NBER WORKING PAPER SERIES

COMPETITION FOR ATTENTION IN THE ETF SPACE

Itzhak Ben-David
Francesco Franzoni
Byungwook Kim
Rabih Moussawi

Working Paper 28369
http://www.nber.org/papers/w28369

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2021, Revised July 2021

We thank Thummim Cho, Nicola Gennaioli, Wes Gray, Denis Gromb, Elisabeth Kempf, Steve Oh, Amin Shams, Matt Sheridan, Andrei Shleifer, Jim Simpson (ETP Resources), René Stulz, David Thesmar, Petra Vokata, and the seminar audience at the University of Colorado at Boulder, The Ohio State University, AEA meetings, the Virtual Finance Seminar in Corporate Finance and Investments, the Frankfurt School of Finance & Management, National University of Singapore, and CFA (Lugano chapter) seminars for helpful comments. We are especially grateful to Alp Simsek for detailed comments. Ben-David is with The Ohio State University and the National Bureau of Economic Research. Franzoni is with USI Lugano, the Swiss Finance Institute, and the Center for Economic and Policy Research. Kim is with The Ohio State University, and Moussawi is with Villanova University and Wharton Research Data Services. Ben-David is a co-founder and a partner in an investment advisor. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Competition for Attention in the ETF Space
Itzhak Ben-David, Francesco Franzoni, Byungwook Kim, and Rabih Moussawi
NBER Working Paper No. 28369
January 2021, Revised July 2021
JEL No. G12,G14,G15

ABSTRACT

The interplay between investors' demand and providers' incentives has shaped the evolution of exchange-traded funds (ETFs). While early ETFs offered diversification at low cost, later ETFs track niche portfolios and charge high fees. Strikingly, over their first five years, specialized ETFs lose about 30% in risk-adjusted terms. This underperformance cannot be explained by high fees or hedging demand. Rather, it is driven by the overvaluation of the underlying stocks. Overall, providers appear to cater to investors' extrapolative beliefs by issuing specialized ETFs that track attention-grabbing themes.

Itzhak Ben-David
The Ohio State University
Fisher College of Business
606A Fisher Hall
Columbus, OH 43210-1144
and NBER
ben-david.1@osu.edu

Francesco Franzoni
Swiss Finance Institute
Via G. Buffi 13
6904, Lugano - Switzerland
and University of Lugano
francesco.franzoni@usi.ch

Byungwook Kim
The Ohio State University
Fisher College of Business
606 Fisher Hall
Columbus, OH 43210-1144
kim.7336@osu.edu

Rabih Moussawi
Villanova University
800 Lancaster Ave
Bartley 2051
Villanova, PA 19085
Rabih.Moussawi@villanova.edu

I freely concede that the ETF is the greatest marketing innovation of the 21st century. But is the ETF a great innovation that serves investors? I strongly doubt it. In my experience…I have learnt to beware of investment "products," especially when they are "new" and even more when they are "hot."

—John Bogle, *Financial Times*, March 15, 2015

1 Introduction

The wide adoption of exchange-traded funds is often celebrated as the democratization of investments (e.g., Novick, 2017).[1] According to this view, thanks to ETFs, investors—no matter how small—can now achieve portfolio diversification at a low cost as well as obtain long and short exposure to a wide variety of investment styles without the intermediation of expensive asset managers. However, this narrative may not accurately and completely describe investors' experience with these products. In practice, the available supply of ETFs results from the interplay of investor demand and the profit-maximizing incentives of ETF providers. Some investors demand ETFs as inexpensive buy-and-hold portfolios, while others may use them to speculate based on their beliefs—rational or not. Therefore, to assess the merit of the greatest financial innovation of the last decades, we need to investigate how providers respond to investor demand.

The goal of this paper is to study the dynamics of financial innovation in the ETF industry and their potential implications for product performance. Our evidence helps explain the evolution of the ETF landscape and sheds new light on investors' experience with these products. Overall, our findings suggest that the ETF industry has evolved along two separate paths. Broad-based ETFs offer investors an opportunity to achieve diversification at a low

[1] An exchange-traded fund (ETF) is a pooled investment vehicle whose shares are traded on exchanges. In 2021, the assets managed by ETFs in the United States alone surpassed the $6 trillion mark, amounting to about 18% of the total assets in U.S. investment companies. To date, over 3,400 ETFs have been launched, covering a wide array of investments, from broad-based indexes like the S&P 500 to niche investment themes, such as a trade war, cannabis, vegan products, work from home, and COVID-19 vaccines.

cost. Other, more expensive, specialized ETFs appear to cater to investor demand for popular, yet overvalued, investment themes. As a result, their performance is on average disappointing.

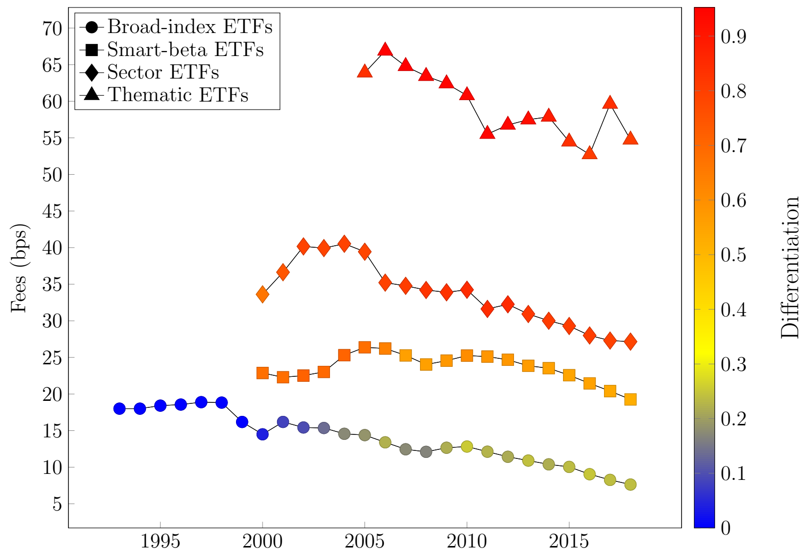
Prior literature has already studied the dynamics of financial innovation, but the specific nature of ETFs motivates a fresh look at these issues. For example, the providers of active mutual funds, relying on the fact that managerial skill is not observable, tend to promote a positive track record as a promise of good future performance (e.g., Jain and Wu, 2000). Also, the sponsors of structured products exploit the opaqueness of these vehicles to tout their high yields and shroud risks.[2] However, ETFs are different from other financial products in that their portfolios are transparent and the investment style is passive; hence, it does not involve managerial skill. Therefore, previously studied competitive strategies may not be relevant in this context.

As a first approximation on the dynamics of innovation in the ETF market, Figure 1 provides a bird's eye view of the evolution of the ETF "species" over time. The left axis shows the average annual fees that these products charge their investors, a proxy for their direct cost. The color of the markers reflects the degree of product differentiation with respect to the existing offering in the market. The first breed of ETFs that came into existence in 1993 tracked broad-based indexes and charged low fees. Over time, tighter competition in this segment of the market has led to even lower fees. To preserve high margins, the response of the ETF industry has been to launch higher priced breeds of ETFs that diverge from existing products, focusing on more specialized indexes. The industry, therefore, appears to have has progressed toward more differentiated products, and this evolution has allowed incumbents and new entrants to remain profitable despite tougher competition.

[2]See Henderson and Pearson (2011), Célérier and Vallée (2017), Henderson, Pearson, and Wang (2020), Gao, Hu, Kelly, Peng, and Zhu (2020), and Vokata (2021). More generally, prior literature has studied the competitive strategies of the providers of financial products in the context of closed-end funds (Lee, Shleifer, and Thaler, 1991), fixed-income securities (Gennaioli, Shleifer, and Vishny, 2012; Greenwood and Hanson, 2013), mutual funds (Elton, Gruber, and Rentzler, 1989; Arteaga, Ciccotello, and Grant, 1998; Massa, 1998; Khorana and Servaes, 1999; Cooper, Gulen, and Rau, 2005; Evans, 2010; Kostovetsky and Warner, 2020, among others), and equity offerings (Baker and Wurgler, 2007).

Figure 1. The Evolution of the ETF Species

The figure shows the average fees and the degree of product differentiation per ETF category weighted by their assets under management (AUM): broad-index ETFs, smart-beta ETFs, sector ETFs, and thematic ETFs. The y-axis shows average fees, and the colors of the markers represent the average degree of product differentiation, computed as one minus the cosine similarity between the ETF portfolio weights and the weights of the aggregate portfolio of all ETFs that exist in the market at that point in time. Section 3 provides information about the classification of ETFs.



