ETFs: The Good, the Bad, and the Ugly*

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ABSTRACT

We document that the massive growth in ETF assets is driven by both retail and institutional investors. Equity, debt, and especially Smart Beta ETFs have experienced the largest growth in recent years. Investors prefer ETFs that are older, have more liquidity, and have lower fees. We develop four measures of Smart Beta quality and find that investors correctly invest more in good and less in bad Smart Beta ETFs. Investors also prefer ETFs that focus on one factor as opposed to many factors. We find clientele effects with institutional investors being more sensitive to ETF liquidity and quality than retail investors.

Keywords: Exchange Traded Funds (ETFs), Institutional Investors, Smart Beta, Factor Models
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*Thanks to seminar participants at Southern Methodist University. All errors are our own.

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1 Introduction

Since 2005, the number of exchange-traded funds (ETFs) and ETF assets have both grown more than ten-fold globally, now accounting for over 5,000 ETFs with $4.5 trillion in assets under management. Bank of America projects the annual growth rate of 25% will persist with total assets reaching $50 trillion by 2030.[1] ETFs are increasingly popular with retail investors because ETFs enable them to create diversified portfolios within and across asset classes for unprecedented low fees. Institutional investors use ETFs for similar reasons and the intraday liquidity of ETFs helps institutions manage cash positions and flows.

Figure 1 plots aggregate U.S. ETF holdings for retail and institutional investors in our sample of ETFs from 2000 until 2018. Both investor types consistently own roughly 50% of all ETF assets over time. This finding suggests that both groups are equally responsible for the growth in ETFs. Our paper sheds light on trends in the ETF market and its investors. Which asset classes have driven the massive growth in ETFs? What are the traits of ETFs that attract investors? Is there a clientele effect, in which retail and institutional investors systematically invest in different types of ETFs?

To answer these questions, we construct a large ETF-quarter level dataset of ETFs listed in the United States from January 2000 through June 2018. We use the Center for Research in Security Prices (CRSP) database and Bloomberg to compile ETF data on many variables including prices, shares outstanding, fees, net asset values (NAVs), bid-ask spreads, and inception dates. We construct total quarterly holdings of institutional investors by aggregating the Thomson Reuters 13F database. After requiring ETFs to have a market capitalization of at least $50 million to enter the sample, we are left with 1,181 unique ETFs and 34,664 ETF-quarters.

We use Lipper codes to categorize these ETFs into five asset classes: Equity, Bond,

[1] https://markets.businessinsider.com/news/stocks/etf-market-grow-50-trillion-assets-2030-bank-america-passive-2019-12-1028763048

Commodity, Currency, and Levered. Figure 2 plots the aggregate holdings over time for each of these asset classes split by retail and institutional investors. Equity and Bond ETFs exhibit similar patterns with persistent growth by both types of investors throughout the sample. Retail ownership was slightly higher than institutional ownership before 2010, with aggregate institutional holdings gaining in recent years. Meanwhile, Commodity, Currency, and Levered ETFs have less aggregate capital, higher retail ownership, and minimal growth over the last decade.

In our sample nearly 80% of the total assets are in Equity ETFs. We use ETF.com to further categorize these ETFs as Regular U.S. Equity, Developed Equity, Emerging Equity, Sector Equity, and Smart Beta Equity ETFs. We conduct additional analysis across these categories because of the myriad of reasons investors use ETFs. Specifically, large U.S. Equity ETFs are likely be used by investors who demand liquidity, while exotic Emerging Equity ETFs allow investors to quickly and easily gain exposure to unique assets. Figure 3 plots the aggregate capital of retail and institutional investors by equity category. Retail ownership is consistently higher than institutional ownership in Regular U.S. Equity. The other categories exhibit a similar pattern to aggregate Equity with institutional ownership being less than retail before 2010 and slowly overtaking retail ownership in the second half of the sample. All five categories exhibit substantial growth over time. Emerging Equity has the least stable growth, perhaps related to the relatively slower growth in asset prices in these markets during the recent sample. Smart Beta ETFs have experienced the largest growth, especially in recent years.

Our first set of tests examine which ETF traits are associated with the ability to attract investors. The dependent variable is the market share of an ETF within its category, defined as the quarter-end market capitalization of an ETF as a proportion of total ETF assets in the asset class-quarter. We find that three common traits for ETFs attract investors across all asset classes. First, the first ETF created in each Lipper category (and older ETFs in general) is more successful at attracting capital. Second, ETFs with better liquidity, as proxied by lower bid-ask spreads and less volatile premiums/discounts to NAV, attract more capital. It is worth noting that this result may be endogenous given that ETF liquidity will tend to improve as a fund becomes larger. Third, ETFs receive more capital if they have lower fees. Overall, it appears that investors are allocating capital to relatively better ETFs when choosing among many choices.

Given the growth in Smart Beta ETFs, we conduct additional analyses in which we hand classify which of seven factors (i.e., Value, Growth, Small Cap, Momentum, Profitability, Low Volatility, and Quality) each ETF claims to get exposure to based on the ETF.com fund description. Value, Growth, and Small Cap are the most common factor exposures (34-40%), while the other four strategies are much less common (4-14%). We estimate three factor models for each ETF to estimate factor exposures. The first model includes eight systematic factors (including the market factor). The second model only includes the market and the factors corresponding to the ETF's reported strategy, and the third model is the market model. There is substantial variation in the betas for these strategies. ETFs are best at providing Small Cap exposure and are reasonable at producing Value, Growth, and Low Volatility exposures. Only a few Smart Beta ETFs are able to provide significant exposure to Momentum, Profitability, and Quality.

We use these models to construct four different measures of Smart Beta performance based on the ETF's ability to meet its stated objectives. Our first measure decomposes the total variance of ETF returns into Market Risk, Smart Beta Risk, Other Factor Risk, and Idiosyncratic Risk. A good ETF should get exposure to the claimed factors without loading on other factors. Our second measure, Factor Purity, measures the improvement in R^2 from models two and three as a proportion of the improvement in R^2 from models one and three. The intuition is similar to that of our first measure in that a good Smart Beta ETF should gain the most explanatory power from the desired risk factors. Our third measure is a set of two time-invariant indicators, Good (Bad) Smart Beta, that identify ETFs that routinely have high (low) exposures to their desired factors. We denote good and bad ETFs if they are statistically significant performers in terms of gaining desired exposures relative to the null of random performance. The fourth measure is Tracking Error relative to the matched Smart Beta regression benchmark.

Using these four measures we find that better Smart Beta ETFs attract more capital. Specifically, coefficients on Smart Beta Risk, Factor Purity, and Good Smart Beta are positive and statistically significant. Meanwhile, coefficients on Other Factor Risk, Tracking Error, and Bad Smart Beta are negative and statistically significant. In addition, we find that investor prefer pure Smart Beta strategies that only have exposure to one or two factors as opposed to ETFs that claim to simultaneously target several factor strategies. Finally, we find that there is substantial variation in the fund sponsors' abilities to provide the reported factor exposures for Smart Beta ETFs. ETFs that are sponsored by iShares, PowerShares, First Trust Exchange, and Invesco are classified as Good Smart Beta ETFs around 60% of the time. Meanwhile, only about 10% of ETFs from SPDR, Schwab, WisdomTree, and other miscellaneous sponsors are classified as Good.

Next, we examine whether there is a clientele effect, in which retail and institutional investors systematically prefer different ETFs within asset classes. Our dependent variable of interest is the percentage of tradeable shares (i.e., shares outstanding scaled by the total short interest) that are held by 13F institutions. We find that institutions are more sensitive to trading liquidity, consistent with their use of ETFs to manage cash balances and flows. We find that retail investors are more sensitive to fees within Equity ETFs, but institutional investors are more sensitive to fees in other ETF categories.

In the final part of our analysis, we repeat the Smart Beta analysis using the institutional ownership variable as our dependent variable. We find that the desired Smart Beta measures are positive and statistically significant and the undesired Smart Beta measures are negative and significant. Institutional investors appear to be more sophisticated than retail investors and are better at finding good Smart Beta ETFs. We also find that institutions are more likely to prefer pure Smart Beta strategies relative to retail investors.

Our paper makes contributions to several literatures. First, by analyzing the determinants of ETF market shares we contribute to the growing ETF literature. To date, most of the ETF literature focuses on the effects of ETFs' size and institutional ownership on the underlying assets.[2] For example, Glosten, Nallareddy, and Zou (2017) and Ben-David, Franzoni, and Moussawi (2018) analyze ETFs' effects on underlying equity assets while Dannhauser (2017) analyzes ETFs' effects on underlying bond assets. In contrast, we focus on what drives ETF ownership itself and provide insight into which fund characteristics are associated with the market's growth. Our analysis suggests that dominant ETFs (less expensive and higher liquidity ETFs that provide their promised factor exposures) tend to attract more assets. However, many dominated ETFs have attracted significant assets under management suggesting that, despite ETFs as a whole being known for low fees, investors may be overpaying for passive management.[3]

Second, we analyze how institutional investors use ETFs and provide insights into the importance of trade-offs for institutions relative to retail investors. We show that institutions are willing to pay higher fees for Equity ETFs (relative to retail investors) in exchange for more liquidity.[4] Moreover, institutions allocate relatively more capital to ETFs that focus on a single factor and deliver high quality exposure to that factor. Our analysis suggests that, on average, institutional investors use ETFs prudently.[5] While other studies have examined

[2]See Ben-David, Franzoni, and Moussawi (2017) for a review of the ETF literature.

[3]For example, the largest ETF in the world, SPY, charges 5 to 6 basis points more than its two major competitors, IVV and VOO. Given that the returns of IVV or VOO are nearly identical to those of SPY (correlated at over 99.8%), investors could save over $150 million in fees per year by moving their assets from SPY to IVV and VOO.

[4]Several studies have examined ETF usage by retail investors (Bhattacharya, Loos, Meyer, & Hackethal, 2017; D'Hondt, Elhichou, & Petitjean, 2020), but those studies focus on individual investors rather than the collective ownership of retail investors.

