Index Providers: Whales Behind the Scenes of ETFs*

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Abstract

Most ETFs replicate indexes licensed by index providers. We show index providers wield strong market power and charge large markups to ETFs, which are passed on to investors. We document three stylized facts: (*i*) the index provider market is highly concentrated; (*ii*) investors care about identities of index providers, although they explain little variation in ETF returns; and (*iii*) over one-third of ETF management fees are paid as licensing fees to index providers. A structural model that incorporates two-tiered competition of index providers and ETFs suggests that 60% of licensing fees are index providers' markups. Eliminating index providers' market power can reduce ETF fees by 30%.

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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, in an interview with the Financial Times, 2019.[1]

Exchange-traded funds (ETFs) have experienced remarkable growth in recent years. According to the 2021 Investment Company Institute (ICI) Fact Book, total assets under management (AUM) in ETFs have 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, which in most cases is constructed and maintained by a designated index provider.[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."[3] Thus, most ETFs exhibit a two-tier organizational structure: (*i*) an index provider builds and maintains the index that underlies an ETF and charges index licensing fees to an ETF sponsor, and (*ii*) the ETF sponsor services ETF investors and charges management fees to ETF investors.

Figure 1 illustrates the two-tier organizational structure for the largest ETF in the world, the SPDR S&P 500 ETF (SPY), as an example. In this case, the ETF sponsor is State Street (SPDR), 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.[4] For another well-known ETF, the Invesco QQQ Trust, 9 bps out of

[1]See https://www.ft.com/content/e886b2d2-e852-3071-85c1-c9a57113d8a5.

[2]More recently, ETF sponsors started offering so-called "actively-managed" ETFs, which do not passively track indexes. Although active ETFs are growing, they are still relatively small, consisting of about 3% of the total ETF markets as of 2020.

[3]See https://www.spglobal.com/spdji/en/index-literacy/who-s-behind-the-index/.

[4]For example, in 2021 the SPY AUM totaled about $400 billion, implying that the total management fee collected by State Street from SPY is roughly $360 million, with more than $120 million paid to S&P Dow Jones in index licensing fees.

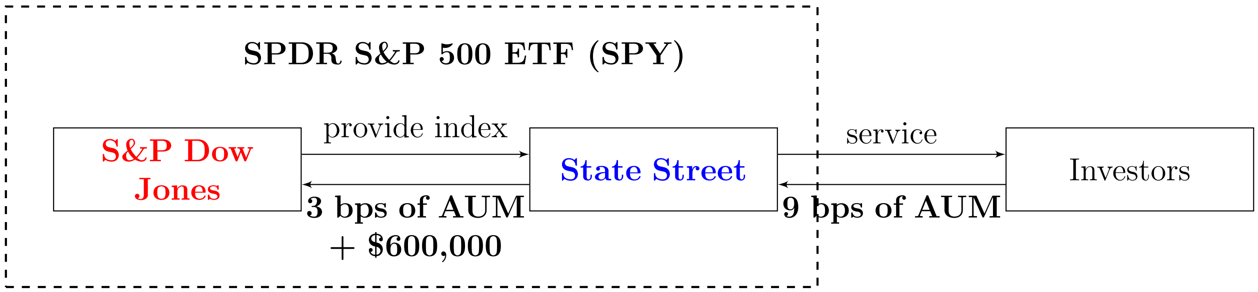


Figure 1. Two-tier organizational structure for SPDR S&P 500 ETF (SPY) as of December 2020. The ETF sponsor is State Street (SPDR). The index provider is S&P Dow Jones, which owns the underlying ETF index —the S&P 500 index. The licensing fees is 3 bps of AUM + $600,000 per year. The management fee is 9bps of AUM.

the 20 bps management fees that the ETF sponsor (Invesco) charges to ETF investors are paid in the form of licensing fees to the index provider (NASDAQ), who owns the underlying NASDAQ-100 Index.

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 sponsors 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, although index providers' identities explain little of the variation in ETF returns. We estimate that about one-third of all ETF management fees 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 sponsors are markups, and the remaining 40% of the index licensing fees reflect 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 onto ETF investors through management fees.[5] Through a counterfactual analysis, we estimate that eliminating index providers' market power can reduce ETF management fees

[5] 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.

by about 30%.

Our paper is structured in two parts. In the first part of the paper, 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.[6]

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.[7] 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."[8] 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 variations in ETF assets. Even after controlling for ETF-sponsor, time, and ETF-category fixed effects, management fees, and past returns, index providers can still explain 8% of additional variations in ETF assets. In contrast, we find that the index-provider fixed effects have literally zero explanatory power for ETF returns. This finding suggests that the brand value of index providers likely arise from more trustworthy brands or better recognition among investors. This interpretation is also consistent with the conclusion drawn in an industry report by BNY Mellon: "There is minimal difference between several index providers that serve the

[6]Markets are classified as unconcentrated if the HHI is below 1500, as moderately concentrated if the HHI is between 1500 and 2500, and as highly concentrated if the HHI is above 2500. See Section 5.3 of Horizontal Merger Guidelines (2010).

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

[8]See https://www.bloomberg.com/news/articles/2017-11-27/index-providers-rule-the-world-for-now-at-least.

U.S. and global equity markets in terms of performance; while methodology varies among indexes, those variances are largely tempered by capitalization weighting."[9]

Third, we show that a large fraction of ETF sponsors' revenues are paid to index providers in the form of index licensing fees. Specifically, we collect the first data on the licensing fees between index providers and ETF sponsors by reading all ETF filings on the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) of the SEC. Since licensing fees are disclosed by ETF sponsors on a voluntary basis,[10] only about 10% of ETFs in our sample disclose their licensing fees. Despite this limitation and possible selection bias, our novel data enable us to conduct the first analysis of ETF index licensing fees.[11]

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 remaining licensing fees 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 management fees that ETF sponsors collect from ETF investors. This fraction has also increased steadily, from 31.4% in 2010 to 35.7% in 2019. Not surprisingly, this trend leads ETF sponsors to complain about the index licensing fees.[12]

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 from the data; and (*iii*) conduct counterfactual analysis of index providers' market power and study the influence on ETF management fees paid by investors.

In our model there are a discrete number of index providers, a discrete number of ETF

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

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

[11] 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).

[12] For example, a Global Head of Vanguard was quoted by Morningstar.com, "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.

sponsors, and a continuum of investors. In the first stage, each index provider lists a licensing fee for using its index, and each ETF sponsor chooses among all available index providers to form an ETF. The competition structure is modeled using a pairwise profit augmenting technology a la Eaton and Kortum (2002). That is, if an ETF sponsor expects a higher profit from using an index provider's index, the probability that ETF sponsor chooses the index provider is higher. Because of market frictions, however, such as persistent relationships and switching costs, the ETF sponsor 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 sponsor, competes for investors. Specifically, each ETF sponsor optimally chooses the ETF management fee that maximizes its own profit. Because the index licensing agreement is signed in the first stage, each ETF sponsor treats the licensing fee as part of its marginal costs when determining ETF management fees. We model investors' choices of ETFs using a standard discrete choice framework. In line with our reduced-form facts, investors care about ETF management fees, past returns, ETF categories, as well as the identities of index providers and ETF sponsors.