Our analysis has two main parts. In the first part, we propose that the dynamics of competition in the ETF industry fit the framework of Bordalo, Gennaioli, and Shleifer (2016). The authors model the behavior of suppliers in a market in which consumers have limited attention. To attract consumers, firms can make different product attributes salient. As a result, competition can occur along the *price* and *quality* dimensions. While in their model the market converges to either a price-salient or a quality-salient equilibrium, to describe the structure of the ETF industry, we extend the interpretation of this framework. We suggest that the two equilibria can coexist and characterize different segments of the ETF industry. Specifically, broad-based ETFs compete on price, while more specialized ETFs compete along the quality dimension. We interpret quality as other salient product attributes, different from price, that investors may find attractive.

The empirical evidence is consistent with segmentation in the ETF industry corresponding to the price-salient and quality-salient equilibria. Our sample consists of nearly all equity

ETFs that ever traded in the U.S. equity market. We classify as *broad-based* all ETFs that track broad market indexes, i.e., the broad-index and smart-beta categories in Figure 1. These two groups differ only in that the latter adopts portfolio weights different from market capitalization. We classify as *specialized* the ETFs that invest in a specific sector or in sectors that are tied by a theme, i.e., the sector and thematic categories in Figure 1. As of December 2019, specialized ETFs managed 18% of the industry's assets, yet they generated about 36% of the industry's fee revenues. In the market for broad-based products, ETFs hold large portfolios and compete on price by offering similar portfolios at a low cost. In the specialized segment, ETFs hold small and differentiated portfolios and charge higher fees.

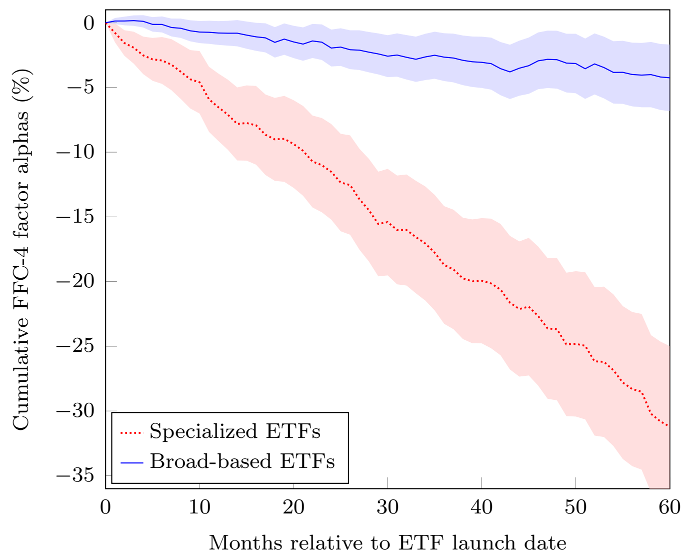
Providing further support for the conjecture of a segmented market, we find a marked difference in the sensitivity of investor demand to the cost of holding the ETF for the two groups of products. Specifically, flows to broad-based ETFs display a significantly higher sensitivity to fees, whereas flows to specialized ETFs are unrelated to fees and respond more strongly to past performance. Moreover, high media exposure of the stocks in an ETF portfolio reduces the sensitivity of flows to fees, suggesting that investors neglect price when their attention is drawn to other product attributes.

In the second part of our analysis, we study what makes specialized ETFs attractive to investors, that is, we investigate the quality of specialized ETFs. The first obvious candidate is that ETF providers are able to identify sectors and themes that deliver positive risk-adjusted returns and issue products that track them.

Our tests show that this is not the case. In fact, we find that the performance of specialized ETFs is disappointing in terms of both raw and risk-adjusted returns. A portfolio of all specialized ETFs achieves risk-adjusted returns of −3.1% per year, after fees. This underperformance is due mostly to recently launched specialized ETFs, which grossly underperform: about −6% annually in the first five years after inception. In comparison, the performance of broad-based ETFs is slightly negative, though statistically indistinguishable from zero. The underperformance of specialized ETFs is not explained by their higher fees, as it persists in terms of gross returns. The absolute size of the underperformance of specialized ETFs is nonnegligible in dollar terms given that the assets in these funds are sizeable—about $460 billion at the end of our sample. Figure 2 illustrates this result.

Figure 2. Performance of ETFs Around Launch

The figure shows the performance of ETFs around launch, split by groups of broad-based and specialized ETFs. We form 60 calendar-time portfolios that include returns of ETFs in their month +1, +2, ..., +60 since the launch date (month 0). The portfolio returns are value-weighted using one-month-lagged market capitalization. To adjust returns for risk factors, we estimate the Fama-French-Carhart four-factor model (FFC-4) alphas of the portfolios (Fama and French, 1993; Carhart, 1997). The lines represent cumulative FFC-4 alphas, and the shaded areas represent 95% confidence intervals.



Given this evidence, we test a second alternative: specialized ETFs serve as a hedging tool against risks to which investors are exposed. More broadly, this explanation relates to the view of financial innovation as a means to achieve market completion and enable risk sharing (Allen and Gale, 1994; Duffie and Rahi, 1995). While, in principle, ETFs can be replicated using the underlying assets, they reduce transaction and search costs for a large swath of investors.

We do not find evidence consistent with such an insurance motive. The portfolio of stocks that are most negatively correlated with the portfolio of all specialized ETFs does not earn positive abnormal returns, which should be the case if it were a risk factor of hedging concern. Importantly, while an insurance motive predicts that investors are willing to sacrifice performance for hedging purposes, specialized ETFs are more likely to experience capital outflows over their existence, which suggests instead that investors are disappointed by the poor performance. Moreover, this finding makes a related explanation unlikely, i.e., that investors accept the underperformance of specialized ETFs because they obtain nonpecuniary benefits from exposure to themes complying with their values (e.g., environmental, social, and corporate governance (ESG) and faith-compliant ETFs). Also indicative of a souring mood around these investment themes after the launch, we document that stocks that are included in specialized ETFs experience a steep drop in their media sentiment right after the time of launch, relative to the prelaunch period.

The final hypothesis is that specialized ETFs cater to investor sentiment (akin to closed-end funds in Lee, Shleifer, and Thaler, 1991).[3] We conjecture that issuers of specialized ETFs identify the popular trends in the market and respond to that demand by issuing products that track these trends. However, by the time new ETFs enter the market, the securities in which they invest have reached their valuation peak. Thus, specialized ETFs underperform after launch. According to this hypothesis, specialized ETFs are chosen as a speculative vehicle by investors who extrapolate past performance into the future.

Our findings are consistent with this interpretation. Newly launched specialized ETFs hold portfolios of securities in attention-grabbing segments of the market: These are stocks that experienced recent price run-ups, had recent media exposure (especially positive exposure), had more positive earnings surprises, and displayed general traits that have been previously shown to indicate overvaluation (high market-to-book and high short interest). We also find evidence of catering to preferences for gambling (Brunnermeier and Parker, 2005; Brunnermeier, Gollier, and Parker, 2007; Mitton and Vorkink, 2007; Barberis and

[3] In line with the literature, we interpret sentiment as the component of expectations about future asset returns not warranted by fundamentals (e.g., De Long, Shleifer, Summers, and Waldmann, 1990a). Lee et al. (1991) find that new closed-end funds are started when the sentiment for the respective asset class is positive. More recently, catering to investor sentiment appears to drive the launch of structured products (Célérier and Vallée, 2017; Henderson et al., 2020; Vokata, 2021) and mutual funds' dividend distributions (Harris, Hartzmark, and Solomon, 2015). More generally, catering to sentiment characterizes different aspects of the interaction between firms and investors (Baker and Wurgler, 2000, 2002, 2004, 2007; Baker, Greenwood, and Wurgler, 2009).

Huang, 2008; Kumar, 2009): Specialized ETFs contain securities with relatively more positively skewed returns. Moreover, the investor clientele of specialized ETFs has a greater fraction of retail investors, who are typically considered less sophisticated and, therefore, more prone to holding incorrect beliefs and engaging in positive feedback trading (De Long, Shleifer, Summers, and Waldmann, 1990b). Relatedly, specialized ETFs are very popular among Robinhood investors, who have become famous in recent years for being prone to investment frenzies (Barber, Huang, Odean, and Schwarz, 2020).

We find additional evidence indicating that specialized ETFs target investors' extrapolative beliefs, i.e., the tendency to expect recent performance of an asset to continue into the future, or to their diagnostic expectations, which lead to overweighting of the best-case scenario.[4] Specifically, after the launch of specialized ETFs, analysts' long-term growth expectations for the underlying securities prove to be too optimistic, and they constantly revise downward their bullish forecasts.

Overall, our results suggest a new narrative for the evolution of the most transformative financial innovation of the last three decades. The early ETFs, which are broad-based products, are beneficial investment platforms, as they reduce transaction costs and provide diversification.[5] Specialized ETFs ride the same wave of financial innovation, but they mainly compete for the attention of performance-chasing investors. Consequently, specialized ETFs, on average, have generated disappointing performance for their investors.