[5]Several studies provide examples of subsets of institutional investors that use ETFs imprudently. Sherrill,

how subsets of institutional investors use ETFs within their portfolios (Joenväärä & Salehi, 2018; Sherrill, Shirley, & Stark, 2019), our study is the first to analyze institutional investors' ETF use broadly.[6]

Third, we develop new measures to gauge how effectively Smart Beta ETFs deliver upon their promised factor exposures. Whereas Glushkov (2016) analyzes Smart Beta ETFs' collective ability to deliver factor exposures, we provide the first analysis of whether individual Smart Beta ETFs deliver their claimed factor exposures. Using multiple measures, we find that considerable variation exists across Smart Beta categories and among ETFs within a category. Smart Beta ETFs tend to be persistently good or persistently bad. Institutional and retail investors both direct more assets to persistently better Smart Beta ETFs, but the bad funds still manage to attract significant assets.

The remainder of the paper is organized as follows. Section 2 describes our data. Section 3 presents our results on time trends in ETF assets and ownership, determinants of ETF market share, and patterns in ownership by retail and institutional investors. Section 4 concludes.

2 Data

Section 2.1 describes our data on characteristics and institutional ownership of ETFs. Section 2.2 presents information about our sample and summary statistics. Section 2.3 discusses the measures we create to examine the performance of ETFs in gaining Smart Beta exposures.

Shirley, and Stark (2017) shows that mutual funds that take large ETF positions underperform and Broman (2019) shows ETFs attract naïve style switchers.

[6] Chen, Ho, Lai, and Morales-Camargo (2011) examines trading behavior of institutional investors from 1993 to 2007, prior to the rapid growth of ETFs and the majority of our sample.

2.1 Data Sources

We study ETF ownership using data from several sources. We collect daily ETF share prices, NAVs, shares outstanding, and trading volumes from Bloomberg and CRSP. We follow Brown, Davies, and Ringgenberg (2019) and use Bloomberg as the primary data source, and we clean these data by removing anomalies that are not verifiable via CRSP. Each day, we calculate the premium (discount) for a given ETF as the difference between the share price and the NAV and report the value as a percentage of NAV. We collect inception dates, share creation methods, derivatives usage, and leverage factors from Bloomberg. From CRSP, we use the fund names and sponsors, Lipper categories, expense ratios, internal turnover ratios, and bid-ask spreads.

We classify ETFs into categories based on their Lipper codes and stated objectives. Lipper codes are used to place ETFs into the broad categories of Equity, Bond, Commodity, and Currency ETFs. Any ETF with a leverage factor different from one is classified as a Levered ETF (e.g., "2x bull" funds have a leverage factor of two and "1x bear" funds have a leverage factor of negative one such that they are both classified as Levered ETFs). Within the Equity category, we make additional distinctions between Regular U.S. Equity, Developed Equity, Emerging Equity, Sector Equity, and Smart Beta Equity based on hand collected classifications from ETF.com and Lipper codes.[7] ETFs with investments in developed international markets or worldwide strategies as indicated on ETF.com are classified as Developed Equity. Those with emerging international investments that are not Developed Equity ETFs are grouped into the Emerging Equity category. Smart Beta Equity funds are identified as such by ETF.com, and we further flag these ETFs as Value, Growth, Small Cap, Momentum, Low Volatility, Quality, and Profitability funds based on their stated strategies. Sector Equity contains ETFs with 12 different sector classifications based on sector Lipper

[7] The five categories are not mutually exclusive, as there are a few Developed or Emerging Equity ETFs that are also classified as either Sector or Smart Beta Equity.

codes.[8] Finally, Regular U.S. Equity ETFs are those Equity funds that do not fall into any other category.

We measure total institutional ownership using Thomson Reuters 13F Holdings Data and we correct for known errors in the holdings data.[9,10] To calculate the percentage of an ETF that is held by institutions, we sum ownership across all institutions and scale by shares outstanding after adjusting for short interest as reported by Compustat. This measure should be strictly less than or equal to 100%. However, there are a handful of ETF-quarter observations with institutional ownership above 100%, presumably due to data errors. We fix these observations in four different ways. First, if there are one or two observations greater than 100% in the early years of the ETF and they are not consistent with the following quarters, we drop these early observations. Second, if there are only a few observations that are less than 105% and the other observations are close to 100%, then we change the problematic observations to 100%. Third, if there is an observation in the middle of the time series that is significantly higher than all other observations, we average the surrounding quarters and replace this observation. Finally, if there are more than two observations above 100% with substantial variation we drop the entire ETF from our sample.

Finally, to analyze ETFs' risk exposures we collect daily factor return data. The SMB, HML, RMW, and CMA factors from the Fama and French (2015) model 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.

[8] The sectors are Financial Services, Consumer Services, Industrials, Real Estate, Natural Resources, Consumer Goods, Utilities, Science and Technology, Health and Biotechnology, Energy MLP, Basic Materials, and Telecommunication.

[9] We intentionally avoid using mutual fund holdings data for several reasons. First, the Thomson Reuters Mutual Fund Holdings (S12) database almost always omits ETFs in the holdings data. Second, CRSP holdings are frequently different than the holdings reported in either Thomson Reuters or Edgar Online. The inconsistencies between the three data sets make it hard to trust any given data source, and thus we avoid directly dealing with mutual fund holdings data.

[10] See Gutierrez and Kelley (2009), Blume and Keim (2011), and Sias, Turtle, and Zykaj (2016) for discussions of issues associated with the Thomson Reuters/WRDS 13F data.

2.2 Sample Characteristics

Our paper studies U.S.-listed ETFs from January 2000 through June 2018.[11] To avoid data errors from non-synchronous prices due to infrequent trading, we include ETFs in our sample from the first month in which end-of-month market capitalization exceeds \$50 million. While this criterion excludes a large number of small ETFs, they collectively account for less than 1% of total ETF market capitalization (Brown et al., 2019).

Table 1 displays the number and total market capitalization of ETFs in our sample for each year across five categories: Equity, Bond, Commodity, Currency, and Levered. Overall, our sample grows from 19 ETFs with a total value of \$34 billion in 2000 to 950 ETFs with a total value over \$3.1 trillion in 2018. Equity ETFs make up over 80% of our sample, and Bond ETFs are another 14%.[12] Commodity, Currency, and Levered ETFs make up the rest of the sample. We pool these ETFs together in our analysis because there are relatively few observations, these ETFs only became prevalent in the last decade, and they are all likely to rely on derivatives in their portfolios.

Table 2 summarizes our dependent and independent variables across the categories of Equity, Bond, and Other (Commodity, Currency, and Levered) ETFs. Our first dependent variable measures the percentage of total ETF dollars within category that are allocated to an ETF in a quarter:

$$\% \text{ Category}_{i,t} = \frac{\text{Market Cap}_{i,t}}{\sum_{j \in J(i,t)} \text{Market Cap}_{j,t}},$$

in which Category is a sub-category of ETFs (one of Equity, Bond, Other, Regular US Equity, Developed Equity, Emerging Equity, Sector Equity, or Smart Beta Equity), Market $\text{Cap}_{i,t}$ is

[11]Our sample stops in June 2018 because Thomson Reuters 13F reports almost no institutional holdings in the last two quarters of 2018.

[12]Equity ETFs also make up more than 80% of our ETF-quarter observations, and Bond ETFs are approximately 8% of our observations.

the market capitalization of ETF i in quarter t, and $J(i,t)$ is the set of ETFs in the same category as ETF i in quarter t. We use % Category to study the relative size of ETFs. For Equity ETFs, the mean (median) of % Category is small at only 30 (3) basis points (bps). The small mean is due to the large number of ETFs in the Equity category. The mean (median) of % Category is higher for Bond ETFs at 123 (18) bps and for Other ETFs at 93 (16) bps.

Our second dependent variable measures the ownership of institutional investors relative to retail investors:

$$\% \text{ Institution}_{i,t} = \frac{\sum_{k \in K(i,t)} \text{Shares Owned}_{i,t,k}}{\text{Shares Outstanding}_{i,t} \times (1 + \text{Short Interest } \%_{i,t})},$$

in which $K(i,t)$ is the set of institutional investors who report 13F holdings of ETF i at time t. Note that the total shares held by institutions is scaled by the tradeable shares of the ETF, which is equal to the total shares outstanding plus any shares that have been shorted. We use % Institution to study the ETF preferences of institutional relative to retail investors.[13] For Equity ETFs, mean (median) institutional ownership is 39% (37%) and the 10th to 90th percentile range is 15% to 64%. Institutional investors tend to own a larger percentage of Bond ETFs and a much smaller percentage of Other ETFs.

To understand the main drivers of overall ETF size and relative preferences between institutional and retail investors, we measure ETFs' characteristics across dimensions of cost, liquidity, turnover, age, structure, and performance. Direct costs are measured by the expense ratio. An indirect cost of ETFs is tracking error risk originating from ETFs' arbitrage mechanism. Because the ETF price is usually at a premium or discount relative to the underlying NAV, investors may buy at a premium and then sell at a discount. We

[13] To analyze relative ownership between institutional and retail investors, we assume that % Retail = $(1 - \%$ Institution), i.e., that retail investors own the shares not held by 13F institutions. We recognize that the this assumption likely overstates retail ownership in ETFs, as not all institutional investors are classified as 13F institutions.

measure this risk as the average of the absolute premium over the quarter. Higher values are consistent with more volatile premia and discounts and higher tracking error risk. The tracking error risk is also related to the liquidity of the ETF. We measure liquidity using the bid-ask spread, trading turnover (defined as the average daily shares traded over the quarter divided by the number of shares outstanding), and market capitalization. In addition to measuring the secondary-market turnover of an ETF with trading turnover, we also measure its internal turnover (i.e., how often the fund changes its positions) via the turnover ratio. We calculate ETF age as the number of years since inception date, and we include an indicator equal to one if the ETF is the first ETF in its Lipper category. Some ETFs are structured to allow for only in-kind creations and redemptions. Other ETFs only allow cash creations and redemptions and some allow both cash and in-kind. We include an indicator variable that is equal to one if only in-kind creations and redemptions are allowed. We also include a variable that indicates which ETF use derivatives in their portfolios. Finally, we include quarterly returns as a measure of lagged performance.[14]

2.3 Smart Beta Measures

Smart Beta ETFs are designed to provide exposure to a specific factor or combination of factors. Ideally, a Smart Beta ETF can provide the desired exposures while minimizing idiosyncratic risk and exposure to other systematic factors. We create four sets of performance measures that we use to evaluate ETFs along these dimensions.