We structurally estimate the model using the top twenty U.S. equity ETFs, while taking the remaining ETFs as an outside option. We choose the top twenty ETFs as of December 2019, and they hold about 60% of all U.S. equity ETF assets. We explicitly model the top twenty 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, Franzoni, Kim, and Moussawi, 2021a). It is worth noting that our results are not sensitive to this particular choice. In Appendix C, we estimate the model using the top fifty 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 profit 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 be always be chosen over 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 implied licensing fees are 4.4 bps of ETF's AUM on average, while the estimated marginal costs of index provision are 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. Aligned with our estimate, Financial Times (2019) estimates the profit margin of the top three index providers to be about 65% as of 2019. In comparison, we estimate that about 40% of management fees that investors pay to ETF sponsors reflect markups of ETF sponsors. This is also aligned with the estimated profit margin of ETF sponsors (Financial Times, 2021).

Third, we conduct two main sets of counterfactual simulations to understand the equilibrium effect of: (*i*) entry by a new competitive index provider, and (*ii*) increased elasticity of ETF sponsors to index providers licensing fees. 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 licensing and management fees almost unaffected. This result is consistent with limited effects from entry when the demand side is inelastic to prices and captured by existing brands (Davis, Murphy, and Topel, 2004; Hastings, Hortaçsu, and Syverson, 2017). Aligned with our findings, the launch of Morningstar's "Open Indexes Project" in 2016, which aimed to provide low-cost substitutes to the major index providers' equity indexes, had little effects on the equity index licensing fees.[13]

Next, we directly promote competition among index providers by increasing the elasticity of

[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 5.3 for more details of the Morningstar Open Indexes Project.

ETF sponsors to index providers licensing fees. In the benchmark case of perfect competition, index providers set licensing fees equal to their marginal costs. The top twenty ETFs, while keeping their equilibrium index providers, jointly change management fees optimally under the counterfactual licensing fees. We find that ETF marginal costs decrease by about 2.8 basis points and the markup charged by ETF sponsors is similar to that in the baseline scenario. As a result, the ETF management fees decline by 2.8 basis points, from 9.3 to 6.5 basis points, which represents a 30% reduction relative to the baseline scenario. 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 sponsors to index providers licensing fees reduce management fees by almost 6%, while a tenfold increase decrease them by almost 18%, achieving more than half of the reduction in a perfectly competitive index provider market.

Overall, our results have several potential policy implications. On the one hand, we show that lowering barriers to entry for index providers may not be effective in promoting competition, if index providers' brand value matters and long-term relationship between index providers and ETF sponsors hinder switching.[14] On the other hand, directly addressing fictions could potentially improve competition. Licensing fees are disclosed on a voluntary basis currently, but the SEC could require mandatory disclosure of such fees. Although investors do not pay the licensing fees directly, our results show that licensing fees are effectively passed on to investors through higher ETF management fees. Improved disclosure on licensing fees could help investors, regulators, and academics better understand the composition of ETF management fees, and potentially decrease them further by improving competition among index providers.[15]

[14]For example, many existing index licensing agreements are 10-year contracts (see https://www.nasdaq.com/articles/why-msci-shares-surged-10.5-in-november-2019-12-09).

[15]Although ETF management fees have been trending downwards in recent years (see, for example, Figure 6.8 of the 2021 ICI Fact Book), our results indicate that high licensing fees hinder the further reduction of management fees. Using a search model, Duffie, Dworczak, and Zhu (2017) show that greater price transparency could lead to more competitive prices.

Related literature. 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 structure of competition between index providers and ETF sponsors and to show that matching and contracting between index providers and ETF sponsors matter to the first order of ETF management fees charged to investors. Relatedly, Robertson (2019) finds that the index providers of 81 of 571 U.S. equity ETFs are affiliated with ETF sponsors (so-called "self-indexing") and that these ETFs charge relatively higher management fees. While affiliated index providers are indeed relevant to small ETFs, the large ETF sponsors and index providers, which capture over 95% of total AUM, are not affiliated with each other. Mahoney and Robertson (2021) discuss the legal aspects of index providers as investment advisers. Akey, Robertson, and Simutin (2021) show that about 20% of ETFs track proprietary indexes and these ETFs charge higher management fees but generate worse returns. Kostovetsky and Warner (2021) show that ETF benchmarks with 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 its effect on index licensing fees and ETF management fees, which are the key to our analysis, are not studied in these papers.

Our paper is also related to the recent research on the bright and dark sides of ETFs. Azar, Schmalz, and Tecu (2018) study the implications of passive investment for corporate governance and corporate power. Huang, Song, and Xiang (2020) find that index providers and ETF sponsors conduct extensive data mining when constructing smart beta indexes so as to attract investment flows, while Ben-David, Franzoni, Kim, and Moussawi (2021a) find evidence that thematic ETFs are constructed and offered to cater to investors' sentiment. Brown, Cederburg, and Towner (2021) find that ETFs that have similar returns but higher management fees and less liquid than their competitors attract excess capital, and Khomyn, Putniņš, and Zoican (2020) show that more liquid ETFs attract shorter horizon investors and charge higher management fees. Moreover, some argue that ETFs increase asset volatility and harm liquidity (e.g., Israeli, Lee, and Sridharan, 2017; Ben-David, Franzoni, and Moussawi, 2018; Da and Shive, 2018; Agarwal, Hanouna, Moussawi, and Stahel, 2019; Pan and Zeng, 2019), while others find evidence that ETFs improve market efficiency (e.g. Box, Davis, Evans, and Lynch, 2020; Glosten, Nallareddy, and Zou, 2020; Huang, O'Hara, and Zhong, 2021).

Finally, our paper contributes to the growing literature that explores the industrial organization of financial markets with structural techniques (Bao and Ni, 2017; Egan, Hortaçsu, and Matvos, 2017; Benetton, 2018; Buchak, Matvos, Piskorski, and Seru, 2018; Koijen and Yogo, 2019; Buchak, Matvos, Piskorski, and Seru, 2020). Our paper is mostly 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, MacKay, and Yang (2020), who study the ETF market with a structural demand model to infer investors' expectations from ETF demand; and Jiang (2020), who builds a quantitative model to understand how relationship lending between shadow and traditional banks affects competition in the downstream mortgage market.

