Dominated ETFs*

David C. Brown† Scott Cederburg‡ Mitch Towner§

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ABSTRACT

Within the growing market for U.S. equity exchange-traded funds (ETFs), we identify many dominated ETFs with returns that are highly correlated with those of cheaper, more liquid competitors. Despite ETF market features that mitigate broker incentive misalignments and other barriers to efficient allocations, these dominated ETFs survive and thrive. We estimate the aggregate cost to investors from allocating capital to dominated ETFs to be \$1.0 billion to \$6.7 billion from 2000 to 2018. This cost is growing over time as newly listed ETFs claim unique strategies despite high correlations with cheaper ETFs.

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†Eller College of Management, University of Arizona, McClelland Hall, Room 315D, 1130 E. Helen Street, P.O. Box 210108, Tucson, AZ 85721-0108, Phone: (520)621-0746, Fax: (520)621-4261, Email: dcbrown@arizona.edu

‡Eller College of Management, University of Arizona, Email: cederburg@arizona.edu

§Eller College of Management, University of Arizona, Email: mitchtowner@arizona.edu

1 Introduction

Financial markets are riddled with dominated products. These products attract substantial market share despite the existence of nearly identical, cheaper products. Blame for the billions of dollars in losses to investors and customers is often cast on advisor conflicts of interest, search costs, and financial illiteracy. Motivated by these issues, lawmakers and regulators have proposed and implemented laws that address advisor incentives, financial transparency, and financial education.[1] Recent academic studies highlight the roles of broker incentives and search costs in the markets for mutual funds (e.g., Bergstresser, Chalmers, & Tufano, 2009), bonds (e.g., Egan, 2019), and mortgage loans (e.g., Allen, Clark, & Houde, 2014), among others. From an empirical perspective, the message is clear that advisor incentive fees exacerbate investor search costs. From a theoretical perspective, Roussanov, Ruan, and Wei (2021) suggest that eliminating the mutual fund fees that directly incentivize financial advisors would reduce equilibrium fees, shift capital away from dominated funds, and improve investor welfare. Given this context, one may hypothesize that investor allocations would be reasonably efficient in markets with no incentive misalignments for financial advisors, particularly for those retail investors who can overcome search costs and financial literacy shortfalls by receiving unconflicted investment advice.

In this paper, we examine dominated products in the market for exchange-traded funds (ETFs). ETFs have no incentive fees. Brokers and advisors have no conflicts of interest. The ETF market, thus, provides an ideal setting for studying dominated products in the absence of this friction. An additional feature of this market further assists in identifying dominated products relative to the market for open-end mutual funds. Most open-end funds have multiple share classes. Investor access to mutual fund share classes varies, such that considering each share class as a separate option or treating a mutual fund as an asset-weighted combination of its share classes does not reflect the investment opportunity set for a given investor.[2] ETF investors, in contrast, have access

[1]Advisor incentives have been addressed by legislation that covers specific situations, such as the fiduciary duties bestowed on employers and service providers for retirement plans by the Employee Retirement Income Security Act of 1974 (ERISA). In 2015, the Department of Labor proposed new, hotly debated fiduciary rules to greatly expand the coverage of fiduciary duties to include financial advisors, brokers, and others who provide financial advice. The Fifth Circuit Court of Appeals vacated these new rules in 2018, ruling in favor of the co-plaintiffs: U.S. Chamber of Commerce, Financial Services Institute, Financial Services Roundtable, Insured Retirement Institute, and Securities Industry and Financial Markets Association. A multitude of laws and regulations are aimed at promoting financial market transparency, including the Investment Company Act of 1940 and the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010. Financial education laws are currently only at the state level, and 25 states have requirements for financial literacy education in high schools (most recently passed in Florida in May 2022).

[2]Access to the share class with the lowest expense ratio often requires a large minimum investment, such as the $5 billion minimum for the Vanguard Total Stock Market Index Fund Institutional Select Shares (VSTSX). Share class access within collective investment structures like 401(k) retirement plans can also depend on the total investment in a fund across all participants, such that an individual investor's access to share classes depends on the investment

to all listed ETFs, such that an investment in a dominated ETF is not from lack of access to better alternatives. Open-end funds also have complicated fee structures with different management fees across share classes. Many mutual funds charge 12b-1 fees and front-end or back-end loads, which can distort financial advisor incentives and lead to differences in switching costs across funds. ETFs have simple, transparent fee structures with stated management fees and no broker incentive fees.[3] Thus, the ETF market is structured to eliminate advisor conflicts of interest by avoiding incentive fees, reduce search costs by promoting access and transparency, and mitigate financial illiteracy through the potential for unconflicted advice. Existing studies suggest that, without these traditional frictions, dominated products may struggle to survive. The ETF market serves as an ideal setting to test whether dominated funds can survive and thrive when barriers to efficient allocations are mitigated.

We study U.S. equity ETFs from January 2000 through June 2018. We identify dominated ETFs among the set of funds that deliver returns that are highly correlated with the returns of competing ETFs. Return correlations are calculated using daily returns over the trailing 12 months, and we use correlation thresholds of 95% and 99%. Intra-day liquidity is an important feature of the ETF market structure, and investor heterogeneity produces a tradeoff between fees and liquidity (Khomyn, Putniņš, & Zoican, 2020). We classify an ETF as dominated if it both charges higher fees and offers lower liquidity compared with a highly correlated competitor.

Despite the desirable features of the ETF market, we find that a large number of dominated ETFs collectively manage substantial assets. On average during the sample period, 38% of ETFs in a given quarter are classified as dominated by a competing fund at the 95% correlation threshold. Dominated ETFs constitute 36% of the total market capitalization across all U.S. equity ETFs. Nearly half (46%) of total ETF fees in our sample were garnered by dominated ETFs, and investors could have reduced these expenses by over three-fifths (61%) by switching to the corresponding dominant funds. In aggregate, our estimates of the additional costs of dominated ETFs from higher fees and additional trading costs range from $1.0 billion to $6.7 billion during the sample period depending on the correlation threshold. These costs have steadily increased over time, and we estimate the annual costs as of the end of our sample to be $146 million to $847 million.[4]

choices of other plan participants.

[3]State Street's Select Sector SPDR series of ETFs charges 12b-1 fees, making it the exception in the ETF market. State Street uses the fees for marketing expenses but does not provide incentives to financial advisors. According to Dan Dolan, director of management strategies at Select Sector SPDRs, "There are no broker dealers. And no one is getting paid," (http://https://www.bloomberg.com/news/articles/2017-02-08/where-do-spdr-fees-go-check-the-ice-at-madison-square-garden).

[4]We note that, given our focus on U.S. equity ETFs, these economic costs provide a lower bound for the overall ETF market that includes fixed income, international, commodity, currency, leveraged, and other types of ETFs.

These aggregate-level results show that investors are collectively making large investments in dominated ETFs. We proceed with an ETF-level analysis to further study these allocations. We hypothesize that investors will invest less in a dominated ETF than they otherwise would due to the existence of a dominant alternative. To test this hypothesis, we use a panel regression approach to study ETF size. We focus on fund size rather than fund flows because investors incur excess costs on the full amount of their investments in dominated ETFs. Moreover, investors in a dominated ETF could sell this position and invest in a dominant ETF to avoid these costs, and ETF size reflects the extent to which they fail to do so.

To study fund size, we first classify funds into five mutually exclusive categories: (i) Index ETFs that track well-known indexes; (ii) Quasi-Index ETFs that follow straightforward rule-based strategies (e.g., equal-weighted S&P 500); (iii) Active ETFs that have actively managed portfolios or use proprietary strategies; (iv) Sector ETFs that provide exposure to one of 11 broad industries; and (v) Smart Beta ETFs that pursue exposures to factors such as value, momentum, and low volatility. Within each category, we relate the log of ETF market capitalization to fund characteristics that proxy for the fees, liquidity, performance, uniqueness, and investor awareness of the ETF. In each specification, we include an indicator variable for whether a given ETF is dominated, which allows us to study the size of dominated funds after controlling for fund characteristics. This dominated ETF indicator variable uses the 95% correlation threshold. We include an additional indicator variable using the more stringent 99% correlation threshold, which allows us to compare magnitudes across the 95% and 99% thresholds.[5]

Our initial tests relate ETF size to a set of fund characteristics that are relatively easy for investors to observe. Common intuition suggests that investor allocations to ETFs should decrease in fees and increase in liquidity. Regression results generally confirm these predictions across ETF categories with large economic magnitudes. Relative to fees and liquidity, the relations between the prior quarter return and size are much weaker, both statistically and economically. After controlling for these variables, we test the hypothesis that investors will avoid a dominated ETF because a dominant fund exists. This hypothesis predicts a negative association between ETF size and the dominated ETF indicator variable. The results show a positive coefficient estimate for each category, refuting the hypothesis. The association is weak and insignificant for Index ETFs.

[5] The 99% correlation threshold provides a very high bar given that an ETF's price fluctuates around its NAV and the fund typically trades at a premium or discount. This additional price volatility tends to decrease the daily return correlation across ETFs. As an example of this effect, the SPDR S&P 500 ETF Trust (SPY) and the iShares Core S&P 500 ETF (IVV) both track the S&P 500. The daily return correlation between SPY and IVV was less than 99% (but greater than 95%) during the financial crisis (measured from July 2008 to June 2009) largely due to fund-specific fluctuations in premiums.

Estimates for the Quasi-Index, Active, Sector, and Smart Beta categories are significantly positive, and the economic magnitudes are quite large. Quasi-Index ETFs, for example, are 498% larger on average (t-statistic of 15.42) than would otherwise be expected given their fund characteristics. Across categories, the effect ranges from 40% for Sector ETFs (t-statistic of 4.97) to 760% for Active ETFs (t-statistic of 18.39). The tests further show that the magnitudes are even more pronounced for ETFs that are dominated at the 99% correlation threshold.

To better understand the unexpectedly large size of dominated ETFs, we introduce additional fund characteristics. Investors may seek ETFs that deliver abnormal returns or strategy uniqueness. Investor awareness may also drive investments in the presence of search costs. We therefore include multiple proxies for performance, uniqueness, and awareness to study ETF size.

We estimate abnormal returns and measure strategy uniqueness using category-specific methods. For the Index, Quasi-Index, Active, and Sector categories, we follow in the spirit of Berk and van Binsbergen (2015) and use 21 Vanguard ETFs to develop peer-based benchmarks. For Smart Beta, we benchmark using a factor model that includes factors associated with the claimed strategy. Abnormal performance bears little relation to ETF size, whereas uniqueness plays a more important role. We initially hypothesize that investors desire Index, Sector, and Smart Beta ETFs that closely track their benchmarks. In contrast, we expect that investors want Quasi-Index and Active ETFs to provide unique performance, as these funds charge higher fees for deviating from standard index benchmarks. Across all categories, we find that ETFs with lower measures of uniqueness are larger. The finding that investors are choosing Quasi-Index and Active ETFs that are more similar to their low-cost index benchmarks is consistent with our evidence of substantial allocations to dominated ETFs.

We include three measures that proxy for investor awareness of a given ETF. First, the relations between ETF size and age are significantly positive across categories with large economic magnitudes. Second, we measure search volume from Google Keyword Planner, as investors must be aware of an ETF to search for its ticker. This measure is significantly positively associated with fund size in all categories except Active. Third, we develop a sponsor tilt measure that proxies for institutional investor awareness through the fund family channel. Some institutions tend to concentrate investments in ETFs from the same fund sponsor, and our sponsor tilt measure captures whether a given ETF belongs to a family with loyal institutional investors. Sponsor tilt is significantly positively associated with fund size within each category. Overall, we find strong associations between our proxies for investor awareness and ETF size, consistent with the importance of search costs in investment selection.

After including all of these additional fund characteristics, we find evidence in favor of our hypothesis that dominated ETFs should be smaller, but only for certain types of funds. Specifically, dominated Index ETFs are about 23% smaller (t-statistic of -3.06) than expected given their fund characteristics, and the subset of dominated Sector ETFs that track a broad-based sector index are about 21% smaller (t-statistic of -2.46). In contrast, dominated ETFs in other categories remain statistically significantly larger than expected. Quasi-Index ETFs are 59% larger (t-statistic of 4.91) and non-index Sector ETFs are 28% larger (t-statistic of 4.02). The coefficients are even larger for Active and Smart Beta ETFs, with implied excess sizes of 217% (t-statistic of 9.86) and 116% (t-statistic of 9.90), respectively.

Our results suggest large misallocations by ETF investors as a whole. Many investors, however, have accounts that are managed by financial advisors or other investment professionals. Given the lack of broker incentive fees in the ETF market, it seems ex ante reasonable to expect that accounts managed by institutional investors will better avoid dominated ETFs. We show, however, that retail and institutional investors make similar allocations to dominated ETFs. This finding contrasts with a view in the literature (e.g., Hortaçsu & Syverson, 2004) that institutional investors can better overcome the effects of search costs and financial illiteracy to make superior allocations to funds. It is more consistent with the evidence of Linnainmaa, Melzer, and Previtero (2021) that financial advisors are prone to make the same mistakes in their personal accounts as in their clients' accounts.

Our finding that dominated ETFs manage substantial assets should not overshadow the importance of the financial innovation that created exchange-traded funds. The rise of the ETF market has provided investors with access to a set of index ETFs that offer cheap diversification and high intra-day liquidity. Competition has also contributed to declining fees among these index ETFs. Notwithstanding these benefits, our results indicate that ETF investors are overpaying because of their investment choices. The rapid expansion of non-index ETFs has been accompanied by increasing excess costs to investors in dominated ETFs. Many of these dominated ETFs claim unique strategies despite their high correlations with cheaper alternatives, and investors are making large excess allocations to these funds.

Our results are consistent with other studies that show that investors may not benefit from the increase in the number and variety of available ETFs. Bhattacharya, Loos, Meyer, and Hackethal (2017) show that German ETF investors display poor timing and selection ability in the broad spectrum of ETF listings relative to choosing low-fee, well-diversified ETFs. Box, Davis, and Fuller (2019) document that existing ETFs experience a decline in liquidity when a new related ETF lists and that an increase in listed ETFs does not create downward pressure on expense ratios, and Khomyn et al. (2020) estimate sizable welfare losses when multiple ETFs compete across the fee-liquidity spectrum due to duplicated fixed costs and network inefficiencies. Akey, Robertson, and Simutin (2021) find that ETFs are more active than advertised and this activeness is associated with underperformance. Ben-David, Franzoni, Kim, and Moussawi (2021) show that specialized ETFs, particularly newly listed ones, earn negative risk-adjusted returns. Increasing costs are also consistent with Hortaçsu and Syverson's (2004) prediction of welfare losses from higher search costs as more funds become available. Investors would benefit from focusing on a small set of cheap, liquid index ETFs.

