Journal of Financial Economics 149 (2023) 407–433

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Index providers: Whales behind the scenes of ETFs[☆]

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ARTICLE INFO

Article history:
Received 20 August 2022
Revised 9 June 2023
Accepted 9 June 2023
Available online 29 June 2023

JEL classification:
G23
G12
G5
L1
L2

Keywords:
ETF
Index provider
Licensing fee
Expense ratio
Competition

ABSTRACT

Most ETFs replicate indexes licensed by index providers. We show that index providers wield strong market power and charge large markups to ETFs that are passed on to investors. We document three stylized facts: (*i*) the index provider market is highly concentrated; (*ii*) investors care about the identities of index providers, although they explain little variation in ETF returns; and (*iii*) over one-third of ETF expense ratios are paid as licensing fees to index providers. A structural decomposition attributes 60% of licensing fees to index providers' markups. Counterfactual analyses show that improving competition among index providers reduces ETF expense ratios by up to 30%.

1. Introduction

> *"Index fees are a real problem. These providers are an oligopoly and the prices they charge are out of line with the value they add."*
> — Yves Perrier, CEO of Amundi (Times, 2019).

Exchange-traded funds (ETFs) have experienced remarkable growth in recent years. According to the 2021 Investment Company Institute Fact Book, total assets under management (AUM) in ETFs increased from $992 billion in 2010 to $5.4 trillion by the end of 2020. By design, the vast majority of ETFs passively replicate the performance of an underlying index,[1] which in most cases is constructed and

☆ Toni Whited was the editor for this article. We thank the editor, an anonymous referee, Samuel Antill, Zahi Ben-David, Philip Bond, Mark Egan, Jarrad Harford, Davidson Heath, Terry Hendershott, Erica Jiang, Elisabeth Kashner (FactSet), Camelia Kuhnen, Yiming Ma, Ananth Madhavan, Alexander Matturri (S&P Dow Jones), Filippo Mezzanotti, Nagpurnanand Prabhala, Matt Ringgenberg, Nancy Rose, Enrique Schroth, Chester Spatt, Zhaogang Song, Yang Sun, Andrea Vedolin, Kelsey Wei, Mindy Xiaolan, Xiaoyan Zhang, as well as seminar/conference participants at UC Berkeley, National University of Singapore, Johns Hopkins University, University of Washington, PBC Tsinghua, 2021 Stanford IO Fest, 2022 NYU School of Law/the American Bar Association Antitrust, Data Privacy and Data Protection Conference, 2022 SEC Conference on Financial Market Regulation, 8th SAFE Asset Pricing Workshop, MFA 2022, 2022 AIM Investment Conference, 2022 University of Kentucky Finance Conference, 2022 Four Corners Academic Meeting, FIRS 2022, WFA 2022, and AFA 2023 for helpful comments. We thank Haoliang Jiang, Wenzhi Wang, Chupei Zhang, and Zheng (Jacky) Zhang for excellent research assistance.

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[1] More recently, ETF issuers have started offering so-called actively-managed ETFs, which do not passively track indexes. The market share

https://doi.org/10.1016/j.jfineco.2023.06.003
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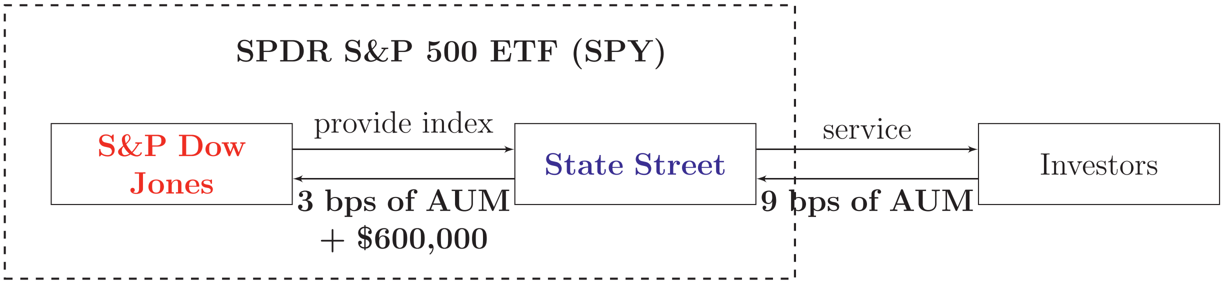


Fig. 1. Two-tiered organizational structure for SPDR S&P 500 ETF as of December 2020. In Fig. 1, the ETF issuer is State Street. The index provider is S&P Dow Jones, which owns the underlying index —the S&P 500 index. The annual licensing fee is 3 bps of AUM + $600,000. The expense ratio is 9 bps of AUM.

maintained by a designated index provider.[2] Thus, most ETFs exhibit a two-tiered organizational structure: (*i*) an index provider builds and maintains the index that underlies an ETF and charges index licensing fees to an ETF issuer, and (*ii*) the ETF issuer services ETF investors and charges expense ratios to ETF investors.

Fig. 1 illustrates the two-tiered organizational structure for the largest ETF in the world, the SPDR S&P 500 ETF (SPY), as an example. In this case, the ETF issuer is State Street, and the index provider is S&P Dow Jones, which owns the underlying ETF index — the S&P 500 index. State Street charges SPY investors 9 basis points (bps) per year and in turn, pays 3 bps of the ETF assets plus a flat fee of $600,000 per year to S&P Dow Jones. In other words, more than one-third of SPY's total revenue is paid to the index provider as index licensing fees. For example, the SPY AUM totaled about $400 billion in 2021, implying that the total fees collected by State Street from SPY investors were roughly $360 million in 2021, with more than $120 million paid to S&P Dow Jones in index licensing fees.[3]

Even though index providers play an indispensable role in the ETF marketplace and capture a substantial fraction of the total ETF business revenue, the competitive landscape between ETF issuers and index providers and how their interactions influence ETF investors have not been studied so far. Our paper takes on this task through both reduced-form analysis and structural modeling.

We document that the index provider market is highly concentrated and dominated by a few large players. Moreover, when choosing ETFs, investors care about the identities of index providers, even though index providers' identities explain little of the variation in ETF returns. We estimate that about one-third of all ETF expense ratios are paid to index providers in the form of licensing fees. Our structural estimation reveals that about 60% of the index licensing fees charged by index providers to ETF issuers are markups, and the remaining 40% of the index licensing fees reflects the marginal costs of index provision. Overall, our findings show that index providers wield strong market power, and their high indexing licensing fees are passed on to ETF investors through expense ratios.[4] Through a counterfactual analysis, we estimate that eliminating index providers' market power can reduce ETF expense ratios by about 30%.

Our paper is structured in two parts. In the first part, we establish three stylized facts about index providers in the U.S. equity ETF market. First, the ETF indexing business is highly concentrated among a few large index providers. For example, about 53% of all ETF assets in our sample track the indexes built by S&P Dow Jones. The five largest index providers in the U.S. equity ETF market—S&P Dow Jones, CRSP, FTSE Russell, MSCI, and NASDAQ—capture in aggregate about 95% of the entire ETF market. Specifically, over our sample period from January 2010 to the end of 2019, the time-series average of the Herfindahl-Hirschman index (HHI) of the index provider industry is 3,294, which is deemed highly concentrated according to the U.S. Department of Justice and the Federal Trade Commission.[5]

Second, we find that, when choosing among ETFs, investors care about the identities of index providers, although there is no material difference in return profiles between indexes that various index providers construct. Indeed, as the global head of iShares and index investments at BlackRock noted, "One of our close partners is MSCI. Often it'll be MSCI that brings us to a client" (see Bloomberg (2017)). Consistent with the "brand-value" view expressed by this senior market participant, we find that index-provider fixed effects alone can explain about 21% of the variation in ETF assets. Even after controlling for ETF-issuer, time, and ETF-category fixed effects, expense ratios, and past returns, index providers can still explain 8% of the residual variation in ETF assets.

of active ETFs is still relatively small (about 3% of the total ETF assets as of 2020).

[2] As S&P Dow Jones, the world's largest index provider, writes on its website, "An index provider is a specialized firm that is dedicated to creating and calculating market indices and licensing its intellectual capital as the basis of passive products." See https://www.spglobal.com/spdji/en/index-literacy/who-s-behind-the-index/.

[3] For another well-known ETF, the Invesco QQQ Trust, 9 bps out of the 20 bps expense ratio that the ETF issuer (Invesco) charges to ETF investors are paid in the form of licensing fees to the index provider (NASDAQ), which owns the underlying NASDAQ-100 Index.

[4] There is ample evidence of an increased role of market power in the U.S. economy; see Philippon (2019) for a full treatment of this concern.

[5] Markets are classified as unconcentrated if the HHI is below 1,500, as moderately concentrated if the HHI is between 1,500 and 2,500, and as highly concentrated if the HHI is above 2500. See Section 5.3 of Horizontal Merger Guidelines of the U.S. Department of Justice and the Federal Trade Commission.

In contrast, we find that the index-provider fixed effects have literally zero explanatory power for ETF returns.[6] This finding suggests that the brand value of index providers likely arises from more trustworthy brands or better recognition among investors. This interpretation also echoes the conclusion drawn by BNY Mellon: "There is minimal difference between several index providers that serve the U.S. and global equity markets in terms of performance; while methodology varies among indexes, those variances are largely tempered by capitalization weighting."[7]

Third, we show that a large fraction of ETF issuers' revenues are paid to index providers in the form of index licensing fees. Specifically, we manually collect the *first* data on the licensing fees between index providers and ETF issuers by reading all ETF filings on the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system of the Securities and Exchange Commission (SEC). Since licensing fees are disclosed by ETF issuers on a voluntary basis,[8] only about 10% of ETFs in our sample disclose their licensing fees.[9] Despite this limitation and possible selection bias, our novel data enable us to look into the black box of ETF index licensing fees.[10]

Based on the best available information that we can obtain, we find that more than 95% of the licensing fees are imposed in the form of "percentage-of-AUM" fees, with the remainder applied as flat fees. In other words, index licensing fees are mostly tied to the assets of ETFs. We estimate that the index licensing fees comprise about one-third of all ETF expense ratios that ETF issuers collect from ETF investors. This fraction has also increased steadily over time, from 31.4% in 2010 to 35.7% in 2019. Not surprisingly, this trend leads ETF issuers to complain about the index licensing fees.[11]

In the second part of the paper, we build a structural model that incorporates the two-tiered competition among index providers for ETFs and among ETFs for investors. This structural approach allows us to (*i*) quantitatively assess the (un)competitiveness among index providers behind ETFs; (*ii*) decompose index providers' costs and markups, which are unobserved in the data; and (*iii*) conduct counterfactual analyses of index providers' market power and study the influence on ETF expense ratios paid by investors.

In our model, there are a finite number of index providers, a finite number of ETF issuers, and a continuum of investors. In the first stage, each index provider lists a licensing fee for using its index, and each ETF issuer chooses among all available index providers to form an ETF. The competition structure is modeled using a pairwise profit-augmenting technology in the manner of Eaton and Kortum (2002). That is, if an ETF issuer expects a higher profit from using an index provider's index, the probability that that ETF issuer chooses the index provider is higher. Because of market frictions, however, such as persistent relationships and switching costs, the ETF issuer may not always choose the index provider that generates the highest expected profit.

In the second stage, each ETF, which is formed by a pair consisting of an index provider and an ETF issuer, competes for investors. Specifically, each ETF issuer optimally chooses the ETF expense ratio that maximizes its own profit. Because the index licensing agreement is signed in the first stage, each ETF issuer treats the licensing fee as part of its marginal costs when determining ETF expense ratios. We model investors' choices of ETFs using a standard discrete choice framework. In line with our reduced-form facts, investors care about ETF expense ratios, past returns, as well as the identities of index providers and ETF issuers.

We structurally estimate the model using the top-20 U.S. equity ETFs (based on AUM at the end of 2019), while holding the remaining ETFs as an outside option. These top-20 ETFs held about 60% of all U.S. equity ETF assets. We explicitly model the top-20 ETFs because they are mostly broad-market ETFs and, importantly, there exists significant market segmentation between broad-market ETFs and smaller and more specialized ETFs, such as thematic ETFs (Ben-David et al., 2023). We note that our results are not sensitive to this particular choice. In Appendix C, we estimate the model using the top-50 ETFs, which hold about 80% of all equity ETF assets, and we obtain similar conclusions.

Our structural estimation reveals several results. First, the key structural parameter shows that the index provider market is highly uncompetitive. Specifically, if index provider A can offer 1% higher profits for ETFs than index provider B, the probability that an ETF chooses index provider A is only 0.53% higher than the probability that the ETF chooses index provider B. In contrast, if index providers were perfectly competitive, index provider A should always be chosen over index provider B. Such a low elasticity implies very limited substitutability across index providers, which is consistent with persistent indexing relationships and significant market power wielded by index providers.

Second, we estimate that about 60% of index licensing fees are markups. In 2019, the estimated licensing fees were 4.4 bps of an ETF's AUM on average, while the estimated marginal costs of index provision were about 1.6 bps on average. Hence, average markups are about 2.8 bps and the Lerner index (=markup/licensing fees) of index providers is about 63%, indicating that index providers charge very high markups for index provision. In comparison, we estimate that about 40% of the expense ratios that

[6] In addition, we find that index providers also explain little of the variation in ETF premiums and discounts.

[7] See https://www.morningstar.com/lp/asset-management-in-an-era-of-cost-pressure.

[8] Licensing fees are the operating expenses of the ETF, which are reflected in its expense ratios. However, because the SEC does not consider index providers to be advisers, licensing fees are not required to be disclosed separately.

[9] We also attempt to collect licensing fees for index mutual funds, but find that this information is not disclosed by index funds in the same way as it is for ETFs.

[10] Our sample does include some of the large and heavily traded ETFs, such as the SPDR S&P 500 ETF (SPY), the Invesco QQQ ETF (QQQ), and the SPDR Dow Jones Industrial Average ETF (DIA).

[11] For example, a Global Head of Vanguard was quoted, "What we have seen over the last several years is that a larger and larger percentage of the total expense ratio has been eaten by index licensing fees." See https://www.morningstar.com/articles/569429/vanguard-index-swap-all-about-cost.

investors pay to ETF issuers reflect markups of ETF issuers. Aligned with our findings, the Financial Times estimated the profit margin of the top three index providers to be about 65% as of 2019 (Times, 2019) and the profit margin of ETF issuers to be lower (Times, 2021).

Third, we conduct two main sets of counterfactual analyses to understand the equilibrium effect of (*i*) entry by a new competitive index provider and (*ii*) increased elasticity of ETF issuers to index providers' licensing fees.[12] We find that the entry of a new index provider that charges low licensing fees is ineffective in promoting competition in the market, leaving equilibrium index licensing fees and ETF expense ratios almost unaffected. This result is consistent with limited effects from entry when the demand side is inelastic to prices and is captured by existing brands (Davis et al., 2004; Hastings et al., 2017). Aligned with our findings, the launch of Morningstar's "Open Indexes Project" in 2016, which aimed to provide low-cost substitutes for the major index providers' equity indexes, had little effect on equity index licensing fees.[13]

Next, we directly promote competition among index providers in our model by increasing the elasticity of ETF issuers to index providers' licensing fees. In the benchmark case of perfect competition, index providers set licensing fees equal to their marginal costs. The top-20 ETFs, while keeping their equilibrium index providers, jointly and optimally change expense ratios under the counterfactual licensing fees. We find that ETF marginal costs decrease by about 2.8 bps and that the markup charged by ETF issuers is similar to that in the baseline scenario. As a result, the ETF expense ratios decline by 2.8 bps, from 9.3 to 6.5 bps, which represent a 30% reduction relative to the baseline scenario. Given the large amount of assets invested in the top-20 ETFs, this decrease will generate approximately $700 million in yearly savings for ETF investors. While useful as a benchmark, perfect competition is an unlikely outcome in the extremely concentrated index provider market. Therefore, we simulate more realistic increases in competition and find that doubling the elasticity of ETF issuers to index providers' licensing fees reduces ETF expense ratios by almost 6%. Further, a tenfold increase leads to an almost 18% reduction in ETF expense ratios, achieving more than half of the reduction in a perfectly competitive index provider market.

Overall, our results show that lowering barriers to entry for index providers alone may not be effective in promoting competition, given that index providers' brand value matters and that the long-term relationship between index providers and ETF issuers hinders switching. On the other hand, policies that increase ETF elasticity to licensing fees could increase competition among index providers, with benefits passed on to investors in terms of lower expense ratios.[14]

The rest of the paper is structured as follows. Section 2 reviews the literature. Section 3 describes the data. Section 4 documents the three stylized facts about index providers in the U.S. equity ETF market. Section 5 presents a structural model of index providers and ETF issuers. Section 6 discusses the model estimation and counterfactual analyses. Section 7 concludes. The appendices provide additional results and robustness checks.