Our work relates to a few recent studies. Easley, Michayluk, O'Hara, and Putniņš (2018) propose that ETFs with a narrow focus are used as alpha-generating building blocks for active strategies. As such, they contribute positively to price formation, reducing mispricing. Our results, instead, suggest that specialized ETFs are not randomly launched, but rather issued

[4]See models and studies of extrapolative beliefs in Barberis and Shleifer (2003), Greenwood and Shleifer (2014), Barberis, Greenwood, Jin, and Shleifer (2018), and Da, Huang, and Jin (2020). Egan, MacKay, and Yang (2019) recover expectations of leveraged ETF investors and show that these beliefs are consistent with extrapolative expectations. See models and studies of diagnostic expectations in Bordalo, Gennaioli, and Shleifer (2018) and Bordalo, Gennaioli, La Porta, and Shleifer (2019)

[5]An important way in which broad-based ETFs reduce transaction costs is by being more tax-efficient than mutual funds (Moussawi, Shen, and Velthuis, 2020).

in overvalued corners of the market and return negative alphas. Thus, they can, in principle, contribute to overvaluation if they attract a new layer of investor demand to the underlying securities (see Ben-David, Franzoni, and Moussawi, 2018). In later work, Akey, Robertson, and Simutin (2021) confirm that less diversified ETFs underperform major benchmarks. Huang, Song, and Xiang (2020) focus on smart-beta ETFs and show that their providers overfit index weights in a way that generates in-sample alpha but does not produce abnormal performance after launch. Different from that study, we focus on specialized ETFs and find that they yield negative alphas after launch as a result of investing in securities that tend to be overvalued. Our description of financial innovation via ETFs resonates with the model of Simsek (2013a,b), in which new financial products are used for both risk sharing and speculation. In the case of ETFs, it appears that broad-based products are primarily geared toward the risk-sharing goal, while specialized ETFs are catering to speculative behavior.

2 Testable Conjectures

The ETF market has grown substantially since the introduction of the first ETF in the early 1990s. In the United States alone, over 3,400 exchange-traded funds have been launched; of these, more than 1,000 invest in U.S. equities. Equity ETFs differ in the breadth of their holdings—ranging from a few stocks to over 3,000 stocks—and in the fees they charge—ranging from 4 basis points (bps) to over 150 bps per year.

This paper aims to identify the main competitive strategies adopted by the ETF industry along this path of extraordinary growth and, in particular, the features that have made these products successful among investors. The evidence in Figure 1 suggests that the market is segmented into low-cost, broad-based products and more expensive, highly differentiated ETFs.

2.1 Price Competition versus Quality Competition

The model of industrial organization by Bordalo et al. (2016) provides a fitting framework to describe the evolution and the current structure of the ETF industry.[6] This theory suggests that producers, facing consumers with limited attention, choose to compete on either of two dimensions, price or quality. For example, Walmart sells cheap commoditizied goods, while Starbucks emphasizes product quality and charges high prices. As a consequence, a market can gravitate around either (*i*) a price-salient equilibrium in which products are commoditized and firms compete by offering low prices or (*ii*) a quality-salient equilibrium in which prices are high and firms differentiate themselves by offering distinct product features.

While the theory predicts that one of these equilibria will emerge in a given market, we extend this interpretation by suggesting that the two equilibria can co-exist in different segments of the same industry (e.g., airline industry). We apply the framework to the ETF industry and conjecture that the inexpensive and highly diversified ETFs are the commoditized products that can be mapped into the price-salient equilibrium. This group of ETFs allows investors to achieve market exposure and diversification at a low cost. In contrast, the more expensive and specialized ETFs are part of the quality-salient equilibrium. Investors who buy these ETFs are willing to overlook the high fees or loss of diversification as long as they can gain exposure to their desired investment themes. In this segment of the market, ETF issuers attract investor attention by designing products that lead investors to expect high utility and to neglect their expensive price tag.

2.2 The Nature of Quality Competition

In mapping the Bordalo et al. (2016) model to the ETFs market, it is crucial to understand the nature of "quality competition." Specifically, what is the value proposition that investors find attractive and that allows providers to charge high fees? After all, the specialized

[6]The authors propose that their model can be applied to financial innovation, and Célérier and Vallée (2017) use this framework to describe competition in the market for structured products.

segment of the market accounts for 36% of the industry's revenues at the end of our sample period, despite managing only 18% of the assets.

We next formulate conjectures on the unique features that make specialized ETFs appealing to investors. In particular, we consider three potential explanations to describe the nature of quality competition.

2.2.1 Delivering Alpha?

The first hypothesis is that specialized ETFs provide access to investment opportunities that would be otherwise unattainable to investors because of information or transaction costs.

The resulting prediction is that specialized ETFs generate a positive alpha after fees. As such, ETFs benefit investors by delivering higher risk-adjusted returns.

2.2.2 Providing Hedging Services?

The second hypothesis is that investors use specialized ETFs for hedging some risks to which they are exposed. In this light, specialized ETFs are beneficial as they enable risk sharing among investors (Allen and Gale, 1994; Duffie and Rahi, 1995). Even though ETFs replicate cash flow profiles of securities that already exist in the market, they increase the accessibility of these portfolios to investors by reducing search and trading costs. Thus, the variety of products coming to the market reflects the heterogeneity in investors' endowments and in their need to insure against the risks associated with these endowments—i.e., their hedging demand. Viewed through this lens, the growth in the ETF market, including the specialized segment, responds to investors' rational demand and is, therefore, welfare improving.

According to this hypothesis, investors hold specialized ETFs even if their performance is negative because they provide insurance. Thus, we would expect investors not to abandon specialized ETFs following poor performance. The same prediction would emerge if specialized ETFs provided nonpecuniary benefits in the form of access to themes complying with investors' values (e.g., ESG, faith-compliant ETFs). Moreover, if the risks for which specialized ETFs provide hedging are systematic, a testable corollary of this hypothesis is that the stocks that are exposed to these risks—i.e., they load positively on them—earn positive risk-adjusted returns—i.e., a risk premium.

2.2.3 Catering to Investor Sentiment?

A long literature cited in the introduction suggests that some financial innovators cater to investor sentiment (e.g., Lee et al., 1991), which is broadly defined as the component of expectations about future asset returns that are not warranted by fundamentals. Inspired by this literature, our third hypothesis is that specialized ETFs cater to investors' optimistic expectations about future stock performance.

Thus, according to this hypothesis, new specialized ETFs are designed to appeal to investors' irrational beliefs.[7] For example, some investors may suffer from representativeness bias and they extrapolate past performance into the future (Greenwood and Shleifer, 2014; Barberis et al., 2018; Cosemans and Frehen, 2021). Or they might have diagnostic expectations (Bordalo et al., 2018, 2019), interpreting positive past performance as indicative of the best possible future scenario. These investor audiences would be drawn, for instance, to new ETFs that invest in past winners and stocks that delivered recent positive news.

The catering hypothesis also implies that, if arbitrage is limited in the stock market, high-sentiment stocks are likely to be overvalued (e.g., Miller, 1977; Shleifer and Vishny, 1997). As a result, securities held by specialized ETFs are overvalued at the time of launch

[7] A related catering behavior has been documented for the mutual fund industry when, in the late 1990s, mutual fund families changed the names of their products to attract flows of investors chasing popular investment styles (Cooper et al., 2005).

and their post-launch alpha would be negative.[8]

3 Data

3.1 Data Sources

We use data on ETFs traded in the U.S. market from the Center for Research in Security Prices (CRSP) between 1993 and 2019. We restrict our sample to equity-focused ETFs that hold U.S. stocks in their portfolios. This choice allows us to more closely benchmark the ETF portfolios to broad-based U.S. stock indexes. Therefore, we exclude ETFs that are classified as non-equity, foreign equity, inverse and/or leveraged, and active. The final sample contains 1,080 U.S. equity ETFs. Appendix A introduces the mechanics of ETFs. We provide detailed data sources in Appendix B and variable descriptions in Appendix C.

We compute ETFs' portfolio holdings by combining the Thomson Reuters Global Mutual Fund Ownership and the CRSP Mutual Fund Holdings databases. We start with the data set that includes holdings information on the earliest date (closest to the launch date). We then use the other data set to complement missing data. We use Bloomberg and Morningstar Direct as guides for classifying ETFs, as described below.

In addition, we use stock-level data from additional sources: market data from CRSP, short interest from Compustat, analyst expectations from I/B/E/S, firm-level news from RavenPack News Analytics, 13F institutional ownership data from Thomson Reuters, and Robinhood user data from Robintrack.

[8]Simsek's (2013b) theory provides additional theoretical background for our third hypothesis. In his model, based on investor disagreement, financial products are used both by investors seeking risk sharing and by those with diverging beliefs interested in speculation. Financial innovators, to maximize their revenues, offer products for which the speculation motive is strongest. Therefore, this theory provides a rationalization for the two segments of the ETF market, where broad-based products are primarily geared toward the risk-sharing goal, while specialized ETFs are designed for speculators.