Our study of dominated products in the ETF market is related to a literature that focuses on mutual funds.[6] Elton, Gruber, and Busse (2004) and Hortaçsu and Syverson (2004) demonstrate considerable variation in expense ratios across S&P 500 index funds despite their nearly identical portfolios. In our setting, investors are able to choose any ETF, such that allocations to inferior funds do not result from a lack of access to mutual fund share classes or limited flexibility within workplace retirement account menus. Free of these frictions, we find that investors are actually diverting their investments away from dominated Index ETFs. Boldin and Cici (2010) attribute most of the losses from higher-fee index funds to retail investors who are influenced by brokers and financial advisors with incentives to guide investors into high-fee funds. Our focus on ETFs, which have no broker incentives, allows us to rule out a similar explanation for dominated ETFs. Cooper, Halling, and Yang (2021) find that fee dispersion has persisted both in index funds and in other types of mutual funds, and they estimate large costs to investing in high-fee funds. We contribute to the literature by demonstrating economically large, growing costs in the ETF market, and we provide evidence that dominated funds are pervasive within the set of newcomers capitalizing on recent trends toward more complex investment strategies (e.g., Smart Beta).

2 Data

Section 2.1 describes our data sources for ETF characteristics. Section 2.2 discusses the measures we create to examine the performance and uniqueness of ETFs. Section 2.3 presents information about our sample and summary statistics.

[6] In addition to the mutual fund literature, prior literature documents dominated products in the markets for money market funds (Christofferson & Musto, 2002), bonds (Green, Hollifield, & Schürhoff, 2007; Egan, 2019), insurance (Brown & Goolsbee, 2002; Bhargava, Loewenstein, & Sydnor, 2017), and mortgages (Allen, Clark, & Houde, 2014, 2019; Gurun, Matvos, & Seru, 2016). Our study also relates to the broader literature on household finance (see, e.g., Campbell, 2006), although we find similar allocations to dominated ETFs by institutional and retail investors.

2.1 Data Sources

We focus on the universe of U.S. equity ETFs.[7] We identify ETFs as U.S. equity using Lipper codes from The Center for Research in Security Prices (CRSP), and we remove leveraged ETFs by dropping any fund with a leverage factor from Bloomberg that does not equal one. Our sample period is January 2000 through June 2018, and we measure ETF characteristics quarterly to form the panel dataset.

Our ETF characteristic data are from Bloomberg and CRSP. We collect daily ETF share prices, net asset values (NAVs), shares outstanding, and trading volumes from both Bloomberg and CRSP. We follow Brown, Davies, and Ringgenberg (2021) and use Bloomberg as the primary data source, and we clean these data by removing anomalies that are not verifiable via CRSP. We collect inception dates from Bloomberg. From CRSP, we use the fund sponsors, expense ratios, internal turnover ratios, and bid-ask spreads.

We classify ETFs into five categories based on their strategies: Index, Quasi-Index, Active, Sector, and Smart Beta. We hand classify each ETF in the sample based on Lipper codes and fund descriptions from ETF.com and ETFDB.com. Sector ETFs are identified using Lipper codes, and these funds are further classified into 11 sectors.[8] Smart Beta funds are identified as such by ETF.com, and we hand collect information on each ETF's stated strategy. Collectively, these ETFs claim exposures to cross-sectional factors related to value, growth, small cap, momentum, profitability, quality, and low volatility.

The set of ETFs that are not identified as Sector or Smart Beta ETFs are assigned to the Index, Quasi-Index, and Active categories using fund descriptions from ETF.com and ETFDB.com. Index ETFs are those designed to closely track an index. Whereas many ETFs track indexes that are specifically designed and constructed for use by the ETF (Huang, Song, & Xiang, 2020; Akey et al., 2021), we only classify funds as Index ETFs if they track standard indexes from well-known index providers (CRSP, Morningstar, Russell, or S&P Dow Jones) or an exchange (Nasdaq or New York Stock Exchange).[9] Quasi-Index ETFs follow relatively straightforward rule-based strategies

[7] Our sample includes U.S. equity ETFs with various legal structures, including ETFs that are organized as open-end mutual funds (e.g., the iShares Core S&P 500 ETF, IVV), unit investment trusts (e.g., the SPDR S&P 500 ETF Trust, SPY), and share classes of open-end mutual funds (e.g., the Vanguard 500 Index Fund ETF, VOO).

[8] The U.S. ETF sectors are Basic Materials, Consumer Goods, Consumer Services, Energy MLP, Financial Services, Health and Biotechnology, Industrials, Natural Resources, Real Estate, Science and Technology, Telecommunications, and Utilities. We reclassify Energy MLP ETFs as Natural Resources ETFs because the Energy MLP sector is relatively small and does not have a natural benchmark in the data as described further below.

[9] Several Index ETFs track small cap indexes such as the S&P 600. These ETFs could reasonably be considered to be either small cap Smart Beta funds or Index funds. We follow the ETF.com classification system to designate these funds as Index ETFs rather than Smart Beta ETFs. ETFs that track, for example, the S&P 500 Value index are classified as Smart Beta by ETF.com, and we follow this classification system.

but do not directly track a previously established index. Examples of Quasi-Index ETFs are the Guggenheim S&P 500 Equal Weight ETF (RSP), the SPDR S&P 500 Buyback ETF (SPYB), and the SPDR S&P 500 High Dividend ETF (SPYD). Active ETFs follow more complicated proprietary strategies or have actively managed portfolios.

Each ETF is assigned a benchmark to create performance and uniqueness measures. The benchmarks depend on the ETF category, and we describe how we use these benchmarks in Section 2.2. For the Smart Beta ETFs, we use daily return data for a set of commonly used factors from the asset pricing literature that mirror the stated Smart Beta strategies. The MKT, SMB, HML, and RMW factors of Fama and French (2015) and the MOM factor are from Kenneth French's website. The BAB factor of Frazzini and Pedersen (2014) and the QMJ factor of Asness, Frazzini, and Pedersen (2019) are from AQR's website. For the remaining categories we use Vanguard ETFs as benchmarks, and we use daily returns from these funds to create our measures. Vanguard was an early entrant into the ETF market, such that the benchmark time series span most of our sample, and the Vanguard ETFs we use track highly diversified indexes with low expense ratios. Vanguard funds are also used in the literature as peer-based benchmarks (e.g., Berk & van Binsbergen, 2015). Each Index ETF is matched to a Large-Cap Balanced, Mid-Cap Balanced, or Small-Cap Balanced Vanguard benchmark ETF. To create benchmarks for Quasi-Index and Active ETFs, we use nine Vanguard ETFs in the two-dimensional style grid of Large-Cap, Mid-Cap, and Small-Cap interacted with Value, Balanced, and Growth as well as the Vanguard High Dividend Yield ETF. We detail the construction of the Quasi-Index and Active benchmarks in Section 2.2.2. The Sector ETFs are each assigned the Vanguard ETF from the same sector as a benchmark.[10]

2.2 Performance and Uniqueness Measures

We create measures of performance and uniqueness. Given that ETFs in different categories can have very different strategies and goals, we adopt category-specific approaches to calculating and interpreting these measures. This section describes measures for each category.

2.2.1 Index ETFs

We calculate performance and uniqueness measures for Index ETFs relative to the benchmark Index ETFs that are described in Section 2.1. Specifically, we use the following regression,

$$R_{i,t} = \alpha_i + \beta_i R_{BENCH,t} + \epsilon_{i,t}, \tag{1}$$

[10]The full set of Vanguard benchmarks is VAW, VB, VBK, VBR, VCR, VDC, VDE, VFH, VGT, VHT, VIS, VNQ, VO, VOE, VOT, VOX, VPU, VTV, VUG, VV, and VYM.

in which $R_{i,t}$ is the daily ETF excess return and $R_{BENCH,t}$ is the daily excess return on the benchmark ETF. Each regression uses daily data over the past 12 months. We require that each fund has at least 120 daily return observations during this period to estimate the regression. The alpha from this regression measures abnormal performance relative to the benchmark, which can reflect operational efficiencies and costs for Index ETFs. Uniqueness is calculated as $(1 - R^2)$, such that it is inversely related to the regression R^2 from equation (1). Given that investors in Index ETFs are likely seeking funds that closely track a diversified index, they may prefer a low uniqueness measure for Index ETFs.

2.2.2 Quasi-Index and Active ETFs

Quasi-Index and Active ETFs in our sample follow a variety of strategies that range from simple to complex. To account for this strategy variation, we use a relatively large set of ten Vanguard benchmark ETFs that span many potential strategies. As described in Section 2.1, these ten ETFs include nine funds in the style grid and a dividend yield ETF. For each Quasi-Index or Active ETF, we estimate the regression

$$R_{i,t} = \alpha_i + \sum_{j=1}^{10} \beta_{i,j} R_{BENCH(j),t} + \epsilon_{i,t}. \tag{2}$$

This regression estimates the portfolio of benchmark ETFs that most closely mimics the returns of the ETF under consideration. The R^2 from this regression is informative about the uniqueness of the ETF's strategy (Amihud & Goyenko, 2013), and we calculate the uniqueness measure as $(1 - R^2)$. A Quasi-Index or Active ETF that is nearly perfectly spanned by the benchmarks provides relatively little value in terms of helping to complete the market. More unique ETFs may be desirable to investors for these categories. The regression alpha is informative about the ETF's performance relative to the fitted benchmark.

2.2.3 Sector ETFs

We estimate a regression for each Sector ETF following equation (1) with the sector-specific Vanguard benchmark ETF. Alpha and $(1-R^2)$ from this regression are the performance and uniqueness measures.

2.2.4 Smart Beta ETFs

We measure the abnormal returns and strategy uniqueness of Smart Beta ETFs using a matched factor model regression. Specifically, we estimate a restricted version of the following general regression:

$$R_{i,t} = \alpha_i + \beta_{i,MKT} R_{MKT,t} + \beta_{i,SMB} R_{SMB,t} + \beta_{i,HML} R_{HML,t} + \beta_{i,MOM} R_{MOM,t} + \beta_{i,RMW} R_{RMW,t} + \beta_{i,QMJ} R_{QMJ,t} + \beta_{i,BAB} R_{BAB,t} + \epsilon_{i,t}. \tag{3}$$

For each Smart Beta ETF, we estimate a restricted version of the regression in equation (3) that only includes the market factor and the factors that are associated with the ETF's reported strategy. For example, for an ETF that claims value and small cap strategies, we include the MKT, HML, and SMB factors. We include as factors HML for both value and growth ETFs, SMB for small cap, MOM for momentum, RMW for profitability, QMJ for quality, and BAB for low volatility. Each factor model regression uses daily data over the past 12 months.

The alpha and $(1 - R^2)$ from the matched factor regression are our measures of abnormal performance and strategy uniqueness for the Smart Beta category. Given that the factor model includes the factors that are associated with a Smart Beta ETF's claimed strategy, low strategy uniqueness is consistent with the ETF delivering on its strategy with relatively little idiosyncratic risk. As such, lower uniqueness may be desirable for investors in Smart Beta funds.

2.3 Sample Characteristics

Table 1 displays the number and total market capitalization of ETFs in our full sample for each year as well as information across the five categories. The ETF market originated with a small set of Index and broad-based Sector ETFs. The substantial assets drawn by these ETFs invited competition from new fund sponsors and additional listings from early sponsors, and the Index and Sector categories quickly grew in the early years of the ETF market. As the market progressed, many ETFs began to track custom-built indexes, and the Securities and Exchange Commission granted conditional regulatory approval to actively managed ETFs beginning in February 2008.[11] In recent years, large numbers of Quasi-Index, Active, more specialized Sector, and Smart Beta ETFs have been listed, whereas the set of Index and broad-based Sector ETFs has been relatively stable.[12] Newer entrants into the Quasi-Index, Active, Sector, and Smart Beta categories have filled the ETF market with a wide variety of stated strategies that promise investors unique exposures. As of the end of our sample, the 39 Index ETFs (9% of listed funds) combine to manage over \$1.0 trillion (52% of total market capitalization). The remaining categories contain a multitude of ETFs, most of which are much smaller than the average Index ETF. Recent growth in the Smart

[11] See https://www.sec.gov/rules/proposed/2008/33-8901.pdf.

[12] Recent ETF market growth is consistent with Betermier, Schumacher, and Shahrad (2021), who find mutual fund proliferation is driven by incumbent firms' efforts to "fill up the style grid."

Beta ETF market is particularly notable, and the 144 Smart Beta funds (32% of listed funds) collectively manage $428.0 billion (22% of total market capitalization) by the end of the sample period.

Table 2 summarizes ETF characteristics across categories. The table shows counts of ETFs and observations in our sample and the sample means of fund characteristics. The dependent variable in the panel regressions in Section 3.2 is the log of market capitalization. We consider several additional characteristics to better understand the main drivers of ETF size. Fees are measured by the expense ratio. We include bid-ask spread and trading turnover as liquidity measures. The average bid-ask spread is calculated as a percentage of NAV, and trading turnover is defined as the average shares traded divided by the average shares outstanding. In addition to measuring the secondary-market turnover of an ETF with trading turnover, we measure its internal turnover (i.e., how often the fund changes its positions) via the turnover ratio.

We include three measures of investor awareness. ETF age is the number of years since the inception date. Search volume is calculated each quarter as the average monthly Google Keyword Planner volume for the ETF ticker from Keywords Everywhere. Finally, sponsor tilt is an ETF-level variable that captures the effect from 13F institutions' tendencies to hold ETFs from the same sponsor. For a given ETF, sponsor tilt measures the relation across 13F institutions between the holdings in the ETF and investments in same sponsor ETFs (excluding the ETF under consideration).[13]

Table 2 indicates that ETF characteristics generally have monotonic patterns across the Index, Quasi-Index, and Active categories. Index ETFs are larger, cheaper, and more liquid than their Quasi-Index and Active counterparts. They are also less unique and have greater investor awareness. Sector and Smart Beta ETFs are generally similar to Quasi-Index ETFs on these dimensions.