As a first step to forming our measures, we examine factor models for each Smart Beta ETF to estimate factor exposures. Each factor model 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 regressions. For each Smart Beta ETF, we estimate three factor models. The first and most comprehensive model includes the full set of eight factors that

[14]Detailed variable descriptions can be found in Table A1 of the Appendix.

we consider,

$$\begin{aligned} R_{i,t} =& \alpha_i + \beta_{i,MKT} R_{MKT,t} + \beta_{i,SMB} R_{SMB,t} + \beta_{i,HML} R_{HML,t} + \beta_{i,RMW} R_{RMW,t} \\ &+ \beta_{i,CMA} R_{CMA,t} + \beta_{i,MOM} R_{MOM,t} + \beta_{i,BAB} R_{BAB,t} + \beta_{i,QMJ} R_{QMJ,t} + \epsilon_{i,t}. \end{aligned} \tag{1}$$

where $R_{i,t}$ is the excess return on the ETF, $R_{MKT,t}$ is the excess return on the market portfolio, and the remaining factor returns are for the SMB, HML, RMW, and CMA factors from the Fama and French (2015) model, the MOM factor, the BAB factor of Frazzini and Pedersen (2014), and the QMJ factor of Asness et al. (2019). The second model, a matched Smart Beta factor model, is a restricted version of equation (1) that only includes the market factor and the factors that are associated with a Smart Beta ETF's reported strategy. For example, for an ETF that claims the Small Cap and Value strategies, we only include the market, SMB, and HML factors. We include as factors SMB for the Small Cap ETFs, HML for both Value and Growth, RMW for Profitability, MOM for Momentum, BAB for Low Volatility, and QMJ for Quality. The third factor model we consider is the single-factor market model.

The first set of Smart Beta ETF measures decomposes the total variance of ETF returns into four components: (i) Market Risk, (ii) Smart Beta Risk, (iii) Other Factor Risk, and (iv) Idiosyncratic Risk. Market Risk is the square root of the total explained variance from the market model. Smart Beta Risk is the square root of the difference between the explained variances from the matched Smart Beta factor model and the market model, and Other Factor Risk is the square root of the additional explained variance from the full factor model in equation (1) relative to the Smart Beta factor model. Finally, Idiosyncratic Risk is the square root of the residual variance from equation (1). Smart Beta Risk measures the ETF's exposure to the desired factors. Idiosyncratic Risk captures return variation that is unrelated to the eight factors and may, thus, be more diversifiable, whereas Other Factor Risk measures the impact of unwanted systematic factor exposures that may be more difficult to diversify away.

The second measure is Factor Purity, which captures the proportion of systematic factor risk that is in line with the Smart Beta ETF's stated objective. To calculate Factor Purity, we use the unadjusted R^2s from the market model, the matched Smart Beta model regression that includes an ETF's factors, and the full factor model in equation (1). Factor Purity is given by

$$\text{Factor Purity} = \frac{\text{Smart Beta Model } R^2 - \text{Market Model } R^2}{\text{Full Model } R^2 - \text{Market Model } R^2}. \tag{2}$$

The numerator represents the difference in explained variance from adding the desired factors to the market model, and the denominator measures the additional explained variance from considering all seven systematic factors relative to the market model. This ratio is bound by zero and one, with a value of zero indicating that the Smart Beta ETF generates no desired factor exposure and a value of one showing that the fund has no unwanted exposure to additional systematic factors.

The third set of measures is a pair of indicator variables that classify ETFs as Good Smart Beta ETFs and Bad Smart Beta ETFs. Our classification approach is designed to identify ETFs that consistently produce exposures to the desired factor that are better than or worse than competing ETFs. That is, a Value ETF that consistently delivers higher (lower) $\hat{\beta}_{i,HML}$ compared with other Value ETFs will be classified as a Good (Bad) Smart Beta ETF. Formally, in each quarter we begin by ranking all ETFs with a particular Smart Beta factor strategy (i.e., Small Cap, Value, Growth, Momentum, Profitability, Low Volatility, or Quality) by their estimated betas on the associated factor.[15] The time-series average of percentage rank provides a relative performance measure for each ETF that ranges from zero to one with a value of one indicating that the ETF always provides the highest factor

[15] Growth ETFs are ranked on the basis of $-\hat{\beta}_{i,HML}$.

exposure compared with other ETFs following the same strategy. To determine whether a given ETF performs significantly above or below its peers, we simulate the distribution of the average rank statistic for each ETF under the null that the fund's rank is random each quarter. The simulation retains the structure of the data in terms of how many and which ETFs were in the sample in each quarter, which affects the null distribution of the average rank statistic for each ETF. Finally, we identify ETFs for which the average rank statistic is statistically significant at the 1% level in a two-tailed test. The ETFs with high average rank are classified as Good Smart Beta ETFs and those with low rank are Bad Smart Beta ETFs. An ETF that follows multiple Smart Beta strategies receives a one for the Good (Bad) indicator if it is Good (Bad) across any of the relevant factors.

The fourth measure is Tracking Error relative to the matched Smart Beta regression benchmark. This measure is calculated as the standard deviation of the daily residuals from a restricted version of equation (1) that includes only the market and the matching factors. We include Tracking Error alongside either the Factor Purity or Good/Bad Smart Beta measures in our tests. We do not include it with our first set of Smart Beta measures because it is closely related to a combination of Other Factor Risk and Idiosyncratic Risk.

Table 3 displays summary statistics for our Smart Beta Equity sample, our four sets of Smart Beta performance measures, and a summary of how effective the fund sponsors are at delivering Smart Beta. Panel A shows the percentage of funds that claim to provide each factor exposure. The most prominent factor exposures are Value (40%), Growth (36%), and Small Cap (34%). Somewhat less popular is the Momentum strategy with 14% of Smart Beta ETFs, and 9% and 8% of funds claim to provide exposure to the Profitability and Low Volatility factors, respectively. Only 4% of ETFs claim a Quality strategy. As is clear from the fact that the percentages sum to greater than 100%, some Smart Beta ETFs claim to provide exposures to more than one factor (1.44 factors on average). For example, while 61 funds specify Value exposure and 56 funds specify Small Cap exposure, 20 of those ETFs claim both strategies.[16]

Panel B of Table 3 summarizes our Smart Beta variables, most notably the factor loadings associated with each strategy and the four sets of Smart Beta performance measures. The statistics on estimated factor loadings help to indicate how successfully Smart Beta ETFs gain exposure to the various factors. We provide summary statistics for the estimated betas only for the ETFs that claim a particular strategy. That is, the 2,005 observations for Value Beta are the estimated HML loadings for the ETFs that claim a Value strategy.[17] Small Cap ETFs as a whole are able to provide substantial exposure to SMB with an average beta of 0.78, and 90% of Small Cap ETF quarters have a beta on SMB greater than 0.53. Among the remaining factors, Smart Beta ETFs are most successful at creating exposures to the Value (average beta of 0.25), Growth (average of 0.19), and Low Volatility (average of 0.21) factors. Average exposures tend to be smallest for the Quality (0.09), Momentum (0.08), and Profitability (0.04) factors. Momentum strategies require substantial turnover in the underlying assets, and many of the ETFs are long only such that they cannot short past losers. These challenges in strategy implementation may help explain the relatively low average factor exposure for that strategy. The Quality and Profitability characteristics of underlying assets tend to be more stable, such that these strategies should be relatively straightforward to implement and would require relatively less turnover in the ETF portfolio. It is possible that the construction of the RMW and QMJ factors does not provide a good match to the Profitability and Quality strategies that are actually being implemented by ETFs.

While some average factor exposures are relatively small, this finding does not imply that all funds fail to provide their claimed exposures. In particular, the 10th to 90th percentile range is quite large for each of the factors, which indicates substantial variation in the

[16]Furthermore, within those 20 funds, five also claim Quality exposure, five claim Momentum exposure, three claim Low Volatility exposure, two claim Profitability exposure, and one claims Growth exposure.

[17]Growth Beta is the negative of the ETF's estimated HML beta.

performance of Smart Beta ETFs in gaining factor exposures. For example, the 10th to 90th percentile ranges are -0.14 to 0.33 for Momentum Beta and 0.01 to 0.46 for Value Beta. The highest betas indicate that some ETFs are generating substantial risk exposures, but the low end shows that a significant portion of Smart Beta ETFs are actually producing negative exposures to their claimed factors.

Turning to the performance measures, our decomposition of ETF return variance into Market Risk, Smart Beta Risk, Other Factor Risk, and Idiosyncratic Risk shows that, on average, funds gain more volatility from their stated factor risk than from other factors. However, Other Factor Risk is still about 68% of the magnitude of Smart Beta Risk (on average), suggesting that ETFs are not overly effective at isolating factor exposures. Factor Purity shows that ETFs vary significantly in their abilities to provide Smart Beta exposures. While on average 58% of the systematic factor risk that an ETF is exposed to is explained by its stated risk factors, the 10th percentile is only 8% while the 90th percentile is 96%. Thus, it appears that some funds are doing very well at delivering on their stated purpose, while others are doing very poorly. Finally, Good Smart Beta and Bad Smart Beta show that funds are persistently good or bad at delivering their claimed factor exposures. If factor loadings were random, only 0.5% of funds would be classified as Good Smart Beta and 0.5% of funds would be Bad Smart Beta. However, 46% of funds are Good Smart Beta and 33% of funds are Bad Smart Beta.

Panel C summarizes the major fund sponsors in our sample as of the end of 2017. iShares (Blackrock), Vanguard, and SPDR (State Street) collectively manage 82% of the ETF assets in our sample. PowerShares, Schwab, Invesco, First Trust Exchange, and WisdomTree make up another 13% of our sample, and 38 other sponsors make up the other 5%. Interestingly, there is substantial variation in the fund sponsors' abilities to provide the claimed factor exposures for Smart Beta ETFs. For example, whereas about 60% of the ETFs from iShares, PowerShares and First Trust Exchange are classified as Good (and only about 20% are classified as Bad), about 10% of ETFs from SPDR, Schwab, WisdomTree, and the 38 other sponsors are classified as Good (and about 50% are classified as Bad).[18]

3 Results

We now turn to our empirical evidence on ETFs and the holdings of institutional and retail clients. Section 3.1 discusses time-series trends in the ETF market. Section 3.2 examines how the characteristics of ETFs are related to their ability to attract investors. Section 3.3 studies the relative preferences of institutional and retail investors in choosing ETFs.

