Mkt FE | X | X | X | X |
| IV | | X | | X |
| Retail Sample | X | X | | |
| Inst. Sample | | | X | X |
| Elasticity of Demand | 1.4 | 2.6 | 2.4 | 5.6 |

Note: Table A5 displays the estimates corresponding to a linear regression model (Eq. 11), where we compute market shares using new sales. Observations are at the index fund-by-month-by-investor type (i.e., retail vs. institutional) level. In all specifications we control for: the log number of funds offered by the management company; the standard deviation of daily fund returns over the past 12 months; 1-, 3-, 6-, 12-month, and year-to-date cumulative returns; and whether the fund is an ETF, has a front load, or has a rear load. Robust standard errors are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A6: Robustness of Investor Preferences including Spread Instrument

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Expense Ratio | -360.688*** | -294.593*** | -571.920*** | -508.283*** |
| | (34.617) | (43.793) | (15.740) | (18.636) |
| | | | | |
| Observations | 50,818 | 50,818 | 62,583 | 62,583 |
| R-squared | 0.029 | 0.030 | 0.111 | 0.137 |
| Year-Month-Mkt FE | X | X | X | X |
| Other Firm Assets | | X | | X |
| IV | X | X | X | X |
| Retail Sample | X | X | | |
| Inst. Sample | | | X | X |
| Elasticity of Demand | 2.0 | 1.7 | 3.2 | 2.8 |

Note: Table A6 displays the estimates corresponding to an instrumental variable regression model (Eq. 11). In all specifications, we use asset-weighted average trading cost (bid-ask spreads) of the securities held by the fund as an instrument for expense ratios in addition to the standard Hausman instrument. Observations are at the index fund-by-month-by-investor type (i.e., retail vs. institutional) level. In all specifications we control for: the log number of funds offered by the management company; the standard deviation of daily fund returns over the past 12 months; 1-, 3-, 6-, 12-month, and year-to-date cumulative returns; and whether the fund is an ETF, has a front load, or has a rear load. In columns (2) and (4) we also control for other firm assets since this may affect trading cost. Robust standard errors are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A7: Robustness of Investor Preferences including Top 3 Firm Indicator

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Expense Ratio | -216.803*** | -217.663*** | -278.464*** | -497.866*** |
| | (5.321) | (24.234) | (2.462) | (10.774) |
| Top 3 Firm | 1.016*** | 1.334*** | 0.535*** | -0.126*** |
| | (0.085) | (0.165) | (0.018) | (0.038) |
| | | | | |
| Observations | 332,165 | 122,593 | 322,146 | 133,535 |
| R-squared | 0.118 | 0.023 | 0.268 | 0.133 |
| Year-Month-Mkt FE | X | X | X | X |
| IV | | X | | X |
| Retail Sample | X | X | | |
| Inst. Sample | | | X | X |
| Elasticity of Demand | 1.2 | 1.2 | 1.6 | 2.8 |

Note: Table A7 displays the estimates corresponding to a linear regression model (Eq. 11) including an indicator for whether the fund manager is one of the top three firms measured by total assets (Black-Rock, State Street Bank, and Vanguard). Observations are at the index fund-by-month-by-investor type (i.e., retail vs. institutional) level. In columns (2) and (4) we use the Hausman instrument as an instrument for expense ratios. In all specifications we control for: the log number of funds offered by the management company; the standard deviation of daily fund returns over the past 12 months; 1-, 3-, 6-, 12-month, and year-to-date cumulative returns; whether the fund is an ETF, has a front load, or has a rear load; and the top 3 indicator. Robust standard errors are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A8: Estimated Investor Preferences Using the Sample of Funds in the 401(k) Data

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Expense Ratio | -450.093*** | 284.683 | -449.961*** | -208.229* |
|  | (79.726) | (365.189) | (27.426) | (124.891) |
|  |  |  |  |  |
| Observations | 3,906 | 2,658 | 2,624 | 1,697 |
| R-squared | 0.301 | 0.005 | 0.596 | 0.367 |
| Year-Month-Mkt FE | X | X | X | X |
| IV |  | X |  | X |
| Retail Sample | X | X |  |  |
| Inst. Sample |  |  | X | X |
| Elasticity of Demand | 2.5 | -1.6 | 2.5 | 1.2 |