3.2 Classification of ETFs

To analyze the evolution and motives behind the launch of new ETF products, we classify ETFs in two steps. First, we classify ETFs into four groups based on their investment objective (as was presented in Figure 1). The *thematic* group comprises ETFs that, according to Bloomberg and CRSP, track multiple industries that are tied by a "theme" (e.g., clean energy). If ETFs track a single industry, they belong to the *sector* category.[9] *Smart-beta* ETFs are identified using the *Strategic Beta* field in Morningstar. Finally, we identify as *broad-index* those ETFs for which the Morningstar category *Index Selection* variable has the value *Market Capitalization* and that are not smart beta funds.[10] We do not create a separate category for ETF products specializing in environmental, social, and corporate governance topics (ESG) because they cut across multiple ETF classes with different degrees of diversification.[11]

In the second step, we consolidate ETFs into two broader groups to facilitate the analysis and presentation. We classify as *broad-based ETFs* all ETFs that track broad market indexes, that is, the broad-index and smart-beta categories in Figure 1. The two types differ only in that smart-beta ETFs do not use capitalization-based weights. We classify as *specialized ETFs* those that invest in a specific sector or in sectors that are tied by a theme, that is, sector and thematic categories in the figure.

In most of our analysis, we start the sample in 2000, when sufficient variety in the ETF

[9]Specifically, we reference the Bloomberg field *FUND_INDUSTRY_FOCUS*. Moreover, ETFs with a CRSP Objective Code (*CRSP_OBJ_CD* variable) starting with *EDS* are classified as sector funds. Also, those with Lipper Classification (*LIPPER_CLASS* variable) with value *S* are classified as thematic ETFs if they track religious, artificial intelligence, clean energy, or gender themes, and as sector ETFs otherwise.

[10]For the remaining equity ETFs, we rely on the variable *LIPPER_CLASS* in CRSP to classify funds as either broad-index or smart-beta. *LIPPER_CLASS* values of *LCVE*, *MCVE*, *MLVE*, *SCVE*, *LCGE*, *MCGE*, *MLGE*, or *SCGE*; alternative funds; and funds that include factors in their names (e.g., value, growth, momentum, quality, sentiment, low volatility, dividends, earnings, profitability, alpha, multifactor, equal-weighted) are classified as smart-beta ETFs. We drop actively managed ETFs and ETFs with industry exclusions (e.g., S&P 500 ex-Technology ETF) from the list. The remaining funds are classified as broad-index ETFs.

[11]In particular, ESG ETFs are classified as specialized if they are sector ETFs according to the CRSP classification codes (e.g., ALPS Clean Energy ETF). The remaining ESG ETFs, which are more diversified products (e.g., iShares ESG Screened S&P 500 ETF), are included in the broad-based category.

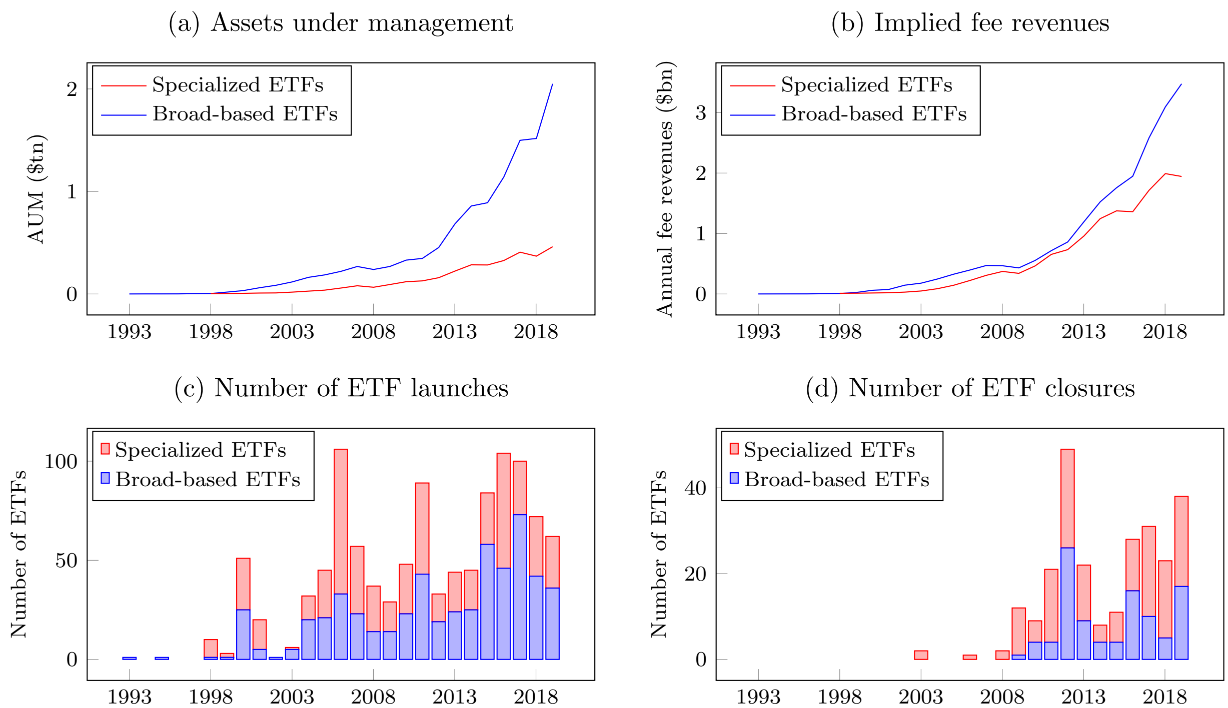
offering allows for a meaningful classification, and end it in 2019. This sample contains 554 broad-based ETFs (90 broad-index and 464 smart beta ETFs) and 526 specialized ETFs (411 sector and 115 thematic ETFs).

3.3 Descriptive Statistics

Figure 3 shows the time-series evolution of the assets under management (AUM) and implied revenues (percentage fees times the average AUM in each year), as well as the time series of ETF launches and closures.

Figure 3. Evolution of the ETF Industry

The figure presents the evolution of the stock-focused ETF industry, split by ETF category. Panel (a) reports the aggregate assets under management (AUM), and Panel (b) shows implied revenues, computed as the sum across ETFs in the category of fee times the average AUM in each year. Panel (c) presents the number of ETF launches, and Panel (d) shows the number of ETF closures.



Panel (a) of Figure 3 shows that the assets managed by broad-based ETFs have grown exponentially over the years, whereas the growth of the assets in specialized ETFs is less striking. By the end of 2019, broad-based ETFs accounted for about 82% of the assets invested in equity-based ETFs, and specialized ETFs accounted for the remaining 18%. Despite their relatively small market share, specialized ETFs at the end of the sample accounted for about 36% of the industry's revenues, and broad-based ETFs generate 64% of it (Panel (b)). The disproportionate share of revenues of specialized ETFs is due to the higher fees that they charge on average (Table 1). Over the entire sample period, broad-based and specialized ETFs generated cumulative revenues of \$22.6bn and \$14.6bn, respectively.

Panels (c) and (d) of Figure 3 present the time series of ETF launches and closures. In the early years, most newly launched ETFs were broad-based. A large batch of specialized ETFs was launched in 2006, and another in 2011. Interestingly, the rate of ETF closures is more pronounced for specialized ETFs.

In Table 1, we present summary statistics for our sample of ETFs. Specialized ETFs hold portfolios with fewer stocks than broad-based ETFs do: The median broad-based ETF holds 247 stocks, while the median specialized ETF holds 53 stocks. Broad-based ETFs charge lower fees than specialized ETFs (medians of 35 versus 58 basis points, respectively).[12]

There are other marked differences between the two groups of ETFs. Specialized ETFs generate more volatile returns than do broad-based ETFs. Furthermore, turnover is materially higher for specialized ETFs, reflecting a different use of these products by their investors relative to broad-based ETFs. Appendix Table D.1 breaks the two groups into the four categories of ETFs and provides summary statistics.

[12]The apparent discrepancy between the means of fees reported in Table 1 and Figure 1 is because the mean is equally weighted in Table 1 but AUM-weighted in Figure 1.

Table 1. ETF Summary Statistics

The table shows summary statistics at the ETF level. Panel A reports summary statistics for broad-based ETFs, and Panel B reports summary statistics for specialized ETFs. *Number of holdings* represents the average number of stocks in the portfolios of ETFs. *Fee* refers to the annualized expense ratio. *Turnover* is the average daily turnover over the six months after launch. *Market-adjusted return* is the monthly ETF return in excess of the CRSP value-weighted return over the 60 months after launch. *Delisted* is an indicator for whether the ETF was liquidated as of the end of 2019. *Assets under management* (AUM) is the total market value of the investments in 2019. Implied revenues are calculated by multiplying fees by AUM in 2019.