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

2 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 identify its underlying index manually 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 and provide summary

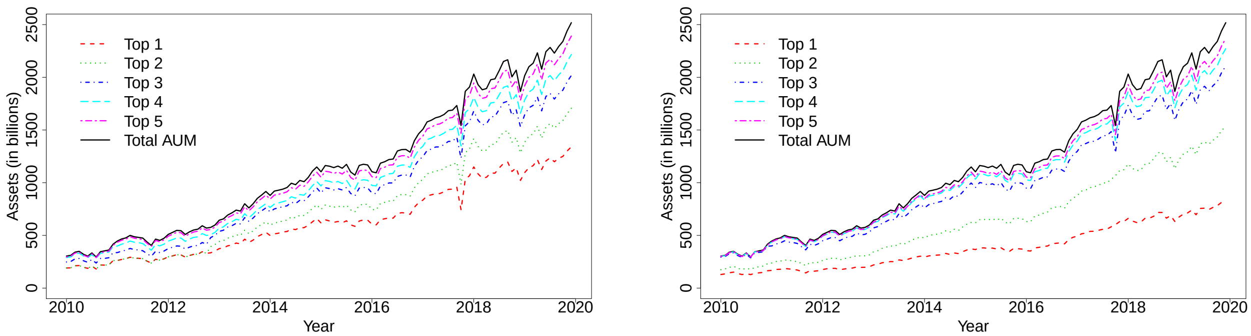
Table 1
Summary statistics

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

	Mean	SD	25th	50th	75th
Panel A: ETF level					
AUM ($ million)	2037.29	9121.63	47.70	209.16	814.13
Monthly return (%)	1.07	0.47	0.91	1.06	1.20
Management fee (%)	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 sponsor level					
Total AUM ($ million)	16939.70	68657.61	35.43	142.25	1154.38
# 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)	15635.70	77678.42	45.52	126.43	1136.98
# of ETF	5.91	18.16	1.00	1.00	3.00
# of matched ETF sponsors	1.43	1.45	1.00	1.00	1.00

statistics in Table 1.

The results reported in Panel A of Table 1 indicate the average ETF AUM of the ETFs 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 of Table 1 focuses on the 68 ETF sponsors in our sample. Each ETF sponsor offers, on average, 6.79 ETF products, which track the indexes constructed by 1.68 index providers. Panel C reports instead statistics for the 77 index providers in our sample. Each index provider has, on average, about 5.91 ETFs tracking their constructed indexes and works with 1.43 ETF sponsors. In the next section, we provide a more detailed analysis of the matching between ETF sponsors and index providers.



(A) Assets tracking the top five index providers

(B) Assets invested in the top five ETF sponsors

Figure 2. Assets related to the top five index providers and ETF sponsors. Panel (A) 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 sponsors (by AUM as of December 2019): iShares, Vanguard, State Street, Invesco, and Schwab.

3 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 no significant differences in returns among indexes constructed by various index providers; and (*iii*) about one-third of all ETF management fees are paid to index providers in the form of index licensing fees.

3.1 Concentration of the Index Provider Industry

We begin by showing that ETF markets and index markets are highly concentrated. Specifically, Figure 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 sponsors (iShares, Vanguard, State Street, Invesco, and Schwab). As we can see, the top index providers and ETF sponsors capture a very large market share. The extremely high market shares of top index providers and ETF sponsors is especially striking given that the total AUM of all ETFs has grew more than fivefold from 2010 to 2019.

Table 2

Market share of top index providers and ETF sponsors in December 2019

In this table, we provide the individual and cumulative market shares of the top five index providers and ETF sponsors in the U.S. equity ETF market as of December 2019.

Index provider			ETF sponsor		
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%

In Table 2, we also report the market share captured by the top index providers and ETF sponsors, measured by total AUM, as of December 2019. The top five index providers and the top five ETF sponsors both capture about 95% of the market. The top ETF sponsor, iShares, has captured about 33% market share, and the top index provider for U.S. equity ETFs, S&P Dow Jones, itself has captured more than 50% of the market.

To quantify market concentration, we calculate the Herfindahl-Hirschman index (HHI) of ETF sponsors and ETF index providers for each month. Over our sample period, the monthly average of the HHI of ETF sponsors 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, we show that most ETF sponsors match with one major index provider and that most index providers match with one major ETF sponsor. In Table 3, we report the matching between index providers and ETF sponsors.[16] Panel A lists the distributions of AUM across various index providers from a given ETF sponsor'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 index providers. We highlight cells that are over 50%. As can be seen, every top ETF sponsor 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

[16]The results are similar when using total revenue=AUM×management fees, and shown in Table B.1.

Table 3

Matching between index providers and ETF sponsors

In this table, we report matching between index providers and ETF sponsors. We use "others" to represent all index providers or ETF sponsors other than the top five. Panel A reports the distribution of AUM across various index providers from a given ETF sponsor's perspective. Panel B reports the distribution of AUM across various ETF sponsors from a given index provider's perspective. We highlight cells where the figure is above 50%. The sample period is December 2019.

Panel A: From ETF sponsors' 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%**

Panel B we report the distribution of AUM across various ETF sponsors 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 use iShares as ETF sponsors. With the exception of S&P Dow Jones, all other index providers rely mainly on one ETF sponsor. This matching between index providers and ETF sponsors could be caused by persistent relationships over time.

Regarding the results we report 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 sponsors and index providers is rather stable over time, because during our sample period most ETFs never switch index providers.

3.2 The Identity of Index Providers Matters for Investor Choice

We proceed now to 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 framework, and we estimate various variations of the following regression specification:

$$y_{kt} = \beta X_{kt} + \gamma_i + \gamma_j + \gamma_c + \gamma_t + \epsilon_{kt}, \tag{1}$$

where X_{kt} are characteristics of ETF k offered by index provider i and ETF sponsor j in category c and month t, and γ_i, γ_j, γ_c, and γ_t are index-provider, ETF-sponsor, 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 variable of interest, (log) AUM y_{kt} 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 sponsors are also important in capturing variation in AUM with an R^2 of around 30%. Category and time fixed effects are less important than index provider and ETF sponsor 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. Investors do not care about the identities of index providers per se but do care about index returns, which correlates with index providers. To address this concern, we include additional controls in regression (1).

In column (5) of Table 4 we show the estimate of equation (4) with ETF sponsor, category, and time fixed effects, while controlling for ETF management fees and past returns. As expected, if investor demand is downward sloping in price, higher management fees are

Table 4
Index providers matter for investor choices

This table reports the estimates of equation (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.

	Separate fixed effects				Role of index providers	
	(1)	(2)	(3)	(4)	(5)	(6)
	Index provider	ETF sponsor	Category	Time	ETF sponsor Category Time	Index provider ETF sponsor Category Time
Management fees (bps)					-0.039^{***}	-0.052^{***}
					(0.001)	(0.001)
Past 1-year return (%)					0.193^{***}	0.211^{***}
					(0.011)	(0.010)
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

associated with lower AUM. Also, consistent with Dannhauser and Pontiff (2019), higher past ETF returns are associated with higher AUM.[17] The overall R^2 is 0.43. We also report the interquartile range (IQR) as a measure of dispersion in (log) AUM. In the data the interquartile range of (log) AUM is 2.9. The interquartile range of the residuals from the 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 of column (5). After controlling for ETF sponsor, category, time, management fees, and past returns, index-provider fixed effects increases the R^2 by about 0.07, from 0.43 to 0.50. Additionally, the dispersion in the IQR of the residuals declines to 1.6, which represents an additional 10-percentage-point decline relative to the specification without index-provider fixed effects.

Overall, the results reported in Table 4 show that index providers contribute significantly to explaining dispersion in AUM. The identity of index providers matters even after control-

[17] It is well documented that investors chase past performance (e.g. Chevalier and Ellison, 1997; Ben-David, Li, Rossi, and Song, 2021b).

ling for ETF management fees and past returns, suggesting that investors value non-price characteristics of index providers such as brand reputation. Consistent with our findings, Mahoney and Robertson (2021) also find that large index providers can help to attract ETF flows.