Table 3 shows additional summary statistics for Sector and Smart Beta ETFs. The most popular sectors as shown in Panel A are Natural Resources (15.6% of observations), Financial Services (14.7%), and Science and Technology (13.3%). Among Smart Beta ETFs, Panel B shows that value (44.1%), small cap (29.4%), and growth (27.6%) are the most popular strategies. Some Smart Beta ETFs claim to provide exposures to more than one factor (1.75 factors on average). For example, while 75 funds specify value exposure and 50 funds specify small cap exposure, 24 of those ETFs claim both strategies.[14]

[13] Detailed variable descriptions are in Table A1 of the appendix.

[14] Furthermore, within those 24 funds, seven also claim momentum exposure, seven claim quality exposure, four claim low volatility exposure, two claim profitability exposure, and one claims growth exposure.

3 Results

Section 3.1 presents information about dominated ETFs and the aggregate costs associated with investments in these funds. Section 3.2 studies allocations to the dominated ETFs with a panel regression design. Section 3.3 discusses our findings.

3.1 Dominated ETFs

We identify dominated ETFs as those for which a highly correlated, lower-fee, higher-liquidity ETF exists. ETFs that are highly correlated with a given ETF are identified based on return correlations calculated using daily returns over the past 12 months, and we require at least 120 days of returns. We use primary correlation thresholds of 95% and 99% to classify highly correlated ETFs, but we also consider a range of correlations from 90.0% to 99.5% in some analyses. Fee comparisons are based on a weak inequality of expense ratios. Liquidity comparisons use both average bid-ask spreads and average dollar trading volume. An ETF must have a lower bid-ask spread and higher volume than a competing fund to be classified as more liquid.

As an illustration of our dominated ETF classifications, consider the three largest Index ETFs that track the S&P 500 index during our sample period: IVV, SPY, and VOO. The ETFs are highly correlated such that they are candidates for domination. Still, none is dominated in most of the recent quarters in our sample. Taking the fourth quarter of 2017 as an example, VOO charged the lowest expense ratio at 0.04%, followed by IVV at 0.05% and SPY at 0.09%. Although SPY is the most expensive of the three ETFs, it is also more liquid than IVV and VOO such that it is not dominated by either fund. IVV is cheaper than SPY and more liquid than VOO, and VOO is cheaper than both IVV and SPY. Hence, none is dominated in both fees and liquidity during this quarter. IVV subsequently lowered its expense ratio to 0.04% in the second quarter of 2018, matching the low fee of VOO. In this quarter, VOO is dominated by IVV, which is more liquid and equally cheap, but it is not dominated by SPY, which is more expensive.

ETFs with relatively high fees and low liquidity are often dominated by multiple highly correlated ETFs. When we analyze the costs of dominated ETFs, we compare each dominated ETF with the lowest-fee fund in the set of dominant ETFs.[15] An alternative approach of comparing each dominated fund to the dominant fund with the lowest bid-ask spread gives qualitatively similar results.

Figure 1 provides information about ETF classifications as of June 2018. Panel A shows the

[15] If multiple dominant ETFs share the lowest fee, we choose the ETF with the lowest bid-ask spread among this group.

percentage of ETFs that are classified as dominated as well as the percentages for three types of ETFs that are not dominated: those with the lowest fees among their group of highly correlated ETFs, those with higher liquidity than related ETFs with lower fees, and those that are unique in the sense that no other ETF is highly correlated. We consider a range of correlations from 90.0% to 99.5% in this figure to demonstrate sensitivity to the threshold. Panel B repeats the analysis with total market capitalization.

Figure 1 demonstrates that significant capital is allocated to a large number of dominated ETFs. For example, using the correlation threshold of 95% (99%), about 39% (8%) of ETFs are dominated. These dominated funds collectively manage about 46% (17%) of total ETF assets.

The remaining types of ETFs in Figure 1 provide insights into the funds that are not dominated. Many ETFs are not highly correlated with any other ETF. About 26% of ETFs are unique at the low correlation threshold of 90%, and that figure increases to 78% at the 99% threshold. These unique ETFs tend to be small, however, and they collectively manage only 1% of total assets at the 90% threshold and 25% at the 99% threshold. ETFs with low fees or high liquidity, on the other hand, are relatively few in number but manage about half of ETF assets at higher correlation thresholds.

Figure 2 shows that the large allocation to dominated ETFs is not unique to June 2018. We plot the time series of the percentage of total market capitalization that is invested in dominated ETFs for the 95% and 99% correlation thresholds. Dominated assets were relatively low early in the sample period when most ETFs faced little competition from highly correlated ETFs. As the market grew and more competing ETFs were listed, the percentage of assets in dominated funds increased. Since 2005, the average percentage of assets in dominated ETFs using the 95% (99%) correlation threshold is 42% (11%). Large investments in dominated ETFs have persisted in the market.

Table 4 provides insights into dominated and dominant ETFs. Panel A reports the number of distinct ETFs and the proportions of ETF-quarter observations for dominated and dominant funds that occur within each of the five categories. A striking number of the 569 total funds in our sample are dominated in at least one quarter, as 322 (109) distinct ETFs have been dominated by 164 (66) distinct ETFs at the 95% (99%) correlation threshold. At the 95% correlation threshold, dominated ETFs tend to fall into the Smart Beta (41%) and Sector (27%) categories, whereas dominant ETFs tend to be Index ETFs (62%).

Panel B of Table 4 compares the characteristics of dominated ETFs versus their dominant counterparts. By construction, dominated ETFs have higher expense ratios, higher bid-ask spreads, and lower volume. The reported averages reveal economically significant differences in these characteristics. At the 95% correlation threshold, for example, the average fees of dominant funds (0.12% per year) are a small fraction of those for dominated ETFs (0.34%), and the dominant ETFs are also highly liquid in comparison. Dominated funds are significantly smaller than their dominant counterparts on average. Dominated ETFs also have lower values for our three measures of investor awareness, as they are younger and have lower search volume and sponsor tilt measures. To a large degree, these differences in characteristics reflect the fact that many ETFs are dominated by large, well-known Index ETFs.

A possibility for why dominated ETFs attract significant assets is that they could outperform relative to their peers. The evidence does not support this conjecture. The only significant difference in alpha in Panel B of Table 4 shows outperformance by dominant ETFs for the 95% correlation threshold. Panel C further compares the return moments of dominated and dominant ETFs for both the lagged quarter and the next quarter. There is no evidence of better performance by dominated ETFs in terms of average returns. Dominated ETFs have significantly higher standard deviations relative to dominant ETFs, and there are no consistent patterns of significant differences in skewness and kurtosis across specifications.

We now quantify the aggregate costs of investing in relatively high-fee, low-liquidity ETFs. We calculate costs by comparing dominated ETFs to their dominant ETFs for the 95% and 99% correlation thresholds. The aggregate cost calculations include both direct costs from expense ratios and indirect costs from higher trading costs of less liquid funds. The costs are calculated as if each dominated ETF had the same expense ratio and bid-ask spread as its dominant fund. For each quarter, we calculate the extra fees as one-fourth of the difference in annual expense ratios multiplied by the quarterly average market capitalization. We calculate the extra trading costs as one-half of the difference in bid-ask spreads multiplied by the quarterly volume.

Figure 3 displays aggregate quarterly costs from higher fees and additional trading costs. Panel A shows the time series of excess costs based on the 95% correlation threshold. The average annual cost from investing in dominated ETFs is $255 million from higher fees and $105 million from higher trading costs. The aggregate cost from extra fees in the last quarter of our sample is more than three times the average. These large excess costs reflect a broader trend of increasing potential cost savings from moving to lower-fee funds, which mirrors the shift in our sample toward a more crowded market of ETFs promising unique exposures at the cost of higher fees. Near the peak of the financial crisis, extra trading costs were nearly an order of magnitude higher than extra fees. As such, the evidence suggests that expense ratios drive the cost of dominated ETFs in normal times, but trading costs loom large when volatile markets lead to wide bid-ask spreads and high trading volumes.

Table 5 tabulates the aggregate costs of investing in dominated ETFs. Panel A shows the average annual costs for each correlation threshold. The costs decrease as the correlation threshold increases because fewer ETFs are defined as dominated under stricter criteria. Nonetheless, the average annual costs remain economically large across all thresholds. Panel B reports the annualized costs from the last quarter in our sample period, so it provides a better representation of current costs given the growth in the ETF industry. Using the correlation threshold of 95% (99%), the annualized aggregate additional costs of dominated ETFs in the second quarter of 2018 totaled \$847 (\$146) million. Panel C reports that the total additional cost estimates from investing in dominated ETFs during our sample period range from \$1.0 billion (using the 99% correlation threshold) to \$6.7 billion (using the 95% correlation threshold), such that costs to investors from suboptimally investing in U.S. equity ETFs are economically large.[16] For completeness, Panel B of Figure 3 provides total excess fees and trading costs across correlations from 90.0% to 99.5% to show sensitivity to the threshold.

3.2 Allocation of Capital to ETFs

The results in Section 3.1 show that dominated ETFs, in aggregate, manage substantial assets. We now turn to ETF-level evidence to study these allocations by investors. We study ETF size to test whether investors allocate fewer dollars to dominated ETFs when dominant alternatives exist. We focus on ETF size rather than fund flows because the excess costs that investors incur from investing in dominated ETFs depend on the total amount invested in the ETF rather than on the quarterly net flow.[17] Investors in a dominated ETF can sell and immediately invest in a corresponding dominant ETF, so the excess costs from maintaining an allocation to the dominated ETF are avoidable. A potential friction for taxable investors is that they may have unrealized capital gains in the dominated ETF, such that selling would produce a tax liability. In the appendix, we demonstrate that inferences are robust to using an indicator of positive ETF flow, which reflects active decisions by ETF investors to increase allocations, rather than size as the dependent variable (Table A2). This result indicates that selling frictions do not explain our findings. Our focus on ETF size is reflective of the total costs from maintaining positions in dominated ETFs.

[16]As previously noted, we compare dominated ETFs with the lowest-fee candidate dominant fund for the primary analysis. If we instead use the dominant ETF with the lowest bid-ask spread, the analogous aggregate costs are \$0.9 billion (using the 99% correlation threshold) and \$6.0 billion (using the 95% correlation threshold). The large majority of potential savings in this scenario continues to come from lower expense ratios.

[17]Clifford, Fulkerson, and Jordan (2014) and Dannhauser and Pontiff (2019), among others, study fund flows.

We study the relations between ETF size and fund characteristics using panel regressions. The dependent variable in each regression specification is the log of the ETF's quarter-end market capitalization.[18] We include a dominated ETF indicator variable based on the 95% correlation threshold as an independent variable in each specification to estimate the marginal effect of the existence of a dominant competitor after controlling for other fund characteristics. We also include an indicator variable using the 99% correlation threshold, such that an ETF that is dominated at the 99% threshold receives a one for both the dominated ETF variable and the more stringent 99% variable. We include quarter fixed effects and cluster standard errors at the quarter level.[19] When we consider economic magnitudes using one-standard-deviation changes in independent variables, the standard deviations account for the fixed effects such that they are interpretable as within-quarter standard deviations across ETFs in a given category.

Table 6 begins with an examination of ETFs in the Index, Quasi-Index, Active, Sector, and Smart Beta categories with easily observable fund characteristics that measure fees, liquidity, portfolio turnover, and prior quarter returns. Expenses are strongly negatively related to fund assets within each category, consistent with investors' preferences for lower-fee investment options. Within the Index category, a one-standard-deviation increase in the expense ratio is associated with a 32% decrease in ETF market cap (t-statistic of -6.18). Other categories have similar magnitudes of effects that range from a 17% decrease in size for Active ETFs (t-statistic of -5.17) to a 40% decrease for the Smart Beta category (t-statistic of -18.85).

Table 6 also shows a role for liquidity. Within the Index category, indications of greater liquidity from lower bid-ask spreads and higher trading turnover are associated with larger ETF market cap. A one-standard-deviation improvement in liquidity is associated with an increase in ETF size of 95% (t-statistic of -4.25) for bid-ask spread and 88% (t-statistic of 6.04) for trading turnover. Liquidity also appears particularly important for Sector ETFs. Among Quasi-Index and Active ETFs, on the other hand, the liquidity measures are not as consistently associated with ETF size.

We also find that trading in the underlying ETF portfolio is related to fund size. Among Active ETFs, investors allocate more to funds that are more active in trading (as measured by the turnover ratio). A one-standard-deviation increase in the turnover ratio is associated with an 11% increase

[18] We use the log of market cap to study the allocation of capital because the distribution of ETF size is highly skewed, but inferences are robust to using ETF market cap or percentage of total quarterly U.S. equity ETF assets as the dependent variable.

[19] In the appendix, we investigate alternative regression specifications. Our inferences are robust to including ETF fixed effects (Table A3) or ETF family fixed effects (Table A4). We also show robustness to clustering standard errors at the quarter and ETF levels (Table A5). Finally, we show our results are robust to using a continuous measure of excess fees and trading costs for each dominated ETF relative to its dominant ETF (Table A6).

in size (t-statistic of 5.13) for these ETFs. In contrast, funds with less portfolio turnover are larger in the other categories.

Recent returns may be mechanically related to ETF size if existing investors are sticky, and return chasing behavior by investors could also produce a relation. We find that ETF size is significantly associated with the prior quarter return for Index and Sector ETFs. A one-standard-deviation increase in return is associated with a 10% increase in market cap for Index ETFs (t-statistic of 2.15) and a 10% increase for Sector ETFs (t-statistic of 4.14).[20] Prior quarter return is not significantly related to size in the remaining categories, such that sticky investors and return chasing do not appear to be first-order determinants of ETF size.

Finally, we test the hypothesis that investors will invest less in dominated ETFs, all else equal, because of the existence of a dominant alternative. This hypothesis implies that the dominated ETF indicator variable should be negatively associated with ETF size. The coefficient estimates in Table 6 are inconsistent with the hypothesized effects. The coefficient for Index ETFs is small and statistically insignificant. The coefficient estimates are significantly positive in the remaining categories, which implies that dominated funds are larger than would be expected given the other fund characteristics. The economic magnitudes are large at 497% for Quasi-Index ETFs (t-statistic of 15.42), 760% for Active ETFs (t-statistic of 18.39), 40% for Sector ETFs (t-statistic of 4.97), and 522% for Smart Beta ETFs (t-statistic of 30.94). The coefficients for the indicator variable that uses the 99% correlation threshold show that the effects are even more pronounced for ETFs that are dominated at the more stringent level. Dominated ETFs, which are directly competing for assets against dominant funds, are actually larger than would otherwise be expected.