Panel A: Broad-Based ETFs								
	N	Mean	SD	P5	P25	P50	P75	P95
Number of holdings (at launch)	553	403	495	40	100	247	500	1,450
Fee (bps)	491	42	25	12	22	35	60	85
Turnover (months 1–6; %)	543	2.83	3.25	0.19	0.93	2.01	3.48	7.95
Market-adjusted return (months 1–60; %)	551	−0.16	0.39	−0.88	−0.31	−0.11	0.04	0.33
Delisted	554	0.18	0.38	0	0	0	0	1
2019 statistics								
Assets under management ($bn)	431	4.76	21.16	0.01	0.05	0.22	1.46	20.02
Implied revenues ($m)	389	8.94	31.36	0.03	0.22	0.97	5.12	45.36

Panel B: Specialized ETFs								
	N	Mean	SD	P5	P25	P50	P75	P95
Number of holdings (at launch)	515	87	87	21	34	53	100	272
Fee (bps)	455	55	21	18	39	58	70	86
Turnover (months 1–6; %)	530	3.84	6.38	0.37	1.09	2.13	4.16	13.10
Market-adjusted return (months 1–60; %)	526	−0.44	1.42	−1.99	−0.73	−0.21	0.21	0.79
Delisted	526	0.30	0.46	0	0	0	1	1
2019 statistics								
Assets under management ($bn)	354	1.30	3.72	0.01	0.04	0.18	0.82	6.09
Implied revenues ($m)	329	5.91	15.78	0.03	0.24	0.93	4.12	25.20

4 Empirical Analysis: Segmentation in the ETF Space

We begin our empirical examination by studying the joint distribution of fees and specialization.

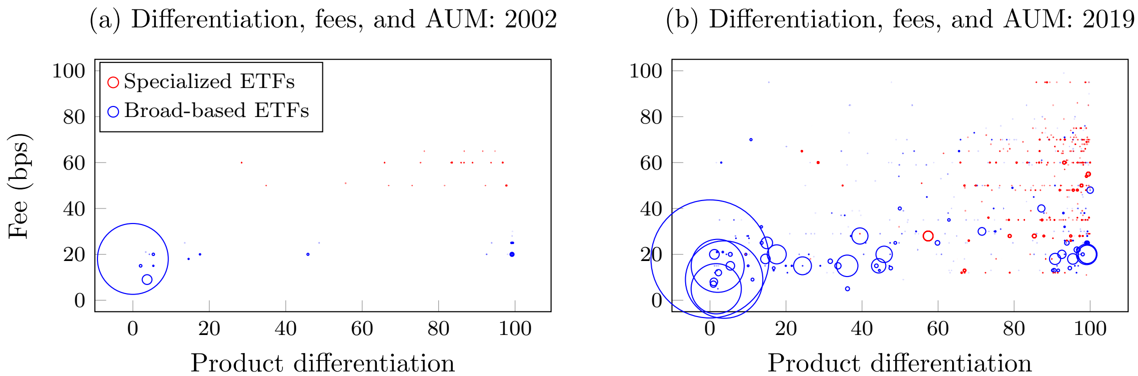
4.1 Segmentation Along the Fee and Diversification Dimensions

Several pieces of evidence support the view of a market segmented into price- and quality-salient equilibria. First, in Figure 4, we plot ETF fees against product differentiation at two points in time: close to the birth of the industry (2002) and toward the end of our sample

(2019).[13] The figure shows that two clusters of products have emerged over time. Broad-based ETFs, the early comers to the market, tend to charge lower fees and appear to be more similar to one another. Specialized products, which proliferate in the late sample, are more differentiated and expensive.

Figure 4. Segmentation in the ETF Market

The figure presents the ETF market configuration at two points in time. Panel (a) shows a snapshot as of December 2002, and Panel (b) shows a snapshot as of December 2019. Product differentiation is computed for each category as one minus the cosine similarity between the ETF portfolio weights and the weights of the portfolio of all ETFs in that category that exist in the market at that point in time. The panels show the universe of ETFs at each date, on two dimensions: product differentiation and fees. Each circle represents one ETF, and the size of the circles represents relative share of assets under management across all ETFs. Blue circles represent broad-based ETFs, and red circles represent specialized ETFs.



In Appendix Table D.2, we show that the difference in fees between broad-based and specialized ETFs is statistically significant, even controlling for time and management company fixed effects. The latter set of controls allows us to rule out the possibility that the difference in fees results from different pricing power of different providers, for example due to their brand recognition. Even within the same provider, specialized products are priced significantly higher.

Based on the size of the circles in Figure 4, which is proportional to the ETF's AUM,

[13] Product differentiation is computed for each category as one minus the cosine similarity between the ETF portfolio weights and the weights of the aggregate portfolio of all ETFs in that category that exist in the market at that point in time. Kostovetsky and Warner (2020) develop an alternative measure of product differentiation for active mutual funds using textual analysis of the fund prospectus. They show that despite differentiation in strategy description, mutual fund holdings are similar. Likewise, we find that some portfolios that are marketed as differentiated products have almost identical holdings. A noticeable example are the ETFs offering investments based on religious or political values. Most of these ETFs hold portfolios that are very similar to broad-based indexes, but charge high fees.

we also conclude that the broad-based segment of the market is more concentrated. This is probably a consequence of price competition leading to a winner-takes-all equilibrium. In the specialized segment, multiple differentiated products with smaller portfolio sizes can charge higher fees and survive, leading to lower concentration. Interestingly, the distribution of revenues generated by broad-based ETFs largely matches that of specialized ETFs, as can be seen in Table 1. For example, as of 2019, the median annual fee revenue was nearly \$1m in each group and the revenues at the 75$^{\text{th}}$ percentile were above \$5m and \$4m for broad-based and specialized ETFs, respectively. The main difference between the groups is in the extreme right tail, where the large broad-based ETFs (like State Street's SPDR tracking the S&P 500 index) generate higher revenues due to their sheer portfolio size.

At the level of providers, the concentration also differs markedly between the two sets of products. Appendix Table D.3 reports that the concentration among providers declines uniformly across the four categories depicted in Figure 1. Finally, the Venn diagram in Appendix Figure D.1 shows that while a significant fraction of providers (41%) operate in both segments of the market, nonnegligible shares of asset managers offer only broad-based (37%) or specialized (23%) ETFs.

In sum, the dynamics of competition in the ETF market appear to differ markedly in the broad-based and specialized segments. In the broad-based segment, a small number of issuers benefit from economies of scale, which allows them to spread the costs across a bigger customer base—e.g., the costs of data licensing. Thus, they can charge lower fees. At the same time, due to their large clientele, broad-based ETFs are a catalyst of significant trading volume, which constitutes a source of liquidity that investors value (Khomyn, Putniņš, and Zoican, 2020). The large scale creates barriers to entry for new contenders. On the other hand, for specialized ETFs, fees decline only slightly (see Figure 1), even though the supply of specialized products increases substantially over time. These products are very differentiated, so new entrants do not directly compete with the incumbents, preserving some of the monopolistic rents.

4.2 Segmentation of Investor Demand

Next, we more directly investigate the conjecture that a price-salient and quality-salient equilibria characterize different segments of the ETF industry. To this purpose, Table 2 presents an analysis of the product features that attract investor demand. We report estimates from regressions of monthly capital flows into each ETF, a proxy for demand, on product characteristics. In particular, we focus on fees, as a measure of price, and on past returns, which approximate expected returns for investors with extrapolative beliefs and, in this sense, are a measure of quality.

The results in Panel A suggest that investors pay more attention to price when trading broad-based ETFs than specialized products, as the sensitivity to fees is significantly more negative in the former products. In the late sample (2010–2019), when the bulk of specialized ETFs are present in the market, specialized ETFs' sensitivity to fees is indistinguishable from zero providing clear evidence in support of a quality-salient equilibrium in which consumers disregard price.[14] To address the issue that fees are fairly constant over the life of an ETF while flows vary considerably, Appendix Table D.4 reports estimates from a regression of cumulative flows over one- or two-year windows after the launch of the ETF onto average fees in the same window. The result that investors in specialized ETFs are significantly less sensitive to fees remains unchanged.

In Panel B of Table 2, we study how the salience of an ETF in investors' perception, proxied by media attention to the stocks in its portfolio, modifies investors' response to different product attributes. Again, the evidence suggests that two separate equilibria prevail in the industry. The investors in ETFs holding stocks that attract the most attention are almost insensitive to price and, instead, care mostly about past performance. As we show below, media attention is highest for the stocks in specialized ETFs.

[14]An additional reason for investors in specialized ETFs to overlook the high fees is their higher turnover in these products, i.e., shorter holding period, relative to broad-based ETFs (see Table 1). If investors expect a high return in the short run for specialized ETFs, then fees can be disregarded as they will only be born for a limited time.