2. Literature review

Our paper contributes to the growing literature on ETFs by unpacking the black box of index providers. To the best of our knowledge, we are the first to study the competition structure among index providers and ETF issuers and to show that matching and contracting between index providers and ETF issuers matter to the first order of ETF expense ratios charged to investors. Related, Mahoney and Robertson (2021) discuss the legal aspects of index providers as investment advisers. Kostovetsky and Warner (2021) show that ETFs tracking indexes from larger index providers are able to attract more capital from investors, consistent with our stylized fact regarding the brand value of index providers. The competition between index providers and that competition's effect on index licensing fees and ETF expense ratios, which are the key to our analysis, are not studied in these papers.[15]

While one of the stylized facts that a few large index providers possess significant market share is mentioned in several news articles and academic papers qualitatively,[16] our reduced-form exercises are the first to study the index provision market and index licensing fees quantitatively. Our structural approach also produces deeper insights into the market structure of index providers. For example, the structural model allows us to differentiate index providers' markups and marginal costs and to conduct counterfactual analysis.

Our paper is also related to recent research on the bright and dark sides of ETFs. Azar et al. (2018) study the implications of passive investment for corporate governance and corporate power. Huang et al. (2023) find that index providers and ETF issuers conduct extensive data mining when constructing smart beta indexes so as to attract investment flows, while Ben-David et al. (2023) find evidence that thematic ETFs are constructed and offered to cater to investor sentiment. Akey et al. (2021) show that some ETFs are active in their strategies and their performance is negatively related to activeness. Brown et al. (2021) find that ETFs that have similar returns but higher expense ratios and less liquidity than their competitors attract excess capital. In addition,

[12] We also consider the effect of increasing the elasticity of ETF investors to expense ratios.

[13] According to Morningstar, "The goal of this project is to lower the cost of equity indexes and improve outcomes for all investors." See Section 6.3 for more details about the Morningstar Open Indexes Project.

[14] The Security and Exchange Commission (SEC) and the Financial Conduct Authority (FCA) have recently called for studies about disclosure and competition in the index provision markets in the US and the UK (See, for example, https://www.sec.gov/rules/other/2022/ia-6050.pdf and https://www.ft.com/content/58946854-72b8-4c0d-9507-b9ec1c350a85).

[15] Robertson (2019) finds that the index providers of 81 of 571 U.S. equity ETFs are affiliated with ETF issuers (so-called self-indexing). While affiliated index providers are indeed relevant to small ETFs, the large ETF issuers and index providers, which capture over 95% of total AUM, are not affiliated with each other.

[16] See, for example, Adams et al. (2010), Times (2019), Robertson (2019), and Petry et al. (2021).

Table 1
Summary statistics

	Mean	SD	25th	50th	75th
Panel A: ETF level					
AUM ($ million)	2,037.29	9,121.63	47.70	209.16	814.13
Monthly return (%)	1.07	0.47	0.91	1.06	1.20
Expense ratio (%)	0.37	0.20	0.20	0.35	0.50
Turnover ratio (%)	62.85	209.15	16.19	32.32	61.14
Panel B: ETF issuer level					
Total AUM ($ million)	16,939.70	68,657.61	35.43	142.25	1,154.38
# of ETF	6.79	15.56	1.00	1.77	4.14
# of matched index providers	1.68	1.58	1.00	1.00	1.89
Panel C: Index provider level					
Total AUM ($ million)	15,635.70	77,678.42	45.52	126.43	1,136.98
# of ETF	5.91	18.16	1.00	1.00	3.00
# of matched ETF issuers	1.43	1.45	1.00	1.00	1.00

Table 1 reports summary statistics for our sample at the ETF, ETF issuer, and index provider levels. Our sample includes U.S. equity ETFs (excluding leveraged, inverse, and synthetic ETFs) and spans from January 2010 to December 2019.

Khomyn et al. (2020) show that more liquid ETFs attract shorter-horizon investors and charge higher expense ratios. Moreover, some argue that ETFs increase asset volatility and harm liquidity (e.g., Israeli et al., 2017; Ben-David et al., 2018; Da and Shive, 2018; Agarwal et al., 2019; Pan and Zeng, 2019), while others find evidence that ETFs improve market efficiency (e.g. Box et al., 2021; Glosten et al., 2021; Huang et al., 2021).

Finally, our paper contributes to the growing literature that explores the industrial organization of financial markets using structural techniques (Bao and Ni, 2017; Egan et al., 2017; Buchak et al., 2018; Koijen and Yogo, 2019; Benetton, 2021; Antill, 2022; Buchak et al., 2022; Craig and Ma, 2022). Our paper is most closely related to Hortaçsu and Syverson (2004), who develop a search model to understand fund proliferation and fee dispersion in S&P 500 index funds; Egan et al. (2022), who study the ETF market with a structural demand model to infer investors' expectations from ETF demand; and Jiang (2023), who builds a quantitative model to understand how relationship lending between shadow and traditional banks affects competition in the downstream mortgage market.

3. Data

We take several steps to construct the sample. First, we obtain a list of U.S. equity ETFs from Morningstar spanning a 10-year period from January 2010 through December 2019. Specifically, we exclude leveraged ETFs, inverse ETFs, and synthetic ETFs. Second, for each ETF, we manually identify its underlying index and collect the information on the index from its official website or from professional third-party websites (e.g., ETF.com). We then merge the list of ETFs with the CRSP mutual fund database to obtain monthly returns, expense ratios, and AUM. After this step, we obtain 598 U.S. equity ETFs.

Table 1 provides summary statistics for our data set. The results reported in Panel A indicate an average ETF AUM of $2.04 billion with a standard deviation of $9.12 billion. The distribution of ETF AUM is highly skewed, with a median AUM of $209 million. The average expense ratio is 37 bps per year with a standard deviation of 20 bps. Panel B focuses on the 68 ETF issuers in our sample. Each ETF issuer offers, on average, 6.79 ETF products, which track the indexes constructed by 1.68 index providers. Panel C reports statistics for the 77 index providers in our sample. Each index provider has, on average, 5.91 ETFs tracking its constructed indexes and works with 1.43 ETF issuers. While Panels B and C might suggest that index providers and ETF issuers are matched one-to-one, this pattern is driven by a large number of small index providers and small ETF issuers. We will provide more details on the matching between large index providers and large ETF issuers in Section 4.1.

4. Stylized facts about index providers

In this section, we document three stylized facts about index providers in ETF markets: (*i*) the ETF indexing market is highly concentrated among only a few large index providers; (*ii*) investors care about the identities of index providers when choosing ETFs, even though there are limited differences in returns among indexes constructed by various index providers; and (*iii*) about one-third of all ETF expense ratios are paid to index providers in the form of index licensing fees.

4.1. Concentration of the index provider industry

We begin by showing that ETF markets and index markets are highly concentrated. Fig. 2 plots the total assets tracking indexes provided by the top five index providers (S&P Dow Jones, CRSP, FTSE Russell, MSCI, and NASDAQ) and the total assets managed by the top five ETF issuers (iShares, Vanguard, State Street, Invesco, and Schwab). The top index providers and ETF issuers capture a very large market share. The high market shares of top index providers and ETF issuers are especially striking, given that

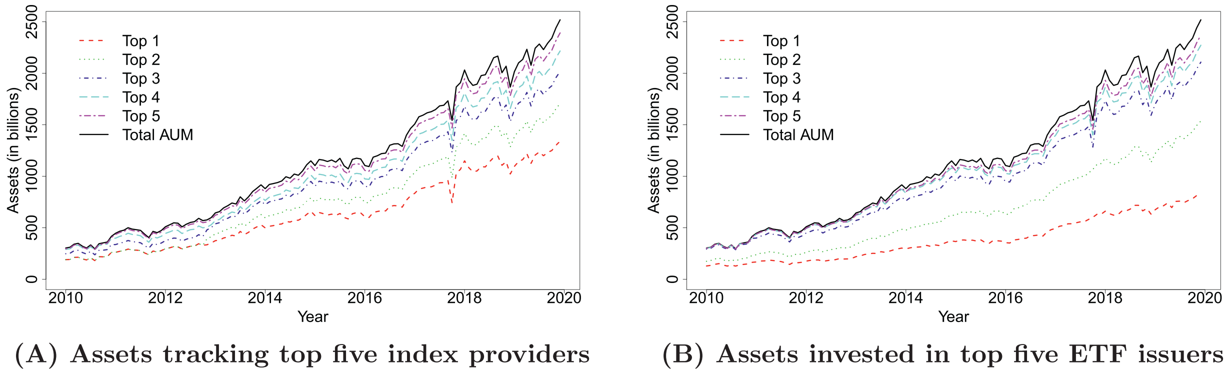


Fig. 2. Assets related to the top five index providers and ETF issuers. Panel (a) of Fig. 2 shows the total assets of ETFs that use indexes constructed by the top five index providers (by tracking assets as of December 2019): S&P Dow Jones, CRSP, FTSE Russell, MSCI, and NASDAQ. Panel (b) shows the total assets of ETFs offered by the top five ETF issuers (by AUM as of December 2019): iShares, Vanguard, State Street, Invesco, and Schwab.

Table 2
Market share of top index providers and ETF issuers in December 2019

Index provider			ETF issuer		
Name	Market share	Cum. market share	Name	Market share	Cum. market share
S&P Dow Jones	53.24%	53.24%	iShares	33.17%	33.17%
CRSP	14.51%	67.75%	Vanguard	27.82%	60.99%
FTSE Russell	12.37%	80.12%	State Street	22.69%	83.68%
MSCI	7.86%	87.98%	Invesco	6.52%	90.20%
NASDAQ	6.97%	94.95%	Schwab	3.87%	94.07%

Table 2 provides the individual and cumulative market shares of the top five index providers and ETF issuers in the U.S. equity ETF market as of December 2019.

total ETF AUM grew more than fivefold from 2010 to 2019. Table 2 reports the market share captured by the top index providers and ETF issuers, measured by total AUM, as of December 2019. The top five index providers and the top five ETF issuers both capture about 95% of the market. The top ETF issuer, iShares, has about a 33% market share, and the top index provider for U.S. equity ETFs, S&P Dow Jones, alone has more than 50% of the market.

To quantify market concentration, we calculate the HHI of ETF issuers and ETF index providers for each month. Over our sample period, the monthly average of the HHI of ETF issuers is 2,527.31, and the HHI of index providers is even higher, averaging 3,293.59, much higher than the 2,500 level, which the U.S. Department of Justice and the Federal Trade Commission regard as a highly concentrated industry.

Next, Table 3 reports the matching between the largest index providers and ETF issuers.[17] Different from the full sample in Table 1, the match between the largest ETF issuers and index providers is not one-to-one. However, most ETF issuers still have one major index provider and most index providers have one major ETF issuer. Panel A lists the distributions of AUM across various index providers from a given ETF issuer's perspective, and the panel should be read left to right. For example, the top left cell indicates that 57.1% of iShares' AUM uses S&P Dow Jones as the index provider. We bold cells where the figure is above 50%. The results show that every top ETF issuer has a major index-providing partner. Specifically, iShares, State State, and Schwab rely mainly on S&P Dow Jones, Vanguard uses CRSP, and Invesco uses NASDAQ. In Panel B, we report the distribution of AUM across various ETF issuers from a given index provider's perspective, and the panel should be read top to bottom. For example, the top left cell indicates that 35.6% of S&P Dow Jones' AUM uses iShares as the ETF issuer. With the exception of S&P Dow Jones, all other index providers rely mainly on one ETF issuer. This matching between index providers and ETF issuers could be caused by persistent relationships over time.

In additional analyses presented in Table B.2 and Table B.3 of Appendix B, we find that the results reported in Table 3 do not change much when we use a time snapshot other than December 2019, such as December 2013 or December 2016. The matching between ETF issuers and index providers is rather stable over time. We summarize the findings in this section as follows.

Fact 1. The US equity ETF market is highly concentrated among a few large index providers and ETF issuers, which have persistent relationships over time.

4.2. The identity of index providers matters for investor choice

We next show that the identity of index providers matters for investor choices. Specifically, we explore the role of index providers in the ETF market using a regression

[17] The results are similar when using Total Revenue = AUM × Expense Ratio, as shown in Table B.1.

Table 3
Matching between index providers and ETF issuers

Panel A: From ETF issuers' perspective						
	S&P Dow Jones	CRSP	FTSE Russell	MSCI	NASDAQ	Others
iShares	**57.1%**	0.0%	29.3%	9.3%	1.2%	3.1%
Vanguard	21.1%	**52.2%**	5.8%	14.9%	6.0%	0.0%
State Street	**97.7%**	0.0%	0.2%	0.1%	0.0%	2.0%
Invesco	33.2%	0.0%	5.1%	0.0%	**58.1%**	3.6%
Schwab	**88.4%**	0.0%	10.7%	0.0%	0.0%	1.0%
Others	11.3%	0.0%	3.9%	10.1%	18.9%	**55.8%**
Panel B: From index providers' perspective						
	S&P Dow Jones	CRSP	FTSE Russell	MSCI	NASDAQ	Others
iShares	35.6%	0.0%	**78.6%**	39.3%	5.5%	20.4%
Vanguard	11.0%	**100.0%**	13.1%	**52.8%**	24.0%	0.0%
State Street	41.6%	0.0%	0.5%	0.3%	0.0%	8.8%
Invesco	4.1%	0.0%	2.7%	0.0%	**54.3%**	4.6%
Schwab	6.4%	0.0%	3.3%	0.0%	0.0%	0.7%
Others	1.3%	0.0%	1.9%	7.6%	16.1%	**65.5%**

Table 3 reports matching between index providers and ETF issuers. "Others" comprise all index providers or ETF issuers other than the top five. Panel A reports the distribution of AUM across various index providers from a given ETF issuer's perspective. Panel B reports the distribution of AUM across various ETF issuers from a given index provider's perspective. We bold cells where the figure is above 50%. The sample period is December 2019.

Table 4
Index providers matter for investor choices

	Separate fixed effects				Role of index providers	
	(1) Index provider	(2) ETF issuer	(3) Category	(4) Time	(5) ETF issuer Category Time	(6) Index provider ETF issuer Category Time
Expense ratio (bps)					-0.039^{***}	-0.052^{***}
					(0.016)	(0.018)
Past 1-year return (%)					0.193^{***}	0.211^{***}
					(0.038)	(0.036)
R^2	0.21	0.30	0.05	0.01	0.43	0.50
Adjusted R^2	0.21	0.30	0.05	0.01	0.42	0.50
Y IQR	2.9	2.9	2.9	2.9	2.9	2.9
Residuals IQR	2.3	2.2	2.7	2.7	1.9	1.6
Observations	38,757	38,757	38,757	38,757	38,757	38,757

Table 4 reports the estimates of Eq. (1) with various sets of fixed effects and controls. The dependent variable is (log) AUM. We report the interquartile range (IQR) of the y variable and residuals. The sample consists of each ETF × Month observation of U.S. equity ETFs from January 2010 through December 2019. Standard errors double clustered at the ETF issuer and time level are shown in the parentheses.

framework, and we estimate variations of the following regression specification:

$$y_{kt} = \beta X_{kt} + \gamma_i + \gamma_j + \gamma_c + \gamma_t + \epsilon_{kt}. \quad (1)$$

Here, X_{kt} captures characteristics of ETF k offered by index provider i and ETF issuer j in category c and month t, and γ_i, γ_j, γ_c, and γ_t are index-provider, ETF-issuer, category, and month fixed effects, respectively. By shutting down various fixed effects and comparing the corresponding adjusted R^2s, we study the contribution of multiple variables in explaining variations in the outcome variable y_{kt}.

Table 4 reports the results derived from regression (1) on our main dependent variable of interest, (log) AUM of ETF k in month t. The first column shows that index-provider fixed effects alone can explain more than 20% of the variation in AUM. ETF issuers are also important, accounting for 30% of the variation in AUM. Category and time fixed effects are less important than index provider and ETF issuer in explaining variation in AUM. The R^2 with category fixed effects is 5%, while time fixed effects account for only about 1% of the variation in AUM, suggesting that aggregate time-series trends mask a lot of cross-sectional heterogeneity.

A key empirical concern is that the return profiles of indexes can vary across index providers. It is possible that investors do not care about the identities of index providers per se, but do care about index returns, which correlate with index providers. To address this concern, we include additional controls in regression (1).