Given these unexpected findings, we expand the set of fund characteristics in Tables 7 and 8 in an attempt to explain the excess allocations to dominated ETFs. We specifically include variables related to performance, uniqueness, and investor awareness. The independent variables from Table 6 are used as controls in these tables.

Table 7 shows results when we include the performance and uniqueness measures from the benchmark analyses developed in Section 2.2.[21] The coefficient estimate on alpha for Quasi-Index ETFs of 0.93 (t-statistic of 3.16) implies a 11% increase in size for a one-standard-deviation increase in alpha. The coefficient estimates for Alpha are insignificant for the remaining categories and negative for Index, Sector, and Smart Beta ETFs. These results suggest that past abnormal

[20] The positive relation between prior quarter return and size in Sector ETFs is consistent with the style-level feedback trading documented by Broman (2022).

[21] The sample size decreases from Table 6 to Table 7 because of data requirements for the performance and uniqueness variables. We show in the appendix (Table A7) that inferences for the tests in Table 6 are the same using the sample from Table 7.

performance explains relatively little variation in ETF allocations.

We predict that the relation between strategy uniqueness and ETF size will be negative for Index, Sector, and Smart Beta ETFs, as investors likely desire products in these categories that more closely track their stated strategies. This prediction is supported in the data. A one-standard-deviation decrease in uniqueness among Index ETFs is associated with a 164% increase in size (t-statistic of -6.56). Sector ETFs show a weaker relation between uniqueness and market capitalization with an implied 56% increase in size (t-statistic of -9.47). Finally, Smart Beta ETFs have an implied 70% increase in size (t-statistic of -14.36) with a one-standard-deviation decrease in uniqueness.

Surprisingly, Table 7 also shows that uniqueness and size are negatively related among Quasi-Index and Active ETFs. Ex ante, we expect a positive relation because investors in these categories are paying higher fees on average for funds with strategies that deviate from straight index investments. Nonetheless, we find economically large increases in size of 182% for Quasi-Index ETFs (t-statistic of -23.76) and 173% for Active ETFs (t-statistic of -19.49) associated with one-standard-deviation decreases in uniqueness. Given the higher fees for ETFs in these categories relative to their Index ETF peer benchmarks, the finding of a strong negative association between uniqueness and market cap is consistent with our observation that many dominated ETFs manage substantial assets. Across all categories, investors display a preference for ETFs that more closely track low-cost alternatives even with the large differences in average fees.

Controlling for the performance and uniqueness measures in Table 7 produces changes in inferences about dominated ETFs in some categories. After accounting for investor preferences for funds that more closely track their benchmarks, dominated Index ETFs are about 33% smaller (t-statistic of -2.52) than would otherwise be expected and the Sector ETF coefficient is negative and statistically insignificant. The coefficient estimates remain significantly positive in the remaining categories. Dominated ETFs are excessively large in the Quasi-Index (138% larger, t-statistic of 8.66), Active (213% larger, t-statistic of 8.90), and Smart Beta (281% larger, t-statistic of 19.33) categories. The 99% correlation coefficients indicate the effects are significantly stronger at the higher correlation threshold for the Quasi-Index, Active, and Smart Beta categories.

Table 7 shows that including ETF performance and uniqueness measures is not sufficient to explain the excess allocations to dominated ETFs. We supplement these variables with fund characteristics related to investor awareness. Search costs may be important in fund selection (e.g., Hortaçsu & Syverson, 2004; Roussanov et al., 2021), and the salience of a particular ETF may explain investor allocations despite the other fund characteristics.

Table 8 introduces three ETF characteristics related to investor awareness.[22] ETF age is likely positively related to investor awareness. Older ETFs initially competed in a less-crowded ETF market and may have been more salient to investors, and investors may remember owning these older funds in the past. We find that age is significantly positively associated with size across all categories. The economic magnitudes are large. For example, doubling the age of an Index ETF is associated with a 406% increase in size (t-statistic of 29.42). Age is likely related to several aspects of a fund, but this variable's strong positive relation with size provides initial evidence that funds with greater investor awareness attract more capital.

The remaining two awareness variables—search volume and sponsor tilt—are also positively and significantly related to ETF size across almost all categories. Internet search volume proxies for investor awareness and attention, and it likely captures retail investor awareness given the sheer number of retail investors and the fact that institutions have alternative platforms for information (e.g., Bloomberg). Sponsor tilt, on the other hand, is designed to measure the effect of institutional investor tendencies to invest in ETFs from the same sponsor. A one-standard-deviation increase in the log of search volume for Index ETFs, for example, is associated with a 17% increase in market cap (t-statistic of 4.74). Search volume is insignificantly related to size for Active ETFs but positive and significant for the remaining three categories. The coefficient estimate for sponsor tilt is significantly positive for each category. A one-standard-deviation increase in sponsor tilt is associated with a 39% increase in size (t-statistic of 7.92) for Index ETFs. Overall, these results indicate that investor awareness is a significant predictor of ETF size. This finding is consistent with a substantial role of search costs in determining allocations in the ETF market.

Table 8 shows that dominated Index ETFs are about 23% smaller (t-statistic of -3.06) than predicted based on our full set of fund characteristics. In contrast, we continue to find significant excess sizes in the Quasi-Index, Active, and Smart Beta categories. Dominated Quasi-Index ETFs remain 59% larger (t-statistic of 4.91). The coefficients are even larger in magnitude for Active and Smart Beta ETFs, with implied excess sizes of 217% (t-statistic of 9.86) and 116% (t-statistic of 9.90), respectively. For these three categories, the coefficient estimates for the 99% domination threshold suggest the effects are only magnified for ETFs that are dominated under the more stringent definition.

Dominated ETFs in the Sector category as a whole have insignificant excess assets. Sector ETFs can be further classified into two groups: those that simply track a sector index (Sector Index ETFs)

[22] A version of Table 8 that includes the coefficient estimates for all control variables is available in the appendix (Table A8).

and those that develop more complex strategies (Sector Active ETFs). In the appendix (Table A9), we estimate the regressions from Table 8 separately for Sector Index ETFs and Sector Active ETFs. We find that dominated Sector Index ETFs are significantly smaller with an effect on size of −21% (t-statistic of −2.46), whereas dominated Sector Active ETFs are 28% larger (t-statistic of 4.02) than would otherwise be expected.

Our analysis of dominated ETFs in Section 3.2 reveals a distinction between the relatively straightforward Index and Sector Index ETFs and the more specialized Quasi-Index, Active, Sector Active, and Smart Beta ETFs. On the one hand, dominated ETFs that track well-known indexes (whether they are non-sector or sector indexes) are smaller on average. On the other hand, dominated ETFs that promise more complex or active strategies manage significant excess assets. This dichotomy suggests investors are more capable of identifying dominated products when comparisons are simpler.

The specification in Table 8 includes many fund characteristics related to ETF fees, liquidity, turnover, performance, uniqueness, and awareness. In the appendix (Table A10), we introduce additional control variables. ETFs that belong to large fund families may have more assets, so we control for the log of family size (excluding the ETF itself). We also control for whether ETFs allow for in-kind creation and redemption, which may affect tax efficiency, as well as whether a given fund has a focus on environmental, social, and governance (ESG) issues. Finally, the share price of an ETF can deviate from the NAV during trading, and the creation and redemption mechanism generally maintains a close relation between the two. We include the average absolute premium, where the premium is calculated as the difference between the share price and the NAV scaled by the NAV, as a measure of the magnitude of deviations. Inferences about excess allocations to dominated ETFs are unchanged after including these additional fund characteristics.

Our finding that dominated ETFs are abnormally large is surprising given the structure of the ETF market. The lack of broker incentive fees as well as the relative transparency and simplicity of ETFs would seem to promote efficient allocations, particularly for more sophisticated investors and for retail investors who can rely on unconflicted investment professionals. To study the potential effects of investor sophistication, we study institutional allocations to ETFs. Figure 4 plots time series of the average institutional ownership of ETFs across all ETFs and for dominated ETFs using the 95% and 99% correlation thresholds.[23] The figure shows that retail and institutional investors have similar allocations to dominated ETFs. At the 95% correlation threshold, institutions have

[23] We calculate quarterly holdings of institutional investors by aggregating the Thomson Reuters 13F database and scaling by market capitalization plus short interest. We correct for known errors in the database (e.g., Sias, Turtle, & Zykaj, 2016).

held 34% of dominated ETF shares on average during the sample period versus 36% for all ETFs. The time-series patterns are also quite similar across the groups.[24] Accounts that are managed by retail and institutional traders alike are accruing excess costs in dominated ETFs, despite the lack of conflicts of interest from incentive fees. This finding suggests that search costs and financial illiteracy are significant barriers to maintaining efficient investment allocations even in the absence of misaligned advisor incentives.

3.3 Discussion

The cross-sectional findings from Section 3.2 appear consistent with the time-series observation in Section 3.1 that the aggregate costs of dominated ETFs have been increasing over time. The origins of the ETF market are rooted in Index ETFs. These ETFs provide low-cost diversification, similar to open-end index mutual funds, with added features of intraday trading and tax efficiencies. Investors seem able to identify and avoid dominated products in this category. Our sample period coincides with a time of increasing emphasis on choosing low-fee funds, and investors may be heeding this advice for relatively simple-to-compare Index ETFs. In line with this trend, Figure 5 shows that the average fee of Index ETFs has declined from 0.21% in 2000 to 0.13% in 2018. This decline in Index ETF fees over time is consistent with a competitive market in which fee-sensitive investors allocate less to Index ETFs that are dominated by cheaper funds.

Recent years are marked by a proliferation of listed ETFs, a variety of more complex stated ETF strategies, and greater potential for closet indexing by ETFs that claim to provide unique exposures. As ETF market complexity increases, investors are allocating more and more capital to ETFs that are dominated by highly correlated, lower-fee, higher-liquidity ETFs. Many of these dominated ETFs are newly listed. Strikingly, 46% of the dominated ETFs from the second half of our sample are immediately dominated by an already existing fund upon listing (compared with 11% of dominated ETFs from the first half), and dominated ETFs are dominated by an older ETF in 92% of their ETF-quarter observations.

Excess allocations to dominated ETFs in the non-Index categories could leave funds feeling less pressure to compete on fees. Consistent with this possibility, Figure 5 demonstrates that average fees have been relatively stable throughout the sample for the non-Index categories.[25] Apparent

[24] In untabulated results, we also study institutional ownership within the five ETF categories. Average institutional ownership is significantly lower for dominated ETFs relative to other ETFs within the Index, Active, and Sector categories. The lower allocations to dominated funds in the Index and Sector categories are consistent with institutions being able to identify dominated products when comparisons are relatively simple. In contrast, institutional ownership is higher for dominated ETFs in the Quasi-Index and Smart Beta categories, which suggests there may be limits to institutions' ability to compare funds with more complicated strategies.

[25] Box, Davis, and Fuller (2020) also find that average ETF expense ratios are steady over this period even though

differentiation in strategy may be enough for an ETF to attract assets, even when its returns are closely tracking those of cheaper alternatives. Our results suggest investors–both retail and institutional–would benefit from simplifying their search process and focusing on a set of low-cost index ETFs.

4 Conclusion

This paper studies dominated products in the U.S. equity ETF market. The ETF market provides an ideal setting for examining dominated products given its lack of broker incentives to avoid conflicts of interest, the relative transparency and simplicity of the market to reduce search costs, and the potential for investors to receive unconflicted advice to overcome financial illiteracy. Despite these market features, we find that investors collectively make substantial investments in a large number of ETFs that are dominated by highly correlated, lower-fee, higher-liquidity ETFs. We find evidence that investors are able to identify and allocate less capital to dominated Index and Sector Index ETFs. Dominated ETFs in other categories, however, counterintuitively receive excess allocations from investors. This finding persists after controlling for a multitude of fund characteristics relating to fees, liquidity, turnover, performance, uniqueness, and investor awareness.

The aggregate cost to investors of allocations to dominated ETFs is economically large. We estimate the total cost of using high-fee, low-liquidity ETFs in the U.S. equity ETF market to be $1.0 billion to $6.7 billion during our sample period. The cost is increasing over time, and annualized excess cost estimates at the end of our sample period range from $146 million to $847 million. These large costs exist in portfolios managed by retail and institutional investors even in the absence of incentive misalignment, suggesting that search costs and financial illiteracy are significant barriers to efficient investment allocations.

Regardless of the underlying cause, our findings suggest that allocations to dominated ETFs are eroding potential gains from the increases in the number of available ETFs and the variety of ETF strategies. Given the totality of our evidence, we believe the growing complexity of the ETF market in recent years is costly to investors. We conclude that investors, whether short-term or long-term oriented, would benefit from isolating their attention to a small set of low-cost, high-liquidity ETFs.

news coverage has emphasized competition on fees.