Table 2. ETF Flow Sensitivity to Fees and Past Performance

The table presents the flow sensitivity of ETFs to their fees and past performance. Panel A compares flow sensitivity between broad-based and specialized ETFs. Panel B compares flow sensitivity between ETFs that recently received high media attention and those that recently received low media attention. The dependent variable is ETF flows in month $t+1$, computed as $100 \times (\text{AUM}_{t+1} - \text{AUM}_t \times \text{ETF return}_{t+1})/\text{AUM}_t$. In each month t, we calculate the percentile rank of ETF returns. *Specialized* is a dummy variable that equals 1 if an ETF is a specialized ETF. *High media* is a dummy variable that equals 1 if the AUM-weighted media sentiment of an ETF's underlying securities computed in month t ranks in the top 20%. *AUM* is an ETF's assets under management ($million) in month t, and *Age* is an ETF's age in months. Standard errors are clustered at the ETF and the calendar-month levels. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Flows and Specialized ETFs

Dependent variable:	Flows$_{t+1}$ (%)		
Sample period:	2000–2019	2000–2009	2010–2019
Fee (bps)	−0.04***	−0.08***	−0.03***
	(−6.97)	(−4.15)	(−5.91)
Fee	0.01**	−0.00	0.02**
× Specialized	(2.01)	(−0.14)	(2.60)
Return rank$_t$	0.04***	0.03***	0.04***
	(10.08)	(3.21)	(9.88)
Return rank$_t$	0.01***	0.02*	0.01***
× Specialized	(2.88)	(1.72)	(2.61)
Specialized	−1.48***	−0.54	−1.73***
	(−3.15)	(−0.42)	(−3.73)
log(AUM$_t$)	−0.12**	−0.86***	0.01
	(−1.98)	(−3.53)	(0.13)
log(Age$_t$)	−1.84***	−1.42***	−1.93***
	(−12.37)	(−2.95)	(−12.28)
Calendar month FE	Yes	Yes	Yes
Observations	81,485	17,821	63,664
Adj R^2	0.063	0.067	0.059

Panel B: Flows and High Media Sentiment

Dependent variable:	Flows$_{t+1}$ (%)		
Sample period:	2000–2019	2000–2009	2010–2019
Fee (bps)	−0.03***	−0.07***	−0.03***
	(−6.28)	(−3.9-)	(−5.19)
Fee	0.02**	0.01	0.02*
× High media	(2.07)	(0.48)	(1.89)
Return rank$_t$	0.05***	0.04***	0.05***
	(12.94)	(5.20)	(12.33)
Return rank$_t$	0.00	0.01	0.00
× High media	(0.59)	(0.82)	(0.22)
High media	−0.96*	−1.70	−0.62
	(−1.81)	(−1.24)	(−1.09)
log(AUM$_t$)	−0.12*	−1.14***	0.03
	(−1.72)	(−3.53)	(0.54)
log(Age$_t$)	−1.85***	−1.20**	−1.98***
	(−12.15)	(−2.10)	(−13.10)
Calendar month FE	Yes	Yes	Yes
Observations	64,425	12,282	52,143
Adj R^2	0.069	0.080	0.060

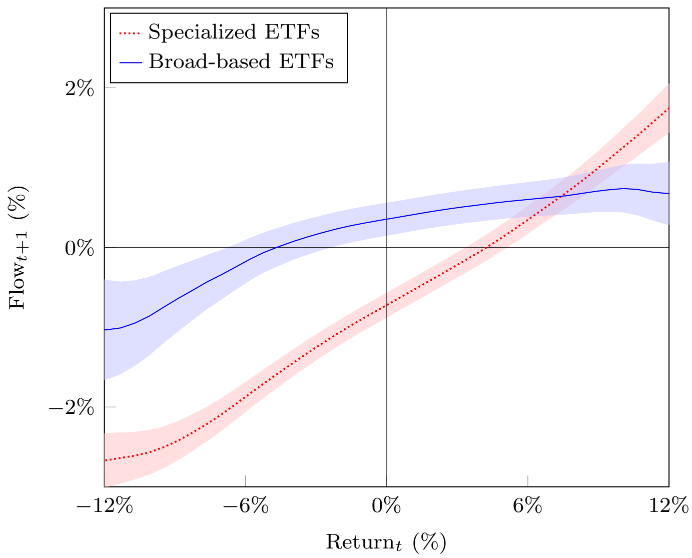
Figure 5 provides a graphical representation of flow-performance sensitivity for broad-based and specialized ETFs. In each month t, we compute next-period flows as $100 \times (\text{AUM}_{t+1} - \text{AUM}_t \times \text{ETF return}_{t+1})/\text{AUM}_t$. Then, we estimate a nonparametric relation between next-period flows and period-t raw returns using local polynomials approximations.[15]

Consistent with the results in Table 2, the figure shows that the return-chasing behavior of investors in broad-based ETF differs from that of investors in specialized ETFs. The results

[15] In Appendix Figure F.1, we replicate the analysis using either market-adjusted returns or percentile rank of returns within month and category. The conclusions remain unchanged.

Figure 5. Flow-Performance Sensitivity

The figure presents the flow-performance sensitivity of ETFs per ETF category. Flows are computed as $100 \times (\text{AUM}_{t+1} - \text{AUM}_t \times \text{ETF return}_{t+1})/\text{AUM}_t$. Returns are raw ETF returns. We estimate a nonparametric relation between flows and returns using local polynomials approximations obtained with Stata's `-lpoly-` command with bandwidth of 0.04. The shaded areas represent 95% confidence intervals.



are consistent with performance-chasing in the ETF market, as documented in Dannhauser and Pontiff (2019); however, here we find that the sensitivity of flows to past returns is significantly higher for specialized ETFs, consistent with more attention to past performance in this segment of the market.[16]

One legitimate concern is that the difference in flow-performance sensitivity between the two groups of ETFs could result from a difference in the horizons at which the clienteles for the two types of products evaluate them. The monthly frequency in Figure 5 may be too restrictive, e.g., it may not capture the behavior of investors who rebalance their portfolios at lower frequencies. To address this concern, Appendix Figures F.2 and F.3 show that the same pattern is present when we measure performance at the quarterly and annual frequency, respectively.

[16]One might interpret these results as consistent with an extended version of the Berk and Green (2004) model, in which Bayesian investors learn about the risk-adjusted performance of the strategies underlying specialized ETFs, and flows are the result of this inference. We consider this explanation to be unlikely because, conditioning on the ETF launch, we find that specialized ETFs significantly underperform on average (see Figure 2). This finding is inconsistent with rational learning in Berk and Green (2004), in which flows (or ETF launch) do not predict future performance and certainly not negative performance.

5 The "Quality" of Specialized ETFs

In contrast to the clear benefits to investors offered by broad-based ETFs, via facilitated market access and low-cost diversification, the case for value creation by specialized ETFs is less obvious. Given the high fees that investors are willing to pay to hold these products, we investigate two conjectures that fall within the framework of rational investor behavior.

The first possibility is that specialized ETFs deliver superior performance. Under this conjecture, the rationale for investing in high-fee ETFs is simply to achieve positive risk-adjusted returns (alphas). Specialized ETFs, therefore, would provide a low-cost tool for accessing these investment ideas.

The second possibility is that specialized ETFs create value by providing a hedging tool against some risks that investors care about. In other words, these products might operate like insurance policies. Hence, their risk-adjusted returns do not have to be positive, as long as their performance insulates against risks that investors care about.

5.1 The Performance of Specialized ETFs

To measure the performance of specialized ETFs, we use a calendar-time portfolios approach, a standard approach in the asset pricing literature. We form portfolios that separately hold the universes of broad-based and specialized products. The portfolios are reformed each month and are market-capitalization-weighted.[17] Then, we regress the (net of fees) returns of these portfolios in excess of the risk-free rate on commonly used risk factors, as is customary in asset pricing studies.[18]

In Panel A of Table 3, we present excess returns as well as the alphas from these risk models. In general, specialized ETFs have negative performance across the different specifications. Focusing on the Fama-French-Carhart four-factor model (Fama and French,

[17]The results with equal-weighted portfolios are similar and are shown in Appendix Table E.1.

[18]Risk factor returns are downloaded from Professor French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html and Professors Hou, Xue, and Zhang's website: http://global-q.org/factors.html.

1993; Carhart, 1997), specialized ETFs generate negative alphas of about −3.24% per year (−0.27% × 12). Underperformance is smaller (but still negative) when using more elaborate factor models. In comparison, using the same risk model, broad-based ETFs generate negative alpha of about −0.48% a year (−0.04% × 12), which is closer to their average fees.

Importantly, the relative underperformance of specialized ETFs cannot be accounted for by the higher fees that they charge. The difference in annual fees between specialized and broad-based ETFs is about 0.13% on average (see Table 1). Thus, the difference in alphas of specialized and broad-based ETFs (about −2.9% per year for the four-factor model) is an order of magnitude larger than the difference in fees between the two groups.