Column (5) of Table 4 shows the estimates of Eq. (1) with ETF issuer, category, and time fixed effects, and controlling for ETF expense ratios and past returns. As expected, if investor demand is downward sloping in price, higher expense ratios are associated with lower AUM. Also, consistent with Dannhauser and Pontiff (2019), higher past ETF returns are associated with higher AUM.[18] The overall R^2 is 0.43. We also report the interquartile range (IQR) as a measure of dispersion in (log) AUM. In our dataset, the IQR of (log) AUM is 2.9. The IQR of the residuals from the

[18] It is well documented that investors chase past performance (e.g. Chevalier and Ellison, 1997; Ben-David et al., 2022).

Table 5
Index providers: Expense ratios and returns

	Separate fixed effects				Role of index providers	
	(1) Index provider	(2) ETF issuer	(3) Category	(4) Time	(5) ETF issuer Category Time	(6) Index provider ETF issuer Category Time
Panel A: Expense ratios						
R^2	0.64	0.67	0.19	0.01	0.76	0.84
Adjusted R^2	0.64	0.66	0.19	0.00	0.76	0.84
Y IQR (bps)	30	30	30	30	30	30
Residuals IQR (bps)	10.4	17.6	22.7	32.2	12.8	8.9
Observations	38,757	38,757	38,757	38,757	38,757	38,757
Panel B: Returns						
R^2	0.01	0.01	0.06	0.49	0.56	0.56
Adjusted R^2	0.01	0.01	0.06	0.49	0.56	0.56
Y IQR (%)	1.2	1.2	1.2	1.2	1.2	1.2
Residuals IQR (%)	1.2	1.2	1.2	0.6	0.6	0.6
Observations	38,757	38,757	38,757	38,757	38,757	38,757

Table 5 reports the estimates of Eq. (1) with various sets of fixed effects and controls. The dependent variable for Panel A is ETF expense ratios. The dependent variable for Panel B is ETF monthly net returns. We report the interquartile range (IQR) of the y variable and residuals. The sample consists of each ETF $\times$ Month observation of U.S. equity ETFs from January 2010 through December 2019.

estimates reported in column (5) is 1.9, which represents approximately a 35% decline in dispersion.

Finally, in column (6) of Table 4, we show the estimates after adding index-provider fixed effects to the specification used in column (5). After controlling for ETF issuer, category, time, expense ratios, and past returns, index-provider fixed effects increases the adjusted R^2 by about 0.08, from 0.42 to 0.50. Additionally, the dispersion in the IQR of the residuals declines to 1.6, which represents an additional 10% decline relative to the specification without index-provider fixed effects (column (5)).

Overall, the results reported in Table 4 show that index providers contribute significantly to dispersion in AUM. The identity of index providers matters even after controlling for ETF expense ratios and past returns, suggesting that investors value nonprice characteristics of index providers such as brand reputation. Consistent with our findings, Mahoney and Robertson (2021) also find that large index providers can help attract ETF flows.

To further understand the role of index providers, we estimate Eq. (1) using expense ratios and monthly returns as the dependent variable. Table 5 shows the results. Column (1) of Panel A shows that index-provider fixed effects alone explain about 64% of the variation in expense ratios. The IQR of expense ratios is about 30 bps. Controlling for index providers alone reduces the IQR by about two-thirds, to about 10 bps. The large explanatory power of index providers for expense ratios can come from two channels: (a) index providers' licensing fees could affect ETFs' costs, which are then passed on to investors via expense ratios; and/or (b) index providers could affect the attractiveness of ETFs to investors, which allows ETFs to charge differential expense ratios. We incorporate both effects in our structural model.

Panel A of Table 5 also shows that ETF issuer fixed effects have considerable explanatory power for ETF expense ratios, with an R^2 equal to 0.67. As in the case with AUM as the dependent variable, category and time fixed effects have weaker explanatory power for dispersion in ETF expense ratios. The R^2s for category and time fixed effects are 0.19 and 0.01, respectively. Aggregate time-series variation in expense ratios hides much of the cross-sectional dispersion, as also documented in Ben-David et al. (2023). Comparing the results reported in columns (5) and (6) shows that adding index-provider fixed effects to ETF issuer, category, and time fixed effects raises the R^2 by about 0.08 and reduces the IQR of the residuals by an additional 13% (from 12.8 to 8.9).

Finally, Panel B of Table 5 examines ETF net returns. In contrast to the results for AUM and expense ratios, index-provider and ETF-issuer fixed effects have little explanatory power for returns.[19] In both cases, the R^2 is about 0.01. Category fixed effects have an R^2 of about 0.06. The single most important variable in explaining dispersion in returns is time fixed effects, which alone captures almost 50% of the variation in returns.

Overall, our findings suggest that index providers have significant brand value, which could arise from more trustworthy brands or from better recognition among investors. This interpretation is also consistent with the views expressed by market participants, as quoted in Petry et al. (2021): "At the end of the day, those products (i.e., indexes) are homogeneous and exchangeable. Those are minimal differences, but the price tags are very different! MSCI is famous for being expensive — not because they have better data or indices, but because they are the brand that is most used in the world. Brand is everything!" We collect the findings from these analyses in the following fact.

Fact 2. Index providers' identities matter for ETF AUM even after controlling for other determinants of investor demand (e.g., expense ratios, past returns, ETF issuer) and explain

[19] In an untabulated exercise, we also find that index-provider fixed effects have an R^2 of 0.01 and almost zero marginal R^2 in explaining ETF premiums and discounts.

Table 6
Comparing ETFs with and without licensing fee disclosure

	Mean	SD	25th	50th	75th
Panel A: 52 ETFs that report licensing fees					
AUM ($ million)	6,915.85	24,682.11	213.40	714.65	3,410.53
Monthly return (%)	1.00	0.40	0.89	1.05	1.16
Expense ratios (%)	0.50	0.23	0.19	0.60	0.66
Panel B: 546 ETFs that do not report licensing fees					
AUM ($ million)	1,568.37	5,582.83	44.32	165.75	740.98
Monthly return (%)	1.08	0.47	0.91	1.07	1.20
Expense ratios (%)	0.35	0.19	0.20	0.35	0.47

Table 6 compares ETFs that report licensing fees and ETFs that do not. Specifically, we search all ETF filings on the SEC's EDGAR system. Out of the 598 ETFs in our sample, 52 report their index licensing fees.

a large (tiny) fraction of dispersion in expense ratios (returns).

4.3. Analysis of index licensing agreements

In this section, we provide the first analysis of index licensing fees. In doing so, we collect index licensing agreements and fees between index providers and ETF issuers by manually searching all ETF filings on the EDGAR system of the SEC. Specifically, we search for the keywords "licensing fee" and "license fee" within the ETF filings. Because ETFs disclose licensing fees on a voluntary basis, we obtain licensing fees for 52, or about 9%, of the U.S. equity ETFs in our sample. Admittedly, whether an ETF discloses licensing fees is an endogenous choice, and our data, despite our best efforts, suffer selection bias. Nevertheless, because our sample does include some of the largest and most heavily traded ETFs, such as the SPDR S&P 500 ETF (SPY), the Invesco QQQ ETF (QQQ), and the SPDR Dow Jones Industrial Average ETF (DIA), as well as some small ETFs, the agreements we obtain are likely to be representative of the wider universe of ETFs.[20]

Table 6 compares various characteristics of ETFs that disclose licensing fees and ETFs that do not. As we can see, ETFs that disclose licensing fees have, on average, larger AUM and charge higher expense ratios to investors than ETFs that do not disclose licensing fees. The return profiles of these two types of ETFs are similar.

Fig. 3 shows the cross-sectional relationship in licensing fee, ETF expense ratio, and ETF size. For the 52 ETFs that disclosed licensing fees, we find that (*i*) larger ETF AUM is associated with a lower licensing fee (Panel (a)); (*ii*) larger ETF AUM is associated with a lower expense ratio (Panel (b)); (*iii*) a higher expense ratio is associated with a higher licensing fee (Panel (c)).[21] These patterns are consistent with our model estimations in Section 6. However, due to the limited observations of index licensing fees, we acknowledge the patterns presented here might not be conclusive.

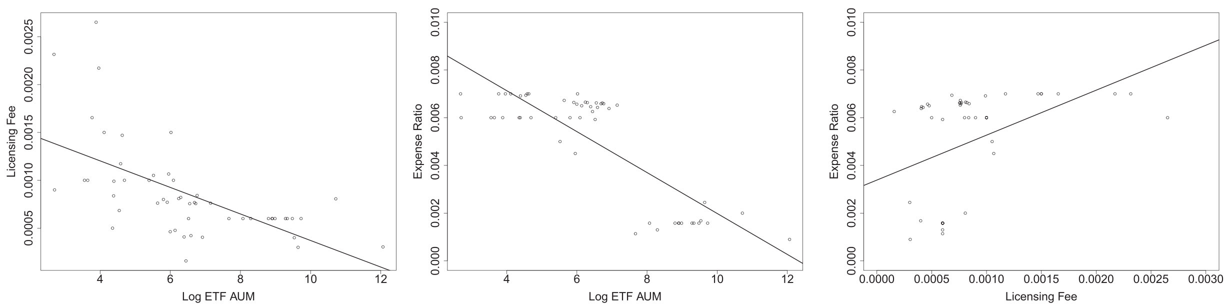
Next we study the details of the licensing fee agreement. Across the 52 ETFs for which we observe licensing fees, the typical licensing fee contract is "x bps of AUM + \$y" per year, where x can have various breakpoints depending on AUM, and y can be 0. The other less common contractual form, which is used by only three of the 52 ETFs, is "max of x bps of AUM and \$y" per year. For example, consider three well-known ETFs:

- The SPDR S&P 500 ETF has a licensing fee of $x = 3$ bps of AUM plus a flat fee of $y = \$600,000$.
- The SPDR Dow Jones Industrial Average ETF has a licensing fee of $x = 4$ bps of AUM and no flat fee, so $y = \$0$.
- The Invesco QQQ ETF has no flat fee $y = \$0$ and charges $x = 9$ bps for AUM under \$25 billion and $x = 8$ bps for AUM above \$25 billion. Thus, the formula for the licensing fee for the Invesco QQQ ETF is $9 \text{ bps} \times \min(\text{AUM}, \$25\text{b}) + 8 \text{ bps} \times \max(\text{AUM} - \$25\text{b}, 0)$.

Table 7 presents summary statistics for licensing fees for each year from 2010 through 2019. Columns (1) to (3) of Table 7 report index licensing fees as a fraction of the total expense ratio that ETF investors pay. The ETF licensing fees are on average 21% of the ETF expense ratio, and the AUM-weighted average ranges from about 32% to about 36%, suggesting that larger ETFs pay out a higher fraction of total expense ratios to index providers. Another pattern revealed in Table 7 is that, as a fraction of the ETF expense ratio, the AUM-weighted licensing fee increases steadily over time, from about 31% in 2010 to 36% in 2019. This is because ETF expense ratios are on average declining over time, yet the index licensing fees are relatively stable. Finally, the last two columns show that the AUM-based component comprises more than 95% of the total licensing fee, and the flat-fee component is just a tiny fraction of the licensing fee. We collect the findings for the subset

[20] Out of the 52 ETFs that report licensing fees, SPY, QQQ, DIA, and SPDR S&P MidCap 400 ETF (MDY) are formed as unit-investment trust (UIT), while others are formed as the open-ended funds. The institutional features of UIT may give index providers extra power in charging high licensing fees. However, our findings are robust after removing these four UITs from the sample. We thank Elisabeth Kashner for pointing out the institutional features of UIT.

[21] In Appendix B, we also conduct an event study. We identify 20 cases in which ETF sponsors change index providers for certain ETFs in our sample. We find that when ETF sponsors switch from (likely) more expensive index providers to (likely) cheaper index providers, ETF expense ratios almost always decrease (in 18 out of 20 cases).



(A) AUM & licensing fee (B) AUM & expense ratio (C) Licensing fee & expense ratio

Fig. 3. Cross-sectional relationship in licensing fee, expense ratio, and AUM. Panel (a) of Fig. 3 shows the relationship between the time-series average log(AUM) and the average index licensing fee of the 52 ETFs with licensing fee disclosed; Each data point represents an ETF observation, and we also plot the fitting regression line. Panel (b) shows the relationship between the average log(AUM) and the average expense ratio of the 52 ETFs; Panel (c) shows the relationship between the average licensing fee and the average expense ratio of the 52 ETFs.

Table 7
Analysis of licensing fees

	Licensing fees as fractions of expense ratios			Decomposition of licensing fees	
Year	AUM-weighted mean (%)	Simple mean (%)	Median (%)	AUM-based fee (%)	Fixed fee (%)
	(1)	(2)	(3)	(4)	(5)
2010	31.4	23.2	19.3	97.3	2.7
2011	32.5	20.3	16.7	98.1	2.0
2012	32.6	19.7	16.7	97.9	2.1
2013	32.7	17.8	16.7	95.8	4.2
2014	33.9	21.6	19.3	91.7	8.3
2015	33.7	21.7	19.8	93.4	6.6
2016	34.4	20.8	17.8	94.9	5.1
2017	35.0	21.1	19.0	97.3	2.7
2018	35.7	21.3	18.5	98.3	1.7
2019	35.7	21.3	19.3	98.6	1.4

Table 7 presents the results of an analysis of index licensing fees. Columns (1) to (3) calculate the AUM-weighted average, the simple average, and the median licensing fees, respectively, as a fraction of ETF expense ratios. Columns (4) and (5) report the fractions of licensing fees related to ETF AUM and the fractions of fixed licensing fees, respectively.

of ETF with information on licensing fees in the following fact.

Fact 3. Index providers capture a large fraction of the total revenue of the ETF business via licensing fees that are about one-third of ETF expense ratio.

5. A model of index providers and ETF issuers

Based on the three stylized facts documented in the previous section, we next present a structural equilibrium model of the ETF market that accounts for the two-tiered competition of index providers and ETF issuers. This structural approach allows us to (*i*) quantitatively assess the (un)competitiveness among index providers behind ETFs; (*ii*) decompose costs and markups of index providers, which are unobserved in the data; and (*iii*) conduct counterfactual analyses of index providers' market power and study the influence on ETF expense ratios paid by investors.

The model works as follows. In each period t, a continuum mass L_t of investors, indexed by l, choose among a discrete number of differentiated ETFs, indexed by $k = 1, 2, \ldots, K_t$. Each ETF k consists of an ETF issuer $j = 1, \ldots, J_t$ and an index provider $i = 1, \ldots, I_t$. Within each period t, the timing is as follows:

- Each index provider i sets licensing fees ρ_i for using its index.
- Each ETF k, which is set up by a given ETF issuer, chooses an index provider.
- Each ETF k sets expense ratios f_k.
- Investors choose the ETFs in which to invest their money.

In the subsections that follow, we specify each agent's optimization problem in turn. Our model is static for each period t. In the notation, for simplicity we omit the subscript t, which indexes time.

5.1. Investors

There are K ETFs available, and each investor l seeks to buy one unit of an ETF from the list. We follow the characteristics approach and assume that (*i*) each ETF can be represented as a bundle of attributes and (*ii*) investor have preferences over these attributes. The indirect utility enjoyed by investor l for choosing ETF k that is issued by j with the index provided by i is given by the following equation:

$$u_{lk} = -\alpha f_k + \beta X_k + \gamma_{ij} + \xi_k + \epsilon_{lk}, \tag{2}$$

where f_k is the expense ratio charged by ETF k, and X_k corresponds to vectors of observable features of ETF k, such as past returns. The interacted fixed effects γ_{ij} for index provider i and ETF issuer j capture observable and unobservable characteristics such as index provider brand value and ETF issuer quality, as well as potential synergies between index providers and ETF issuers. In addition, ξ_k is an error term capturing additional unobservable characteristics of ETF k, and ϵ_{lk} is an idiosyncratic shock that varies across investors and ETFs.

The identity of index provider i matters through the interaction term γ_{ij} in Eq. (2) for investors' utility. For a given ETF issuer j, choosing an index provider i that offers a higher γ_{ij} leads to greater investor utility and higher market share for ETF k, holding all else equal. The term γ_{ij} thus captures the brand value of index providers as we have documented in the reduced-form evidence, which could arise from more trustworthy brands or from better recognition among investors.