3.1 ETF Market Trends

Figure 1 demonstrates impressive growth in the aggregate ETF market. Further, the gains in market size have been driven jointly by retail and institutional investors with each investor type contributing about half of aggregate capital in recent periods. In this section, we examine how retail and institutional investors have contributed to growth within the broad categories of Equity, Bond, Commodity, Currency, and Levered ETFs. Within Equity ETFs, we also study subcategories of ETFs that compete in different market segments.

Figure 2 plots the time series of total capital invested in long positions for the Equity (Panel A), Bond (Panel B), Commodity (Panel C), Currency (Panel D), and Levered (Panel E) ETF categories. The lighter solid gray line is the total market cap multiplied by one plus the short interest within each category. The darker solid blue line represents total holdings by institutions and the dotted blue line is retail.

Panels A and B of Figure 2 reveal relatively similar time trends for Equity and Bond ETFs. Both categories experienced rapid growth during the sample period. As of sample end in Q2 2018, positions in Equity ETFs total \$2.56 trillion and Bond ETFs sum to \$0.47

[18] Vanguard has an equal number of Good and Bad Smart Beta ETFs.

trillion. While retail investors held over 60% of Equity and Bond ETF assets on average during the 2000s, retail and institutional investors have owned similar proportions of the total Equity and Bond ETF markets in the 2010s. As of the end of our sample period, retail investors own slightly more Equity ETFs than institutions, while the opposite holds for Bond ETFs.

Panels C to E of Figure 2 show trends for Commodity, Currency, and Levered ETFs. There are three notable findings for these categories. First, unlike the Equity and Bond ETF markets, the other three ETF market categories have not experienced consistent growth throughout the sample period. Whereas the Equity and Bond ETF categories achieve their largest aggregate values in the last quarter of our sample, the aggregate dollar peaks occurred in Q4 2009 for Currency ETFs and Q3 2012 for Commodity ETFs. Levered ETFs are near their peak at the end of the sample period but experienced only modest growth in the 2010s. Second, the aggregate capital invested across these three categories is small compared with the Equity and Bond categories. Third, ETF investments tend to be dominated by retail investors in these categories, particularly for Levered ETFs. Given the relatively small scale of the Commodity, Currency, and Levered ETF markets, we combine them to create an "Other ETFs" category for subsequent analyses.

Figure 3 shows time series for five subcategories of Equity ETFs: Regular U.S. (Panel A), Developed (Panel B), Emerging (Panel C), Sector (Panel D), and Smart Beta (Panel E). Regular U.S. Equity in Panel A is the largest subcategory, and it makes up a little less than half of the broader Equity category in terms of total capital. Relative to the remaining four categories, a greater proportion of Regular U.S. Equity is held by retail investors. Emerging Equity (Panel C) has experienced relatively less stable growth over the sample, but the category grew to over $200 billion late in the period. The sharpest recent growth occurs for Smart Beta Equity ETFs, which doubled in aggregate size from $264 billion in Q3 2015 to $534 billion in Q2 2018. This surge in growth is perhaps unsurprising given the recent focus on Smart Beta strategies and ETFs among institutions and the media, but it is interesting to note that retail investors have contributed as much as institutions to the increase in Smart Beta capital.

3.2 Allocation of Capital to ETFs

The enormous growth of the aggregate ETF market evident in Figures 1 to 3 masks the underlying variation in ETF outcomes. While several ETFs gained tens of billions of dollars in assets, 975 other U.S.-listed ETFs failed during the 2010s.[19] In this section, we examine the characteristics of ETFs that are associated with market capitalization to determine what types of ETFs tend to be most successful in attracting investors. We study the relation between ETF assets and fund characteristics using panel regressions. The dependent variable in each specification is the market share within the category, which is measured as the ETF's quarter-end market cap as a proportion of total ETF assets within the category under consideration. As such, the dependent variables are % Equity, % Bond, and % Other. We include quarter fixed effects and cluster standard errors at the quarter level.

Table 4 begins with a broad-level examination of ETFs in the Equity, Bond, and Other categories. There are several notable patterns in Table 4. First, ETFs tend to benefit from a first mover or early mover advantage. The first ETF in a given Lipper category has additional market share ranging from 0.40% (t-statistic of 12.76) for Equity to 4.27% (t-statistic of 31.25) for Other ETFs. Older funds also tend to have more assets, consistent with an early mover advantage. Expenses are strongly negatively related to fund assets within each category, consistent with the increasing focus on lower-fee investment options. Within the Equity category, a one-standard-deviation decrease in Expense Ratio is associated with a 0.18% (t-statistic of 12.92) increase in fund market share relative to the mean of 0.30%.

Table 4 also shows a role for measures that capture aspects of liquidity. Within the

[19] See https://www.etf.com/etf-watch-tables/etf-closures.

Equity category, indications of greater liquidity from Average Absolute Premium, Bid-Ask Spread, and Trading Turnover are each associated with higher ETF market share. A one-standard-deviation improvement in liquidity is associated with an increase in ETF market share of 0.05% (t-statistic of 4.82) for Average Absolute Premium, 0.23% (t-statistic of 3.10) for Bid-Ask Spread, and 0.24% (t-statistic of 11.23) for Trading Turnover. Bid-Ask Spread remains consistently negatively related to fund size across categories, whereas evidence for the other two measures is mixed. Finally, there is evidence that ETFs with more trading in their underlying portfolios (as measured by Turnover Ratio) have additional market share.

The results for Bond and Other ETFs tell a similar story. ETFs that are the first in their Lipper category and older ETFs are associated with a greater market share. Investors tend to allocate more capital to ETFs with lower fees. Lastly, ETFs that are more liquid as measured by Bid-Ask Spread and Trading Turnover are associated with larger market shares.

Given the diversity of equity ETF strategies, we split the Equity funds into five subcategories in Table 5. We specifically study Regular U.S. Equity, Developed Equity, Emerging Equity, Sector Equity, and Smart Beta Equity ETFs. We estimate a panel regression within each subcategory, and the dependent variable in each specification is the ETF's % Equity.

The results in column (1) of Table 5 suggest that the Regular U.S. Equity ETFs display similar relations between market share and fund characteristics as the broader category of Equity ETFs. In particular, more capital is invested in ETFs that are first movers or early movers, ETFs with lower expense ratios, and more liquid ETFs. Across the five groups in Table 5, Regular U.S. Equity funds have the strongest first mover and early mover advantages. Expense ratios are negatively related to size within each category, but with differing magnitudes of the relation. A one-standard-deviation decrease in Expense Ratio is associated with increases in market share of 0.17% (t-statistic of 3.70) in Regular U.S. Equity, 0.13% (t-statistic of 11.61) in Developed Equity, and 0.18% (t-statistic of 8.84) in Emerging

Equity versus only 0.06% (t-statistics of 22.15 and 11.10) in both Sector Equity and Smart Beta Equity. Investors thus appear to be relatively less sensitive to fees in the Sector and Smart Beta categories. Finally, results across the categories are relatively consistent for liquidity with more liquid ETFs tending to have higher market shares.

Table 6 introduces measures for Smart Beta Equity ETFs that quantify the effectiveness of their strategies. We include three panel regression specifications. The dependent variable in each case is the ETF's market share of the Smart Beta Equity market, % Smart Beta. The first regression includes measures of Market Risk, Smart Beta Risk, Other Factor Risk, and Idiosyncratic Risk; the second includes our Factor Purity and Tracking Error measures; and the third includes indicators for Good Smart Beta and Bad Smart Beta ETFs along with Tracking Error. Within each regression, we also include indicators for whether a fund follows the Value, Growth, Momentum, Profitability, Low Volatility, and Quality strategies, with the indicator for Small Cap being the omitted category. Finally, we include indicators for 2+ Smart Beta Flags and 3+ Smart Beta Flags in each of the three regressions to capture the effects of pure versus combination Smart Beta strategies.

The Smart Beta Equity results in Table 6 produce two broad takeaways: (i) Smart Beta ETFs seem to be rewarded for implementing their stated strategies well and (ii) investors have some preference for purer Smart Beta strategies that provide exposure to only one or two strategies. Column (1) includes the Market Risk, Smart Beta Risk, Other Factor Risk, and Idiosyncratic Risk variables. An ETF's share of the Smart Beta Equity market is positively related to Smart Beta Risk with a one-standard-deviation increase corresponding to a 0.31% (t-statistic of 3.44) increase in market share relative to the mean of 1.38%. On the other hand, one-standard-deviation increases in Market Risk, Other Factor Risk, and Idiosyncratic Risk are associated with decreases in market share of 0.76% (t-statistic of 5.21), 0.32% (t-statistic of 5.94), and 0.49% (t-statistic of 4.87), respectively. These results suggest that investors reward ETFs for providing the exposures they promise and penalize them for producing unwanted exposures. This general conclusion is supported by the alternative measures. Column (2) shows that Factor Purity, which captures the proportion of systematic factor risk that is spanned by the stated strategy, is strongly positively associated with Smart Beta ETF market share. A one-standard-deviation increase in Factor Purity is associated with a 0.45% (t-statistic of 7.07) increase in market share, whereas Tracking Error is associated with a negative effect of -0.56% (t-statistic of 5.29). In column (3), Good Smart Beta ETFs have 0.36% (t-statistic of 5.55) higher market share while Bad Smart Beta ETFs have 0.45% (t-statistic of 4.21) lower market share. Overall, these findings suggest that investors are able to identify and invest in the Smart Beta ETFs that are the most effective at delivering on their stated strategy.

The results in Table 6 also indicate that investors have preferences over Smart Beta strategies. We concentrate our discussion on columns (1) and (2) because the Smart Beta flags interact with the Good and Bad Smart Beta ETF flags in column (3). Examining the individual strategy flags, funds with Momentum, Quality, and Profitability strategies tend to manage more assets relative to the Small Cap baseline. The Low Volatility flag is statistically significantly positive in column (2) but not in column (1). The historically important Value and Growth strategies seem to have roughly the same popularity as Small Cap. Perhaps more interesting are the indicators for 2+ Smart Beta Flags and 3+ Smart Beta Flags. In column (1), ETFs with two stated Smart Beta strategies are significantly smaller than those with one (-0.33% smaller market share with a t-statistic of -2.44), and ETFs with three or more strategies are significantly smaller than those with two (-0.46% smaller with a t-statistic of -3.36). These effects are somewhat larger in column (2). The results in Table 6 suggest that investors reward Smart Beta ETFs that adopt purer objectives that target only one (or perhaps two) Smart Beta strategies.