To further understand the role of index providers we estimate equation (1) using management fees 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 management fees. The IQR of management fees 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 management fees can come from two channels: (a) index providers' licensing fees affect ETFs' costs, which are then passed on to investors via management fees and (b) index providers affects the attractiveness of ETFs to investors, which allows ETFs to charge differential management fees. We incorporate both effects in our structural model.

Panel A also shows that ETF sponsor fixed effects have considerable explanatory power with an R^2 equal to 0.67. As is the case with the results obtained using AUM as the dependent variable, here category and time fixed effects have weaker explanatory power. The R^2s for category or time fixed effects are 0.19 and 0.01, respectively. Aggregate time-series variation in fees hides much of the cross-sectional dispersion, as also documented in Ben-David, Franzoni, Kim, and Moussawi (2021a). Comparing the results reported in columns (5) and (6) shows that adding index-provider fixed effects to ETF sponsor, category, and time fixed effects raises the R^2 by about 0.08 and reduces the IQR of the residuals from 12.8 to 8.9.

Finally, Panel B studies ETF returns. In contrast to what the results for AUM and management fees imply, index-provider and ETF-sponsor fixed effects have little explanatory power for returns. 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 are time

Table 5

Index providers: fees and returns

This table reports the estimates of equation (1) with various sets of fixed effects and controls. The dependent variable for Panel A is ETF management fees. The dependent variable for Panel B is ETF monthly returns. 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.

	Separate fixed effects				Role of index providers	
	(1)	(2)	(3)	(4)	(5)	(6)
	Index provider	ETF sponsor	Category	Time	ETF sponsor Category Time	Index provider ETF sponsor Category Time
Panel A: Management fees						
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

fixed effects, which alone capture almost 50% of the variation in returns.[18]

To summarize, we find that index providers' identities: (*i*) matter for AUM even after controlling for other determinants of investors demand (e.g., management fees, past returns, ETF sponsor) and (*ii*) explain a large (tiny) fraction of dispersion in fees (returns). These findings suggest that index providers have significant brand value, which could arise from more trustworthy brands or better recognition among investors. This interpretation is also consistent with the views expressed by market participants as quoted in Petry, Fichtner, and Heemskerk (2019):"At the end of the day, those products (i.e., indexes) are homogeneous and exchangeable. It's like water, there are small differences why Evian is more expensive.

[18]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, suggesting that index providers are homogeneous in terms of the liquidity of ETFs tracking their indexes.

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!"

3.3 Analysis of Index Licensing Agreements

In this section, we provide an analysis of index licensing fees. To this end, we collect index licensing agreements and fees between index providers and ETF sponsors by manually searching ETF filings on the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) of the U.S. SEC.[19] Specifically, we look for the keywords "licensing fee" and "license fee" within the ETF prospectus. 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 effort, suffer selection bias. Nevertheless, our analysis is the first analysis on the index licensing agreements, and the qualitative properties of these agreements that we obtain likely remain robust in the full sample.

Table 6 provides a comparison of various ETF characteristics 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 management fees to investors than ETFs that do not disclose licensing fees. The return profiles of these two types of ETFs are similar.

Across the 52 ETFs for which we are able to obtain 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 out of 52 ETFs, is "max of x bps of AUM and \$y" per year. For example, consider three well-known ETFs:

- SPDR S&P 500 ETF has a licensing fee of $x = 3$ bps of AUM plus a flat fee $y = \$600,000$
- SPDR Dow Jones Industrial Average ETF has a licensing fee of $x = 4$ bps of AUM and

[19] See deHaan, Song, Xie, and Zhu (2021) for more details on EDGAR.

Table 6

Comparing ETFs with and without licensing fee disclosure

This table compares ETFs that report licensing fees and ETFs that do not report licensing fees. Specifically, we search all ETF filings on the EDGAR of the SEC. Out of the 598 ETFs in our sample, 52 ETFs report the index licensing fees.

	Mean	SD	25th	50th	75th
Panel A: 52 ETFs with licensing fees reported					
AUM ($ million)	6915.85	24682.11	213.40	714.65	3410.53
Monthly return (%)	1.00	0.40	0.89	1.05	1.16
Management fees (%)	0.50	0.23	0.19	0.60	0.66
Panel B: 546 ETFs without licensing fees reported					
AUM ($ million)	1568.37	5582.83	44.32	165.75	740.98
Monthly return (%)	1.08	0.47	0.91	1.07	1.20
Management fees (%)	0.35	0.19	0.20	0.35	0.47

no flat fee $y = \$0$

- 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. So the formula for the licensing fee for Invesco QQQ ETF is $9\text{bps} \times \min(\text{AUM}, \$25\text{b}) + 8\text{bps} \times \max(\text{AUM} - \$25\text{b}, 0)$

In Table 7, we provide summary statistics for licensing fees for each year from 2010 through 2019. As can be seen in the last two columns, 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.

Columns (1) to (3) of Table 7 further report index licensing fees as a fraction of the total ETF management fees that ETF investors pay. The ETF licensing fee is on average 21% of the ETF management fee, and the AUM-weighted average ranges from about 32% to about 36%, suggesting that larger ETFs pay out a higher fraction of total management fees to index providers. Another striking pattern revealed in Table 7 is that, as a fraction of the ETF management fee, the AUM-weighted licensing fee increases steadily over time, from about 31% in 2010 to 36% in 2019.

In summary, this section shows that index providers capture a large fraction of the total

Table 7
Analysis of licensing fees

This table 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 as a fraction of ETF management fees. Columns (4) and (5) report the fractions of licensing fees related to ETF AUM and the fractions of fixed licensing fees, respectively.

	Licensing fees as fractions of management fees			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

revenue of the ETF business. In the next section, we build a structural model to further analyze the market power of index providers.

4 A Model of Index Providers and ETF Sponsors

Based on the three stylized facts documented above, in this section, we present a structural equilibrium model of the ETF market that accounts for the two-tiered competition of index providers and ETF sponsors. 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 from the data, and (iii) conduct counterfactual analysis of index providers' market power and study the influence on ETF management fees 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 sponsor $j = 1, \ldots, J_t$ 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 sponsor, chooses an index provider
- Each ETF k sets management fees f_k
- Investors choose the ETFs in which they invest their money

In what follows, 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.

4.1 Investors

Each investor l seeks to buy one indivisible unit of an ETF. The indirect utility enjoyed by investor l for choosing ETF k that is sponsored by j with the index provided by i is given by:

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

where f_k is the management fee charged by ETF k; 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 sponsor j capture observable and unobservable characteristics such as index provider brand value and ETF sponsor quality, as well as potential synergies between index providers and ETF sponsors; 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. Given our focus on the competition between index providers for ETFs, assuming homogeneity in the error term ϵ_{lk} across ETF investor l in (2) simplifies our model. In practice, ETF investors are mostly retail investors.[20]

The identity of index provider i matters through the interaction term γ_{ij} in (2) for investors' utility. For a given ETF sponsor j, choosing an index provider i that offers a higher γ_{ij} leads

[20] Kostovetsky and Warner (2021) find that for an average ETF, retail investors hold about two thirds of shares.

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 better recognition among investors. In addition, as we have also shown in the reduced-form evidence, indexes offer by various providers have literally no differences in return profile, so we do not explicitly model the investors' portfolio allocation problem.