Investor l chooses the ETF k that delivers the highest utility among the K ETFs available on the market. As an alternative to choosing one of the K ETFs, each investor also has the option of not choosing any ETF and investing its money in other asset classes. We normalize the utility of such a choice to zero ($u_{l0} = 0$). Hence, the probability that investor l chooses to invest in ETF k is given by the following:

$$s_{lk} = \text{Prob}(u_{lk} \geq u_{lk'}, \forall k' \in \{0, 1, \ldots, K\}). \tag{3}$$

When taking the model to the data, we assume that unobservables ϵ_{lk} in Eq. (2) follows an i.i.d. type-1 extreme value distribution, as is standard in discrete choice logit models. Given our focus on the competition among index providers for ETFs, assuming homogeneity in the error term ϵ_{lk} across ETF investor l in Eq. (2) simplifies our model. Hence, the probability that investor l chooses to invest in ETF k is given by the following:

$$s_{lk} = s_k = \frac{e^{-\alpha f_k + \beta X_k + \gamma_{ij} + \xi_k}}{1 + \sum_{k'=1}^{K} e^{-\alpha f_{k'} + \beta X_{k'} + \gamma_{i'j'} + \xi_{k'}}}, \tag{4}$$

where the first equality comes from the common parameters across investors. Summing across the continuum mass L of investors in the market, we obtain the AUM of ETF k: $\text{AUM}_k = \sum_l s_{lk} = s_k L$.

5.2. ETF issuers

ETF issuers maximize profits by setting optimal expense ratios f_k for the ETFs they offer given their costs, which depend on the index provider they choose.[22]

Given the choice of index provider i, the profit of ETF k, which is issued by ETF issuer j, is given as follows:

$$\pi_{ki}(\rho_i) = \max_{f_k}(f_k - c_k(\rho_i))s_k L, \tag{5}$$

where $c_k(\rho_i)$ is the marginal cost of offering ETF k, conditional on the choice of index provider i; ρ_i is the licensing fee that index provider i charges as a fraction of the ETF's AUM; and s_k is the market share of ETF k from Eq. (4). Consistent with the results reported in the last two columns of Table 7, we assume that licensing fee ρ_i is paid as a percentage-of-AUM fee. In Eq. (5), both licensing fee ρ_i and the equilibrium market share s_k depend on index provider i (the market share s_k depends on index provider i through the interacted fixed effect γ_{ij} in Eq. (2)).

The first-order condition of profits in Eq. (5) relative to expense ratios gives the standard markup pricing formula:

$$f_k(\rho_i) = c_k(\rho_i) + \overbrace{\frac{1}{\alpha(1 - s_k)}}^{\text{markup}}. \tag{6}$$

We assume that the marginal cost of ETFs consists of two components:

$$c_k(\rho_i) = \tilde{c}_k + \rho_i. \tag{7}$$

First, ETFs incur a marginal operating cost $\tilde{c}_k$, which could vary across ETFs. The component $\tilde{c}_k$ is exogenous in the model and does not depend on index providers. Second, ETF issuers pay a licensing fee ρ_i to index provider i as a fraction of the ETF's AUM.

An assumption in Eq. (7) is that index provider i offers the same licensing fee ρ_i to different ETFs k, which could have different issuers j. We make this assumption because licensing fees are mostly unobserved, and this assumption allows us to exploit the limited observations of licensing fees to estimate structural cost parameters. In practice, index licensing agreements are signed bilaterally, and index provider i can, in principle, offer different licensing fees to competing ETF issuers. Because of the limitation of our hand-collected data on licensing fees, we cannot estimate a model with fully flexible bilateral licensing fees between index providers and ETF issuers. Nevertheless, in Appendix F, we consider an alternative specification where licensing fees are proportional to the equilibrium expense ratios. Such a specification allows for some variations of licensing fees across ETFs for the same index provider because the expense ratios could vary across ETFs. We find that the alternative proportional-fee model delivers similar results to our baseline model.[23]

In equilibrium, the licensing fees are optimally chosen by index providers, and ETF issuers choose between various providers. We model this choice parsimoniously us-

[22] In practice, large ETF issuers usually offer multiple ETFs (see Table 1). For tractability, we assume that ETFs make the profit-maximization decision independently, regardless of whether they belong to the same issuer. We leave the investigation of multiproduct strategies adopted by ETF issuers to future research.

[23] We also provide an upper bound on the market power of index providers in the baseline model, which we report in Appendix E. Specifically, we consider the extreme case in which the marginal cost of ETF is entirely due to the index licensing fee. We find that the index providers' market power only increases slightly relative to our baseline case, because the index licensing fees already account for 82% of ETFs' marginal cost in our baseline estimation.

ing a pairwise profit-augmenting technology in the manner of Eaton and Kortum (2002), which has also recently been applied by Jiang (2023) in structural work on the U.S. mortgage market. Formally, ETF k chooses among index providers $i = 1, \ldots, I$ to maximize its total profits:

$$\Pi_{ki} = \pi_{ki}(\rho_i) \times \xi_{ki}, \tag{8}$$

where $\pi_{ki}(\rho_i)$ is the profits conditional on choosing index provider i given in Eq. (5), and ξ_{ki} is an unobserved error term, capturing ETF k's additional profit if it chooses index provider i. ETF k chooses the index provider i that delivers the highest total profits Π_{ki} among the I index providers that exist in the market. Hence, the probability that ETF k chooses index provider i is given by

$$q_{ki}(\rho_i) = \text{Prob}(\Pi_{ki} \geq \Pi_{ki'}, \forall i' \in \{1, 2, \ldots, I\}). \tag{9}$$

Our model captures the ETF's trade-off between index providers' licensing fee and brand value. Specifically, the profits $\pi_{ki}(\rho_i)$ and $\pi_{ki'}(\rho_{i'})$ (as defined in Eq. (5)) differ on two fronts for two index providers i and i'. First, the licensing fee ρ differs, and a cheaper index implies a higher ETF profit, all else equal. Second, if index provider i has a higher brand value than i', then $\gamma_{ij} > \gamma_{i'j}$ in Eq. (2). This implies that ETF k matching with index provider i can offer a higher utility to investors and thus earn a greater profit, all else equal. The trade-off between licensing fee and brand value determines the relative magnitude of the profits $\pi_{ki}(\rho_i)$ and $\pi_{ki'}(\rho_{i'})$, which then determines the choice probability in Eq. (9).

The additional unobserved error term ξ_{ki} captures unobservable factors affecting the choice of index providers by ETF issuers, on top of the trade-off between licensing fee and brand value just discussed. For example, given the same licensing fees ($\rho_i = \rho_{i'}$) and brand value ($\gamma_{ij} = \gamma_{i'j}$), a multi-year contract between index provider i and ETF issuer j may affect the profits from choosing (or switching to) an alternative index i'.

When taking the model to the data, we assume that unobservables ξ_{ki} in Eq. (8) follow an i.i.d. type-2 extreme value distribution $G(\xi, \sigma) = e^{-(\xi\Gamma(1-1/\sigma))^{(-\sigma)}}$. Our assumption on unobservables ξ_{ki} includes an extra parameter $\sigma \in [0, \infty)$, which structurally captures the competitive landscape of index providers for ETFs. By Eq. (9) and the distribution assumption, the probability that ETF k chooses index provider i is given by

$$q_{ki}(\rho_i) = \frac{\pi_{ki}(\rho_i)^{\sigma}}{\sum_{i'=1}^{I} \pi_{ki'}(\rho_{i'})^{\sigma}}. \tag{10}$$

At one extreme of $\sigma = \infty$, ETF k chooses the index provider i that offers the highest profit $\pi_{ki}(\rho_i)$. At the other extreme of $\sigma = 0$, ETF k chooses any index provider i with equal probability, regardless of the profit $\pi_{ki}(\rho_i)$. In general, a higher σ implies a higher degree of competition among index providers.

5.3. Index providers

We now characterize the problem of index providers. Each index provider i optimally chooses the licensing fee ρ_i that maximizes its profits. The total profit of index provider i is given by

$$\pi_i = \max_{\rho_i}(\rho_i - \kappa_i)L\sum_k q_{ki}(\rho_i)s_k^*(\rho_i), \tag{11}$$

where κ_i is the marginal cost of index provider i; $q_{ki}(\rho_i)$ is the probability that ETF k chooses index provider i given by Eq. (10); and $s_k^*(\rho_i)$ is the market share of ETF k when choosing (potentially counterfactual) index provider i with licensing fee ρ_i. This market share is evaluated under the corresponding optimal choice of expense ratio $f_k^*(\rho_i)$, given by Eq. (6).

In Eq. (11), we model the costs of providing an index as the per-AUM marginal costs κ_i. These marginal costs could arise from, for example, higher operational costs for educating a larger investor base about the index and greater litigation risks.[24] In practice, there could also be fixed costs for providing an index that do not vary with AUM. We do not explicitly model these potential fixed costs, which could affect entry, and focus instead on the index providers' maximization problem, conditional on the observed market structure.

We also clarify the off-the-equilibrium-path assumption for Eq. (11) to compute the first-order condition. We assume that if index provider i offers a licensing fee $\tilde{\rho}_i$ that deviates from the equilibrium ρ_i to an ETF k, the ETF interprets this deviation as specific to itself. The ETF calculates the optimal expense ratio $f_k^*(\tilde{\rho}_i)$ and market share $s_k^*(\tilde{\rho}_i)$ using the deviated licensing fee $\tilde{\rho}_i$, assuming that all other ETFs follow the equilibrium strategy.

By Eq. (11), the first-order condition of index provider i's profits relative to licensing fees yields:[25]

$$\rho_i = \kappa_i + \underbrace{\frac{\sum_k q_{ki}(\rho_i)s_k^*(\rho_i)}{\sum_k \alpha q_{ki}(\rho_i)s_k^*(\rho_i)(1-s_k^*(\rho_i))\big(\sigma(1-q_{ki}(\rho_i))+1-s_k^*(\rho_i)\big)}}_{\text{markup}}. \tag{12}$$

Two aspects of the index provider's first-order condition are worth emphasizing. First, index providers internalize the fact that setting a higher licensing fee reduces both the probability $q_{ki}(\rho_i)$ of being selected by an ETF and the market share $s_k^*(\rho_i)$ of the ETF itself, which passes on some of the higher licensing fees to investors through higher expense ratios. Second, if ETFs are perfect substitutes (i.e., investors are perfectly elastic, $\alpha = \infty$) or if index providers are perfect substitutes ($\sigma = \infty$), licensing fees equal the marginal costs that index providers incur. In our model, although index providers do not face investors directly, the competitive landscape for ETF investors indirectly affects the optimal licensing fee of index providers.

To sum up, index providers' optimal licensing fees, ETFs' optimal expense ratios and choice of index provider, and investors' optimal ETF choices characterize the equilibrium in the ETF market.

[24] Litigation risk and fines could scale with AUM. For example, the SEC recently fined the S&P Dow Jones $9 million for failing to update the VIX index in a timely fashion. See https://www.sec.gov/news/press-release/2021-84.

[25] Appendix A provides the detailed derivation.

6. Estimation, results, and counterfactual analysis

In this section, we estimate our structural model, report results, and present counterfactual analyses.

6.1. Model estimation

We estimate the structural model using the top-20 U.S. equity ETFs (based on AUM in December 2019). The investors' outside option, which is normalized to 0, is not investing in any top-20 ETFs. Despite the increase in the number of ETFs in the last 10 years, these top-20 ETFs held almost 60% of total U.S. equity ETF AUM as of December 2019.[26]

We focus on the 20 largest ETFs for several reasons. First, the top-20 ETFs are mostly broad-market ETFs, and significant market segmentation and product differentiation exist between broad-market ETFs and smaller or more specialized ETFs (Ben-David et al., 2023). Thus, focusing on the top-20 ETFs allows us to study the impact of index providers across relatively homogeneous products. Second, our assumption that index providers offer the same licensing fees to different ETFs is less likely to be satisfied if we consider smaller and more specialized ETFs. Third, investors in ETF markets may experience search frictions, which can limit investors' knowledge of product availability (Hortaçsu and Syverson, 2004). Hence, the standard assumption that investors know the products in their choice set may be less likely to be satisfied if we include less popular ETFs. Restricting our sample to the top-20 ETFs alleviates this concern, as investors are likely aware of and able to compare the top ETFs.[27] Note that our results are not sensitive to this particular choice. In Appendix C, for example, we obtain similar conclusions using the top-50 ETFs, which in aggregate hold more than 80% of total U.S. equity ETF AUM.

We use a monthly panel from January 2010 through December 2019, and we estimate the model in several steps.

Step 1. In the first step, we estimate investors' preferences. The logit demand system in Eq. (4) results in the following linear regression specification:

$$\ln(s_{kt}) = -\alpha f_{kt} + \beta X_{kt} + \gamma_{ij} + \gamma_t + \xi_{kt}, \tag{13}$$

where we also include fixed effects for time (month-year) t to absorb the outside option. In the estimation of Eq. (13), we control for ETF issuer and index provider time-invariant quality with fixed effects γ_{ij}. Changes in unobserved ETF quality (ξ_{kt}) that are correlated with contemporaneous changes in expense ratios (f_{kt}) could, however, be a source of bias for our estimates. For example, if an ETF expects a negative shock to its own quality ξ_{kt}, it may reduce the expense ratio f_{kt} as a response. This endogeneity causes the OLS estimate of α to be biased downward.

To address this endogeneity concern, we adopt an instrumental variable approach. Specifically, we instrument expense ratios with: (i) the average expense ratios of other ETFs in other categories of non-top ETFs offered by the same index provider; (ii) the number of ETFs in other categories of non-top ETFs offered by the same ETF issuer; and (iii) the interactions between the two. These instruments are likely to be exogenous to an ETF's own quality ξ_{kt} because we explore variations in other ETFs of the same index provider or ETF issuer. To mitigate the endogeneity concern of ETFs competing for customer demand, we deliberately use variations of *non-top ETFs in other categories*, as these ETFs are less likely to directly compete with our given ETF k. This choice is motivated by Ben-David et al. (2023), who document significant investor segmentation in ETF markets, especially between larger broad-market ETFs and smaller thematic ETFs.

The intuition for our first instrument is that variations in expense ratios of other ETFs using the same index provider likely reflect common shocks to the index provider's licensing fees, which then affect the ETF's expense ratio f_{kt}.[28] The idea for the second instrument is that issuers that offer more ETFs could potentially spread fixed operational costs across multiple ETFs, resulting in a lower average marginal cost per ETF, which is passed on to investors through a lower expense ratio f_{kt}.

Step 2. In the second step, we estimate ETFs' cost parameters. Using the estimated investors' demand parameters, together with observed expense ratios and market shares, we can back out the marginal cost of ETF k at time t from Eq. (6), as follows:

$$c_{kt} = f_{kt} - \frac{1}{\hat{\alpha}(1 - s_{kt})}, \tag{14}$$

where $\hat{\alpha}$ represents the estimated coefficients on expense ratios, and f_{kt} and s_{kt} are the observed equilibrium expense ratios and market share of ETF k, respectively. We then project estimated marginal costs on index-provider, ETF-issuer, and time fixed effects as follows:

$$c_{kt} = \gamma_i^c + \gamma_j^c + \gamma_t^c + \omega_{kt}, \tag{15}$$

where γ_i^c, γ_j^c, and γ_t^c are index-provider, ETF-issuer, and time fixed effects, respectively; and ω_{kt} is a structural error term capturing unobservable determinants of costs.

Step 3. This third step is the most challenging because licensing fees ρ_{it} are also unobservable in most cases.[29] Our hand-collected data set of licensing fees contains only

[26] In Fig. B.1 in Appendix B, we plot the distribution of market shares of the 20 largest ETFs as of December 2019. These ETFs are used in our structural estimation.

[27] An alternative approach for modeling investor demand for ETFs could be a search model along the lines of Hortaçsu and Syverson (2004). Given our main question of interest—understanding the role of large index providers' brand value and licensing fees for the equilibrium in the ETF market—we think that a discrete choice approach with differentiated ETFs, whose heterogeneity is a function of index providers, is a reasonable and transparent approach.

[28] This idea resembles the common approach in industrial organization research to use the price of a specific brand in other cities as an instrument for the price in a given city, under the assumption that the correlation in prices is due to common marginal costs (Nevo, 2001; Hausman, 2008).

[29] As noted in the introduction, licensing fees are disclosed voluntarily. In the standard inversion of the first-order conditions, prices are observable and, together with estimated markups, allow us to back out marginal costs. We adopt this approach in the second step of the estimation to infer ETFs' marginal costs using observable expense ratios (see Eq. (14)).

about 10% of ETFs, so we cannot directly use the observed licensing fees because of potential selection biases. Instead, we use the following structural approach to back out licensing fees.

Most notably, we assume that the fixed effects on index providers γ_i^c in Eq. (15) capture the effect of licensing fees on ETF's marginal costs. This identifying assumption is consistent with our model that each index provider i charges the same licensing fee ρ_{it} to different ETFs.[30] The same index provider can in principle charge differential licensing fees for different category of indexes to different ETF issuers (for example, more specialized indexes may have a higher licensing fee than broad-market indexes). As discussed above, our focus on the top-20 ETFs alleviates this concern, as these top ETFs track broad-market indexes.