To understand whether the observed underperformance of specialized ETFs crucially hinges on the valuation of their portfolios at the time of launch, we focus next on recently launched ETFs. In Panel B of Table 3, we form calendar-time portfolios that hold all the ETFs in each of the two categories that were launched in the prior five years. The results show that the underperformance of specialized ETFs is stronger in the years following their launch. For example, the four-factor alpha is −6% per year (−0.50% × 12). The estimates show also a stark underperformance of recently launched specialized ETFs relative to the broad-based ones with a four-factor alpha difference of −0.36% per month. For completeness, Appendix Table E.2 shows that, after the first five years, the risk-adjusted underperformance of specialized ETFs is substantially reduced and statistically indistinguishable from zero.[19] Nevertheless, this evidence raises questions about the timing of specialized ETF issuance, which we address in the next section.

Similar results are depicted in Figure 2 in the Introduction. Each point in the chart is produced by one regression based on the four-factor model (Fama and French, 1993; Carhart, 1997). The alpha associated with month one, for example, is produced from a regression on the performance of a portfolio that includes all the ETFs that are exactly one-month

[19] We also verify that our results are not driven by ETFs that hold a majority of foreign stocks. In Appendix Table E.3, we restrict the sample to ETFs for which at least 80% of their market capitalization is invested in stocks traded in the United States. The results of the analysis are similar to those reported in Table 3.

old; the alpha associated with month two is produced by a portfolio that comprises ETFs that are exactly two months old. We repeat the process up to the 60-month life span. The striking result is that, over the first five years of their life, specialized ETFs lose about 30% on average in terms of risk-adjusted returns.

Table 3. Calendar-Time Portfolios of ETFs

The table presents the risk-adjusted performance of ETFs from 2000 to 2019. In Panel A, we form portfolios consisting of all ETFs in the same category. In Panel B, we identify *new* ETFs that were launched in the previous five years in each month. We then form portfolios consisting of all *new* ETFs in the same category. The portfolio returns are value-weighted using one-month-lagged market capitalization. *Excess return* refers to the average monthly return in excess of the risk-free rate. *CAPM*, *FF3*, *FFC4*, *FF5*, *FF6*, and *Q* alpha denote alphas with respect to the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; Mossin, 1966), the Fama-French three-factor model (Fama and French, 1993), the Fama-French-Carhart four-factor model (Carhart, 1997), the Fama-French five-factor model (Fama and French, 2015), the Fama-French six-factor model (Fama and French, 2018), and the Q-factor model (Hou et al., 2015), respectively. The portfolios of all broad-based (specialized) ETFs comprise 171 (189) ETFs on average. *SP minus BB* denotes the specialized ETF portfolio minus the broad-based ETF portfolio. The excess return and alphas are in percentage points, and t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: All Months							
	Excess return	CAPM	FF3	FFC4	FF5	FF6	Q
Broad-Based ETFs	0.44	−0.06	−0.05	−0.04	0.04	0.04	0.03
	(1.45)	(−0.98)	(−1.00)	(−0.74)	(0.79)	(0.85)	(0.55)
Specialized ETFs	0.20	−0.32***	−0.29***	−0.27***	−0.11	−0.11	−0.13
	(0.62)	(−3.37)	(−3.49)	(−3.34)	(−1.43)	(−1.41)	(−1.61)
SP minus BB	−0.24***	−0.26***	−0.23***	−0.24***	−0.15*	−0.16*	−0.16**
	(−3.03)	(−3.31)	(−3.06)	(−3.06)	(−1.94)	(−1.96)	(−2.04)
Panel B: Months ≤ 60							
	Excess return	CAPM	FF3	FFC4	FF5	FF6	Q
Broad-Based ETFs	0.31	−0.22*	−0.18	−0.13	0.10	0.11	0.05
	(0.90)	(−1.68)	(−1.58)	(−1.23)	(0.96)	(1.07)	(0.50)
Specialized ETFs	−0.01	−0.55***	−0.53***	−0.50***	−0.34***	−0.34***	−0.34***
	(−0.02)	(−4.10)	(−4.22)	(−4.04)	(−2.71)	(−2.68)	(−2.78)
SP minus BB	−0.31**	−0.32**	−0.35**	−0.36**	−0.44***	−0.45***	−0.39***
	(−2.20)	(−2.26)	(−2.44)	(−2.58)	(−2.96)	(−2.99)	(−2.62)

The underperformance of specialized ETFs is robust to using other intuitive approaches to define this group. Appendix Table E.4 shows that the evidence in Table 3 is confirmed when we identify specialized products using heterogeneity along the investment strategy (i.e., active share), the portfolio size (i.e., number of holdings), and the cost dimensions. In particular, for this analysis, we define specialized ETFs as those with either a large active share, or a small number of portfolio holdings, or those charging high fees. Finally, Appendix Table E.5 shows that both categories in the specialized segment, sector and thematic ETFs, display significant underperformance.

To summarize, this analysis suggests that specialized ETFs generate an economically and statistically significant negative alpha in the order of magnitude of -6% a year in the first five years of their existence. As such, they do not create value for their investors by providing outperforming investment strategies. Consequently, the combination of underperformance, high fees, and lack of diversification of these products remains a puzzle. For this reason, we entertain more closely the hypothesis that specialized ETFs provide insurance against some underlying risks that investors care about.

5.2 Are Specialized ETFs Used for Hedging Purposes?

To explain investors' demand for specialized ETFs in spite of their underperformance, we investigate whether these products deliver value as a form of insurance. Specialized ETFs might serve as a hedging tool for aggregate risks, in which case their underperformance is a negative risk premium, or for idiosyncratic risks to which some subsets of investors are exposed. A related conjecture is that specialized ETFs generate nonpecuniary benefits by being compliant with investors' values.

5.2.1 Is the Underperformance a Hedging Premium?

It is possible that our earlier tests fail to capture some unobserved risk factors that investors care about, and that specialized ETFs might be the right vehicle that allows these investors to hedge against these unobserved risk factors. For this reason, investors are willing to accept lower returns.[20]

[20] The hedging motive we discuss here is different from the specific notion that arbitrageurs use industry ETFs as hedging tools within long-short strategies (Huang, O'Hara, and Zhong, 2020). More broadly, our notion of hedging refers to the interpretation of financial innovation as a tool to improve risk sharing among investors (Allen and Gale, 1994).

A testable implication of this conjecture is that the performance of specialized ETFs has a negative correlation with a portfolio of assets that investors dislike, i.e., a portfolio that earns a positive risk premium. We emphasize that in the current analysis we are looking for a risk factor that accounts for the evidence of negative average performance of the portfolio of *all* specialized ETFs. It remains possible that different specialized ETFs serve as hedging tool for different groups of investors, a possibility that we entertain later on in the analysis.

To test this prediction, we construct a portfolio of stocks that have negative correlation with the portfolio of all specialized ETFs. In particular, each month, we form five portfolios of stocks sorted on their betas on the specialized-ETF factor, constructed as the excess return of the market-capitalization-weighted portfolio of specialized ETFs.[21] Portfolio 1 has the stocks with the lowest correlation with the aggregate specialized ETF portfolio, and portfolio 5 has the highest correlation.

Our test results, shown in Table 4, indicate no support for the conjecture that specialized ETFs provide hedging for an underlying risk factor. The table reports the alphas from regressions of these portfolios' returns on different factor models. In no specification are the alphas of low-specialized-beta stocks consistent with a positive risk premium.

5.2.2 Capital Allocation Over the Life Cycle

Failing to find an aggregate risk factor of hedging concern points to the lack of a *systematic* insurance motive behind the portfolio of *all* specialized ETFs. However, it is still possible that different specialized ETFs provide insurance for different *idiosyncratic* risks. For this reason, investors may still be willing to hold specialized ETFs in spite of their negative risk-adjusted returns.[22]

[21]The beta is estimated using 60-month rolling-window regressions, requiring each stock to have at least 36 months of available return observations. In these regressions, we control for the market factor. Then, we form five portfolios corresponding to the quintiles of the estimated betas on the specialized-ETF factor based on the breakpoints of the distribution of NYSE-listed stocks, to avoid giving disproportionate influence to smaller stocks listed on other exchanges (Fama and French, 1992).

[22]This story, however, does not explain why specialized ETFs generate negative risk-adjusted returns to begin with.

Table 4. Hedging Motive?