Our results are broadly consistent with good ETFs being rewarded by investors. ETFs that can deliver greater liquidity with lower fees tend to have larger market share. Early mover ETFs that introduce new strategies into the ETF market are also consistently larger than later entrants. Finally, investors allocate more capital to Smart Beta ETFs that deliver on their stated objectives while minimizing other risks. These findings indicate that ETF investors as a whole are able to identify relatively better ETFs when choosing among the large set of choices.

3.3 Clientele Effects for Institutional and Retail Investors

Institutional and retail investors each contribute about half of the aggregate capital to ETFs. Given that these investor types differ in terms of size, sophistication, liquidity needs, and their situations outside their ETF portfolios, we examine the relative preferences of institutional versus retail investors in this section. We specifically study the relation between the institutional ownership percentage (% Institution) and ETF characteristics. The panel regressions include quarter fixed effects and standard errors are clustered at the quarter level.

Table 7 shows results for the broad categories of Equity, Bond, and Other ETFs. We concentrate first on the Equity category in column (1). Interestingly, relative to retail investors the institutional investors hold higher proportions of ETFs with higher expense ratios (coefficient of 12.80 with a t-statistic of 11.44). A one-standard-deviation increase in Expense Ratio is associated with an increase in institutional ownership percentage of 2.26% relative to the mean of 38.9%. This finding suggests that institutions may be relatively less sensitive to expenses compared with retail investors. A potential explanation for this pattern is that expense ratios are particularly salient on retail trading platforms given the increasing emphasis on minimizing fees.

The results in Table 7 also suggest that institutions are more sensitive to liquidity needs compared with retail investors. The coefficients for Trading Turnover and Log Market Cap, which is also likely related to trading liquidity, are strongly significantly positive. One-standard-deviation increases in Trading Turnover and Log Market Cap are associated with larger institutional ownership percentages with magnitudes of 3.52% and 4.93%, respectively. Bid-Ask Spread and Average Absolute Premium are insignificantly related to institutional ownership percentage. Finally, the marginally significant negative coefficient on Turnover Ratio suggests that institutions tend to hold higher percentages of low-turnover ETFs.

The Bond ETF category in Table 7 indicates that institutions are more sensitive to fees in this asset class compared with retail investors. Institutional investors hold higher proportions of the large and relatively more liquid Bond funds, consistent with their liquidity needs. Overall institutional ownership percentages are relatively lower for the Other category, but institutions appear to prefer first mover and lower fee ETFs.

We examine institutional ownership percentages for Smart Beta Equity ETFs in Table 8. Given that institutional investors are likely more sophisticated than retail investors, we expect they may be better able to identify better Smart Beta funds. Our findings strongly support this intuition. In column (1), institutions hold greater percentages of ETFs with higher Smart Beta Risk and lower Other Factor Risk. A one-standard-deviation increase in Smart Beta Risk is associated with a 1.70% increase in institutional ownership percentage (t-statistic of 4.56), and the corresponding effect of Other Factor Risk is a 2.27% decrease in institutional ownership (t-statistic of -6.61). A similar finding appears in column (2) with the strongly significant positive coefficient on Factor Purity with a t-statistic of 9.01. A one-standard-deviation improvement in this variable corresponds to a 2.72% increase in institutional ownership percentage. Interestingly, Idiosyncratic Risk is insignificantly positive in column (1) and Tracking Error is insignificantly negative in column (2) after controlling for Factor Purity. Institutions may be particularly sensitive to undesired systematic factor exposures given how these risks can interact with other assets in their portfolios, whereas non-systematic risk can be more easily diversified. The coefficients in columns (1) and (2) support this interpretation. Finally, column (3) shows that the institutional ownership percentage is 1.11% higher for Good Smart Beta ETFs (t-statistic of 2.90) and 3.26% lower for Bad Smart

Beta ETFs (t-statistic of -6.33). In this specification, which does not otherwise control for unwanted exposure to systematic factors, Tracking Error is negatively related to institutional ownership. Overall, these results suggest that institutions are better than retail investors at identifying the best Smart Beta ETFs. Further, institutions appear particularly sensitive to additional risk from systematic, rather than idiosyncratic, sources.

Table 8 also shows that, relative to retail investors, institutional investors are more favorable to focused Smart Beta strategies. Concentrating on column (1), the institutional ownership percentage is 1.60% lower for ETFs that chase multiple factor exposures. Relative to funds with two strategies, institutional ownership is 12.21% lower (t-statistic of -8.00) for funds with three or more stated strategies. These results are consistent with additional value of focused ETFs for institutions given the clearer effects on overall portfolio risk exposures from adding them to a broader portfolio.

Overall, the results in this section indicate that institutional and retail investors tend to hold somewhat different ETFs. Interestingly, institutions appear to be less sensitive to fees for ETFs with equity strategies compared with retail investors. Rather, institutions tend to focus more on liquidity and an ETF's ability to deliver on its promised strategy.

4 Conclusion

This paper studies the trends in ETF markets since 2000. We find that both retail and institutional investors are responsible for the enormous growth in ETF assets. We find that Equity ETFs and specifically Smart Beta ETFs have grown the most in recent years. ETFs that are older, have lower fees, and have more liquidity are able to attract more capital across all asset classes. We construct four measures of ETF Smart Beta performance, and we find that investors are allocating more capital to better ETFs and that investors prefer pure play ETFs relative to ETFs that claim multiple factor exposures. Institutions are more concerned with liquidity and ETF quality, while retail investors are more concerned with low fees.

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Figure 1: The figure plots the total market capitalization multiplied by one plus the short interest of all ETFs (lighter gray line), the total retail holdings (dashed blue line), and the total institutional holdings (darker solid blue line).

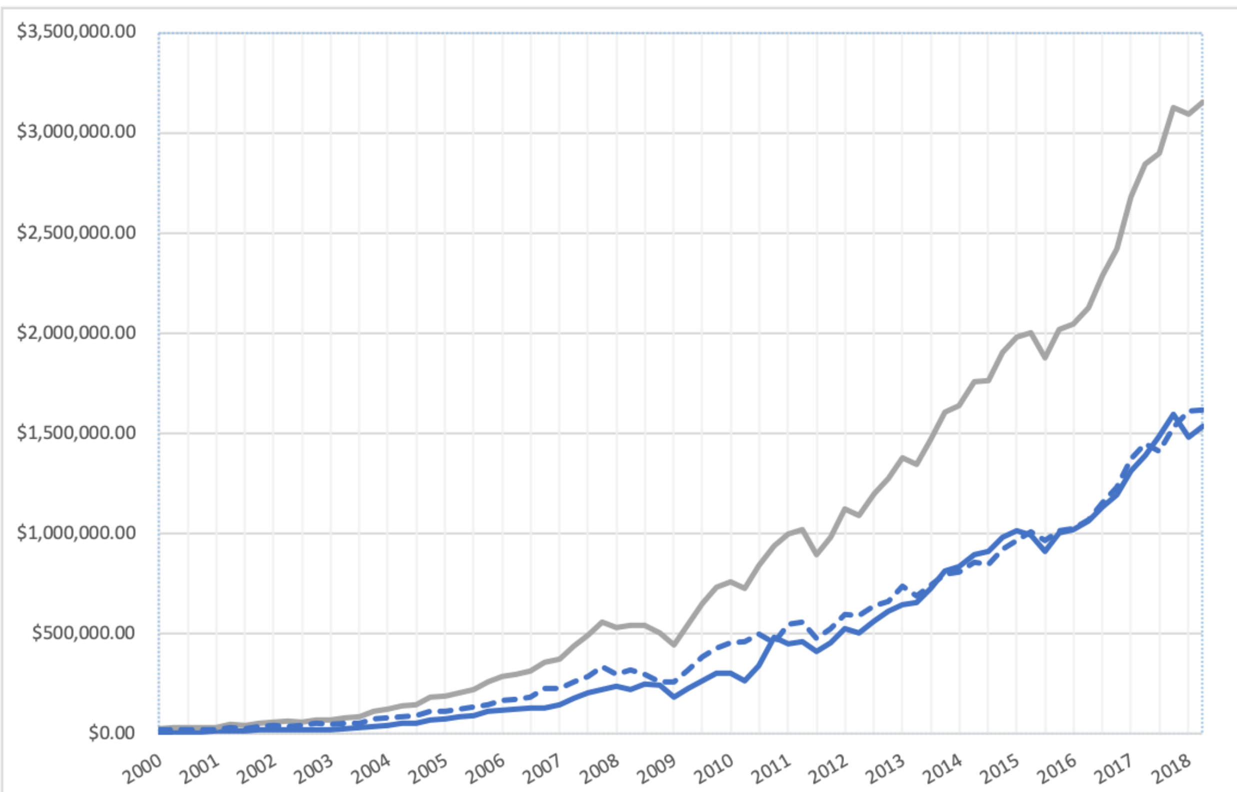
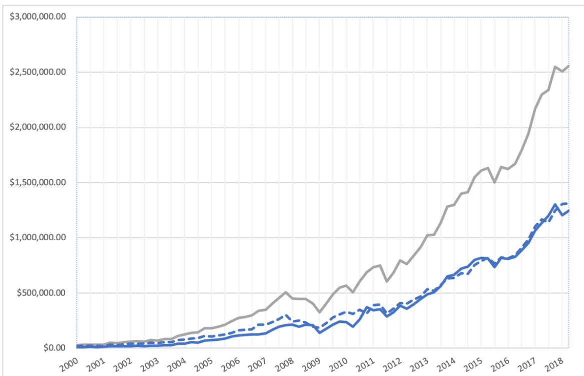
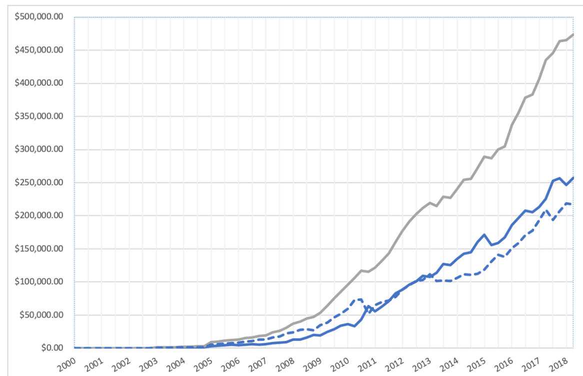


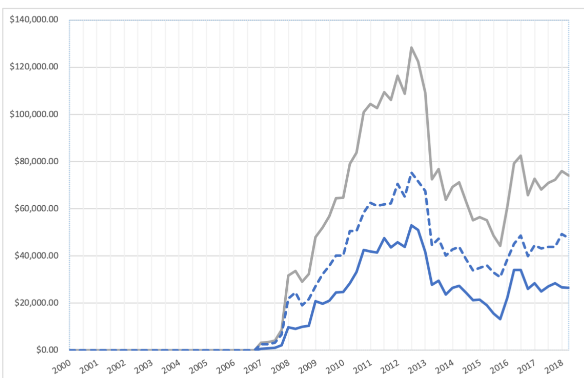
Figure 2: The figure plots the total market capitalization multiplied by one plus the short interest of ETFs in the asset class (lighter gray line), the total retail holdings (dashed blue line), and the total institutional holdings (darker solid blue line). Panel A is Equity, Panel B is Bond, Panel C is Commodity, Panel D is Currency, and Panel E is Levered ETFs.