Note: Table A8 displays the estimates corresponding to a linear regression model (Eq. 11), where we restrict the sample of fund-year observations to be the same as in our 401(k) sample. Observations are at the index fund-by-month-by-investor type (i.e., retail vs. institutional) level. In all specifications we control for: the log number of funds offered by the management company; the standard deviation of daily fund returns over the past 12 months; 1-, 3-, 6-, 12-month, and year-to-date cumulative returns; and whether the fund is an ETF, has a front load, or has a rear load. Robust standard errors are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A9: Active Demand for Index Funds: Accounting for Brokers

|  | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES |  |  |  |  |
|  |  |  |  |  |
| Expense Ratio | -321.516*** | -286.738*** | -523.909*** | -517.056*** |
|  | (32.030) | (34.418) | (10.525) | (10.899) |
| 12b-1 Fees | 109.453*** | 26.650 | 351.730*** | 227.684*** |
|  | (37.784) | (44.888) | (16.560) | (20.521) |
|  |  |  |  |  |
| Observations | 122,593 | 119,722 | 133,535 | 130,887 |
| R-squared | 0.023 | 0.022 | 0.144 | 0.145 |
| Year-Month-Mkt FE | X | X | X | X |
| Exp Ratio IV | X | X | X | X |
| 12b-1 IV |  | X |  | X |
| Retail Sample | X | X |  |  |
| Inst. Sample |  |  | X | X |
| Elasticity of Demand | 1.8 | 1.6 | 2.9 | 2.9 |
| $\omega$ | 0.25 | 0.09 | 0.40 | 0.31 |

Note: Table A9 displays the estimates corresponding to a linear regression model (Eq. 15). Observations are at the index fund-by-month-by-investor type (i.e., retail vs. institutional) level. In all specifications we control for: the log number of funds offered by the management company; the standard deviation of daily fund returns over the past 12 months; 1-, 3-, 6-, 12-month, and year-to-date cumulative returns; and whether the fund is an ETF, has a front load, or has a rear load. Robust standard errors are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

# B  Extension: Accounting for Financial Advisers

Previous research has highlighted the importance of brokers/financial advisers in a household's investment decision. To understand how brokers impact the index fund choices of investors, we also consider the extension where we assume that investors choose index funds with the help of a broker.

## B.1  Setup

We follow the setup developed in Robles-Garcia (2019) and further used in Egan et al. (2022) where we assume that all financial advisers are ex-ante identical. For each client $i$, the financial adviser chooses the index fund $j$ from the set $\mathcal{J}_{T(i),m(j),t}$ that maximizes a weighted average of the financial adviser's and consumer's incentives, denoted $\pi_{i,j,t}$:

$$\pi_{i,j,t} = \omega_{T(i)} f_{j,t} + (1 - \omega_{T(i)}) \tilde{u}_{i,j,t}.$$

The variable $f_{j,t}$ measures the commissions a financial adviser earns from selling index fund $j$, and the parameter $\omega_{T(i)}$ measures conflicts of interest and reflects the weight that financial advisers place on their own financial incentives (i.e., commissions) versus the financial incentives of their clients (i.e., consumer utility). If $\omega_{T(i)} = 0$ then there are no conflicts of interest. We also allow for conflicts of interest to vary potentially across retail and institutional investors. Note that we also assume that financial advisers maximize the subjective utility of investors $\tilde{u}_{i,j,t}$, which implies that financial advisers observe investor-product-specific demand shocks ($\epsilon_{i,j,t}$) and that financial advisers are subject to the same search frictions as investors.