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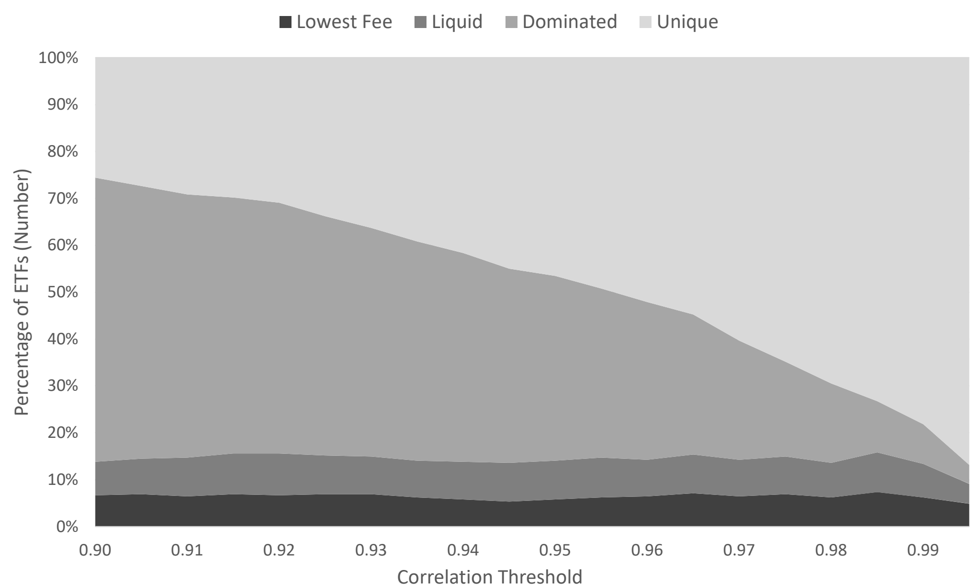
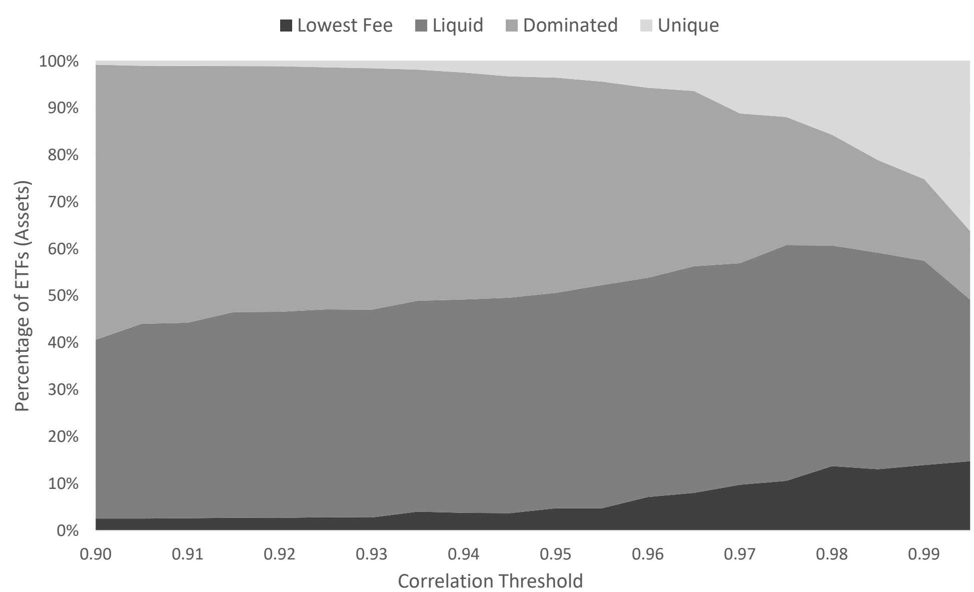
Figure 1: ETFs and Assets in Dominated and Non-Dominated Categories. The figure displays percentages associated with the number of ETFs (Panel A) and total market capitalization (Panel B) for four categories of ETFs (lowest fee, liquid, dominated, and unique) as a function of the correlation threshold. Dominated ETFs are defined as those with a dominant ETF that exceeds the return correlation threshold, has a weakly lower expense ratio, has a lower bid-ask spread, and has higher trading volume. Lowest fee ETFs have the lowest fee of all correlated ETFs. Liquid ETFs are correlated with other ETFs, do not have the lowest fee among these ETFs, but are also not dominated. Thus, they provide better liquidity (along at least one dimension) relative to the correlated lowest fee ETF. Unique ETFs have correlations with all other ETFs that are strictly less than the correlation threshold. The sample period is June 2018.



Panel A: Percentage of ETF Types by Number



Panel B: Percentage of ETF Types by Assets

Figure 2: Total Market Capitalization of Dominated ETFs. The figure plots the total market capitalization of dominated ETFs as a percentage of the total market capitalization of all ETFs in the sample using correlation thresholds of 95% (solid line) and 99% (dashed line). Dominated ETFs are defined as those with a dominant ETF that exceeds the return correlation threshold, has a weakly lower expense ratio, has a lower bid-ask spread, and has higher trading volume. The sample period is January 2000 through June 2018.

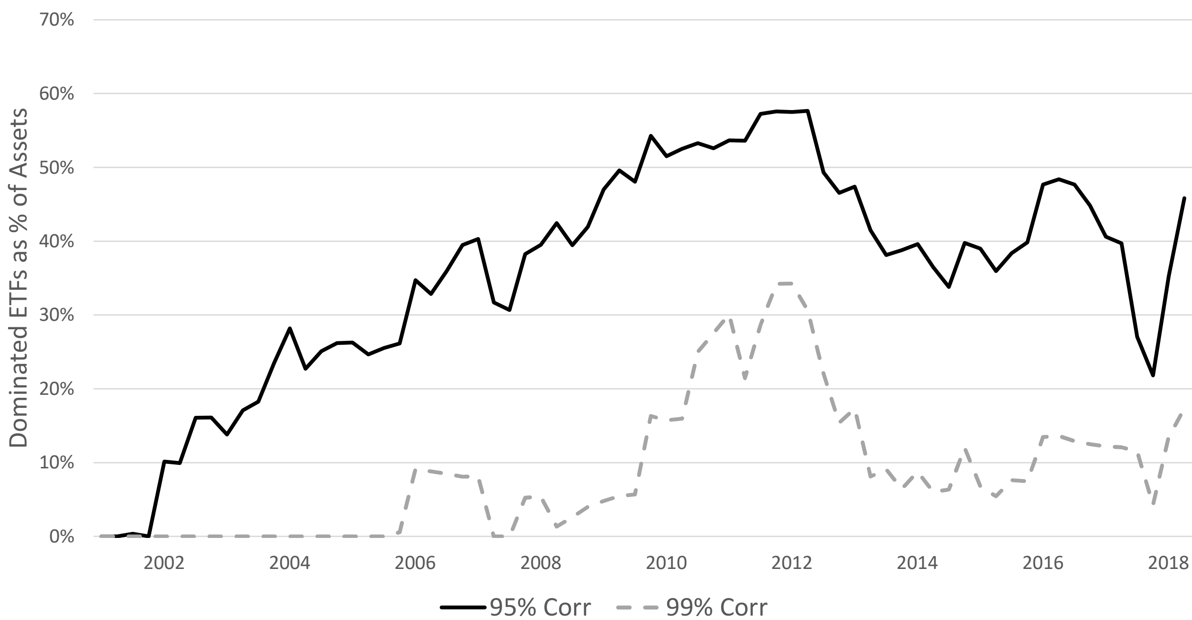
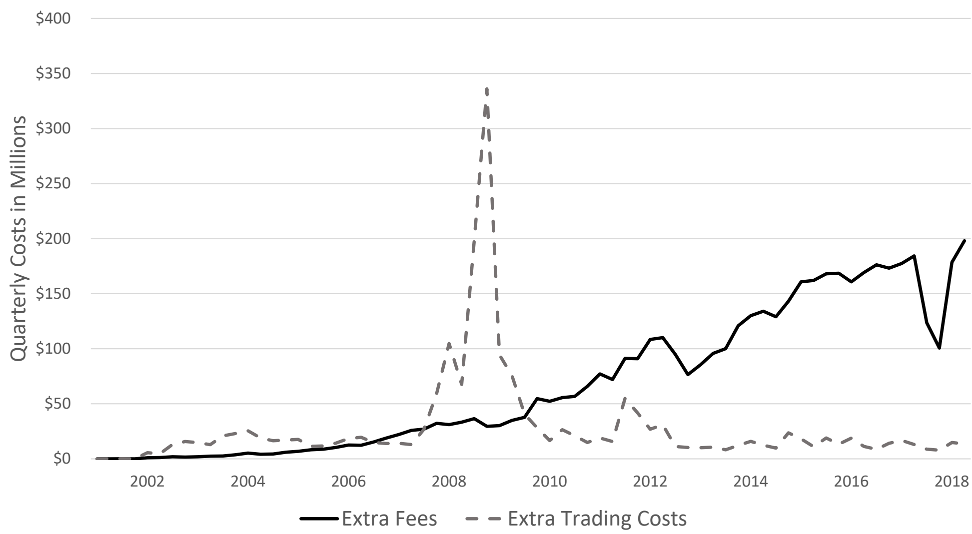
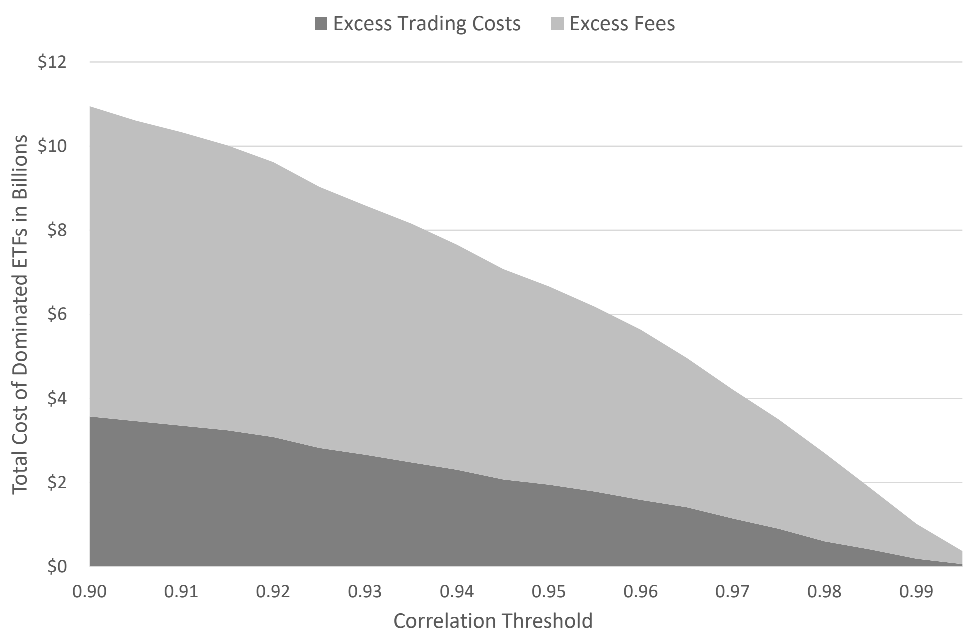


Figure 3: Aggregate Excess Costs of Dominated ETFs. The figure plots the costs of dominated funds. Panel A plots the quarterly cost of dominated ETFs broken down by extra fees (solid line) and extra trading costs (dashed line), based on the 95% correlation threshold. Panel B plots the total extra fees and extra trading costs over our full sample as a function of the correlation threshold. Extra trading costs are measured as one-half of the difference in bid-ask spreads between the dominated and dominant ETFs multiplied by the trading volume. Dominated ETFs are defined as those with a dominant ETF that exceeds the return correlation threshold, has a weakly lower expense ratio, has a lower bid-ask spread, and has higher trading volume. The sample period is January 2000 through June 2018.



Panel A: Quarterly Dominated Costs (95% Correlation)



Panel B: Total Dominated Costs across Correlations

Figure 4: Institutional Ownership of Dominated ETFs. The figure plots the average institutional ownership of all ETFs in the sample (solid line) and of dominated ETFs using correlation thresholds of 95% (dashed line) and 99% (dotted line). Dominated ETFs are defined as those with a dominant ETF that exceeds the return correlation threshold, has a weakly lower expense ratio, has a lower bid-ask spread, and has higher trading volume. The sample period is January 2000 through June 2018.

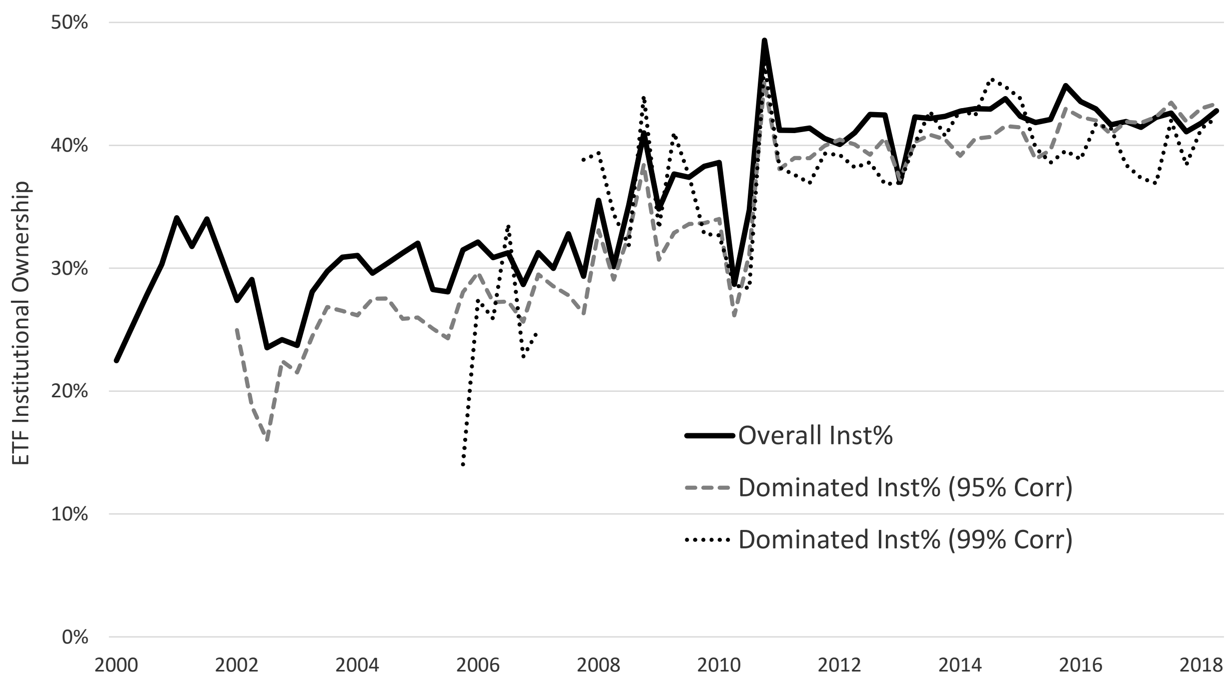


Figure 5: Average ETF Expense Ratio by Category. The figure plots the average quarterly expense ratio of ETFs in the Index, Quasi-Index, Active, Sector, and Smart Beta categories. The sample period is January 2000 through June 2018.