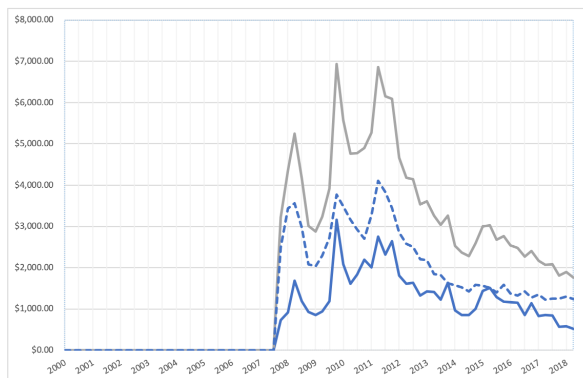
(a) Equity



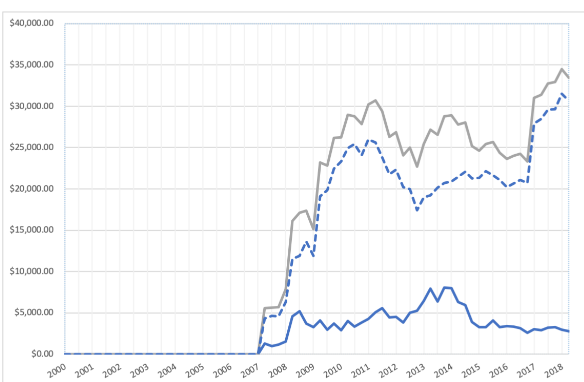
(b) Bond



(c) Commodity

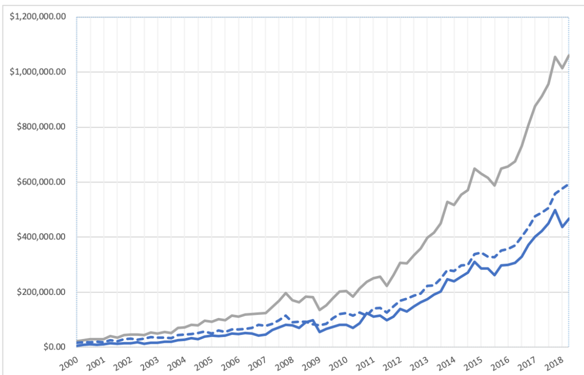


(d) Currency

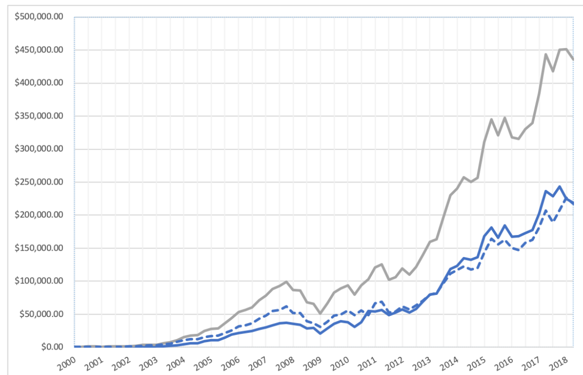


(e) Levered

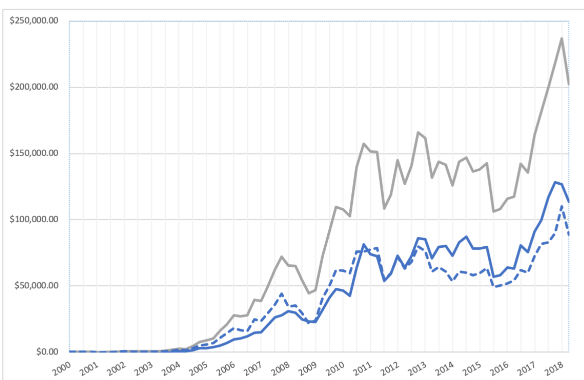
Figure 3: The figure plots the total market capitalization multiplied by one plus the short interest of ETFs in the Equity subcategory (lighter gray line), the total retail holdings (dashed blue line), and the total institutional holdings (daerker solid blue line). Panel A is Regular U.S. Equity, Panel B is Developed Equity, Panel C is Emerging Equity, Panel D is Sector Equity, and Panel E is Smart Beta Equity ETFs.



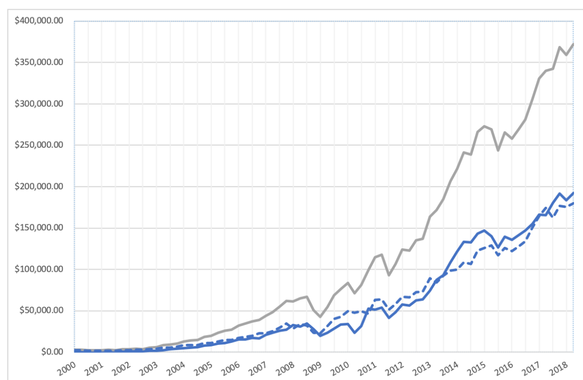
(a) Regular U.S. Equity



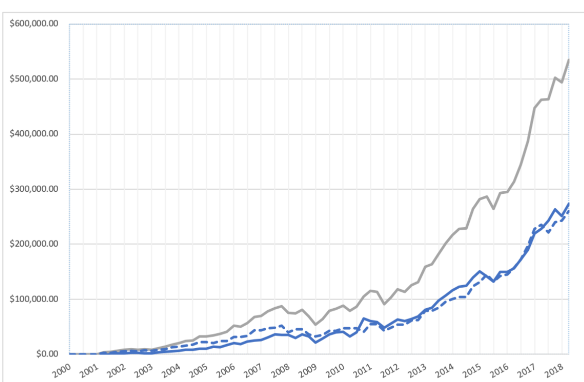
(b) Developed Equity



(c) Emerging Equity



(d) Sector Equity



(e) Smart Beta Equity

Table 1: Annual ETF Sample

The table reports the number and aggregate market capitalization of ETFs in our sample. ETFs are included in our sample from the first month in which end-of-month Market Cap exceeds $50 million. ETF classifications are based on Lipper categories and leverage data. Number and Market Cap are measured at the end of each calendar year, except for 2018 which is measured at the end of June due to 13F data limitations. Market Cap is reported in billions.

	Equity ETFs		Bond ETFs		Commodity ETFs		Currency ETFs		Levered ETFs		All ETFs	
Year	Number	Market Cap	Number	Market Cap	Number	Market Cap	Number	Market Cap	Number	Market Cap	Number	Market Cap
2000	19	$34									19	$34
2001	43	$55									43	$55
2002	68	$72									68	$72
2003	82	$111	2	$2							84	$113
2004	103	$178	2	$3							105	$181
2005	130	$247	5	$13							135	$259
2006	168	$337	6	$18							174	$355
2007	238	$508	18	$31	10	$9	8	$3	13	$6	287	$556
2008	289	$405	40	$47	13	$32	10	$3	40	$17	392	$504
2009	331	$548	52	$85	16	$64	12	$7	61	$26	472	$731
2010	396	$690	71	$115	23	$101	13	$5	76	$28	579	$939
2011	447	$682	90	$161	23	$106	14	$6	80	$26	654	$981
2012	491	$914	115	$212	23	$123	13	$4	84	$23	726	$1,275
2013	559	$1,285	142	$227	23	$64	13	$3	88	$29	825	$1,608
2014	631	$1,549	157	$272	26	$55	14	$3	94	$25	922	$1,904
2015	684	$1,641	176	$305	29	$44	14	$3	99	$24	1002	$2,017
2016	739	$1,942	191	$383	32	$66	13	$2	103	$23	1078	$2,417
2017	696	$2,550	180	$463	30	$72	12	$2	111	$33	1029	$3,121
2018	637	$2,560	162	$474	28	$74	12	$2	111	$33	950	$3,143

Table 2: Sample Summary Statistics

The table reports summary statistics for ETFs in our sample. Panel A focuses on Equity ETFs, Panel B focuses on Bond ETFs, and Panel C focuses on Other ETFs including Commodity, Currency, and Levered ETFs. All variables are defined in Table A1.