Under the assumption that financial advisers are myopic in the sense that they maximize current flow profits, the market share of active investors of type $T$ investing in fund $j$ is given by:

$$s_{T,j,t} = \frac{\exp\left(\frac{\frac{\omega_T}{1-\omega_T} f_{j,t} - p_{j,t} + X'_{j,t}\theta_T + \xi_{j,T(i),t}}{\sigma_{\eta,T(i)}}\right)}{\sum_{l \in \mathcal{J}_{T,m(j),t}} \exp\left(\frac{\frac{\omega_T}{1-\omega_T} f_{l,t} - p_{l,t} + X'_{l,t}\theta_T + \xi_{l,T(i),t}}{\sigma_{\eta,T(i)}}\right)}, \tag{14}$$

which is the core of our estimation strategy.

## B.2 Estimation

We estimate Eq. (14) in terms of log active market shares following our empirical strategy described in Section 4 to recover investors' preferences and the brokers' preferences ($\omega_T$):

$$\ln s_{T,j,t} = \underbrace{\varpi_T}_{\frac{\omega_T}{\sigma_{\eta,T}(1-\omega_T)}} f_{jt} - \underbrace{\alpha_T}_{\frac{1}{\sigma_{\eta,T}}} p_{jt} - X'_{j,t} \underbrace{\Gamma_T}_{\frac{\theta_{T(i)}}{\sigma_{\eta,T}}} + \underbrace{\mu_{T,m(j),t}}_{\ln\left(\sum_{l \in \mathcal{J}_{T,m(j),t}} \exp\left(\frac{\frac{\omega_T}{1-\omega_T} f_{l,t} - p_{l,t} + X'_{l,t}\theta_T + \xi_{l,T(i),t}}{\sigma_{\eta,T(i)}}\right)\right)} + \underbrace{\zeta_{T,j,t}}_{\frac{\xi_{T,j,t}}{\sigma_{\eta,T}}}.$$

$$(15)$$

An empirical challenge is how to measure broker commissions. We measure broker incentives using 12b-1 fees. 12b-1 fees are used to compensate financial intermediaries for providing services to investors and to pay advertising and marketing expenditures. Evidence from The Investment Company Institute indicates that, on average, 92% of 12b-1 fees are paid to brokers/financial advisers, 6% are paid to underwriters, and 2% are used for marketing expenditures.[32] Because brokers are also compensated with front and rear loads, we calculate load-adjusted 12b-1 fees where we add 1/3rd of total loads to the 12b-1 fees.

One concern is that 12b-1 fees are potentially endogenous and correlated with unobserved demand shocks. To account for this potential endogeneity, we instrument for the actual 12b-1 fees a fund pays using the maximum contractual 12b-1 fee lagged by one year. Funds are required to report the maximum annual charge deducted from fund assets to pay for distribution and marketing costs (12b-1 fees) which may be larger than the actual fee paid in a given year. We use the maximum contractual 12b-1 fee as an instrument because it appears highly sticky in the data (e.g., the 1-year autocorrelation is 0.96) and we lag it by a year with the idea that contractual fees are uncorrelated with future demand shocks.

We report our corresponding estimates in Table A9. Consistent with intuition, we find a positive relationship between our measures of broker incentives and index fund demand. We also estimate elasticities of demand ranging from 1.6 to 1.8 for retail investors and 2.9 for institutional investors, which are consistent with our baseline demand estimates (Table 3). In the bottom of the panel we report the value of $\omega$, which measures how a broker trades off her private financial incentives with the financial incentives of her client. The results in column (1) indicate that brokers are willing to trade-off a 1 percentage point increase in 12b-1 fees (92% of which are historically paid to brokers) with a 0.33 ($= 0.25/(1 - 0.25)$) percentage point increase in expense ratios. In other words, the estimates suggest that brokers place roughly 3 times ($= (1 - 0.25)/0.25$) the weight on their client incentives relative to their own. While still relevant, the conflicts of interest in the index fund market we estimate are smaller than what has been estimated in other markets such as the structured product and variable annuity market (Egan, 2019; Egan et al., 2022). This is intuitive because the index fund market is more transparent than each of those markets. One might also expect broker incentives to potentially

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[32]https://www.ici.org/system/files/attachments/fm-v14n2.pdf

be more relevant for actively managed funds.