The fixed effect estimates of index providers give only the *relative* magnitude of licensing fees. We then use our estimates in Section 4.3 to pin down the average level of licensing fees ρ_{it} in each period t. Specifically, we assume:

$$\rho_{it} = \tau_t + \widehat{\gamma}_i^c, \tag{16}$$

where $\widehat{\gamma}_i^c$ is the estimated index-provider fixed effect from the ETF-marginal-cost regression (15). For each month t, we choose parameter τ_t such that the AUM-weighted average fraction of licensing fees over expense ratios equals the empirical estimates reported in column (1) of Table 7. This AUM-weighted average fraction of licensing fees over expense ratios, which is about one-third, is the only input from our hand-collected data on licensing fees that goes into our structural estimation. Despite possible selection biases on whether an ETF discloses licensing fees, we believe that the average fraction is likely to be close to one-third in the full sample.

Step 4. With estimated ρ_{it}, we then identify the structural parameter σ via maximum likelihood. Most notably, for each period t, we construct the log-likelihood of observing ETFs choosing their index providers:

$$\mathcal{L}_t = \sum_k \sum_i \mathbb{I}_{kit} (\log(q_{kit}(\rho_{it}))), \tag{17}$$

where $\mathbb{I}_{kit}$ is an indicator variable that equals one if ETF k chooses index provider i in month t, and zero otherwise, and the probability q_{kit} is given by Eq. (10). As we have discussed after Eq. (9), our model captures ETF's trade-off between index providers' licensing fees and brand value. Intuitively, our maximum likelihood estimation is asking whether ETF is choosing the index with the best trade-off between licensing fees and brand value. The closer the actual choice is to the model-implied optimal, the higher σ we would estimate.

To calculate q_{kit}, we need to compute the (counterfactual) optimal profit $\pi^*_{kt}(\rho_{i't})$ of ETF k for all possible index providers $i' = 1, \ldots, I_t$. Specifically, we use Eqs. (4) and (6) to calculate the counterfactual market share $s_{kt}(\rho_{i't})$ and optimal expense ratio $f^*_{kt}(\rho_{i't})$, respectively, when ETF k chooses index provider i'.[31] We then compute the optimal profits $\pi^*_{kt}(\rho_{i't})$ for each possible match with different index providers and construct the index provider choice probabilities given by Eq. (10).

Step 5. Finally, using the estimated structural parameters α and σ, index providers' choice probabilities $q_{kit}(\rho_{it})$, ETFs' market shares $s_{kt}(\rho_{it})$, and calibrated licensing fees ρ_{it}, we compute index providers' markup and then back out their unobservable marginal costs κ_{it}, by inverting the first-order condition given by Eq. (12).

6.2. Estimation results

In this section, we report the results obtained by estimating the structural model. Table 8 shows the results for investor demand parameters (columns (1) and (2)) and ETFs' cost parameters (column (3)).

Column (1) of Table 8 shows the OLS estimates of Eq. (13) with time fixed effects and interacted fixed effects for ETF issuers and index providers.[32] Consistent with Fig. 3, we find that higher fees are associated with a lower market share. The coefficient is highly significant with an implied elasticity of about 2.2. That is, if an ETF lowers its expense ratio by 1%, its market share will increase by 2.2%. While the interacted ETF issuers and index-provider fixed effects capture all time-invariant characteristics that can affect demand, time-varying demand shocks to specific ETFs that are correlated with expense ratios could still bias our estimates.

Hence, in column (2) of Table 8, we report the IV estimates of Eq. (13). Our first stage is strong, with an F statistic on the excluded instruments of about 29. Once we instrument for expense ratios, the coefficient increases in (absolute) magnitude, consistent with a downward bias in the OLS specification. The average elasticity to ETF expense ratios is about 3.0. Table B.4 in Appendix B reports a robustness using lagged expense ratios at different horizon rather than contemporaneous expense ratios. The results are robust.

Column (3) of Table 8 shows the estimates from Eq. (15). The dependent variable is the marginal costs at the ETF-month level. We find an average marginal cost of about 7.4 bps. In the regression, our aim is to capture the impact of licensing fees. We therefore control for time fixed effects and ETF-issuer fixed effects to isolate the effect of index providers. We find that S&P Dow Jones is associated with the lowest ETF marginal costs, followed by CRSP. FTSE Russell and MSCI have the highest and second-highest marginal costs, respectively. Given that marginal cost $\widehat{\gamma}_i^c$ reflects the relative level of licensing fees ρ_i as in Eq. (16), this ranking also applies to licensing fees. That

[30] There may be other costs when ETFs interact with index providers, such as infrastructure costs of ETFs tracking specific indices. However, these costs are likely to be small relative to the licensing fees.

[31] Some Index Provider × ETF Issuer interacted fixed effects γ_{ij} cannot be estimated from regression (13) because the corresponding index providers and ETF issuers do not match with each other (see Table 3). To address this issue, we regress the observed interacted fixed effects on separate fixed effects ($\gamma_{ij} = \gamma_i + \gamma_j + \psi_{ij}$) and use this regression to estimate unobserved interacted fixed effects, which are used to calculate counterfactual market shares and expense ratios.

[32] Fig. B.3 in Appendix B reports the estimated fixed effects on the interaction of ETF issuer and index provider.

Table 8
Structural parameters

	Investors demand parameters Dep Var: Market share (log)		ETF cost parameters Dep Var: Marginal costs (bps)
	(1) OLS	(2) IV	(3)
Expense ratio (bps)	−0.197***	−0.261***	
	(0.006)	(0.030)	
CRSP			3.512***
			(0.180)
FTSE Russell			8.583***
			(0.189)
MSCI			7.489***
			(0.198)
NASDAQ			5.709***
			(0.180)
FE year-month	Yes	Yes	Yes
FE ETF issuer × IP	Yes	Yes	
FE ETF issuer			Yes
Control	Yes	Yes	
Elasticity to expense ratio	2.24	2.97	
First-stage F stat		28.72	
Mean dep. var.	−3.92	−3.92	7.37
SD dep. var.	0.82	0.82	5.54
R^2	0.66	0.63	0.81
Observations	2,100	2,100	2,100

Table 8 reports the structural parameters for investor demand from Eq. (13) and ETF marginal costs from Eq. (15). In columns (1) and (2), the dependent variable is the (log) market share. We also include the past-12-month average returns as a control. For column (3), the dependent variable is ETF marginal costs in basis points. The excluded dummy for index providers is the S&P Dow Jones. Heteroskedasticity robust standard errors are shown in the parentheses.

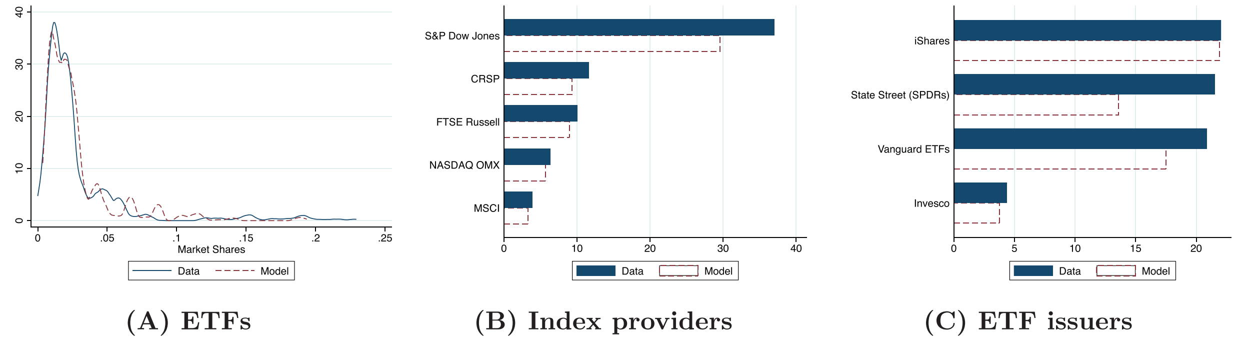


Fig. 4. Market shares: data and model. Panel (a) of Fig. 4 shows the market shares of ETF in the data and in the model; Panel (b) shows the market shares of index providers in the data and in the model; Panel (c) shows the market shares of ETF issuers in the data and in the model.

is, S&P Dow Jones has the lowest licensing fees, CRSP has the second-lowest, and FTSE Russell and MSCI charge the highest licensing fees.[33]

We also show some measures of model fit in Fig. 4. Panel (a) shows that our model captures the variation in ETF market shares well. In Panel (b), we sum across all ETFs for the same index providers. Our model captures the ranking across index providers correctly, despite slightly under-predicting the market shares of some of the largest ETFs. Finally, in panel (c), we sum all ETFs for the same ETF issuer. Our model matches the market shares of iShares and Invesco precisely, while it under-predicts the market share of State Street. Overall, our model fits the data reasonably well.

Table 9 presents the main estimation results. We report the results using the cross section of the model in December 2019.[34] The first column of Table 9 shows the baseline estimates. The structural parameter σ, which governs the competition among index providers, is 0.53 with a standard error of 0.25. By Eq. (10), we have:

$$\sigma = \frac{\ln(q_{ki}(\rho_i)) - \ln(q_{ki'}(\rho_{i'}))}{\ln(\pi_{ki}(\rho_i)) - \ln(\pi_{ki'}(\rho_{i'}))}. \tag{18}$$

[33] These findings are consistent with the interview of a former asset manager in New York: "MSCI is famous for being expensive—not because they have better data or indices, but because they are the brand that is most used in the world" (Petry et al., 2021).

[34] The results are similar when using different time snapshots.

Table 9
Baseline results and counterfactual analysis

	Baseline	Supply-side: Entry of new competitive IP				Demand-side: Increase ETF profit elasticity						Increase investor demand elasticity			
	$\sigma=0.53$	Average cost		Minimum cost		$\sigma=1$		$\sigma=5$		$\sigma=\infty$		$\alpha=0.6$		$\alpha=\infty$	
	level (1)	level (2)	Δ (%) (3)	level (4)	Δ (%) (5)	level (6)	Δ (%) (7)	level (8)	Δ (%) (9)	level (10)	Δ (%) (11)	level (12)	Δ (%) (13)	level (14)	Δ (%) (15)
Panel A: Index providers															
Marginal costs (bps)	1.6	1.6	0.0	1.6	0.0	1.6	0.0	1.6	0.0	1.6	0.0	1.6	0.0	1.6	0.0
Licensing fees (bps)	4.4	4.4	-0.2	4.4	-0.9	3.9	-12.2	2.8	-37.3	1.6	-63.4	3.0	-32.6	1.6	-63.4
Markups (bps)	2.8	2.8	-0.4	2.8	-1.4	2.3	-19.3	1.2	-58.8	0.0	-100.0	1.4	-51.5	0.0	-100.0
Lerner index (%)	63.4	63.3	-0.1	63.1	-0.5	58.3	-8.0	41.6	-34.3	0.0	-100.0	45.7	-28.0	0.0	-100.0
Panel B: ETFs															
Marginal costs (bps)	5.4	5.4	-0.2	5.4	-0.7	4.9	-10.0	3.8	-30.6	2.6	-52.0	4.0	-26.7	2.6	-52.0
Expense ratios (bps)	9.3	9.3	-0.1	9.3	-0.4	8.8	-5.8	7.7	-17.6	6.5	-29.8	5.7	-39.2	2.6	-72.1
Markups (bps)	3.9	3.9	-0.0	3.9	-0.0	3.9	0.1	3.9	0.4	3.9	0.9	1.7	-56.4	0.0	-100.0
Lerner index (%)	42.0	42.0	0.1	42.1	0.4	44.6	6.2	51.1	21.8	60.3	43.7	30.1	-28.3	0.0	-100.0

Table 9 reports several variables of interest for December 2019 in the baseline case and counterfactual scenarios. The Lerner index is defined as the difference between the price and marginal costs divided by the price. We calculate expense ratios, licensing fees, marginal costs, markups, and the Lerner index for each ETF, and then report the average of each variable across ETFs. For supply-side counterfactuals, we consider the effect of entry by a new competitive index provider that charges licensing fees equal to its marginal cost, which is set to the average or minimum cost of all existing index providers. For demand-side counterfactuals, we consider the effect of varying σ to 1, 5, and ∞ and varying α to 0.6 and ∞. For each counterfactual scenario, we also report the percentage change in the variables compared to the baseline scenario.

Hence, if an index provider i can offer a 1% higher profit for ETFs than another index provider i', the probability that the ETF chooses index provider i is only 0.53% higher than the probability that the ETF chooses index provider i'. If index providers were perfectly competitive, index provider i should be always be chosen over i' ($\sigma=\infty$). Such a low elasticity implies very limited substitutability across index providers, consistent with index providers having significant market power. Additionally, if index providers and ETFs have a sticky and persistent relationship, high switching costs would also lead to a low σ in our static model.

As we can see from Panel A of Table 9, the licensing fees charged by index providers are about 4.4 bps on average. Out of the 4.4 bps, our model shows that only 1.6 bps can be attributed to index providers' marginal costs, with the remaining 2.8 bps due to markups. As a result, index providers experience very high margins, with a Lerner index (= markup / licensing fees) of 63.4%. Although our model does not calibrate the Lerner index, our estimate is aligned with the Times (2019), which estimates the profit margin of the top three index providers to be about 65% as of 2019.

In Panel B of Table 9, we report results for the ETF variables. Index licensing fees, which are on average 4.4 bps, constitute the biggest part of ETFs' marginal costs, which are about 5.4 bps.[35] ETFs also charge an expense ratio of about 9.3 bps on average, which leads to a markup of about 3.9 bps. As a result, the Lerner index (= markup / expense ratios) is about 42% for ETF issuers. This percentage also aligns with the estimated profit margin of ETF issuers (Times, 2021).

Overall, the baseline evidence shows that index providers charge high markups in their index licensing fees. These high licensing fees increase the marginal costs of ETFs and are passed on to investors through increased expense ratios. In what follows, we use our model to study several counterfactual scenarios. The counterfactual analyses guide us on ways to understand and address index providers' market power.

6.3. Counterfactual analysis: Entry of a new competitive index provider

We first simulate the entry by a new competitive index provider. As we have shown in Table 2, only five index providers control 95% of the market share. Given the highly profitable index-providing business, one may wonder whether some new index provider could be incentivized to enter the market and increase competition. Even when ETFs keep their existing partnerships with index providers, the entry of a new index provider could still exert downward pressure on index licensing fees through the outside-option effect. We quantitatively assess this argument through the lens of our model.

[35] The ratio of licensing fees (4.4 bps) over expense ratios (9.3 bps) is about 47% because we report simple average in the table. In the estimation, we calibrate the AUM-weighted average ratio to 35.7%, as reported in Table 7.

Specifically, we make the following assumptions about the new entering index provider. First, we assume that the index provider has the average brand value of existing index providers. Second, we consider the case in which the new index provider's marginal costs are the average of all other index providers, as well as an alternative case in which the new index provider's marginal costs are the minimum of all other index providers. Third, we assume that the entrant index provider charges a licensing fee that equals to its marginal cost. This assumption is realistic if the new entrant's goal is to attract market shares from incumbents by making a competitive offer. Additionally, we recompute the new licensing fees and corresponding ETF market equilibrium, preserving the matching between existing ETFs and index providers, such that the new index provider affects the equilibrium only through the outside option effect. We discuss in detail the algorithm to compute the equilibrium in Appendix D.

In column (2) of Table 9, we report the counterfactual results following the entry of the new competitive index provider. We see that the equilibrium barely changes, with licensing fees declining by only 0.2% and expense ratios by only 0.1% (column (3)). Column (4) reports the results when the new index provider has the lowest marginal cost among all existing index providers. The magnitudes are slightly larger, given the more attractive pricing by the new entrant, but still small. As a result of entry, licensing fees decline by less than 1% and expense ratios by 0.4%.