Investor l chooses the ETF k that delivers the highest utility among the K ETFs that are 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:

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

When taking the model to the data, we assume that unobservables ϵ_{lk} in equation (2) follow an i.i.d. type-1 extreme value distribution, as standard in discrete choice models. Hence the probability that investor l chooses to invest in ETF k is given by:

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

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: $\text{AUM}_k = \sum_l s_{lk} = s_k L$.

4.2 ETF Sponsors

ETF sponsors maximize profits by setting optimal management fees f_k for the ETFs they offer given their costs, which depend on the index provider they choose.[21]

[21] In practice, large ETF sponsors 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

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

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

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 ETF's AUM; and s_k is the market share of ETF k from equation (4). Consistent with the results reported in last two columns of Table 7, we assume that licensing fee ρ_i is paid as a percentage-of-AUM fee. In equation (5), both licensing fee ρ_i and the equilibrium market share s_k depend on index provider i, because the market share s_k implicitly depends on the interacted fixed effect γ_{ij} in equation (2).

The first-order condition of profits in equation (5) relative to management fees 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 sponsors pay a licensing fee ρ_i to index provider i as a fraction of ETF's AUM. A key assumption in (7) is that index provider i offers the same licensing fee ρ_i to different ETF k, which could have different sponsor j. We make this assumption because licensing fees are mostly unobserved, and such an assumption allows us to recover some useful variation in licensing fees (see Section 5.1 for details). In practice, index licensing agreements are signed bilaterally,

sponsor. We leave the investigation of multi-product strategies adopted by ETF sponsors to future research.

and index provider i can in principle offer different licensing fees to different competing ETF sponsors. Estimating such a model would require finer and more complete information on licensing fees, which is beyond our hand-collected data.

In equilibrium, the licensing fees are optimally chosen by index providers, and ETF sponsors choose between various providers. We model this choice parsimoniously using a pairwise profit augmenting technology a la Eaton and Kortum (2002), which has also recently being applied by Jiang (2020) in structural work on the U.S. mortgage market. Formally, ETF k chooses among index providers $i = 1, \dots, I$ to maximize its total profits:

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

where $\pi_{ki}(\rho_i)$ are the profits conditional on choosing index provider i given in equation (5) and ξ_{ki} is an unobserved error term, capturing additional ETF k's 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:

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

When taking the model to the data, we assume that unobservables ξ_{ki} in equation (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. Specifically, 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 between index providers.

4.3 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 that chooses index provider i given by equation (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 management fee $f_k^*(\rho_i)$ given by (6).

In (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.[22] 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.

The implicit assumption underlying (11) is that each ETF k observes only the licensing fee contracts offered by various index providers to itself, but not to other ETFs. This is reasonable because, in practice, index agreements are rarely disclosed (see Section 3.3). Under this assumption, if index provider i offers a licensing fee $\tilde{\rho}_i$ that deviates from equilibrium ρ_i to an ETF k, the ETF interprets this deviation as specific to itself. ETF k calculates the optimal (counterfactual) management fee $f_k^*(\tilde{\rho}_i)$ and market share $s_k^*(\tilde{\rho}_i)$ using the deviated licensing fee $\tilde{\rho}_i$, but assumes that other ETFs' index provider matching and management fees

[22]For example, SEC recently fined 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.

remain as equilibrium outcomes.

The first-order condition of index provider i's profiting from equation (11) relative to licensing fees yields

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

Appendix A provides the detailed derivation.

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 in terms of higher management fees. 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 pay. In our model, although index providers do not face investors directly, the competitive landscape α for ETF investors affects the optimal licensing fee of index providers indirectly.

Index providers' optimal licensing fees, ETFs' optimal management fees and choice of index provider, and investors' optimal ETF choices, characterize the equilibrium in the ETF market.

5 Estimation, Results, and Counterfactual Analysis

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

5.1 Model Estimation

We estimate the structural model using the top twenty U.S. equity ETFs (based on AUM in December 2019) while taking the remaining ETFs as an outside option.[23] Our focus on the largest twenty ETFs is motivated by three main reasons. First, the ETF market is quite concentrated. Despite the increase in the number of ETFs in the last ten years, the top twenty ETFs as of December 2019 hold almost 60% of total U.S. equity ETF AUM.[24] Second, the top twenty 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. (2021a)). Thus, focusing on the top twenty ETFs allows us to study the impact of index providers across relatively homogeneous products. Finally, 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 twenty ETFs alleviates this concern, as investors are likely aware of and able to compare the top ETFs.[25]

We use the monthly panel from January 2010 through December 2019, and we estimate the model in several steps. In the first step, we estimate investors' preferences. The logit demand system in equation (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

[23]It is also worth highlighting that our results are not sensitive to this particular choice. In Appendix C, for example, we obtain similar conclusions using the top fifty ETFs, which in aggregate hold more than 80% of total U.S. equity ETF AUM.

[24]In Figure B.1 in Appendix B we plot the distribution of market shares of the largest twenty ETFs used in our structural estimation.

[25]An alternative modeling approach for 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—a discrete choice approach with differentiated ETFs whose heterogeneity is a function of index providers, is a reasonable and transparent approach.

the estimation of equation (13), we control for ETF sponsor 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 management fees (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 management fee f_{kt} as a response. This endogeneity causes the OLS estimate of α to be biased downwards.

To address this endogeneity concern, we adopt an instrumental variable approach. Specifically, we instrument management fees with 1) average management fees of other ETFs in other categories of non-top ETFs offered by the same index provider; 2) number of ETFs in other categories of non-top ETFs offered by the same ETF sponsor; 3) interactions of 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 sponsor. To mitigate the endogeneity concern of ETFs competing for customer demands, we especially use variations of *non-top ETFs in other categories*, so that these ETFs are less likely to directly compete with our given ETF k. This is motivated by Ben-David, Franzoni, Kim, and Moussawi (2021a), who document significant investor segmentation in ETF markets, especially between larger broad-market ETFs and smaller thematic ETFs. The idea for our first instrument is that variations in management fees 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 management fee f_{kt}.[26] The idea for the second instrument is that sponsors that offer more ETFs could potentially spread fixed operational costs across multiple ETFs, resulting in a lower average marginal cost per ETF, which passes to investors through a lower management fee f_{kt}.

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

[26] This idea resembles the common approach in industrial organization 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 correlation in prices is due to common marginal costs (Nevo, 2001; Hausman, 2008).

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

where $\hat{\alpha}$ represents the estimated coefficients on management fees; and f_{kt} and s_{kt} are the observed equilibrium management fees and market share of ETF k. We then project estimated marginal costs on index-provider, ETF-sponsor, 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-sponsor and time fixed effects; and ω_{kt} are structural error terms capturing unobservable determinants of costs.