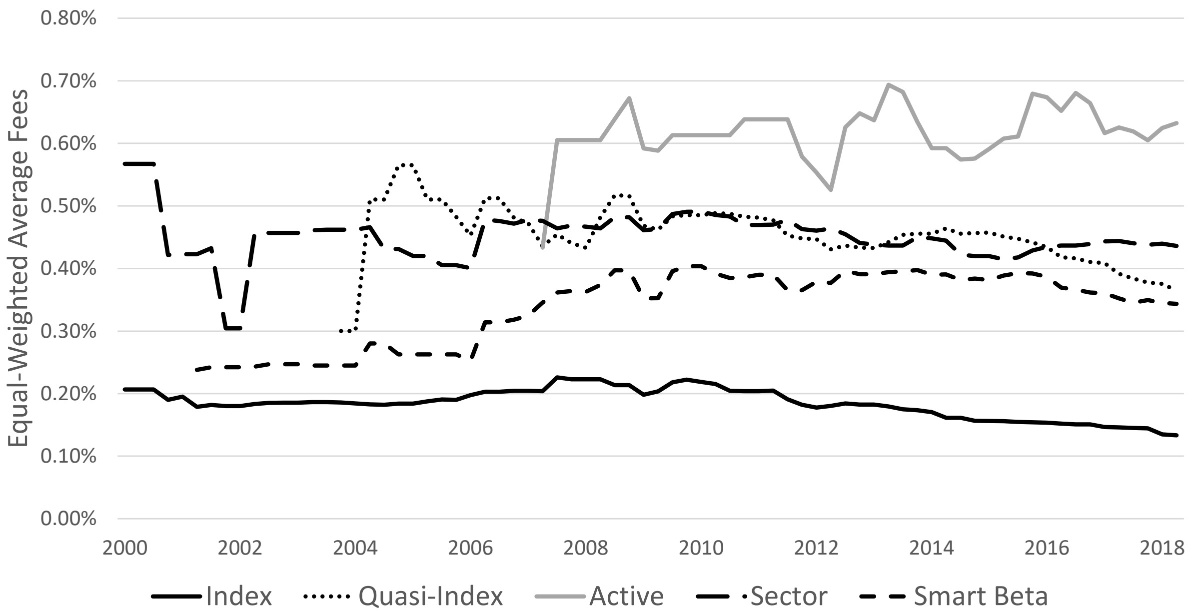


Table 1: Annual ETF Sample

The table reports the number and aggregate market capitalization of ETFs in our sample. ETF classifications are based on Lipper codes and fund descriptions on ETF.com and ETFDB.com. Number and Market Cap are measured at the end of each calendar year, except for 2018 which is measured at the end of June. Market Cap is reported in millions.

	Index ETFs		Quasi-Index ETFs		Active ETFs		Sector ETFs		Smart Beta ETFs		All ETFs	
Year	Number	Market Cap	Number	Market Cap	Number	Market Cap	Number	Market Cap	Number	Market Cap	Number	Market Cap
2000	3	$29,988	0	$0	0	$0	7	$2,259	0	$0	10	$32,247
2001	10	$46,742	0	$0	0	$0	9	$3,469	14	$4,172	33	$54,382
2002	11	$56,407	0	$0	0	$0	26	$5,402	16	$6,965	54	$68,805
2003	12	$76,126	2	$331	0	$0	27	$10,371	16	$13,366	57	$100,195
2004	17	$106,196	2	$732	0	$0	34	$17,656	22	$25,248	75	$149,832
2005	22	$117,744	4	$9,416	0	$0	38	$24,926	30	$33,077	94	$185,164
2006	25	$132,550	10	$11,978	0	$0	57	$35,000	44	$54,270	137	$233,813
2007	28	$201,121	21	$12,006	6	$386	91	$53,846	54	$73,995	200	$341,354
2008	30	$188,103	28	$8,723	10	$230	107	$44,586	69	$55,798	244	$297,440
2009	30	$207,749	31	$12,316	10	$449	115	$63,407	71	$65,789	257	$349,709
2010	33	$235,522	36	$24,781	11	$688	126	$83,719	75	$81,228	281	$425,938
2011	43	$238,173	42	$39,066	8	$802	136	$90,162	86	$83,768	315	$451,970
2012	41	$322,893	49	$50,977	10	$1,203	147	$118,239	100	$106,794	347	$600,106
2013	41	$485,034	43	$81,797	16	$2,912	145	$182,625	108	$159,525	353	$911,893
2014	40	$581,881	52	$103,160	19	$4,224	160	$243,872	119	$213,995	390	$1,147,132
2015	40	$586,250	57	$97,406	29	$4,025	166	$245,604	129	$242,534	421	$1,175,819
2016	40	$739,591	66	$127,953	29	$5,484	176	$280,787	150	$311,833	461	$1,465,648
2017	40	$979,235	71	$155,043	33	$8,689	191	$349,069	152	$405,598	487	$1,897,634
2018	39	$1,020,377	61	$136,924	27	$9,104	178	$352,477	144	$427,979	449	$1,946,861

Table 2: Sample Summary Statistics

The table reports summary statistics for ETFs in our sample split by Index, Quasi-Index, Active, Sector, and Smart Beta ETFs. All variables are defined in Table A1. The sample period is January 2000 through June 2018. Market cap is reported in millions.

	Index	Quasi-Index	Active	Sector	Smart Beta
Number of ETFs	46	92	50	211	170
Number of Observations	2,047	2,057	698	7,046	5,041
Market Cap	$10,262	$1,433	$171	$1,068	$1,555
Expense Ratio	0.180	0.441	0.626	0.450	0.365
Bid-Ask Spread	0.097	0.222	0.456	0.170	0.180
Trading Turnover	2.22	0.53	0.60	1.82	0.67
Turnover Ratio	0.151	0.498	1.505	0.353	0.559
Quarter Return	2.63	2.63	2.38	2.60	2.69
Alpha	−0.041	−0.026	−0.052	−0.009	−0.040
Uniqueness	0.080	0.147	0.246	0.193	0.146
ETF Age	8.38	5.65	3.70	6.94	6.49
Search Volume	638,735	302,295	245,603	553,146	283,815
Sponsor Tilt	0.086	0.035	0.053	0.049	0.073
Dominated	0.586	0.489	0.182	0.283	0.595
Dominated at 99%	0.212	0.039	0.010	0.062	0.084

Table 3: Sector and Smart Beta Summary Statistics

The table reports summary statistics for Sector and Smart Beta ETFs. Panel A summarizes which sectors are represented, and Panel B summarizes which Smart Beta strategies are represented and the average number of claimed strategies. The sample period is January 2000 through June 2018.

Panel A: Sector Flags	N	Mean
Basic Materials	211	0.052
Consumer Goods	211	0.057
Consumer Services	211	0.071
Financial Services	211	0.147
Health and Biotechnology	211	0.114
Industrials	211	0.095
Natural Resources	211	0.156
Real Estate	211	0.095
Science and Technology	211	0.133
Telecommunications	211	0.019
Utilities	211	0.057
Panel B: Smart Beta Flags	N	Mean
Value	170	0.441
Growth	170	0.276
Small Cap	170	0.294
Momentum	170	0.235
Profitability	170	0.129
Quality	170	0.153
Low Volatility	170	0.224
Total Flags	170	1.753

Table 4: Dominated ETF Characteristics

The table displays information on characteristics of dominated and dominant ETFs. Panel A shows the numbers of dominated and dominant ETFs and the distributions of observations across ETF categories for each correlation threshold. Panel B displays sample means of ETF characteristics for dominated and dominant ETFs and the differences between the sample means, and Panel C shows return moments for the lagged and next quarters. For each correlation threshold, the samples include quarterly observations for dominated ETFs and the paired dominant ETF. All variables are defined in Table A1, and ***, **, and * indicate statistical significance of differences in sample means at the 1%, 5%, and 10% levels, respectively. The sample period is January 2000 through June 2018. Market cap is reported in millions.

Panel A: Dominated and Dominant ETFs by Category

	95% Correlation			99% Correlation		
	Dominated	Dominant	Difference	Dominated	Dominant	Difference
Distinct ETFs	322	164		109	66	
Observations	7,327	7,327		1,378	1,378	
Index	16%	62%	−46%***	31%	50%	−19%***
Quasi-Index	14%	4%	9%***	6%	3%	3%***
Active	2%	0%	2%***	1%	0%	1%***
Sector	27%	23%	5%***	32%	32%	0%
Smart Beta	41%	11%	30%***	31%	15%	15%***

Panel B: Dominated and Dominant ETF Characteristics

	95% Correlation			99% Correlation		
	Dominated	Dominant	Difference	Dominated	Dominant	Difference
Market Cap	$2,157	$13,749	−$11,592***	$3,288	$17,563	−$14,275***
Expense Ratio	0.34	0.12	0.22***	0.24	0.12	0.12***
Bid-Ask Spread	0.10	0.04	0.06***	0.05	0.03	0.03***
Trading Turnover	0.90	2.46	−1.56***	0.75	2.93	−2.19***
Turnover Ratio	0.33	0.12	0.21***	0.15	0.11	0.05***
Alpha	−0.04%	−0.01%	−0.03%**	0.04%	0.01%	0.03%
Uniqueness	0.06	0.03	0.03***	0.02	0.01	0.01***
ETF Age	7.77	9.00	−1.24***	9.09	10.64	−1.56***
Log Search Volume	9.89	11.21	−1.32***	10.12	11.67	−1.55***
Sponsor Tilt	0.07	0.18	−0.10***	0.10	0.14	−0.05***

Panel C: Dominated and Dominant ETF Return Moments

	95% Correlation			99% Correlation		
	Dominated	Dominant	Difference	Dominated	Dominant	Difference
Quarter t Return Mean	2.64	2.67	−0.03	3.40	3.43	−0.03
Quarter t Return Std. Dev.	8.90	8.42	0.48***	8.25	8.16	0.09***
Quarter t Return Skewness	−0.80	−0.82	0.02	−0.77	−0.80	0.03
Quarter t Return Kurtosis	5.27	5.17	0.10	4.84	4.76	0.08
Quarter $t+1$ Return Mean	3.00	2.99	0.00	3.60	3.61	−0.01
Quarter $t+1$ Return Std. Dev.	8.59	8.20	0.39***	7.74	7.67	0.07*
Quarter $t+1$ Return Skewness	−0.82	−0.91	0.09***	−0.80	−0.86	0.06*
Quarter $t+1$ Return Kurtosis	5.60	5.62	−0.01	5.39	5.34	0.05

Table 5: Dominated ETF Excess Costs

The table displays the excess costs of investors using dominated ETFs relative to using the dominant counterparts. Panel A displays the average annual costs from 2001 through June 2018, Panel B displays the annualized costs for the second quarter of 2018, and Panel C shows the total costs from our sample period of January 2000 through June 2018. Extra fees are calculated using the difference in quarterly expense ratios between the dominated and dominant ETF pairs multiplied by the dominated ETF's average market capitalization during the quarter. Extra trading costs are calculated using one-half the difference in bid-ask spreads between the dominated and dominant ETF pairs multiplied by the dominated ETF's annual volume. Costs are reported in millions.

Panel A: Average Annual Costs		
	95% Correlation	99% Correlation
Extra Fees	\$255	\$45
Extra Trading Costs	\$105	\$10
Total Average Annual Costs	\$360	\$55
Panel B: Annualized Costs for Q2 2018		
	95% Correlation	99% Correlation
Extra Fees	\$792	\$137
Extra Trading Costs	\$54	\$9
Total Annualized Costs	\$847	\$146
Panel C: Total Costs		
	95% Correlation	99% Correlation
Extra Fees	\$4,715	\$827
Extra Trading Costs	\$1,949	\$187
Total Costs	\$6,664	\$1,014

Table 6: ETF Size Determinants by Category

The table displays quarterly panel regressions of Log Market Cap on ETF characteristics. Column (1) focuses on Index ETFs, Column (2) focuses on Quasi-Index ETFs, Column (3) focuses on Active ETFs, Column (4) focuses on Sector ETFs, and Column (5) focuses on Smart Beta ETFs. All variables are defined in Table A1. Standard errors are clustered at the quarter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 2000 through June 2018.

	Log Market Cap				
	(1) Index	(2) Quasi-Index	(3) Active	(4) Sector	(5) Smart Beta
Expense Ratio	-3.53***	-2.13***	-0.69***	-2.50***	-2.21***
	(-6.18)	(-12.22)	(-5.17)	(-11.00)	(-18.85)
Bid-Ask Spread	-6.90***	-1.36***	-0.33***	-4.30***	-1.30***
	(-4.25)	(-6.00)	(-6.46)	(-5.46)	(-6.29)
Trading Turnover	0.13***	-0.22***	-0.06**	0.09***	0.03
	(6.04)	(-3.95)	(-2.10)	(7.14)	(1.03)
Turnover Ratio	-1.11***	-0.09***	0.02***	-0.34***	-0.11**
	(-3.35)	(-3.59)	(5.13)	(-10.14)	(-2.57)
Quarter Return	0.04**	0.00	-0.00	0.01***	0.00
	(2.15)	(0.21)	(-0.15)	(4.14)	(0.39)
Dominated	0.05	1.79***	2.15***	0.34***	1.83***
	(0.37)	(15.42)	(18.39)	(4.97)	(30.94)
Dominated at 99%	0.28***	0.92***	1.29***	0.11	0.95***
	(3.05)	(12.40)	(6.88)	(0.88)	(7.58)
Observations	2,047	2,057	698	7,046	5,041
Adjusted R^2	0.425	0.451	0.372	0.444	0.564
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter	Quarter	Quarter

Table 7: Performance and Uniqueness

The table displays quarterly panel regressions of Log Market Cap on ETF characteristics. Column (1) focuses on Index ETFs, Column (2) focuses on Quasi-Index ETFs, Column (3) focuses on Active ETFs, Column (4) focuses on Sector ETFs, and Column (5) focuses on Smart Beta ETFs. Additional controls are Expense Ratio, Bid-Ask Spread, Trading Turnover, Turnover Ratio, and Quarter Return. All variables are defined in Table A1. Standard errors are clustered at the quarter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 2000 through June 2018.

	Log Market Cap				
	(1)	(2)	(3)	(4)	(5)
	Index	Quasi-Index	Active	Sector	Smart Beta
Alpha	-0.93	0.93***	0.40	-0.02	-0.00
	(-1.54)	(3.16)	(1.43)	(-0.18)	(-0.40)
Uniqueness	-9.95***	-6.41***	-5.90***	-2.59***	-3.57***
	(-6.56)	(-23.76)	(-19.49)	(-9.47)	(-14.36)
Dominated	-0.40**	0.87***	1.14***	-0.04	1.34***
	(-2.52)	(8.66)	(8.90)	(-0.52)	(19.33)
Dominated at 99%	0.06	0.95***	1.14***	0.03	0.88***
	(0.64)	(12.53)	(7.68)	(0.31)	(6.95)
Observations	1,783	2,007	696	6,691	5,041
Adjusted R^2	0.530	0.533	0.520	0.483	0.589
Additional Controls	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter	Quarter	Quarter

Table 8: Investor Awareness

The table displays quarterly panel regressions of Log Market Cap on ETF characteristics. Column (1) focuses on Index ETFs, Column (2) focuses on Quasi-Index ETFs, Column (3) focuses on Active ETFs, Column (4) focuses on Sector ETFs, and Column (5) focuses on Smart Beta ETFs. Additional controls are Expense Ratio, Bid-Ask Spread, Trading Turnover, Turnover Ratio, Quarter Return, Alpha, and Uniqueness. All variables are defined in Table A1. Standard errors are clustered at the quarter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 2000 through June 2018.