Panel A: Equity ETFs

Variable	N	Mean	SD	Median	p10	p25	p75	p90
Quarter Return	24,634	2.181	9.515	2.978	-9.317	-1.881	7.160	12.24
In Kind Creation	24,634	0.981						
Derivatives Based	24,634	0.004						
ETF Age	24,634	7.070	4.308	6.282	2.151	3.679	9.663	13.06
Market Cap	24,634	2,239	9,023	299.2	48.04	99.29	1,126	4,222
Bid-Ask Spread	24,634	0.192	0.300	0.114	0.029	0.058	0.210	0.398
Average Absolute Premium	24,634	0.361	1.629	0.146	0.036	0.068	0.367	0.636
Trading Turnover	24,634	1.253	2.684	0.559	0.219	0.334	1.087	2.359
Expense Ratio	24,634	0.449	0.220	0.480	0.150	0.250	0.610	0.700
Turnover Ratio	24,634	0.392	1.412	0.210	0.0500	0.100	0.430	0.840
First ETF in Lipper	24,634	0.127						
Smart Beta	24,634	0.203						
Sector	24,634	0.342						
% Equity	24,634	0.300	1.848	0.033	0.004	0.010	0.136	0.537
% Institution	24,634	38.86	19.37	36.74	15.32	24.60	51.34	64.44

Panel B: Bond ETFs

Variable	N	Mean	SD	Median	p10	p25	p75	p90
Quarter Return	5,059	0.871	5.016	0.652	-3.023	-0.362	2.306	4.991
In Kind Creation	5,059	0.941						
Derivatives Based	5,059	0.006						
ETF Age	5,059	5.127	2.887	4.603	1.784	2.792	7.038	9.296
Market Cap	5,059	1,913	4,338	421.8	66.37	141.7	1,378	5,124
Bid-Ask Spread	5,059	0.161	0.223	0.099	0.025	0.050	0.183	0.340
Average Absolute Premium	5,059	0.346	1.441	0.208	0.053	0.096	0.394	0.659
Trading Turnover	5,059	0.750	1.406	0.498	0.244	0.345	0.761	1.190
Expense Ratio	5,059	0.309	0.204	0.240	0.100	0.150	0.470	0.580
Turnover Ratio	5,059	0.682	1.504	0.330	0.0700	0.160	0.610	1.150
% Bond	5,059	1.226	4.360	0.180	0.025	0.056	0.592	2.527
% Institution	5,059	46.95	18.25	45.55	24.75	33.86	58.26	70.61

Table 2: continued from previous page

Panel C: Other ETFs

Variable	N	Mean	SD	Median	p10	p25	p75	p90
Quarter Return	4,971	-0.725	17.40	-1.047	-20.44	-9.659	7.600	18.54
In Kind Creation	4,971	0.441						
Derivatives Based	4,971	0.818						
ETF Age	4,971	5.891	2.862	5.764	2.099	3.477	8.132	9.918
Market Cap	4,971	875.8	4,123	156.2	17.59	45.72	436.3	1,325
Bid-Ask Spread	4,971	0.175	0.246	0.0963	0.034	0.056	0.185	0.405
Average Absolute Premium	4,971	1.359	31.27	0.155	0.055	0.086	0.298	0.547
Trading Turnover	4,971	9.583	43.25	1.826	0.412	0.789	5.323	16.90
Expense Ratio	4,971	0.848	0.212	0.950	0.450	0.780	0.950	0.950
First ETF in Lipper	4,971	0.0817						
Commodity	4,971	0.200						
Currency	4,971	0.108						
Levered	4,971	0.693						
% Other	4,971	0.925	3.922	0.157	0.017	0.045	0.420	1.402
% Institution	4,971	23.68	18.41	18.52	5.071	9.212	33.56	50.57

Table 3: Smart Beta Summary Statistics

The table reports summary statistics for the Smart Beta ETFs. Panel A summarizes which Smart Beta Flags are represented, Panel B summarizes key variables, and Panel C summarizes fund sponsors (as of the end of 2017). All variables are defined in Table A1.

Panel A: Smart Beta Flags

Variable	N	Mean
Value	5,007	0.400
Growth	5,007	0.355
Small Cap	5,007	0.339
Quality	5,007	0.035
Momentum	5,007	0.142
Low Volatility	5,007	0.080
Profitability	5,007	0.092

Panel B: Summary Statistics

Variable	N	Mean	SD	Median	p10	p25	p75	p90
Tracking Error	5,007	0.324	0.194	0.284	0.145	0.199	0.384	0.527
Market Risk	5,007	1.016	0.512	0.868	0.582	0.704	1.148	1.627
Smart Beta Risk	5,007	0.219	0.175	0.157	0.048	0.090	0.331	0.450
Other Factor Risk	5,007	0.149	0.010	0.120	0.063	0.083	0.187	0.265
Idiosyncratic Risk	5,007	0.283	0.178	0.241	0.122	0.173	0.340	0.473
Factor Purity	5,007	0.577	0.318	0.624	0.083	0.303	0.885	0.956
Good Smart Beta	5,007	0.460						
Bad Smart Beta	5,007	0.332						
Total Flags	5,007	1.444	0.692	1	1	1	2	2
% Smart Beta	5,007	1.378	3.275	0.206	0.029	0.073	0.985	3.996
Small Cap Beta	1,698	0.779	0.217	0.813	0.530	0.679	0.909	1.000
Value Beta	2,005	0.252	0.181	0.265	0.0122	0.147	0.354	0.458
Growth Beta	1,778	0.187	0.184	0.216	-0.064	0.069	0.299	0.389
Momentum Beta	713	0.080	0.192	0.049	-0.140	-0.049	0.214	0.326
Profitability Beta	461	0.0411	0.217	0.062	-0.233	-0.064	0.178	0.291
Low Vol Beta	402	0.208	0.244	0.191	-0.037	0.034	0.354	0.540
Quality Beta	175	0.087	0.121	0.081	-0.047	0.023	0.158	0.222

Panel C: Fund Sponsors

	Overall		Smart Beta		
Fund Sponsor	N	Market Cap	N	% Good	% Bad
iShares (Blackrock)	213	$1,133	28	64%	21%
Vanguard	70	$856	21	33%	33%
SPDR (State Street)	88	$583	13	8%	46%
PowerShares	111	$136	19	58%	26%
Schwab	21	$99	6	0%	33%
Invesco	132	$59	11	55%	45%
First Trust Exchange	81	$55	19	63%	26%
WisdomTree	49	$45	6	17%	50%
Other	264	$154	27	11%	56%

Table 4: ETF Size Determinants by Asset Class

The table displays quarterly panel regressions of % Category, or relative ETF size (an ETF's Market Cap as a percentage of the concurrent total Market Cap of category ETFs), on ETF characteristics. Each column analyses a sub-sample of ETFs, specified by the ETF Type. All variables are defined in Table A1. Standard errors clustered at the quarterly level, *t*-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) % Equity	(2) % Bond	(3) % Other
Log ETF Age	0.28***	1.36***	1.56***
	(9.65)	(8.20)	(11.43)
First ETF in Lipper	0.40***	1.35***	4.27***
	(12.76)	(12.07)	(31.25)
Quarter Return	-0.00*	0.00	0.00
	(-1.82)	(0.37)	(0.15)
Expense Ratio	-0.83***	-1.17***	-0.55***
	(-12.92)	(-5.67)	(-3.07)
Average Absolute Premium	-0.03***	-0.04***	0.00***
	(-4.82)	(-7.29)	(14.02)
Bid-Ask Spread	-0.76***	-1.95***	-1.00***
	(-3.10)	(-7.47)	(-7.42)
Trading Turnover	0.09***	-0.12***	-0.00**
	(11.23)	(-2.90)	(-2.66)
In Kind Creation	-0.21***	-0.11*	0.34***
	(-5.72)	(-1.73)	(10.11)
Derivatives Based	0.07**	0.88***	-1.81***
	(2.26)	(5.22)	(-16.25)
Turnover Ratio	0.02***	0.11***	
	(4.37)	(5.98)	
Observations	24,634	5,059	4,971
Adjusted R^2	0.131	0.643	0.250
Quarter Fixed Effects	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter
ETF Type	Equity	Bond	Other

Table 5: Equity ETF Size Determinants by Category

The table displays quarterly panel regressions of % Category, or relative ETF size (an ETF's Market Cap as a percentage of the concurrent total Market Cap of category ETFs), on ETF characteristics. Each column analyses a sub-sample of Equity ETFs, specified by the ETF Type. All variables are defined in Table A1. Standard errors clustered at the quarterly level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) % Regular US	(2) % Developed	(3) % Emerging	(4) % Sector	(5) % Smart Beta
Log ETF Age	1.27***	0.13***	0.17***	0.07***	0.17***
	(5.81)	(19.16)	(6.85)	(19.24)	(12.31)
First ETF in Lipper	1.40***	-0.08***	-0.45***	0.21***	0.32***
	(5.01)	(-9.24)	(-11.17)	(33.73)	(15.64)
Quarter Return	-0.05**	-0.00	-0.00	0.00	0.00
	(-2.32)	(-0.37)	(-0.15)	(1.03)	(0.34)
Expense Ratio	-0.76***	-0.59***	-0.81***	-0.26***	-0.29***
	(-3.70)	(-11.61)	(-8.84)	(-22.15)	(-11.10)
Turnover Ratio	0.03***	0.08***	0.03*	0.01**	-0.00
	(5.55)	(8.62)	(1.83)	(2.60)	(-0.14)
Average Absolute Premium	0.05	0.13***	-0.00	0.01***	-0.00
	(1.48)	(3.51)	(-0.10)	(7.98)	(-0.36)
Bid-Ask Spread	-1.73	-0.31***	-0.11***	-0.09***	-0.45***
	(-1.02)	(-5.08)	(-3.82)	(-3.67)	(-3.46)
Trading Turnover	0.38***	0.02	0.08***	0.01***	0.08***
	(5.38)	(1.47)	(10.56)	(8.41)	(10.03)
In Kind Creation	-0.58***	-0.05***	0.01	0.02***	-0.01
	(-5.37)	(-4.34)	(0.64)	(2.71)	(-0.81)
Derivatives Based	-0.29**	0.17***			0.25***
	(-2.12)	(9.73)			(5.04)
Observations	3,578	6,632	3,319	8,417	5,007
Adjusted R^2	0.408	0.092	0.158	0.434	0.431
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter	Quarter	Quarter
ETF Type	Regular US	Developed	Emerging	Sector	Smart Beta

Table 6: Smart Beta ETF Size Determinants

The table displays quarterly panel regressions of % Category, or relative ETF size (an ETF's Market Cap as a percentage of the concurrent total Market Cap of category ETFs), on ETF characteristics for Smart Beta ETFs. All variables are defined in Table A1. Standard errors clustered at the quarterly level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) % Smart Beta	(2) % Smart Beta	(3) % Smart Beta
Market Risk	-1.48***		
	(-5.21)		
Smart Beta Risk	1.75***		
	(3.44)		
Other Factor Risk	-3.19***		
	(-5.94)		
Idiosyncratic Risk	-2.76***		
	(-4.87)		
Tracking Error		-2.90***	-3.67***
		(-5.29)	(-6.91)
Factor Purity		1.43***	
		(7.07)	
Good Smart Beta			0.36***
			(5.55)
Bad Smart Beta			-0.45***
			(-4.21)
2+ Smart Beta Flags	-0.32**	-0.62***	0.18
	(-2.44)	(-4.85)	(1.01)
3+ Smart Beta Flags	-0.46***	-0.82***	0.21**
	(-3.36)	(-5.52)	(2.18)
Momentum	0.29***	0.53***	-0.09
	(2.84)	(6.23)	(-1.21)
Growth	-0.30*	0.04	-0.67***
	(-1.89)	(0.21)	(-3.71)
Value	-0.19	0.15	-0.45***
	(-1.50)	(1.12)	(-3.56)
Quality	0.66***	1.09***	0.31***
	(4.04)	(6.45)	(3.26)
Low Volatility	0.21	0.77***	0.16
	(1.40)	(4.93)	(1.57)
Profitability	0.42***	0.85***	0.12
	(2.84)	(5.79)	(1.40)
Observations	5,007	5,007	5,007
Adjusted R^2	0.454	0.454	0.456
Additional Controls	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter
ETF Type	Smart Beta	Smart Beta	Smart Beta