In our last step we estimate index providers' costs κ_{it} by inverting the first-order condition (12). This last step is the most challenging because licensing fees ρ_{it} are also unobservable in most cases.[27] Our hand-collected data on licensing fees contain only about 10% of ETFs, so we cannot directly use the observed licensing fees because of severe 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 equation (15) capture the effect of licensing fees on ETF's marginal costs. This assumption is consistent with our evidence that index licensing fees represent the single most important cost for ETFs when interacted with index providers.[28] The fixed effect estimates of index providers give only the *relative* magnitude of licensing fees. We then use our estimates in Section 3.3 to pin down the average level of licensing fees ρ_{it} in each period t. Specifically, we assume

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

[27] As we noted in the introduction, licensing fees are disclosed on a voluntary basis. In the standard inversion of the first-order conditions, prices are observables and, together with estimated markups, allow us to back out marginal costs. This is the approach we adopt in the second step of the estimation to infer ETFs' marginal costs using observable management fees.

[28] 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.

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 management fees equals the empirical estimates reported in column (1) of Table 7. This AUM-weighted average fraction of licensing fees over management fees, which is about one-third, is the only input from our hand-collected data on licensing fees into our structural estimation. Despite possible selection biases on whether an ETF disclose licensing fees, we believe that the average fraction is likely close to one-third in the full sample.

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:

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

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 (10).

Notice that, 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 (4) and (6) to calculate the counterfactual market share $s_{kt}(\rho_{i't})$ and optimal management fee $f^*_{kt}(\rho_{i't})$, when ETF k chooses index provider i'.[29] 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 (10).

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 can compute index providers' markup and back out unobservable marginal costs κ_{it} using equation (12).

[29]Some index provider×ETF sponsor interacted fixed effects γ_{ij} cannot be estimated from regression (13), because the corresponding index providers and ETF sponsors 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 management fees.

5.2 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)).

For column (1), we show the OLS estimates of equation (13) with time fixed effects and interacted fixed effects for ETF sponsors and index providers. As expected, we find that higher fees are associated with a lower market share. The coefficient is now highly significant and implies an elasticity of about 2.2. While the interacted ETF sponsors 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 management fees could still bias our estimates.

Hence, in column (2) of Table 8, we report the IV estimates of equation (13). Our first stage is strong, with an F statistics on the excluded instruments about 29. Once we instrument for management fees, the coefficient increases in (absolute) magnitude, consistent with a downward bias in the OLS specification. The average elasticity to ETF management fees is about 3.0.

Column (3) of Table 8 shows the estimates from equation (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, we control for time fixed effects and ETF-sponsor fixed effects, in order to isolate the effect of index providers with the aim of capturing the impact of licensing fees. We find that S&P Dow Jones is associated with the lowest ETF marginal costs, followed by CRSP, while FTSE Russell and MSCI involve 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 (16), this ranking also applies to licensing fees. That is, S&P Dow Jones has the lowest licensing fees, CRSP the second-lowest, and FTSE Russell and MSCI charge the highest licensing fees.[30]

[30] This finding is 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., 2019).

Table 8
Structural parameters

This table reports the structural parameters for investor demand from equation (13) and ETF marginal costs from equation (15). In columns (1) and (2) the dependent variable is the (log) market share. We also include the past-12-month average returns as control. For column (3) the dependent variable is ETF marginal costs in basis points. The excluded dummy for index providers is for S&P Dow Jones. All standard errors are clustered at the ETF sponsor level.

	Investors demand parameters Dep Var: Market share (log)		ETF cost parameters Dep Var: Marginal costs (bps)
	(1) OLS	(2) IV	(3)
Management fees (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 sponsor × IP	Yes	Yes	
FE ETF sponsor			Yes
Control	Yes	Yes	
Elasticity to fees	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 9 presents the main estimation results. We report the estimating results using the cross section of the model in December 2019.[31] The first column of Table 9 shows the baseline estimation results. We estimate the structural parameter σ, which governs the competition among index providers, to be 0.53. By equation (10), we have

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

[31] The results are similar for different time snapshot.

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, which is consistent with the persistence of indexing relationships and significant market power of index providers.

As we can see from Panel A, 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, while the remaining 2.8 bps are 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 Financial Times (2019), which estimates the profit margin of the top three index providers to be about 65% as of 2019.

In Panel B, 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.[32] ETFs also charge a management fee about 9.3 bps on average, which leads to a markup of about 3.9 bps. As a result, the Lerner index (=markup/management fees) is about 42% for ETF sponsors. This is also aligned with the estimated profit margin of ETF sponsors (Financial Times, 2021).

Overall, the baseline evidence shows that index providers charge high markups in their index licensing fees. This high level of licensing fees increases the marginal costs of ETFs, which are passed onto investors through increased management fees. In what follows, we use our model to study several counterfactual scenarios, with the aim of reducing index providers market power.

[32]The ratio of licensing fees (4.4 bps) over management fees (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.

Table 9

Baseline Results and Counterfactual Analysis

This table 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 management fees, licensing fees, marginal costs, markups, and the Lerner index for each ETF, and then report average across ETFs. For supply-side counterfactuals, we consider the effect of entry by a new competitive index provider, who charges licensing fees equal to her marginal cost, which is equal to the average or minimum of all existing index providers. For demand-side counterfactuals, we consider the effect of varying σ to 1, 5, and ∞. For each counterfactual scenario, we also report the percentage change of variables compared to the baseline scenario.

	Baseline	Supply-side: Entry of new competitive IP				Demand-side: Increase ETF profit elasticity					
	$\sigma = 0.53$	Average cost		Minimum cost		$\sigma = 1$		$\sigma = 5$		$\sigma = \infty$	
	level	level	Δ (%)	level	Δ (%)	level	Δ (%)	level	Δ (%)	level	Δ (%)
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
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
Markups (bps)	2.8	2.8	-0.4	2.8	-1.4	2.3	-19.3	1.2	-58.8	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
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
Management fees (bps)	9.3	9.3	-0.1	9.3	-0.4	8.8	-5.8	7.7	-17.6	6.5	-29.8
Markups (bps)	3.9	3.9	-0.0	3.9	-0.0	3.9	0.1	3.9	0.4	3.9	0.9
Lerner index (%)	42.0	42.0	0.1	42.1	0.4	44.6	6.2	51.1	21.8	60.3	43.7

5.3 Counterfactual Analysis: Entry of New Competitive Index Provider

We first consider the counterfactual of 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 that some new index provider may be incentivized to enter the market and increase competition. Even when ETFs keep their existing partnership with index providers, the entry of new index provider can still exert a downward pressure on index licensing fees through the outside-option effect. We quantitatively assess this argument through our model.

Specifically, we make the following assumptions on the new entrant index provider. First, in terms of brand value we assume that the index provider has the average brand value of existing index providers. Second, in terms of costs we consider the case in which the new index provider marginal costs are the average of all other index providers and an alternative case in which the new index provider marginal costs are the minimum of all other index providers. Third, we assume that the entrant index provider price at marginal costs. This assumption is not unrealistic if a new entrant goal is to attract market shares from incumbents with a competitive offer. Additionally, we recompute the new licensing fees ρ_i and corresponding ETF market equilibrium, preserving the matching between existing ETFs and index providers, so 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. Because the new index provider serves only as an outside option, it is reasonable to assume marginal cost pricing. Finally, such an assumption is most favorable to the potential of increasing competition by entry.

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 management fees 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 in magnitude. As a result of entry, licensing fees decline by less than 1% and management fees by less than 0.4%. Overall, the effect of entry in this market is almost non-existent.