The very limited effect of entry in this market might look puzzling at first, but it makes sense once we understand how uncompetitive the index provider market is. Recall that our estimate of the parameter that governs the competition among index providers ($\sigma = 0.53$) is close to that in a perfectly uncompetitive market ($\sigma = 0$).[36] In such a market, any outside option effect, which arises from the ETF's profit-maximization incentives, is ineffective in promoting competition.[37] Hence, in our setting, the entry of the low-price competitor index provider is ineffective, given the common low elasticity of ETFs to licensing fees. This result echoes the "generic competition paradox" in the pharmaceutical industry (Frank and Salkever, 1997; Davis et al., 2004), which has also been documented for financial products (Hastings et al., 2017).[38]

In fact, Morningstar, a prominent financial services firm that offers an array of investment research and investment management services, launched the "Morningstar Open Indexes Project" in 2016. Morningstar began offering more than 100 equity indexes for benchmarking and licensing. According to Morningstar, "The goal of the Morningstar Open Indexes Project is to lower the cost of equity indexes and improve outcomes for all investors."[39] Specifically, in the U.S. equity space, Morningstar's indexes cover all the categories, including broad-market, style, and sector indexes. In addition, Morningstar's indexes have return correlations of between 0.97 and 1 with the corresponding indexes offered by MSCI, FTSE Russell, and S&P Dow Jones.[40] Consistent with our counterfactual analysis, the launch of the Morningstar Open Indexes Project in 2016 did not lead to any meaningful changes in the licensing fees of the major index providers. Moreover, the assets tracking Morningstar equity indexes have also been minimal relative to the top five major index providers.[41]

6.4. Counterfactual analysis: Increased elasticity of ETF issuers and investors

In this second set of counterfactual analyses, we consider the effect of directly increasing the competition among index providers. The competition between index providers is governed by the parameter σ, which equals 0.53 in the baseline equilibrium. We consider three counterfactuals varying sigma, namely $\sigma = 1$, 5, and ∞. As in Section 6.3, we preserve the equilibrium matching between index providers and ETFs, and consider only the effect on equilibrium licensing fees and expense ratios. We compute the counterfactual equilibrium using the same algorithm as in Section 6.3 and discussed in Appendix D, with the assigned counterfactual σ.

Admittedly, varying the parameter governing ETF profit elasticity does not directly map to some well-defined policy. However, the counterfactual results show that increasing ETF profit elasticity is a necessary condition to increase competition among index providers. Columns (6) to (11) of Table 9 show the results for these counterfactual analyses. We see that as σ increases, index providers' markup and licensing fees significantly decrease. Doubling σ already reduces licensing fees by about 12%, while a tenfold increase leads to a decline of about 37%. In the case of perfectly competitive index providers, the licensing fees decrease from 4.4 bps to 1.6 bps (i.e., marginal costs), corresponding to a 63% decline.

The reduced licensing fees, in turn, decrease ETFs' marginal costs. In the perfectly competitive index provider case, the marginal cost decreases from 5.4 bps to 2.6 bps, a 52% decline. We also see that as σ changes, the ETFs' markups remain rather stable. This result implies that the

[36] A perfectly competitive market implies $\sigma = \infty$. A perfectly uncompetitive market, in which ETFs choose index providers without any regard to profit-maximization incentives, implies $\sigma = 0$. In such a market, the ETF's choice of certain index providers is based solely on factors unobservable to econometricians, i.e., the error term.

[37] Technically, the entry of the new index provider reduces the choice probability $q_{ki}(\rho_i)$ for any existing index provider i. As we can see from the licensing fee markup Eq. (12), the main effect of lowering $q_{ki}(\rho_i)$ is through the term $\sigma(1 - q_{ki}(\rho_i))$, which depends crucially on σ. The other effect of $q_{ki}(\rho_i)$ is the weighted-average effect that appears in both the numerator and denominator, and thus it is not important quantitatively.

[38] Hastings et al. (2017) find that the entry of a low-price government competitor can be ineffective and even have unintended consequences, leading existing fund managers to raise prices and sell only to a small inelastic consumer base.

[39] For details on the Morningstar project, see https://indexes.morningstar.com/open-index-project.

[40] For the list of Morningstar indexes and the correlations, see https://www.morningstar.com/content/dam/marketing/shared/Company/Products/Indexes/documents/Open_Index_Correlation_Fact_Sheet.pdf.

[41] BNY Mellon offers three equity ETFs using three of the Morningstar indexes, the total assets of which were less than $0.8 billion as of December 2021.

decreases in ETFs' marginal costs are passed almost one-to-one to ETF investors, through significantly decreased expense ratios. Doubling σ reduces expense ratios by almost 6%, while a tenfold increase decreases them by almost 18%. In the perfectly competitive index provider case, expense ratios decline by 2.8 bps, from 9.3 to 6.5 bps, approximately a 30% decline. Given the large amount of AUM by the top 20 ETFs, this decrease will generate approximately \$700 million in yearly savings for ETF investors.

In the last four columns of Table 9, we also study the implications of increasing the elasticity of demand from ETF investors. Doubling the elasticity of ETF investors to expense ratios (e.g., going from the baseline $\alpha = 0.26$ to $\alpha = 0.6$) leads to a decline in licensing fees by more than 30%, as index providers internalize the higher elasticity to expense ratio downstream. While the effect on index providers is similar in magnitudes to the results from increasing the elasticity of ETF issuers to $\sigma = 5$, the higher investor elasticity directly impacts the markups of ETF issuers. As a result of both lower marginal costs (due to the lower licensing fees) and lower markups, expense ratios decrease by almost 40%. In the extreme case with $\alpha = \infty$, both index providers and ETF issuers price at marginal costs, leading to a 70% reduction of expense ratios, which average 2.6 basis points.

Overall, the results in Table 9 show that index providers wield great market power and that about 60% of index licensing fees are markups, which are passed on to investors through expense ratios. As the index-provider market is highly uncompetitive, relying only on the entry of new index providers has limited effects on index licensing fees. Instead, measures that directly affect the elasticity of ETF issuers (or ETF investors) lead to reduced licensing fees, which are then pass-though to lower expense ratios.

7. Conclusion

Most ETFs passively replicate the performance of an index that is constructed and maintained by an index provider. In this paper, we provide the first analysis of the competition structure between index providers and ETF issuers and the consequences of this structure for ETF investors.

We find that the index provider market is highly concentrated and dominated by a few large players. Moreover, we find that ETF investors care about the identities of index providers, even though the identities of index providers explain little of the variation in ETF returns. We document that about one-third of ETF expense ratios are paid as index licensing fees to index providers.

Using a structural model that incorporates the two-tiered competition among index providers for ETFs and among ETFs for investors, we show that index providers wield very strong market power. We estimate that about 60% of index licensing fees are markups charged by index providers and show that improving competition among index providers can reduce ETF expense ratios by up to 30%. Our analyses suggest that the entry of new index providers has little effect on incumbent index providers and ETF investors in an uncompetitive index provider market.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The code for the paper can be found at https://doi.org/10.17632/d3fd79c9ww.3.

Appendix A. Derivations of the structural model

This appendix provides detailed derivations of formulas used for the structural model.

We derive Eq. (12). From Eq. (4), we have

$$\begin{aligned}\frac{\partial s_k(f_k)}{\partial f_k} &= \frac{1+\sum_{k'} e^{-\alpha f_{k'}+\beta X_{k'}+\gamma_{i'j'}+\xi_{k'}} - e^{-\alpha f_k+\beta X_k+\gamma_{ij}+\xi_k}}{(1+\sum_{k'} e^{\alpha f_{k'}+\beta X_{k'}+\gamma_{i'j'}+\xi_{k'}})^2} \times \frac{\partial e^{-\alpha f_k+\beta X_k+\gamma_{ij}+\xi_k}}{\partial f_k} \\ &= -\alpha s_k(f_k)(1-s_k(f_k)). \end{aligned} \tag{A.1}$$

In addition, we have

$$\begin{aligned}\frac{\partial s^*_k(\rho_i)}{\partial \rho_i} &= \frac{1+\sum_{k'} e^{-\alpha f_{k'}+\beta X_{k'}+\gamma_{i'j'}+\xi_{k'}} - e^{-\alpha f^*_k+\beta X_k+\gamma_{ij}+\xi_k}}{(1+\sum_{k'} e^{\alpha f_{k'}+\beta X_{k'}+\gamma_{i'j'}+\xi_{k'}})^2} \times \frac{\partial e^{-\alpha f^*_k+\beta X_k+\gamma_{ij}+\xi_k}}{\partial \rho_i} \\ &= \frac{1+\sum_{k'} e^{-\alpha f_{k'}+\beta X_{k'}+\gamma_{i'j'}+\xi_{k'}} - e^{-\alpha f^*_k+\beta X_k+\gamma_{ij}+\xi_k}}{(1+\sum_{k'} e^{\alpha f_{k'}+\beta X_{k'}+\gamma_{i'j'}+\xi_{k'}})^2} \times e^{-\alpha f^*_k+\beta X_k+\gamma_{ij}+\xi_k}(-\alpha)\frac{\partial f^*_k(\rho_i)}{\partial \rho_i} \\ &= -\alpha s^*_k(\rho_i)(1-s^*_k(\rho_i))\left(1+\frac{1}{\alpha(1-s^*_k(\rho_i))^2}\frac{\partial s^*_k(\rho_i)}{\partial \rho_i}\right), \end{aligned} \tag{A.2}$$

where the last equality uses Eq. (6). This equation implies

$$\frac{\partial s^*_k(\rho_i)}{\partial \rho_i} = -\alpha s^*_k(\rho_i)(1-s^*_k(\rho_i))^2. \tag{A.3}$$

Moreover, from Eq. (10) and by the envelope theorem of Eq. (5), we have

$$\begin{aligned}\frac{\partial q_{ki}(\rho_i)}{\partial \rho_i} &= \frac{\sum_{i'}\pi_{ki'}(\rho_{i'})^\sigma - \pi_{ki}(\rho_i)^\sigma}{(\sum_{i'}\pi_{ki'}(\rho_{i'})^\sigma)^2}\sigma\pi_{ki}(\rho_i)^{\sigma-1}\frac{\partial \pi_{ki}(\rho_i)}{\partial \rho_i} \\ &= \frac{\sum_{i'}\pi_{ki'}(\rho_{i'})^\sigma - \pi_{ki}(\rho_i)^\sigma}{(\sum_{i'}\pi_{ki'}(\rho_{i'})^\sigma)^2}\sigma\pi_{ki}(\rho_i)^{\sigma-1}(-L)s^*_k(\rho_i)\end{aligned}$$

Table B.1
Matching between index providers and ETF issuers: Total revenue

Panel A: From ETF issuers' perspective						
	S&P Dow Jones	CRSP	FTSE Russell	MSCI	NASDAQ	Others
iShares	45.0%	0.0%	39.0%	9.5%	3.6%	2.9%
Vanguard	14.6%	40.8%	7.5%	30.2%	6.8%	0.0%
State Street	**98.5%**	0.0%	0.4%	0.1%	0.0%	0.9%
Invesco	33.1%	0.0%	7.3%	0.0%	**51.7%**	7.8%
Schwab	**56.9%**	0.0%	42.3%	0.0%	0.0%	0.8%
Others	12.2%	0.0%	2.8%	2.3%	22.9%	**59.8%**
Panel B: From index providers' perspective						
	S&P Dow Jones	CRSP	FTSE Russell	MSCI	NASDAQ	Others
iShares	35.8%	0.0%	**82.3%**	48.3%	10.5%	8.4%
Vanguard	3.5%	**100.0%**	4.7%	45.7%	5.9%	0.0%
State Street	44.8%	0.0%	0.5%	0.4%	0.0%	1.5%
Invesco	9.1%	0.0%	5.3%	0.0%	**51.7%**	7.7%
Schwab	2.2%	0.0%	4.4%	0.0%	0.0%	0.1%
Others	4.7%	0.0%	2.8%	5.6%	32.0%	**82.3%**

Table B.1 reports matching between index providers and ETF issuers. "Others" comprise all index providers or ETF issuers other than the top five. Panel A reports the distribution of total revenue (=AUM×expense ratio) across various index providers from a given ETF issuer's perspective. Panel B reports the distribution of total revenue across various ETF issuers from a given index provider's perspective. We bold cells where the figure is above 50%. The sample period is December 2019.

$$= -\frac{L\sigma q_{ki}(\rho_i)(1-q_{ki}(\rho_i))s_k^*(\rho_i)}{\pi_{ki}(\rho_i)}$$
$$= -\frac{\sigma q_{ki}(\rho_i)(1-q_{ki}(\rho_i))}{f_k^*(\rho_i)-\rho_i-\tilde{c}_k}$$
$$= -\alpha\sigma q_{ki}(\rho_i)(1-q_{ki}(\rho_i))(1-s_k^*(\rho_i)), \tag{A.4}$$

where the last equality uses Eq. (6). Therefore, we have

$$\frac{\partial q_{ki}(\rho_i)}{\partial \rho_i}s_k^*(\rho_i)+\frac{\partial s_k^*(\rho_i)}{\partial \rho_i}q_{ki}(\rho_i)$$
$$= -\alpha q_{ki}(\rho_i)s_k^*(\rho_i)(1-s_k^*(\rho_i))\big(\sigma(1-q_{ki}(\rho_i))+1-s_k^*(\rho_i)\big). \tag{A.5}$$

Plugging this equation into the F.O.C. of Eq. (11) gives us Eq. (12).

Appendix B. Additional empirical results

In Table B.1, we replicate Table 3 but use total revenue (=AUM×expense ratio). The results are similar. In Tables B.2 and B.3, we replicate Table 3 using the snapshot in December 2013 and in December 2016, respectively. The results are again similar, suggesting that the matching between index providers and ETF issuers is stable over time.

In Fig. B.1, we report the market share of the top 20 ETFs as of December 2019, which are used in the structural estimation presented in Section 6. The combined market share of the top 20 ETFs is about 60%.

Figures B.2 and B.3 report the estimated fixed effects on ETF and the interaction of ETF issuer and index provider from the demand side estimation (13) presented in Section 6. Fig. B.2 shows the results using ETF fixed effects, which replace the interacted ETF issuer - index provider fixed effects in Eq. (13). The omitted ETF is Invesco QQQ. The ETF with the highest fixed effect is SPDR S&P 500, which is the oldest existing ETF. Other ETFs with large fixed effects are also tracking broad-based indexes, such as Vanguard Total Stock Market, Vanguard S&P 500, and iShares Core S&P 500. We estimate lower fixed effects within the top 20 for relatively more specialized ETFs, such as Vanguard Information Technology and iShares MSCI U.S. Minimum Volatility. In our demand model described in Section 6, we estimate interacted ETF issuer - index provider fixed effects, which we plot in Fig. B.3. The omitted pair is Invesco - NASDAQ, which is the combination behind the Invesco QQQ ETF.

Table B.4 reports a robustness check for the demand side estimation (13) using lagged expense ratios at different horizons rather than the contemporaneous expense ratio. In particular, we use the 1-month, 6-month, and 1-year lagged expense ratios to avoid the endogeneity concern discussed in the main text. We find that our baseline estimates are robust.

In Table B.5, we conduct an event study. We identify 20 cases in which ETF sponsors change index providers for certain ETFs in our sample. As one can see, when ETF sponsors switch from (likely) more expensive index providers to (likely) cheaper index providers (e.g., from MSCI to CRSP), ETF expense ratios almost always decrease (in 18 out of 20 such cases).[42]

We also exploit these events in a simple OLS regression to study the relation between index provider switch and expense ratios. Table B.6 shows the results. In column (1), we find that after the change to a new index provider, ETF expense ratios experience a significant decline by about 4 bps. In column (2), we control for time-invariant differences across ETF with ticker fixed effect. The point estimate is almost unaffected.

While our post-index-provider-change dummy exploits both variations over time and in the cross-section of ETFs,

[42] Comments from practitioners also seem to be consistent with this finding. For example, Vanguard explicitly said that CRSP gave it a better deal than MSCI. According to the chief investment officer of Vanguard regarding the index provider switch in 2013, "We negotiated licensing agreements for these benchmarks that we expect will enable us to deliver significant value to our index fund and ETF shareholders and lower expense ratios over time." (See https://www.morningstar.com/articles/569258/vanguard-to-switch-benchmarks-for-22-index-funds)

Table B.2
Matching between index providers and ETF issuers: December 2013

Panel A: From ETF issuers' perspective						
	S&P Dow Jones	CRSP	FTSE Russell	MSCI	NASDAQ	Others
iShares	**55.0%**	0.0%	39.6%	1.2%	1.5%	2.7%
Vanguard	10.6%	**54.3%**	4.7%	19.8%	10.7%	0.0%
State Street	**100.0%**	0.0%	0.0%	0.0%	0.0%	0.0%
Invesco	22.6%	0.0%	4.8%	0.0%	**67.2%**	5.4%
Schwab	**99.0%**	0.0%	1.0%	0.0%	0.0%	0.0%
Others	7.6%	0.0%	0.0%	1.1%	17.6%	**73.7%**
Panel B: From index providers' perspective						
	S&P Dow Jones	CRSP	FTSE Russell	MSCI	NASDAQ	Others
iShares	31.5%	0.0%	**90.6%**	9.0%	5.7%	23.6%
Vanguard	3.6%	**100.0%**	6.5%	**90.2%**	23.8%	0.0%
State Street	**58.9%**	0.0%	0.0%	0.0%	0.0%	0.1%
Invesco	3.3%	0.0%	2.8%	0.0%	**64.0%**	12.2%
Schwab	2.3%	0.0%	0.1%	0.0%	0.0%	0.0%
Others	0.4%	0.0%	0.0%	0.8%	6.5%	**64.1%**

Table B.2 reports matching between index providers and ETF issuers. "Others" comprise all index providers or ETF issuers other than the top five. Panel A reports the distribution of AUM across various index providers from a given ETF issuer's perspective. Panel B reports the distribution of AUM across various ETF issuers from a given index provider's perspective. We bold cells where the figure is above 50%. The sample period is December 2013.