Table 7: Relative Ownership Determinants by Asset Class

The table displays quarterly panel regressions of % Institution, or the percentage of the free float of shares owned by institutional investors, on ETF characteristics. Each column analyses a sub-sample of ETFs, specified by the ETF Type. All variables are defined in Table A1. Standard errors clustered at the quarterly level, *t*-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) % Institution	(2) % Institution	(3) % Institution
In Kind Creation	0.45	5.09***	-7.84***
	(0.37)	(6.81)	(-9.80)
Log ETF Age	-4.45***	-7.81***	1.71
	(-6.96)	(-11.49)	(1.38)
First ETF in Lipper	4.11***	-1.53***	7.03***
	(15.34)	(-4.13)	(8.23)
Quarter Return	0.10**	0.01	0.07***
	(2.50)	(0.20)	(4.98)
Expense Ratio	10.27***	-7.74***	-30.08***
	(10.59)	(-10.45)	(-16.08)
Bid-Ask Spread	-1.53*	-0.63	3.23***
	(-1.70)	(-0.44)	(3.24)
Log Market Cap	2.80***	3.02***	0.02
	(16.86)	(19.34)	(0.13)
Average Absolute Premium	0.04	0.63***	-0.01***
	(0.82)	(7.60)	(-5.16)
Trading Turnover	1.31***	1.74***	0.00
	(13.91)	(14.00)	(0.53)
Turnover Ratio	-0.17	1.04***	
	(-1.38)	(6.24)	
Observations	24,634	5,059	4,971
Adjusted R^2	0.163	0.198	0.154
Quarter Fixed Effects	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter
ETF Type	Equity	Bond	Other

Table 8: Relative Ownership Determinants of Smart Beta ETFs

The table displays quarterly panel regressions of % Institution, or the percentage of the free float of shares owned by institutional investors, on ETF characteristics for Smart Beta ETFs. All variables are defined in Table A1. Standard errors clustered at the quarterly level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) % Institution	(2) % Institution	(3) % Institution
Market Risk	0.91		
	(0.63)		
Smart Beta Risk	9.72***		
	(4.57)		
Other Factor Risk	-22.94***		
	(-6.61)		
Idiosyncratic Risk	4.88		
	(1.64)		
Tracking Error		-0.83	-5.30*
		(-0.31)	(-1.91)
Factor Purity		8.56***	
		(9.01)	
Good Smart Beta			1.11***
			(2.90)
Bad Smart Beta			-3.26***
			(-6.33)
2+ Smart Beta Flags	-1.60*	-1.42**	3.64***
	(-1.74)	(-2.45)	(6.96)
3+ Smart Beta Flags	-12.21***	-13.00***	-6.62***
	(-8.00)	(-8.28)	(-4.21)
Momentum	4.42***	4.95***	1.07
	(3.16)	(3.46)	(0.80)
Growth	5.58***	6.18***	1.94***
	(6.52)	(7.84)	(3.07)
Value	4.40***	4.84***	1.15
	(4.34)	(4.89)	(1.31)
Quality	7.63***	8.86***	4.06*
	(3.42)	(3.73)	(1.81)
Low Volatility	-3.19**	-2.62**	-6.32***
	(-2.29)	(-2.21)	(-6.12)
Profitability	2.93	3.87**	-0.77
	(1.62)	(2.13)	(-0.47)
Observations	5,007	5,007	5,007
Adjusted R^2	0.372	0.373	0.372
Additional Controls	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
Cluster	Quarter	Quarter	Quarter
ETF Type	Smart Beta	Smart Beta	Smart Beta

A Variable Definitions

Table A1: Variable Definitions
This table contains the definitions and descriptions of the variables used in the paper.

Variable	**Definition**
% Equity	The quarter-end ETF market capitalization divided by the sum of market capitalizations of ETFs with Equity equal to one (Sources: Bloomberg and CRSP).
% Bond	The quarter-end ETF market capitalization divided by the sum of market capitalizations of ETFs with Bond equal to one (Sources: Bloomberg and CRSP).
% Other	The quarter-end ETF market capitalization divided by the sum of market capitalizations of ETFs with Commodity, Currency, or Levered equal to one (Sources: Bloomberg and CRSP).
% Smart Beta	The quarter-end ETF market capitalization divided by the sum of market capitalizations of ETFs with Smart Beta Equity equal to one (Sources: Bloomberg, CRSP, and ETF.com).
% Institution	The percentage of the ETF shares multiplied by one plus the short interest that are held by 13F Institutions (Sources: Bloomberg, Compustat, CRSP, and Thomson Reuters 13F).
Equity	Indicator equal to one if the ETF is identified as an equity ETF based on Lipper code (Source: CRSP).
Bond	Indicator equal to one if the ETF is identified as a bond ETF based on Lipper code (Source: CRSP).
Commodity	Indicator equal to one if the ETF is identified as a commodity ETF based on Lipper code (Source: CRSP).
Currency	Indicator equal to one if the ETF is identified as a currency ETF based on Lipper code (Source: CRSP).
Levered	Indicator equal to one if the ETF has a leverage factor different from one (Source: Bloomberg).
Regular U.S. Equity	Indicator equal to one if Equity equals one and Developed Equity, Emerging Equity, Sector Equity, and Smart Beta Equity all equal zero (Sources: CRSP and ETF.com).

Table A1: continued from previous page

Variable	Definition
Developed Equity	Indicator equal to one if Equity equals one and the ETF claims a strategy in developed country or world equity (Source: ETF.com).
Emerging Equity	Indicator equal to one if Equity equals one, Developed Equity equals zero, and the ETF claims a strategy in emerging country equity (Source: ETF.com).
Sector Equity	Indicator equal to one if Equity equals one and the ETF has a sector Lipper code (Source: CRSP).
Smart Beta Equity	Indicator equal to one if the ETF claims to be a Value, Growth, Small Cap, Momentum, Low Volatility, Quality, or Profitability ETF (Source: ETF.com).
Quarter Return	The ETF return for the quarter (Sources: Bloomberg and CRSP).
In Kind Creation	Indicator equal to one if only in-kind creations and redemptions are allowed (Source: Bloomberg).
Derivatives Based	Indicator equal to one if the ETF uses derivatives (Source: Bloomberg).
ETF Age	Number of months since fund inception (Source: Bloomberg).
Market Cap	Share price times shares outstanding at quarter end (Sources: Bloomberg and CRSP).
Bid-Ask Spread	The mean of the daily bid-ask spread (Source: CRSP).
Average Absolute Premium	The mean of the daily absolute premium, which is calculated as the difference between the price and NAV as a percentage of NAV (Sources: Bloomberg and CRSP).
Trading Turnover	The mean of the daily trading volume in the ETF divided by shares outstanding (Source: Bloomberg).
Expense Ratio	The annual expense ratio for the ETF (Source: CRSP).
Turnover Ratio	The annual turnover ratio for the ETF portfolio (Source: CRSP).
First ETF in Lipper	Indicator equal to one if the ETF is the first in its Lipper category (Source: CRSP).
Value	Indicator equal to one if the ETF claims to be a Value ETF (Source: ETF.com).
Growth	Indicator equal to one if the ETF claims to be a Growth ETF (Source: ETF.com).
Small Cap	Indicator equal to one if the ETF claims to be a Small Cap ETF (Source: ETF.com).
Quality	Indicator equal to one if the ETF claims to be a Quality ETF (Source: ETF.com).
Momentum	Indicator equal to one if the ETF claims to be a Momentum ETF (Source: ETF.com).

Table A1: continued from previous page

Variable	**Definition**
Low Volatility	Indicator equal to one if the ETF claims to be a Low Volatility ETF (Source: ETF.com).
Profitability	Indicator equal to one if the ETF claims to be a Profitability ETF (Source: ETF.com).
Market Risk	Square root of ETF return variance attributable to exposure to market risk.
Smart Beta Risk	Square root of ETF return variance attributable to exposure to factors associated with claimed strategies.
Other Factor Risk	Square root of ETF return variance attributable to exposure to factors not associated with claimed strategies.
Idiosyncratic Risk	Square root of ETF return variance that is not attributable to systematic factor exposures.
Factor Purity	Proportion of variance that is attributable to systematic factor exposures that is contributed by claimed strategies.
Good Smart Beta	Indicator equal to one if the ETF achieves a significantly higher ranking in desired factor exposures relative to peers.
Bad Smart Beta	Indicator equal to one if the ETF achieves a significantly lower ranking in desired factor exposures relative to peers.
Tracking Error	Residual standard deviation from the Smart Beta regression that includes factors associated with claimed Smart Beta strategies.
Total Flags	The sum of the Value, Growth, Small Cap, Quality, Momentum, Low Volatility, and Profitability indicators.
2+ Smart Beta Flags	Indicator equal to one if Total Flags is two or greater.
3+ Smart Beta Flags	Indicator equal to one if Total Flags is three or greater.
Value Beta	The estimated HML beta from the Smart Beta regression that includes factors associated with claimed Smart Beta strategies.
Growth Beta	The negative of the estimated HML beta from the Smart Beta regression that includes factors associated with claimed Smart Beta strategies.

Table A1: continued from previous page

Variable	**Definition**
Small Cap Beta	The estimated SMB beta from the Smart Beta regression that includes factors associated with claimed Smart Beta strategies.
Quality Beta	The estimated QMJ beta from the Smart Beta regression that includes factors associated with claimed Smart Beta strategies.
Momentum Beta	The estimated MOM beta from the Smart Beta regression that includes factors associated with claimed Smart Beta strategies.
Low Volatility Beta	The estimated BAB beta from the Smart Beta regression that includes factors associated with claimed smart beta strategies.
Profitability Beta	The estimated RMW beta from the Smart Beta regression that includes factors associated with claimed Smart Beta strategies.