This result might look puzzling at first sight, but makes sense once we understand how uncompetitive the index providing market is. Recall that we have estimated that $\sigma = 0.53$, which governs the competition among index providers. A perfectly competitive market implies $\sigma = \infty$. A perfectly uncompetitive market, in which ETF choose index providers without any respect to profit maximization incentives, implies $\sigma = 0$. In such a market, the ETF's choice for certain index providers is all based on unobservables to econometricians, i.e., the error term, and any outside option effect, which arises from ETF's profit maximization incentives, is ineffective in promoting competition.[33] Our baseline estimate of $\sigma = 0.53$ implies that the equilibrium outcome is very close to a perfectly uncompetitive market due to low ETF elasticity, and thus we obtain little effect from entry.

Our result echoes the "generic competition paradox" in the pharmaceutical industry (Frank and Salkever, 1997; Davis et al., 2004), which have also been documented for financial products. For example, 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. In our context, the entry of the low-price competitor index provider is ineffective given the common low elasticity of ETFs.

In fact, Morningstar, a prominent financial service firm that offers an array of investment research and investment management services, launched the "Morningstar Open Indexes Project" in 2016. In this project, Morningstar offered more than 100 equity indexes for benchmarking and licensing, and according to Morningstar, "the goal of the Morningstar

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

Open Indexes Project is to lower the cost of equity indexes and improve outcomes for all investors."[34] Specifically, in the US equity space, Morningstar's indexes cover all the categories, including broad market, style, and sector indexes. In addition, Morningstar's indexes have return correlations between 0.97 to 1 with the corresponding indexes offered by MSCI, FTSE Russell, and S&P Dow Jones.[35] 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.[36]

Given the lack of effect from entry threat, we next study counterfactuals that directly increase competitiveness of index providers.

5.4 Counterfactual Analysis: Increased Elasticity of ETF Sponsors

In this counterfactual analysis, we consider the effect of directly increasing competitiveness of index providers. The competitiveness 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 5.3, we preserve the equilibrium matching between index providers and ETFs, and consider only the effect on equilibrium licensing fees and management fees. We compute the counterfactual equilibrium using the same algorithm as in Section 5.3 and discussed in Appendix D, with the assigned counterfactual σ.

Varying the parameter governing ETF profit elasticity is not a well defined policy. However, the counterfactual results show that increasing ETF profit elasticity is a necessary condition to increase competition among index providers.[37] The last six columns of Table 9 show the results for these counterfactual analyses. We see that as σ increases, index providers' markup

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

[35] 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.

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

[37] One actual policy that could increase ETF profit elasticity is mandatory disclosure of licensing fees. At present licensing fees are disclosed on a voluntary basis which makes comparisons more difficult, potentially decreasing the sensitivity of ETF sponsor to licensing fees.

and licensing fees significantly decreases. Doubling σ already reduce licensing fees by almost 13%, while a tenfold increase lead to a decline by almost 38%. In the perfectly competitive index provider case, the licensing fees decrease from 4.4 bps to 1.6 bps (i.e., marginal costs), which corresponds to a 63% decline.

The reduced licensing fees in turn decreases 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' markup are rather stable. This result implies that the decreases in ETFs' marginal costs are passed almost one-to-one to ETF investors, through significantly decreased management fees. Doubling σ reduce management fees by almost 6%, while a tenfold increase decrease them by almost 18%. In the perfectly competitive index provider case, management fees decline by 2.8 bps, from 9.3 to 6.5 bps. This represents approximately a 30% decline.

Overall, Table 9 shows that index providers wield high market power and about 60% of index licensing fees are markups, which are passed onto investors through high management fees. As the index providing market is highly uncompetitive, relying only on the entry of new index providers has limited effects. Instead, measures that directly increase the competitiveness of index provider market would greatly reduce licensing fees, which could lead to an up to 30% reduction in management fees paid by ETF investors.

6 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 sponsors and the consequences for ETF management fees charged to investors.

We find that the index provider market is highly concentrated and dominated by a few large players and that about one-third of ETF management fees are paid as index licensing fees to index providers. Moreover, we find that ETF investors care about the identities of index providers, although the identities of index providers explain little of the variations in ETF returns. 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 and about 60% of index licensing fees are markups charged by index providers. Eliminating the market power of index providers could reduce ETF management fees by 30%. Our analyses suggest that policies that promote competition among index providers, such as mandatory disclosure of licensing fees, could be effective in increasing the competitiveness of the overall ETF market.

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Appendices

A Derivations of Structural Model

In this appendix, we provide detailed derivations of formulas that we omit in the main text for the structural model.

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

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

In addition, we have

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

where the last equality uses (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 (10) and by the envelope theorem of (5), we have

$$
\begin{aligned}
\frac{\partial q_{ki}(\rho_i)}{\partial \rho_i} =& \frac{\sum_{i'} \pi_{ki'}(\rho_{i'})^\sigma - \pi_{ki}(\rho_i)^\sigma}{(\sum_{i'} \pi_{ki'}(\rho_{i'})^\sigma)^2} \sigma \pi_{ki}(\rho_i)^{\sigma-1} \frac{\partial \pi_{ki}(\rho_i)}{\partial \rho_i} \\
=& \frac{\sum_{i'} \pi_{ki'}(\rho_{i'})^\sigma - \pi_{ki}(\rho_i)^\sigma}{(\sum_{i'} \pi_{ki'}(\rho_{i'})^\sigma)^2} \sigma \pi_{ki}(\rho_i)^{\sigma-1} (-L) s_k^*(\rho_i) \\
=& - \frac{L\sigma q_{ki}(\rho_i)(1 - q_{ki}(\rho_i)) s_k^*(\rho_i)}{\pi_{ki}(\rho_i)} \\
=& - \frac{\sigma q_{ki}(\rho_i)(1 - q_{ki}(\rho_i))}{f_k^*(\rho_i) - \rho_i - \tilde{c}_k} \\
=& - \alpha\sigma q_{ki}(\rho_i)(1 - q_{ki}(\rho_i))(1 - s_k^*(\rho_i)),
\end{aligned}
\tag{A.4}
$$

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

$$
\begin{aligned}
&\frac{\partial q_{ki}(\rho_i)}{\partial \rho_i} s_k^*(\rho_i) + \frac{\partial s_k^*(\rho_i)}{\partial \rho_i} q_{ki}(\rho_i) \\
=& - \alpha q_{ki}(\rho_i) s_k^*(\rho_i)(1 - s_k^*(\rho_i)) \left(\sigma(1 - q_{ki}(\rho_i)) + 1 - s_k^*(\rho_i)\right).
\end{aligned}
\tag{A.5}
$$

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

B Additional Empirical Results

In Table B.1, we replicate Table 3 but using total revenue (=AUM×management fee). The results are similar. In Table B.2 and Table B.3, we replicate Table 3 using the snapshot in December 2013 and in December 2016, respectively. The results are again similar, suggesting the stability of matching between index providers and ETF sponsors over time.

In Figure B.1 we report the market share of top twenty ETFs as of December 2019, which are used in the structural estimation of Section 5. The combined market share of top twenty ETFs is about 60%.