	Log Market Cap				
	(1) Index	(2) Quasi-Index	(3) Active	(4) Sector	(5) Smart Beta
Log ETF Age	2.34***	1.53***	1.03***	1.48***	1.11***
	(29.42)	(21.20)	(9.65)	(20.72)	(24.69)
Log Search Volume	0.05***	0.11***	-0.01	0.01***	0.08***
	(4.74)	(9.05)	(-1.54)	(3.23)	(18.65)
Sponsor Tilt	2.44***	0.51**	1.37***	2.22***	2.69***
	(7.92)	(2.27)	(4.10)	(15.15)	(11.32)
Dominated	-0.26***	0.47***	1.15***	-0.02	0.77***
	(-3.06)	(4.91)	(9.86)	(-0.34)	(9.90)
Dominated at 99%	0.09	0.31***	1.11***	0.22***	0.60***
	(0.97)	(3.30)	(5.22)	(5.03)	(6.33)
Observations	1,783	2,007	696	6,691	5,041
Adjusted R^2	0.775	0.667	0.577	0.627	0.698
Additional Controls	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter	Quarter	Quarter

A Variable Definitions and Additional Results

Table A1: Variable Definitions

This table contains the definitions and descriptions of the variables used in the paper.

Variable	Definition
Market Cap	Share price times shares outstanding at quarter end (Sources: Bloomberg and CRSP).
Expense Ratio	The annual expense ratio (Source: CRSP).
Bid-Ask Spread	The mean of the daily bid-ask spread as a percentage of NAV (Source: CRSP).
Trading Turnover	The mean of the daily trading volume in the ETF divided by shares outstanding (Source: Bloomberg).
Turnover Ratio	The annual turnover ratio for the ETF portfolio (Source: CRSP).
Quarter Return	The ETF return for the quarter (Sources: Bloomberg and CRSP).
Alpha	Alpha from the benchmark regression described in Section 2.2 multiplied by 252 (Sources: CRSP, Kenneth French, and AQR).
Uniqueness	$(1 - R^2)$ from the benchmark regression described in Section 2.2 (Sources: CRSP, Kenneth French, and AQR).
ETF Age	Number of years since fund inception (Source: Bloomberg).
Search Volume	Average monthly Google Keyword Planner search volume (Source: keywordseverywhere.com).
Sponsor Tilt	The target-ETF-share-weighted average of the abnormal sponsor holdings of the 13F institutions that own an ETF. Abnormal sponsor holdings are calculated by subtracting the 13F market share of each sponsor from the sponsor's portfolio weights in each 13F institution excluding the target ETF (Source: Thomson Reuters 13F).
Dominated	Indicator equal to one if the ETF has at least a 95% correlation in daily returns over the last year with another ETF that has a weakly lower expense ratio, lower bid-ask spread, and higher trading volume (Sources: Bloomberg and CRSP).
Dominated at 99%	Indicator equal to one if the ETF has at least a 99% correlation in daily returns over the last year with another ETF that has a weakly lower expense ratio, lower bid-ask spread, and higher trading volume (Sources: Bloomberg and CRSP).
Dominated Cost	The cost, in millions of dollars, of the extra fees and trading costs of the dominated ETF relative to its dominant ETF, where dominated ETFs are defined with the 95% correlation threshold. Extra fees are based on one-quarter of the difference in annual expense ratios and extra trading costs are calculated using one-half the difference in bid-ask spreads (Sources: Bloomberg and CRSP).
Family Size	Sum of market cap at quarter end for all ETFs that share a fund sponsor excluding the target ETF (Sources: Bloomberg and CRSP).
In-Kind Creation	Indicator equal to one if the ETF allows in-kind creation and redemption (Source: Bloomberg).
ESG	Indicator equal to one if the ETF claims to focus on environmental, social, and governance issues (Sources: ETF.com and ETFDB.com).
Average Absolute Premium	The mean of the daily absolute premium, where the premium is calculated as the difference between the price and NAV as a percentage of NAV (Sources: Bloomberg and CRSP).
Institutional Ownership	Quarterly institutional ownership for ETFs as a percentage of available shares. Available shares are shares outstanding plus short interest (Sources: Thomson Reuters 13F and Compustat).
Positive Flow Indicator	An indicator variable for whether next-quarter flows are strictly positive (Sources: Bloomberg and CRSP).

Table A2: Next-Quarter Flows

The table displays quarterly regressions of an indicator variable for whether next-quarter flows are positive (Positive Flow Indicator) on ETF characteristics. Column (1) focuses on Index ETFs, Column (2) focuses on Quasi-Index ETFs, Column (3) focuses on Active ETFs, Column (4) focuses on all Sector ETFs, and Column (5) focuses on Smart Beta ETFs. All variables are defined in Table A1. Standard errors are clustered at the quarter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 2000 through June 2018.

	Positive Flow Indicator				
	(1) Index	(2) Quasi-Index	(3) Active	(4) Sector	(5) Smart Beta
Expense Ratio	-1.01***	-0.19**	-0.26***	-0.26***	-0.31***
	(-7.54)	(-2.37)	(-3.31)	(-5.73)	(-5.13)
Bid-Ask Spread	0.07	-0.04*	-0.01	-0.14	0.03
	(0.43)	(-1.96)	(-0.36)	(-1.67)	(1.03)
Trading Turnover	-0.00	0.03	-0.01	0.00**	0.01
	(-0.85)	(0.77)	(-1.58)	(2.24)	(0.92)
Turnover Ratio	0.09	-0.02	0.01	0.01	-0.00
	(1.17)	(-1.22)	(1.62)	(0.41)	(-0.08)
Quarter Return	0.02**	0.02***	0.02***	0.01***	0.02***
	(2.19)	(5.28)	(2.91)	(3.86)	(5.90)
Alpha	0.07	0.07	0.21	0.01	0.01**
	(0.77)	(0.58)	(1.31)	(0.23)	(2.37)
Uniqueness	-0.62***	-0.35***	-0.03	-0.09	-0.45***
	(-3.28)	(-3.35)	(-0.14)	(-1.60)	(-5.14)
Log ETF Age	-0.14***	-0.05*	-0.08**	-0.08***	-0.18***
	(-7.04)	(-1.70)	(-2.43)	(-4.76)	(-11.14)
Log Search Volume	-0.00	0.01***	0.00	-0.00	0.01***
	(-0.17)	(2.81)	(0.46)	(-0.34)	(3.82)
Sponsor Tilt	0.37***	0.09	0.17	0.07	0.02
	(5.03)	(0.61)	(1.38)	(0.89)	(0.37)
Dominated	0.04*	0.13***	0.25***	0.03*	0.10***
	(1.73)	(4.73)	(5.19)	(1.96)	(4.64)
Dominated at 99%	-0.04	-0.08	0.14	-0.02	0.05**
	(-1.42)	(-1.37)	(0.90)	(-0.54)	(2.40)
Observations	1,739	1,916	646	6,481	4,871
Adjusted R^2	0.188	0.149	0.152	0.073	0.183
Additional Controls	No	No	No	No	No
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter	Quarter	Quarter

Table A3: ETF Fixed Effects

The table displays quarterly panel regressions of Log Market Cap on ETF characteristics with ETF and quarter fixed effects. Column (1) focuses on Index ETFs, Column (2) focuses on Quasi-Index ETFs, Column (3) focuses on Active ETFs, Column (4) focuses on Sector ETFs, and Column (5) focuses on Smart Beta ETFs. All variables are defined in Table A1. Standard errors are clustered at the quarter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 2000 through June 2018.

	Log Market Cap				
	(1) Index	(2) Quasi-Index	(3) Active	(4) Sector	(5) Smart Beta
Expense Ratio	-3.34***	1.11***	-0.27	-0.83**	0.49**
	(-3.72)	(4.25)	(-0.25)	(-2.19)	(2.03)
Bid-Ask Spread	-0.71***	-0.11	-0.01	-0.89***	-0.24***
	(-2.79)	(-1.43)	(-0.50)	(-4.15)	(-2.80)
Trading Turnover	0.00	-0.05*	0.01	0.00	-0.01
	(0.43)	(-1.81)	(0.63)	(1.65)	(-0.35)
Turnover Ratio	0.02	0.26***	0.01	-0.38***	-0.17***
	(0.09)	(2.67)	(1.53)	(-7.94)	(-4.37)
Quarter Return	0.00	-0.00	-0.00	0.01***	-0.00
	(0.38)	(-0.91)	(-0.53)	(5.46)	(-0.12)
Alpha	-0.60***	0.41**	0.88***	0.25***	0.01***
	(-5.37)	(2.31)	(3.30)	(5.03)	(4.05)
Uniqueness	-1.74***	-2.45***	-1.73***	-1.70***	-2.00***
	(-5.77)	(-9.72)	(-4.25)	(-9.78)	(-9.15)
Log ETF Age	1.51***	0.44***	0.38	1.11***	1.12***
	(15.80)	(2.86)	(1.42)	(11.10)	(15.71)
Log Search Volume	0.04***	0.12***	0.04*	0.06***	0.03***
	(4.21)	(6.30)	(1.82)	(4.81)	(5.37)
Sponsor Tilt	0.25*	1.13***	1.70***	2.35***	-0.27
	(1.85)	(4.77)	(4.02)	(12.89)	(-1.47)
Dominated	0.14***	0.26***	0.15	0.03	0.36***
	(5.31)	(4.70)	(1.22)	(1.11)	(9.10)
Dominated at 99%	-0.05**	0.17**	0.93***	-0.10**	0.12***
	(-2.08)	(2.48)	(3.42)	(-2.61)	(3.59)
Observations	1,783	2,007	693	6,691	5,041
Adjusted R^2	0.974	0.934	0.904	0.907	0.940
ETF Fixed Effects	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter	Quarter	Quarter

Table A4: ETF Family Fixed Effects

The table displays quarterly panel regressions of Log Market Cap on ETF characteristics with ETF family and quarter fixed effects. Column (1) focuses on Index ETFs, Column (2) focuses on Quasi-Index ETFs, Column (3) focuses on Active ETFs, Column (4) focuses on Sector ETFs, and Column (5) focuses on Smart Beta ETFs. All variables are defined in Table A1. Standard errors are clustered at the quarter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 2000 through June 2018.

	Log Market Cap				
	(1) Index	(2) Quasi-Index	(3) Active	(4) Sector	(5) Smart Beta
Expense Ratio	-2.56***	-0.41**	-0.15	-1.65***	-3.11***
	(-8.00)	(-2.27)	(-0.27)	(-10.42)	(-16.56)
Bid-Ask Spread	-3.42***	-0.27***	-0.00	-2.06***	-0.60***
	(-2.78)	(-3.33)	(-0.11)	(-4.48)	(-3.87)
Trading Turnover	0.07***	0.04	-0.01	0.03***	0.07***
	(8.47)	(0.83)	(-0.52)	(4.84)	(3.18)
Turnover Ratio	-0.60***	0.00	-0.00	-0.66***	-0.28***
	(-3.11)	(0.27)	(-0.13)	(-13.60)	(-6.89)
Quarter Return	0.01	-0.01	-0.01	0.01***	0.00
	(0.35)	(-0.47)	(-0.86)	(4.52)	(0.18)
Alpha	-1.17***	1.05***	0.48**	0.24***	-0.00
	(-4.19)	(3.95)	(2.13)	(2.94)	(-0.27)
Uniqueness	-6.25***	-3.77***	-3.24***	-1.09***	-2.93***
	(-7.26)	(-11.28)	(-6.30)	(-7.92)	(-14.41)
Log ETF Age	2.87***	1.36***	1.41***	1.59***	1.15***
	(22.35)	(18.37)	(7.70)	(30.75)	(18.88)
Log Search Volume	0.07***	0.12***	-0.00	0.03***	0.10***
	(5.99)	(10.06)	(-0.13)	(7.07)	(18.50)
Sponsor Tilt	1.36***	-0.13	1.19***	2.01***	1.59***
	(4.77)	(-0.38)	(3.07)	(12.06)	(6.37)
Dominated	-0.17**	0.39***	1.02***	-0.06	0.59***
	(-2.61)	(4.94)	(6.21)	(-1.52)	(8.35)
Dominated at 99%	-0.16**	0.43***	0.90***	0.02	0.42***
	(-2.33)	(4.25)	(3.55)	(0.47)	(5.24)
Observations	1,783	2,007	694	6,691	5,041
Adjusted R^2	0.808	0.747	0.752	0.716	0.752
ETF Family Fixed Effects	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter	Quarter	Quarter

Table A5: ETF Clustering

The table displays quarterly panel regressions of Log Market Cap on ETF characteristics. Column (1) focuses on Index ETFs, Column (2) focuses on Quasi-Index ETFs, Column (3) focuses on Active ETFs, Column (4) focuses on Sector ETFs, and Column (5) focuses on Smart Beta ETFs. All variables are defined in Table A1. Standard errors are clustered at the quarter and ETF levels, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 2000 through June 2018.