Table B.3
Matching between index providers and ETF issuers: December 2016

Panel A: From ETF issuers' perspective						
	S&P Dow Jones	CRSP	FTSE Russell	MSCI	NASDAQ	Others
iShares	**53.7%**	0.0%	37.1%	4.4%	1.7%	3.0%
Vanguard	17.6%	**51.4%**	5.8%	19.2%	6.0%	0.0%
State Street	**99.6%**	0.0%	0.3%	0.0%	0.0%	0.1%
Invesco	36.1%	0.0%	6.9%	0.0%	**52.0%**	5.0%
Schwab	**91.4%**	0.0%	8.6%	0.0%	0.0%	0.0%
Others	10.7%	0.0%	1.5%	5.7%	20.4%	**61.8%**
Panel B: From index providers' perspective						
	S&P Dow Jones	CRSP	FTSE Russell	MSCI	NASDAQ	Others
iShares	32.0%	0.0%	**84.2%**	21.9%	9.0%	24.0%
Vanguard	8.1%	**100.0%**	10.1%	**74.2%**	23.9%	0.0%
State Street	**50.4%**	0.0%	0.6%	0.0%	0.0%	0.9%
Invesco	4.2%	0.0%	3.1%	0.0%	**52.7%**	7.8%
Schwab	4.5%	0.0%	1.6%	0.0%	0.0%	0.0%
Others	0.9%	0.0%	0.5%	3.9%	14.5%	**67.3%**

Table B.3 reports matching between index providers and ETF issuers. "Others" comprise all index providers or ETF issuers other than the top five. Panel A reports the distribution of AUM across various index providers from a given ETF issuer's perspective. Panel B reports the distribution of AUM across various ETF issuers from a given index provider's perspective. We bold cells where the figure is above 50%. The sample period is December 2016.

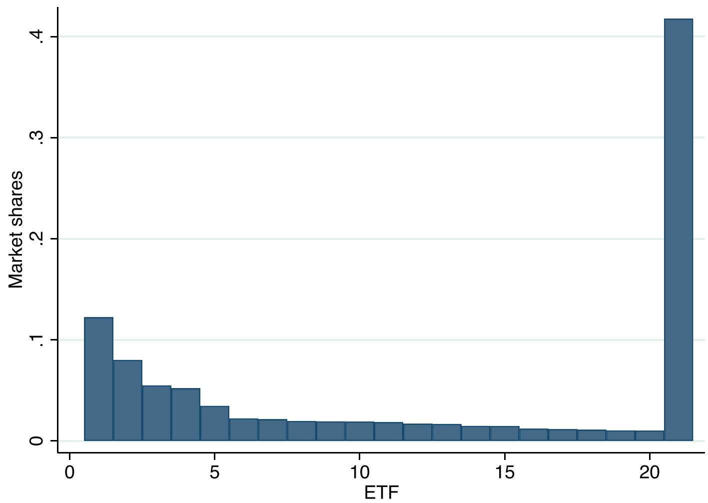


Fig. B.1. Market share of top 20 ETFs. Fig. B.1 shows the market share of the top 20 ETFs as of December 2019, which are used in the structural estimation presented in Section 6. The x-axis shows the market share rank of each ETF. The combined market share of ETFs outside the top 20 is about 42%, as also shown in the rightmost bar of the figure.

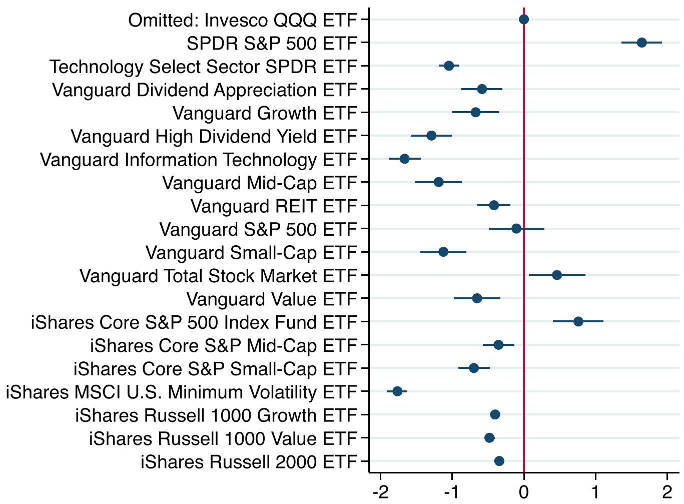


Fig. B.2. Fixed effects for top 20 ETFs. Fig. B.2 shows the estimated fixed effects from Eq. (13) where we replace the interacted ETF issuer - index provider fixed effects with ETF fixed effects.

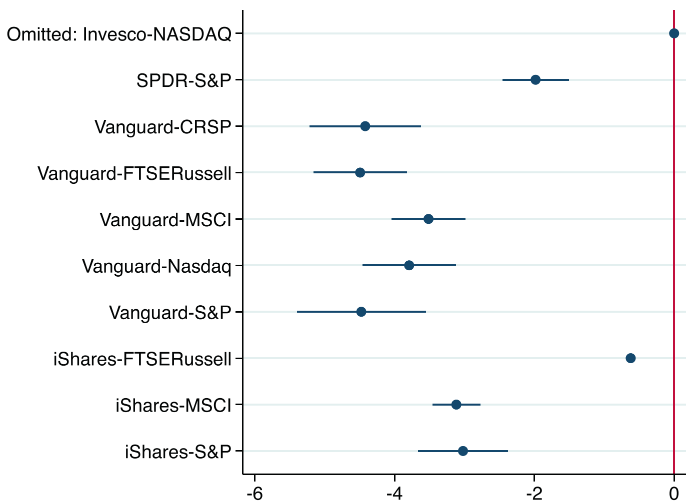


Fig. B.3. Fixed effects for ETF issuer - Index provider pairs. Fig. B.3 shows the estimated interacted ETF issuer - index provider fixed effects from Eq. (13): γ_{ij}.

the period we study has experienced a general decline in expense ratios. For this reason, in column (3) of Table B.6, we include year-fixed effects that absorb the overall industry trend. The point estimate capturing the effect of the index provider change is now lower in magnitude, at about 2 bps, and the effect remains strongly statistically significant.

Appendix C. Robustness checks using the top 50 ETFs

In this section, we present the structural estimation results using the top 50 ETFs as of December 2019, while taking remaining ETFs as an outside option.[43]

[43] We in fact use 49 of the top 50 ETFs. We exclude one that uses the index provided by Morningstar, a non-top-five index provider. All of the other 49 ETFs use one of the top five index providers: S&P Dow Jones, CRSP, FTSE Russell, MSCI, or NASDAQ.

In Table C.1, we present the results using the top 50 ETFs for investor demand parameters (columns (1) and (2)) and ETFs' cost parameters (column (3)). The parameter estimates are similar to those using the top 20 ETFs, as reported in Table 8.

Table C.2 presents the main estimation results and counterfactual analysis using the top 50 ETFs. Similar to the results based on the top 20 ETFs, index providers on average charge a licensing fee of 4.0 basis points (bps). The markup charged by index providers is about 3.1 bps. As a result, the Lerner index of index providers is about 79%. ETF expense ratios on average are 12.9 bps. The markup charged by ETFs is at around 2.7 bps. As a result, the Lerner index for ETFs are about 21%. For the supply-side counterfactual analysis, we see that the entry by a new competitive index provider has little effect in equilibrium, similar to the results based on the top 20 ETFs. For demand-side counterfactual analysis, we see that increas-

Table B.4
Structural demand parameters: Robustness

	Baseline	Robustness		
	(1)	(2)	(3)	(4)
Expense ratio (bps)	-0.197*** (0.006)			
Expense ratio (bps) - lag 1 month		-0.195*** (0.006)		
Expense ratio (bps) - lag 6 months			-0.186*** (0.005)	
Expense ratio (bps) - lag 12 months				-0.178*** (0.005)
FE year-month	Yes	Yes	Yes	Yes
FE ETF issuer × IP	Yes	Yes	Yes	Yes
Elasticity to expense ratio	2.24	2.22	2.13	2.07
Mean dep. var.	-3.92	-3.92	-3.92	-3.92
SD dep. var.	0.82	0.81	0.81	0.81
R^2	0.66	0.66	0.67	0.68
Observations	2100	2098	2098	2098

Table B.4 reports the structural parameters for investor demand from equation 13. The dependent variable is the (log) market share. We also include the past-12-month average returns as a control. Heteroskedasticity robust standard errors are shown in the parentheses.

Table B.5
Case study: ETF expense ratio before and after the change of index providers

Ticker	Issuer	Month	Pre Index	Post Index	Pre ER	Post ER
VB	Vanguard	Jan 2013	MSCI US Small Cap	CRSP US Small Cap	10 bps	9 bps
VBK	Vanguard	Apr 2013	MSCI US Small Cap Growth	CRSP US Small Cap Growth	10 bps	9 bps
VBR	Vanguard	Apr 2013	MSCI US Small Cap Value	CRSP US Small Cap Value	10 bps	9 bps
VO	Vanguard	Jan 2013	MSCI US Mid Cap	CRSP US Mid Cap	10 bps	9 bps
VOT	Vanguard	Apr 2013	MSCI US Mid Cap Growth	CRSP U.S. Mid Cap Growth	10 bps	9 bps
VOE	Vanguard	Apr 2013	MSCI US Mid Cap Value	CRSP U.S. Mid Cap Value	10 bps	9 bps
VV	Vanguard	Jan 2013	MSCI US Prime Market	CRSP US Large Cap	10 bps	9 bps
VUG	Vanguard	Apr 2013	MSCI US Prime Market Growth	CRSP US Large Growth	10 bps	9 bps
VTV	Vanguard	Apr 2013	MSCI US Prime Market Value	CRSP US Large Value	10 bps	9 bps
MGC	Vanguard	Jan 2013	MSCI US Large Cap	CRSP US Mega Cap	12 bps	11 bps
MGK	Vanguard	Apr 2013	MSCI US Large Cap Growth	CRSP US Mega Cap Growth	12 bps	11 bps
MGV	Vanguard	Apr 2013	MSCI US Large Cap Value	CRSP US Mega Cap Value	12 bps	11 bps
VTI	Vanguard	Jun 2013	MSCI US Broad Market	CRSP U.S. Total Market	10 bps	9 bps
SMLV	State Street	Dec 2016	Russell 2000 Low Vol	SSGA US Small Cap Low Vol	12 bps	12 bps
LGLV	State Street	Dec 2016	Russell 1000 Low Vol	SSGA US Large Cap Low Vol	12 bps	12 bps
IUSG	iShares	Jan 2017	Russell 3000 Growth	S&P 900 Growth	8 bps	5 bps
IUSV	iShares	Jan 2017	Russell 3000 Value	S&P 900 Value	8 bps	5 bps
SPLG	State Street	Nov 2017	Russell 1000	SSGA Large Cap	10 bps	3 bps
SPSM	State Street	Nov 2017	Russell 2000	SSGA Small Cap	10 bps	5 bps
SPTM	State Street	Nov 2017	Russell 3000	SSGA Total Stock Market	10 bps	3 bps

Table B.5 identifies the cases of index provider switch among the ETFs in our sample. Ticker is the ETF ticker; Issuer is the ETF issuer; Month is the change month; Pre Index and Post Index are the indexes before and after index change, respectively; Pre ER and Post ER are the expense ratios in the year before and the year after the index changes, respectively.

Table B.6
Case study: Regression for ETF expense ratio after index provider change

	Expense ratio		
	(1)	(2)	(3)
Post Index Provider Change	-3.81*** (0.29)	-3.79*** (0.25)	-1.91*** (0.43)
FE ticker	No	Yes	Yes
FE year	No	No	Yes
Mean dep. var.	8.42	8.42	8.42
SD dep. var.	3.24	3.24	3.24
R^2	0.33	0.72	0.86
Observations	681	681	681

In Table B.6, the dependent variable is the expense ratio in basis points. Post index provider change is a dummy equal to one after the ETF issuer change from the old to the new index provider. Standard errors are clustered at the ticker level.

ing σ significantly reduces index providers' markup and licensing fees. For example, when $\sigma = 5$, the licensing fees drop to 1.4 bps, a 64% reduction relative to the baseline case. When $\sigma = \infty$, the licensing fees drop to 0.8 bps, a 79% reduction relative to the baseline case. The reduced licensing fees decrease ETFs' marginal costs. This decrease is further passed on to ETF investors through reduced expense ratios. At the extreme of $\sigma = \infty$, the average ETF expense ratios decrease to 9.8 bps from 12.9 bps in the baseline case, a 24% reduction. Similar to the baseline results, increasing the investors' demand elasticity α also lowers the expense ratios and licensing fees.

Table C.1
Structural parameters: Based on the top 50 ETFs

	Investors demand parameters Dep Var: Market share (log)		ETF cost parameters Dep Var: Marginal costs (bps)
	(1) OLS	(2) IV	(3)
Expense ratio (bps)	-0.028***	-0.379***	
	(0.002)	(0.054)	
CRSP			-1.377***
			(0.303)
FTSE Russell			3.900***
			(0.365)
MSCI			1.927***
			(0.320)
NASDAQ			-3.631***
			(0.425)
FE year-month	Yes	Yes	Yes
FE ETF issuer × IP	Yes	Yes	No
FE ETF issuer			Yes
Elasticity to fees	0.41	5.63	
First-stage F stat		15.50	
Mean dep. var.	-4.56	-4.56	12.07
SD dep. var.	0.88	0.88	8.38
R^2	0.28	-4.74	0.53
Observations	5,096	5,096	5,096

Table C.1 reports the structural parameters for investor demand from Eq. (13) and ETF marginal costs from Eq. (15). We use the top 50 ETFs as of December 2019. In columns (1) and (2), the dependent variable is the (log) market share. We also include the past-12-month average returns as a control. For column (3), the dependent variable is ETF marginal costs in basis points. The excluded dummy for index providers is the S&P Dow Jones. Heteroskedasticity robust standard errors are shown in the parentheses.

Appendix D. Counterfactual analysis

In this section, we discuss our algorithm for finding the new equilibrium in the counterfactual analysis with the entry of the new competitive index provider, or varying parameter σ or α. We implement the following steps:

1. We start with a set of conjectured licensing fees ρ_i for all existing index providers.
2. Given the conjectured licensing fees, we compute the new marginal cost of each ETF k,

$$c_k(\rho_i) = \tilde{c}_k + \rho_i, \tag{D.1}$$

   where $\tilde{c}_k$ is the non-licensing-fee component of the ETF marginal cost. We use $\tilde{c}_k$ from the baseline estimates and hold it constant throughout the counterfactual analysis.
3. With the marginal costs $c_k(\rho_i)$, we recompute the equilibrium market share s_k and expense ratios f_k for all ETFs k by jointly solving Eqs. (4) and (6) for all ETFs.
4. We then compute the new set of licensing fees ρ_i using the equilibrium condition (12) for index providers. Doing so also requires us to compute the (counterfactual) expense ratio and market share of any ETF k matching with index provider i. The new index provider enters through the counterfactual calculation and thus alters the choice probability $q_{ki}(\rho_i)$ (see Eq. (10)).
5. We iterate through Steps 1 to 4 until the set of licensing fees ρ_i converges.

When we compute the counterfactual of changing σ or α, we follow the same algorithm, except that in Step 4, we only need to compute each ETF's potential matching with existing index providers.

Appendix E. Upper bound on index providers' market power

In this appendix, we provide an upper bound on the market power of index providers for the baseline model. Instead of estimating the unobserved licensing fees using our simplifying assumption, we consider the extreme case in which the marginal cost of ETF is entirely due to the index licensing fee. Under this extreme assumption, we can "observe" the bilaterally-negotiated licensing fee after inverting the ETFs' first-order condition and setting the licensing fee equal to the ETFs' marginal cost. This case gives the highest possible licensing fee that the data can justify, thereby providing an upper bound on index providers' market power.

Table E.1 reports several variables for index providers in the baseline and this extreme case. Licensing fees and markups of index providers increase by about one basis point relative to our baseline model. By construction, the licensing fee as a fraction of ETF marginal cost is 100% in the extreme case. Notice that this fraction is already high in our baseline model at about 82%. For this reason, there is limited room for the index providers' licensing fees to increase further. Therefore, when we allow index provider licensing fees to vary across ETFs and increase up to their full marginal costs, the Lerner index of index providers reaches 70%, which is only about 6.6 percentage points larger than our baseline model.