Table B.1

Matching between index providers and ETF sponsors: total revenue

In this table, we report matching between index providers and ETF sponsors. We use "others" to represent all index providers or ETF sponsors besides the top fives. Panel A reports the distribution of total revenue (=AUM×management fee) across various index providers from a given ETF sponsor's perspective. Panel B reports the distribution of total revenue across various ETF sponsors from a given index provider's perspective. We highlight cells that are over 50%. The sample period is December 2019.

Panel A: From ETF sponsors' 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	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.2

Matching between index providers and ETF sponsors: December 2013

In this table, we report matching between index providers and ETF sponsors. We use "others" to represent all index providers or ETF sponsors besides the top fives. Panel A reports the distribution of AUM across various index providers from a given ETF sponsor's perspective. Panel B reports the distribution of AUM across various ETF sponsors from a given index provider's perspective. We highlight cells that are over 50%. The sample period is December 2013.

Panel A: From ETF sponsors' 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	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.3

Matching between index providers and ETF sponsors: December 2016

In this table, we report matching between index providers and ETF sponsors. We use "others" to represent all index providers or ETF sponsors besides the top fives. Panel A reports the distribution of AUM across various index providers from a given ETF sponsor's perspective. Panel B reports the distribution of AUM across various ETF sponsors from a given index provider's perspective. We highlight cells that are over 50%. The sample period is December 2016.

Panel A: From ETF sponsors' 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%**

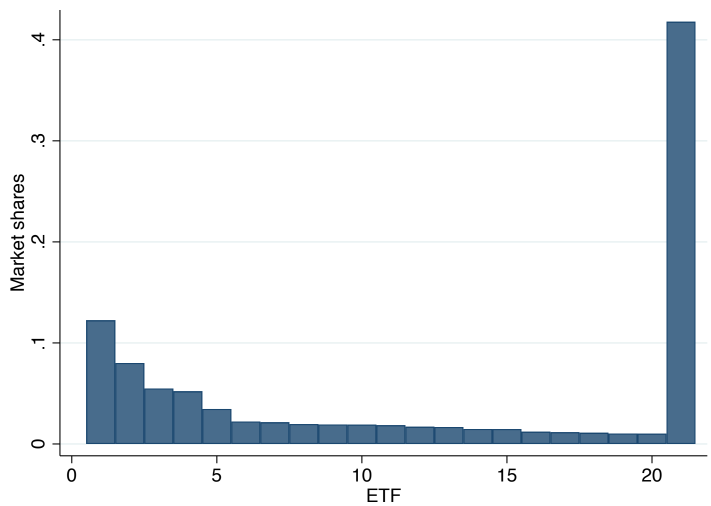

Figure B.1. Market share of top twenty ETFs. In this figure, we show the market share of top twenty ETFs as of December 2019, which are used in the structural estimation of Section 5. The x-axis shows the market share rank of each ETF. The combined market share of ETFs outside top twenty is about 42%, as also shown in the rightmost bar of the figure.

C Robustness Checks Using the Top Fifty ETFs

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

In Table C.1, we present the results using the top fifty ETFs for investor demand parameters (columns (1) and (2)) and ETFs' cost parameters (columns (3) and (4)). The parameter estimates are similar to those using the top twenty ETFs, as reported in Table 8.

Table C.2 presents the main estimation results and counterfactual analysis using the top fifty ETFs. Similar to the results based on the top twenty ETFs, ETF management fees are 12.9 basis points. The markup charged by ETFs is at around 2.7 basis points. As a result, the Lerner index (=markup/management fees) for ETFs are about 21%. In panel B, we see that the licensing fees charged by index providers are about 4.0 basis points. The markup charged by index providers is about 3.1 basis points. As a result, the Lerner index of index providers is about 79%. The last three columns present the counterfactual analysis results using the top fifty ETFs for December 2019. Similar to the results based on the top twenty ETFs, increasing the competitiveness of index providers reduces ETFs' marginal costs by about 3.1 basis points, which corresponds to a 31% decline. The lower marginal costs are passed on to investors, as management fees also decline by 3.1 basis points, from 12.9 to 9.8 basis points. This represents approximately a 24% decline.

Table C.1
Structural parameters: based on the top fifty ETFs

This table reports the structural parameters for investor demand from equation (13) and ETF marginal costs from equation (15). We use the top fifty ETFs as of December 2019. In columns (1) and (2) the dependent variable is the (log) market share. For columns (3) and (4) the dependent variable is ETF marginal costs in basis points. Past return is the average of monthly returns in the past 12 months. The excluded dummy for index providers is for CRSP. All standard errors are clustered at the ETF sponsor level.

	Investors demand parameters		ETF cost parameters	
	Dep Var: Market share (log)		Dep Var: Marginal costs (bps)	
	(1) OLS	(2) IV	(3) OLS	(4) OLS
Management fees (bps)	-0.028***	-0.379***		
	(0.007)	(0.054)		
Past return (12 months)	9.310***	2.078		
	(3.084)	(5.753)		
FTSE Russell			12.005***	5.279***
			(1.613)	(1.960)
MSCI			5.701***	3.311***
			(1.294)	(0.642)
NASDAQ			7.070*	-2.275
			(4.000)	(2.926)
S&P Dow Jones			8.958***	1.371
			(1.773)	(1.733)
FE year-month	Yes	Yes	Yes	Yes
FE ETF sponsor × IP	Yes	Yes	No	No
FE ETF sponsor			No	Yes
Elasticity to fees	0.41	5.63		
First-stage F stat		15.50		
Mean dep. var.	-4.56	-4.56	10.85	10.85
SD dep. var.	0.88	0.88	8.39	8.39
R^2	0.28	-4.74	0.24	0.52
Observations	5,096	5,096	5,096	5,096

Table C.2

Estimation results and counterfactual analysis: based on the top fifty ETFs

This table reports several variables of interest for December 2019 in the baseline case and the perfectly competitive index provider case. We use the top fifty 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 management fees, licensing fees, marginal costs, markups, and the Lerner index for each ETF, and then report average across ETFs. In the last two columns we report the differences in levels and percentages between the perfectly competitive scenario and the baseline scenario.

	Baseline	Competitive IP	Change	Change (%)
Panel A: ETFs				
Management fees (bps)	12.9	9.8	-3.1	-24.3
Marginal costs (bps)	10.2	7.1	-3.1	-30.8
Markups (bps)	2.7	2.7	0.0	0.5
Lerner index (%)	20.8	27.6	6.8	32.7
Panel B: Index providers				
Licensing fees (bps)	4.0	0.8	-3.1	-79.2
Marginal costs (bps)	0.8	0.8	0.0	0.0
Markups (bps)	3.1	0.0	-3.1	-100.0
Lerner index (%)	79.2	0.0	-79.2	-100.0

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. 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 ETF marginal cost. We use $\tilde{c}_k$ from the baseline estimates, and hold constant throughout the counterfactual analysis.

3. With the marginal costs $c_k(\rho_i)$, we recompute the equilibrium market share s_k and management fees f_k for all ETFs k by solving jointly equations (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, which also requires us to compute the (counterfactual) management fee 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 equations (10)) . This is precisely the outside-option effect caused by the new index provider.

5. We iterate through Step 1 to 4 until the set of licensing fees ρ_i converges.