	Log Market Cap				
	(1) Index	(2) Quasi-Index	(3) Active	(4) Sector	(5) Smart Beta
Expense Ratio	-2.80*	-2.13***	0.38	-1.85***	-1.74***
	(-1.82)	(-2.91)	(0.78)	(-3.46)	(-4.38)
Bid-Ask Spread	-2.84	-0.32*	-0.07	-2.60***	-0.71***
	(-1.62)	(-1.83)	(-1.45)	(-3.25)	(-3.02)
Trading Turnover	0.08***	-0.02	-0.04**	0.06***	0.08
	(3.94)	(-0.28)	(-2.31)	(3.62)	(1.50)
Turnover Ratio	-0.07	-0.07	0.03***	-0.30	-0.19*
	(-0.07)	(-1.50)	(4.74)	(-1.25)	(-1.74)
Quarter Return	0.00	-0.01	-0.01	0.01***	-0.01
	(0.15)	(-0.45)	(-0.50)	(3.28)	(-0.54)
Alpha	-1.15**	0.56	0.38	0.18	-0.00
	(-2.22)	(1.32)	(0.82)	(0.99)	(-0.50)
Uniqueness	-7.82***	-4.30***	-4.73***	-0.64	-2.50***
	(-4.30)	(-6.23)	(-5.62)	(-1.15)	(-4.10)
Log ETF Age	2.34***	1.53***	1.03***	1.48***	1.11***
	(8.60)	(4.65)	(3.47)	(11.01)	(7.52)
Log Search Volume	0.05	0.11***	-0.01	0.01	0.08***
	(1.11)	(3.21)	(-0.42)	(0.57)	(5.05)
Sponsor Tilt	2.44***	0.51	1.37*	2.22***	2.69***
	(2.78)	(0.33)	(1.81)	(4.72)	(5.95)
Dominated	-0.26	0.47*	1.15***	-0.02	0.77***
	(-1.28)	(1.86)	(3.28)	(-0.16)	(5.18)
Dominated at 99%	0.09	0.31	1.11***	0.22	0.60***
	(0.32)	(0.77)	(4.74)	(1.52)	(3.65)
Observations	1,783	2,007	696	6,691	5,041
Adjusted R^2	0.775	0.667	0.577	0.627	0.698
Additional Controls	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cluster	ETF-Quarter	ETF-Quarter	ETF-Quarter	ETF-Quarter	ETF-Quarter

Table A6: Continuous Measure for Dominated ETFs

The table displays quarterly panel regressions of Log Market Cap on ETF characteristics. Column (1) focuses on Index ETFs, Column (2) focuses on Quasi-Index ETFs, Column (3) focuses on Active ETFs, Column (4) focuses on Sector ETFs, and Column (5) focuses on Smart Beta ETFs. All variables are defined in Table A1. The Dominated Cost characteristic measures the excess quarterly dollar cost from additional fees and trading costs for each dominated ETF relative to its dominant ETF. Standard errors are clustered at the quarter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 2000 through June 2018.

	Log Market Cap				
	(1) Index	(2) Quasi-Index	(3) Active	(4) Sector	(5) Smart Beta
Expense Ratio	-3.22***	-2.01***	0.24	-1.93***	-1.89***
	(-9.58)	(-21.43)	(1.61)	(-15.93)	(-15.53)
Bid-Ask Spread	-2.55**	-0.28**	-0.06**	-2.61***	-0.53***
	(-2.17)	(-2.62)	(-2.27)	(-4.35)	(-3.78)
Trading Turnover	0.08***	-0.04	-0.04***	0.05***	-0.01
	(9.33)	(-1.10)	(-3.19)	(6.33)	(-0.33)
Turnover Ratio	-0.06	-0.07***	0.03***	-0.29***	-0.13**
	(-0.23)	(-4.60)	(7.07)	(-6.41)	(-2.61)
Quarter Return	-0.00	-0.01	-0.01	0.01***	-0.01
	(-0.06)	(-0.52)	(-0.48)	(3.46)	(-0.83)
Alpha	-1.05***	0.71***	0.21	0.17**	-0.00
	(-3.15)	(2.77)	(1.05)	(2.05)	(-0.57)
Uniqueness	-7.20***	-4.61***	-5.14***	-0.64***	-3.80***
	(-9.88)	(-20.80)	(-15.93)	(-3.75)	(-15.34)
Log ETF Age	2.27***	1.30***	1.00***	1.47***	1.00***
	(28.34)	(17.44)	(8.95)	(19.80)	(19.13)
Log Search Volume	0.06***	0.11***	-0.01*	0.01***	0.07***
	(4.86)	(9.25)	(-1.99)	(3.00)	(18.23)
Sponsor Tilt	2.44***	1.96***	0.95**	2.19***	2.41***
	(7.87)	(6.71)	(2.19)	(15.54)	(10.76)
Dominated Cost	0.07***	0.43***	2.30***	0.07	0.34***
	(3.09)	(17.91)	(10.27)	(1.23)	(7.96)
Observations	1,783	2,007	696	6,691	5,041
Adjusted R^2	0.776	0.724	0.591	0.627	0.725
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter	Quarter	Quarter

Table A7: ETF Size with Constant Sample

The table repeats the regression specifications in Table 6 with the sample used in Tables 7 and 8. The table displays quarterly panel regressions of Log Market Cap on ETF characteristics. Column (1) focuses on Index ETFs, Column (2) focuses on Quasi-Index ETFs, Column (3) focuses on Active ETFs, Column (4) focuses on Sector ETFs, and Column (5) focuses on Smart Beta ETFs. All variables are defined in Table A1. Standard errors are clustered at the quarter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 2000 through June 2018.

	Log Market Cap				
	(1)	(2)	(3)	(4)	(5)
	Index	Quasi-Index	Active	Sector	Smart Beta
Expense Ratio	-2.77***	-1.95***	-0.68***	-2.47***	-2.21***
	(-5.46)	(-10.68)	(-5.15)	(-10.66)	(-18.85)
Bid-Ask Spread	-8.81***	-1.37***	-0.33***	-4.45***	-1.30***
	(-4.23)	(-6.02)	(-6.46)	(-5.09)	(-6.29)
Trading Turnover	0.14***	-0.22***	-0.06**	0.09***	0.03
	(7.42)	(-3.91)	(-2.11)	(7.05)	(1.03)
Turnover Ratio	-1.00**	-0.09***	0.02***	-0.34***	-0.11**
	(-2.46)	(-3.79)	(5.15)	(-10.32)	(-2.57)
Quarter Return	0.02	0.00	-0.00	0.01***	0.00
	(0.81)	(0.28)	(-0.19)	(4.26)	(0.39)
Dominated	0.11	1.75***	2.15***	0.32***	1.83***
	(0.84)	(15.02)	(18.19)	(4.22)	(30.94)
Dominated at 99%	0.25**	0.99***	1.29***	0.10	0.95***
	(2.61)	(12.93)	(6.88)	(0.86)	(7.58)
Observations	1,783	2,007	696	6,691	5,041
Adjusted R^2	0.456	0.439	0.373	0.449	0.564
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter	Quarter	Quarter

Table A8: ETF Size Complete Specification

The table displays quarterly panel regressions of Log Market Cap on ETF characteristics. Column (1) focuses on Index ETFs, Column (2) focuses on Quasi-Index ETFs, Column (3) focuses on Active ETFs, Column (4) focuses on Sector ETFs, and Column (5) focuses on Smart Beta ETFs. All variables are defined in Table A1. Standard errors are clustered at the quarter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 2000 through June 2018.

	Log Market Cap				
	(1)	(2)	(3)	(4)	(5)
	Index	Quasi-Index	Active	Sector	Smart Beta
Expense Ratio	-2.80***	-2.13***	0.38**	-1.85***	-1.74***
	(-7.68)	(-20.16)	(2.35)	(-12.81)	(-12.28)
Bid-Ask Spread	-2.84**	-0.32***	-0.07**	-2.60***	-0.71***
	(-2.30)	(-2.96)	(-2.56)	(-4.36)	(-4.88)
Trading Turnover	0.08***	-0.02	-0.04***	0.06***	0.08***
	(8.43)	(-0.50)	(-3.18)	(6.44)	(3.29)
Turnover Ratio	-0.07	-0.07***	0.03***	-0.30***	-0.19***
	(-0.27)	(-4.64)	(6.76)	(-6.25)	(-4.30)
Quarter Return	0.00	-0.01	-0.01	0.01***	-0.01
	(0.12)	(-0.43)	(-0.56)	(3.37)	(-0.53)
Alpha	-1.15***	0.56*	0.38*	0.18**	-0.00
	(-3.32)	(1.99)	(1.72)	(2.08)	(-0.78)
Uniqueness	-7.82***	-4.30***	-4.73***	-0.64***	-2.50***
	(-8.71)	(-18.04)	(-12.54)	(-3.65)	(-9.79)
Log ETF Age	2.34***	1.53***	1.03***	1.48***	1.11***
	(29.42)	(21.20)	(9.65)	(20.72)	(24.69)
Log Search Volume	0.05***	0.11***	-0.01	0.01***	0.08***
	(4.74)	(9.05)	(-1.54)	(3.23)	(18.65)
Sponsor Tilt	2.44***	0.51**	1.37***	2.22***	2.69***
	(7.92)	(2.27)	(4.10)	(15.15)	(11.32)
Dominated	-0.26***	0.47***	1.15***	-0.02	0.77***
	(-3.06)	(4.91)	(9.86)	(-0.34)	(9.90)
Dominated at 99%	0.09	0.31***	1.11***	0.22***	0.60***
	(0.97)	(3.30)	(5.22)	(5.03)	(6.33)
Observations	1,783	2,007	696	6,691	5,041
Adjusted R^2	0.775	0.667	0.577	0.627	0.698
Additional Controls	No	No	No	No	No
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter	Quarter	Quarter

Table A9: Sector Splits

The table displays quarterly panel regressions of Log Market Cap on ETF characteristics. Column (1) focuses on Index ETFs, Column (2) focuses on Quasi-Index ETFs, Column (3) focuses on Active ETFs, Column (4) focuses on Sector Index ETFs, Column (5) focuses on non-Index Sector ETFs, and Column (6) focuses on Smart Beta ETFs. Additional controls include Expense Ratio, Bid-Ask Spread, Trading Turnover, Turnover Ratio, Quarter Return, Alpha, and Uniqueness. All variables are defined in Table A1. Standard errors are clustered at the quarter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 2000 through June 2018.

	Log Market Cap					
	(1) Index	(2) Quasi-Index	(3) Active	(4) Sector Index	(5) Sector Active	(6) Smart Beta
Log ETF Age	2.34***	1.53***	1.03***	2.08***	1.01***	1.11***
	(29.42)	(21.20)	(9.65)	(22.82)	(13.63)	(24.69)
Log Search Volume	0.05***	0.11***	-0.01	-0.00	0.01**	0.08***
	(4.74)	(9.05)	(-1.54)	(-0.11)	(2.45)	(18.65)
Sponsor Tilt	2.44***	0.51**	1.37***	0.77	1.85***	2.69***
	(7.92)	(2.27)	(4.10)	(1.52)	(9.96)	(11.32)
Dominated	-0.26***	0.47***	1.15***	-0.23**	0.24***	0.77***
	(-3.06)	(4.91)	(9.86)	(-2.46)	(4.02)	(9.90)
Dominated at 99%	0.09	0.31***	1.11***	0.24***	0.51***	0.60***
	(0.97)	(3.30)	(5.22)	(3.79)	(5.56)	(6.33)
Observations	1,783	2,007	696	2,051	4,640	5,041
Adjusted R^2	0.775	0.667	0.577	0.750	0.503	0.698
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter

Table A10: Additional ETF Characteristics

The table displays quarterly panel regressions of Log Market Cap on ETF characteristics. Column (1) focuses on Index ETFs, Column (2) focuses on Quasi-Index ETFs, Column (3) focuses on Active ETFs, Column (4) focuses on Sector ETFs, and Column (5) focuses on Smart Beta ETFs. All variables are defined in Table A1. All Index ETFs in the sample allow for in-kind creation and redemption, and no Index, Sector, or Smart Beta ETFs have an ESG focus. We omit these variables from the corresponding regressions. Standard errors are clustered at the quarter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 2000 through June 2018.

	Log Market Cap				
	(1)	(2)	(3)	(4)	(5)
	Index	Quasi-Index	Active	Sector	Smart Beta
Expense Ratio	-2.77***	-1.55***	0.61***	-1.91***	-1.78***
	(-8.11)	(-13.09)	(4.08)	(-13.31)	(-11.89)
Bid-Ask Spread	-3.22***	-0.31***	-0.05	-2.59***	-0.05
	(-3.67)	(-3.17)	(-0.82)	(-4.35)	(-0.50)
Trading Turnover	0.07***	0.01	-0.02*	0.06***	0.08***
	(8.52)	(0.34)	(-1.97)	(6.59)	(3.05)
Turnover Ratio	-0.34	-0.03	0.03***	-0.31***	-0.20***
	(-1.33)	(-1.56)	(7.12)	(-6.41)	(-4.91)
Quarter Return	0.01	-0.00	-0.00	0.01***	-0.00
	(0.33)	(-0.39)	(-0.39)	(3.53)	(-0.23)
Alpha	-1.15***	0.82***	0.57***	0.19**	-0.01
	(-3.50)	(3.14)	(2.72)	(2.20)	(-1.10)
Uniqueness	-7.04***	-3.99***	-4.10***	-0.64***	-2.07***
	(-7.51)	(-17.77)	(-11.31)	(-3.62)	(-9.90)
Log ETF Age	2.58***	1.15***	1.18***	1.49***	1.13***
	(30.50)	(12.01)	(9.75)	(22.50)	(24.56)
Log Search Volume	0.07***	0.12***	-0.01	0.01***	0.07***
	(5.37)	(10.87)	(-0.85)	(2.80)	(20.72)
Sponsor Tilt	1.79***	0.04	1.55***	2.16***	2.48***
	(5.45)	(0.16)	(4.96)	(14.78)	(10.46)
Log Family Size	-0.29***	0.15***	-0.00	-0.01	-0.02**
	(-6.43)	(14.04)	(-0.19)	(-0.92)	(-2.08)
In Kind Creation		0.06	0.69***	1.01***	0.70***
		(0.66)	(4.52)	(10.61)	(4.66)
ESG		-0.63***	2.01***		
		(-7.10)	(7.72)		
Average Absolute Premium	-1.14	0.19***	-0.09	-0.02***	-2.26***
	(-0.92)	(5.72)	(-0.82)	(-5.73)	(-5.01)
Dominated	-0.13	0.60***	1.25***	-0.03	0.72***
	(-1.45)	(6.58)	(10.73)	(-0.44)	(8.97)
Dominated at 99%	-0.04	0.47***	1.18***	0.20***	0.54***
	(-0.55)	(4.41)	(4.77)	(4.43)	(6.05)
Observations	1,783	2,007	696	6,691	5,041
Adjusted R^2	0.794	0.696	0.595	0.631	0.710
Additional Controls	No	No	No	No	No
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter	Quarter	Quarter