Table C.2
Baseline results and counterfactual analysis: Based on the top 50 ETFs

	Baseline	Supply-side: Entry of new competitive IP				Demand-side: Increase ETF profit elasticity						Demand-side: Increase investor demand elasticity			
	$\sigma=0$	Average cost		Minimum cost		$\sigma=1$		$\sigma=5$		$\sigma=\infty$		$\alpha=0.6$		$\alpha=\infty$	
	level (1)	level (2)	Δ (%) (3)	level (4)	Δ (%) (5)	level (6)	Δ (%) (7)	level (8)	Δ (%) (9)	level (10)	Δ (%) (11)	level (12)	Δ (%) (13)	level (14)	Δ (%) (15)
Panel A: Index providers															
Marginal costs (bps)	0.8	0.8	0.0	0.8	0.0	0.8	0.0	0.8	0.0	0.8	0.0	0.8	0.0	0.8	0.0
Licensing fees (bps)	4.0	3.9	-2.3	3.9	-2.3	2.5	-36.2	1.4	-63.6	0.8	-79.2	3.2	-20.1	0.8	-79.2
Markups (bps)	3.1	3.1	-2.9	3.1	-2.9	1.7	-45.7	0.6	-80.4	0.0	-100.0	2.3	-25.4	0.0	-100.0
Lerner index (%)	79.2	78.7	-0.6	78.7	-0.6	67.4	-14.9	42.8	-46.0	0.0	-100.0	73.9	-6.6	0.0	-100.0
Panel B: ETFs															
Marginal costs (bps)	10.2	10.1	-0.9	10.1	-0.9	8.8	-14.1	7.7	-24.7	7.1	-30.8	9.4	-7.8	7.1	-30.8
Expense ratios (bps)	12.9	12.8	-0.7	12.8	-0.7	11.5	-11.1	10.4	-19.5	9.8	-24.3	11.1	-13.8	7.1	-45.2
Markups (bps)	2.7	2.7	0.1	2.7	0.1	2.7	0.3	2.7	0.5	2.7	0.5	1.7	-36.7	0.0	-100.0
Lerner index (%)	20.8	20.9	0.8	20.9	0.8	23.4	12.8	25.9	24.8	27.6	32.7	15.3	-26.6	0.0	-100.0

Table C.2 reports several variables of interest for December 2019 in the baseline case and counterfactual scenarios. We use the top 50 ETFs as of December 2019. The Lerner index is defined as the difference between the price and marginal costs divided by the price. We calculate expense ratios, licensing fees, marginal costs, markups, and the Lerner index for each ETF and then report the average across ETFs. For supply-side counterfactuals, we consider the effect of entry by a new competitive index provider, which charges licensing fees equal to its marginal cost, which is set to the average or minimum cost of all existing index providers. For demand-side counterfactuals, we consider the effect of varying σ to 1, 5, and ∞ and varying α to 0.6 and ∞. For each counterfactual scenario, we also report the percentage change in the variables compared to the baseline scenario.

Table E.1
Upper bound on the market power of index providers

	Baseline	Upper bound		
	level	level	Δ	Δ (%)
Index providers				
Marginal costs (bps)	1.6	1.6	0.0	0.0
Licensing fees (bps)	4.4	5.4	1.0	22.0
Markups (bps)	2.8	3.8	1.0	34.8
Licensing fees (% ETF marginal costs)	81.9	100.0	18.1	22.0
Lerner index (%)	63.4	70.0	6.6	10.4

In Table E.1, the first column reproduces the results for the baseline fixed-fee model. The second column shows the case in which the index providers' licensing fees equal the estimated ETF marginal costs. Columns (3) and (4) show the changes relative to the baseline in level and percentages, respectively.

Appendix F. Alternative model with proportional licensing fees

In this appendix, we derive and estimate an alternative model, in which each index provider licensing fee φ_i is a fixed proportion of the expense ratio f_k of ETF k. The alternative specification accommodates the possibility of differential licensing fees offered by the same index provider i. Other features are kept the same as in the baseline model.

F1. ETF issuers

Given the choice of index provider i, the profit of ETF k, which is issued by ETF sponsor j, is:

$$\pi_{ki}(\rho_i) = \max_{f_k}(f_k(1-\varphi_i) - \tilde{c}_k)s_k L, \tag{F.1}$$

where $\tilde{c}_k$ is the non-licensing-fee part of ETF k's marginal cost. The key idea of Eq. (F.1) is that with proportional licensing fees, ETF k understands that setting a higher expense ratio f_k also increases the amount $\varphi_i f_k$ of licensing fee paid. The first-order condition of Eq. (F.1) gives

$$f_k = \underbrace{\frac{\tilde{c}_k}{1-\varphi_i}}_{\text{marginal cost}} + \underbrace{\frac{1}{\alpha(1-s_k)}}_{\text{markup}}. \tag{F.2}$$

The ETF marginal cost is computed exactly as before. However, the difference with the baseline model is that the effect of index provider on ETF marginal cost is multiplicative as in Eq. (F.2) instead of being additive as in Eq. (7).

To identify φ_i from the data, we use the estimated marginal cost c_{kt} of ETF k in month t from Eq. (14). Instead of directly using c_{kt} as the left-hand side in regression (15), we use $\ln(c_{kt})$ to account for the multiplicative effect of licensing fees φ_i on ETFs' marginal cost and estimate

$$\ln(c_{kt}) = \gamma_i^c + \gamma_j^c + \gamma_t^c + \omega_{kt}, \tag{F.3}$$

where γ_i^c, γ_j^c, and γ_t^c are index-provider, ETF-issuer, and time fixed effects, respectively; and ω_{kt} is a structural error term capturing unobservable determinants of costs. As in the baseline model, we attribute all the estimated variation

γ_i^c across index providers to licensing fee φ_i,

$$-\ln(1-\varphi_i) = \tau + \widehat{\gamma}_i^c, \text{ or equivalently, } \varphi_i = 1 - e^{-(\tau+\widehat{\gamma}_i^c)}. \tag{F.4}$$

As in the baseline model, we choose level parameter τ such that the AUM-weighted average fraction of licensing fees over expense ratios (i.e., φ_i) equals the empirical estimates reported in column (1) of Table 7.

The choice mechanism of ETF over index providers is kept the same as in the baseline model. Therefore, Eqs. (8) to (10) stay the same as before. As a result, step 4 of our estimation is also the same, with the only difference being when ETF k switches from index provider i to index provider j, the marginal cost changes from $\tilde{c}_k/(1-\varphi_i)$ to $\tilde{c}_k/(1-\varphi_j)$.

F2. Index providers

With proportional licensing fees, the total profit of index provider i in Eq. (11) now becomes

$$\pi_i = \max_{\varphi_i} L \sum_k q_{ki}(\varphi_i) s_k^*(\varphi_i)(f_k^*(\varphi_i)\varphi_i - \kappa_i), \tag{F.5}$$

where κ_i is the marginal cost of index provider i; $q_{ki}(\varphi_i)$ is the probability that ETF k chooses index provider i given by Eq. (10); and $s_k^*(\varphi_i)$ and $f_k^*(\varphi_i)$ are the market share and expense ratio of ETF k when choosing (potentially counterfactual) index provider i with licensing fee φ_i.

The first-order condition of Eq. (F.5) implies that

$$\sum_k q_{ki}(\varphi_i) s_k^*(\varphi_i)\left(f_k^*(\varphi_i) + \varphi_i \frac{\partial f_k^*(\varphi_i)}{\partial \varphi_i}\right) + \sum_k \left(\frac{\partial q_{ki}(\varphi_i)}{\partial \varphi_i} s_k^*(\varphi_i) + q_{ki}(\varphi_i)\frac{\partial s_k^*(\varphi_i)}{\partial \varphi_i}\right) \times (f_k^*(\varphi_i)\varphi_i - \kappa_i) = 0, \tag{F.6}$$

which gives

$$\kappa_i = \frac{\sum_k \left(\frac{\partial q_{ki}(\varphi_i)}{\partial \varphi_i} s_k^*(\varphi_i) + q_{ki}(\varphi_i)\frac{\partial s_k^*(\varphi_i)}{\partial \varphi_i}\right) f_k^*(\varphi_i)\varphi_i}{\sum_k \left(\frac{\partial q_{ki}(\varphi_i)}{\partial \varphi_i} s_k^*(\varphi_i) + q_{ki}(\varphi_i)\frac{\partial s_k^*(\varphi_i)}{\partial \varphi_i}\right)} + \frac{\sum_k q_{ki}(\varphi_i) s_k^*(\varphi_i)\left(f_k^*(\varphi_i) + \varphi_i \frac{\partial f_k^*(\varphi_i)}{\partial \varphi_i}\right)}{\sum_k \left(\frac{\partial q_{ki}(\varphi_i)}{\partial \varphi_i} s_k^*(\varphi_i) + q_{ki}(\varphi_i)\frac{\partial s_k^*(\varphi_i)}{\partial \varphi_i}\right)}. \tag{F.7}$$

To compute the partial derivatives in Eq. (F.6), by Eq. (F.2), we have:

$$\frac{\partial f_k^*(\varphi_i)}{\partial \varphi_i} = \frac{\tilde{c}_k}{(1-\varphi_i)^2} + \frac{1}{\alpha(1-s_k^*(\varphi_i))^2}\frac{\partial s_k^*(\varphi_i)}{\partial \varphi_i}. \tag{F.8}$$

By Eq. (4), we have:

$$\frac{\partial s_k^*(\varphi_i)}{\partial \varphi_i} = -\alpha s_k^*(\varphi_i)(1-s_k^*(\varphi_i))\frac{\partial f_k^*(\varphi_i)}{\partial \varphi_i}. \tag{F.9}$$

Jointly solving these two equations, we obtain:

$$\frac{\partial f_k^*(\varphi_i)}{\partial \varphi_i} = (1-s_k^*(\varphi_i))\frac{\tilde{c}_k}{(1-\varphi_i)^2}, \tag{F.10}$$

$$\frac{\partial s_k^*(\varphi_i)}{\partial \varphi_i} = -\alpha s_k^*(\varphi_i)(1-s_k^*(\varphi_i))^2\frac{\tilde{c}_k}{(1-\varphi_i)^2}. \tag{F.11}$$

Moreover, from Eqs. (10) and (F.2) and by the envelope theorem of Eq. (F.1), we get:

$$\begin{aligned}
&\frac{\partial q_{ki}(\varphi_i)}{\partial \varphi_i} \\
&= \frac{\sum_{i'} \pi_{ki'}(\varphi_{i'})^\sigma - \pi_{ki}(\varphi_i)^\sigma}{(\sum_{i'} \pi_{ki'}(\varphi_{i'})^\sigma)^2}\sigma \pi_{ki}(\varphi_i)^{\sigma-1}\frac{\partial \pi_{ki}(\varphi_i)}{\partial \varphi_i} \\
&= \frac{\sum_{i'} \pi_{ki'}(\varphi_{i'})^\sigma - \pi_{ki}(\varphi_i)^\sigma}{(\sum_{i'} \pi_{ki'}(\varphi_{i'})^\sigma)^2}\sigma \pi_{ki}(\varphi_i)^{\sigma-1}(-L)s_k^*(\varphi_i)f_k^*(\varphi_i) \\
&= -\frac{L\sigma q_{ki}(\varphi_i)(1-q_{ki}(\varphi_i))s_k^*(\varphi_i)f_k^*(\varphi_i)}{\pi_{ki}(\varphi_i)} \\
&= -\frac{\sigma q_{ki}(\varphi_i)(1-q_{ki}(\varphi_i))f_k^*(\varphi_i)}{f_k^*(\varphi_i)(1-\varphi_i)-\tilde{c}_k} \\
&= -\sigma q_{ki}(\varphi_i)(1-q_{ki}(\varphi_i))\frac{\alpha(1-s_k^*(\varphi_i))\tilde{c}_k + 1 - \varphi_i}{(1-\varphi_i)^2}.
\end{aligned} \tag{F.12}$$

Plugging Eqs. (F.10) to (F.12) into Eq. (F.6) gives the expression of the index provider's first-order condition for setting licensing fees φ_i, which allows us to back out the marginal cost κ_i of index providers.

Finally, to compute the counterfactual scenario with competitive index providers, we use the following algorithm. We first start with a set of conjectured licensing fees φ_i for all index providers. We then use Eq. (F.2) to compute the new marginal costs of each ETF $\tilde{c}_k/(1-\varphi_i)$. We next recompute the equilibrium market share s_k and expense ratios f_k for all ETFs k by jointly solving Eqs. (4) and (F.2) for all ETFs. We finally iterate the previous steps until each index provider marginal costs κ_i equal its equilibrium licensing fees $\varphi_i f_k$ across all ETFs that it provides indexes to.

F3. Estimation results

In Table F.1, we present the estimation results using the proportional-fee model and the counterfactual scenarios of competitive index providers. As a comparison, we also reproduce the same results for the baseline fixed-fee model in the last three columns.

We observe that the structural parameter σ that governs the uncompetitiveness of index provider market is estimated to be 0.20 in the proportional-fee model, whereas the number is 0.53 in the fixed-fee model. The standard errors of these two estimates are 0.24 and 0.25, so the estimates are not statistically different from each other.

Because the estimated σ is lower in the proportional-fee model, the index providers' marginal costs are now estimated to be 0.5 bps, while the markups are 4.0 bps. As a result, the index providers' Lerner index is now 89%, higher than our baseline estimates of 63.4%. On the other hand, we observe that the estimation results for the ETFs are similar across the two models. We also conduct the counterfactual analysis of competitive index providers. We observe that with competitive index providers, the ETFs'

Table F.1
Estimation results for the proportional-fee model

	Robustness: proportional fee			Baseline: fixed fee		
	$\sigma = 0.20$	$\sigma = \infty$		$\sigma = 0.53$	$\sigma = \infty$	
	level	level	Δ (%)	level	level	Δ (%)
Panel A: Index providers						
Marginal costs (bps)	0.5	0.5	0.0	1.6	1.6	0.0
Licensing fees (bps)	4.5	0.5	-89.0	4.4	1.6	-63.4
Markups (bps)	4.0	0.0	-100.0	2.8	0.0	-100.0
Lerner index (%)	89.0	0.0	-100.0	63.4	0.0	-100.0
Panel B: ETFs						
Marginal costs (bps)	5.5	1.6	-72.0	5.4	2.6	-52.0
Expense ratios (bps)	9.5	7.6	-19.3	9.3	6.5	-29.8
Markups (bps)	3.9	6.1	55.6	3.9	3.9	0.9
Lerner index (%)	41.3	79.6	92.7	42.0	60.3	43.7

In Table F.1, the first three columns report several variables of interest for December 2019 for the proportional-fee model. The Lerner index is defined as the difference between the price and marginal costs divided by the price. We calculate expense ratios, licensing fees, marginal costs, markups, and the Lerner index for each ETF, and then report the average of each variable across ETFs. We present the model estimation results, the counterfactual of competitive index providers, and the percentage changes. In the last three columns, we reproduce the results for the baseline fixed-fee model from Table 9.

marginal costs drop from 5.5 bps to 1.6 bps, a 72% reduction. At the same time, the ETFs' markups increase from 3.9 bps to 6.1 bps, a 56% increase. The total effect is that the ETFs' expense ratios drop from 9.5 bps to 7.6 bps, a 20% reduction. The overall decrease in the ETFs' expense ratios is broadly similar to our baseline estimate of 30%.

Nevertheless, we note that the pass-through from decreasing licensing fees to decreasing expense ratios differs between the proportional-fee and fixed-fee models. In the fixed-fee model, the pass-through is about 100%, whereas, in the proportional-fee model, the pass-through is only about 50% ($= (9.5 - 7.6)/(5.5 - 1.6)$). To understand the differential pass-through, consider a simple ETF that has a licensing fee of 30% of expense ratios. If this ETF decreases its expense ratio by 10 bps, then the licensing fee and thus its marginal cost also decreases by 3 bps, driving its markup to decrease by 7 bps. Suppose that the ETF's licensing fee decreases from 30% of expense ratios to 10%. Now if this ETF decreases its expense ratio by 10 bps, then the licensing fee and thus its marginal cost decreases only by 1 bp, causing its markup to decrease by 9 bps. Because of this differential effect on markups, when the proportional licensing fee is lower, ETFs have a smaller incentive to decrease expense ratios to compete with each other. As a result, in this alternative model, when index providers lower proportional licensing fees, the ETFs do not pass through all the reduction in the marginal costs to investors, but instead, keep a fraction of the reduction as the increased markups.

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