The table presents the risk-adjusted monthly performance of stocks from 2000 to 2019 by quintiles of loadings on specialized ETFs. In each month, we sort stocks based on their beta on the excess return of the market-capitalization-weighted portfolio of specialized ETFs, controlling for the market factor. The beta is estimated using 60-month rolling-window regressions, requiring each stock to have at least 36 months of observations with returns. We then form five portfolios corresponding to the quintiles of the estimated betas based on NYSE breakpoints. Portfolio Q1 (Q5) contains the stocks with the lowest (highest) correlation with the specialized portfolio. *CAPM*, *FF3*, *FFC4*, *FF5*, *FF6*, and *Q* alpha denote alphas with respect to the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; Mossin, 1966), the Fama-French three-factor model (Fama and French, 1993), the Fama-French-Carhart four-factor model (Carhart, 1997), the Fama-French five-factor model (Fama and French, 2015), the Fama-French six-factor model (Fama and French, 2018), and the Q-factor model (Hou et al., 2015), respectively. The alphas are in percentage points, and t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Exposure to specialized ETFs:	Low	Q2	Q3	Q4	High
CAPM alpha	−0.03	0.04	0.07	0.04	−0.30
	(−0.19)	(0.58)	(1.02)	(0.55)	(−1.64)
FF3 alpha	0.06	0.04	0.05	0.03	−0.32*
	(0.55)	(0.58)	(0.77)	(0.44)	(−1.78)
FFC4 alpha	0.08	0.04	0.06	0.03	−0.31*
	(0.65)	(0.62)	(0.80)	(0.44)	(−1.74)
FF5 alpha	0.13	0.02	0.00	0.04	−0.28
	(1.16)	(0.21)	(0.03)	(0.52)	(−1.52)
FF6 alpha	0.14	0.02	0.01	0.04	−0.27
	(1.24)	(0.25)	(0.07)	(0.53)	(−1.47)
Q alpha	0.02	0.04	0.04	0.02	−0.19
	(0.18)	(0.50)	(0.54)	(0.30)	(−1.04)

Directly testing for a hedging motive would require observing investors endowments, which is not possible given the available data. Thus, we choose a different strategy. We study whether investors are ex-ante aware of the negative risk premium delivered by specialized ETFs and are willing to bear it as a form of insurance premium. In other words, we examine whether investors stick with these products *in spite* of their negative performance.

This empirical strategy also allows us to test the explanation that investors willingly sacrifice performance because specialized ETFs offer nonpecuniary benefits, e.g., in the form of compliance with investors' ethical, political, or religious values. According to this explanation, investors should remain invested over time despite specialized ETFs' underperformance.

To implement this test, we analyze investors' likelihood to allocate capital into specialized ETFs over the life of these products. Because there can be life-cycle patterns in ETF flows that are independent of performance, we benchmark specialized ETFs against broad-based

ETFs. The sample consists of all ETF-months in our data. The dependent variable is an indicator for whether an ETF received positive flows in a particular month. The variable of interest is the interaction of the specialized ETF indicator and the logarithm of ETF age (in months). We include the main effects as well as calendar-month fixed effects.

The estimates in Table 5 suggest that investors are very enthusiastic about specialized ETFs at their inception, but their enthusiasm fades over time. The positive slope on the specialized dummy indicates that investors are more likely to add money to specialized ETFs than to the broad-based ones in the early stages of these products' lives. However, the negative slope on the interaction of the specialized ETF dummy with its age shows that as time passes, investors are increasingly more likely to withdraw capital from specialized products. This disenchantment manifests itself soon after the inception of the ETFs, as suggested by the estimates in the second column, where we restrict the sample to ETFs that are less than five years old. These findings are consistent with the positively sloped flow-performance sensitivity for specialized ETFs shown in Figure 5, and we interpret them as suggestive of investor disappointment following the poor performance of specialized products.

Overall, the evidence in this subsection does not support the conjecture that investors invest in specialized ETFs for their hedging properties or that they willingly sacrifice performance because of nonpecuniary benefits. Therefore, in the next section, we turn to a different hypothesis to explain the demand for specialized products.

Table 5. Disappointment in Flows

The table studies the probability of positive flows into ETFs since launch. The dependent variable is a dummy variable that equals 1 if flow is positive. ETF flows in month $t+1$ are defined as $100 \times (\text{AUM}_{t+1} - \text{AUM}_t \times \text{ETF return}_{t+1})/\text{AUM}_t$. *Specialized* is a dummy variable that equals 1 if an ETF is a specialized ETF. *log(Age)* is an ETF's logged age, in months. The first column reports results using the full sample from 2000 to 2019, and the second column reports results for new ETFs launched in the previous five years. Standard errors are clustered at the ETF and the calendar-month levels, and t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$\text{I}(\text{Positive flows}_{i,t})$	
Sample:	Full sample	Age $\leq$ 60 months
Specialized	0.07***	0.06***
	(3.55)	(2.74)
log(Age)	−0.06***	−0.05***
	(−10.38)	(−8.37)
Specialized $\times$ log(Age)	−0.03***	−0.03***
	(−5.66)	(−3.98)
Calendar month FE	Yes	Yes
Observations	86,554	46,362
R^2	0.110	0.136

6 Do Specialized ETFs Cater to Investor Sentiment?

Given that specialized ETFs generate negative alpha and that there is no evidence that they serve as hedging tools, we turn to our third hypothesis. Specifically, we test whether specialized ETFs are launched in response to investors' demand driven by irrational expectations, such as extrapolative beliefs, which lead them to chase past winners.

We have already found some supporting evidence in Section 5.1 for the notion that securities in specialized ETFs are overvalued. Specifically, we found that specialized ETFs deliver negative risk-adjusted performance, which is consistent with the reversal of overvaluation of the stocks in their underlying portfolios.

In this section, we test predictions linking the underperformance of specialized ETFs to investors' irrational beliefs. First, if newly launched specialized ETFs ride recent trends, then the securities included in their portfolios should (*i*) have attracted investors' attention, and (*ii*) display traits of overvaluation. Second, the stocks in specialized portfolios should be attractive to investors who form expectations in an extrapolative way. Finally, specialized

ETFs are likely to be especially attractive to investors who are, on average, less sophisticated, notably retail investors (Barber and Odean, 2013).

6.1 Characteristics of the Underlying Portfolios

To understand whether the launch of ETFs caters to investors' irrational beliefs, we analyze the characteristics of the stocks included in the portfolios of specialized and broad-based ETFs at the time of their launch. We focus on several characteristics that could indicate heightened investor attention and are likely associated with overvaluation.

For each stock in an ETF portfolio, we measure a specific characteristic in the two-year period before the launch. Then, we compute the value-weighted average characteristic at the ETF level at the time of launch. Table 6 compares the average ETF-level characteristic for specialized and broad-based portfolios.

The table shows that stocks in specialized ETFs display significantly higher pre-launch market-adjusted returns. This fact makes them attractive to investors with extrapolative or diagnostic beliefs (e.g., Greenwood and Shleifer, 2014; Barberis et al., 2018; Bordalo et al., 2018). Moreover, specialized stocks display more positive skewness, which would be appealing for investors who have a preference for lottery-like payoffs (Brunnermeier and Parker, 2005; Brunnermeier et al., 2007; Mitton and Vorkink, 2007; Barberis and Huang, 2008; Kumar, 2009).

Incidentally, we note that stocks in broad-based ETF products also experience positive pre-launch returns. This finding raises the possibility that the sets of broad-based and specialized products are not entirely disjoint or, more likely, that the product classification into broad-based and specialized ETFs is necessarily an approximation.[23]

Next, Table 6 shows that stocks included in the portfolios of specialized ETFs were recently under the spotlight. Relative to broad-based portfolios, stocks in specialized ETFs

[23]For example, smart-beta ETFs are classified as broad-based because they do not have a theme or a sector focus. However, these ETFs hold, on average, stocks that outperformed in the pre-launch period. After launch, these funds generate no alpha. See an analysis of the formation and performance of smart-beta ETFs in Huang et al. (2020).

Table 6. Portfolio Characteristics of ETFs Around Launch

The table reports the portfolio characteristics of ETFs within the two-year period before their launch. For each characteristic of interest, we construct the time series of the ETF–month-level characteristic from month −24 to month −6 using the ETF's initial portfolio weights in the launch month 0. We then calculate the average characteristic across all ETFs in the same category. We report the average characteristics and t-test results. *Market-adjusted return* represents returns in excess of CRSP value-weighted returns. *Return skewness* is the skewness of returns following Ghysels et al. (2016). We use the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles as cutoffs. *Media exposure* is the number of monthly news articles scaled by market capitalization. *Media sentiment* is the sum of each news article's composite sentiment score from RavenPack scaled by market capitalization. For *Media exposure* and *Media sentiment*, we subtract the median in each month to filter out time components, the mean being excessively impacted by outliers. *Earnings surprise* denotes the average EPS surprise scaled by the one-quarter-lagged stock price. In each year, we standardize *Earnings surprise*. *Market-to-book* is market equity divided by book equity. *Short interest* is the monthly short interest ratio. We subtract the median of the short interest ratio in each month to filter out time components. In the right-most column, we present the difference between the averages of specialized ETFs (SP) and broad-based ETFs (BB). t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Broad-based ETFs	Specialized ETFs	SP minus BB
Market-adjusted return	0.66***	1.04***	0.38***
	(11.51)	(9.23)	(4.15)
Return skewness	0.01	0.17***	0.15***
	(0.40)	(4.80)	(4.12)
Media exposure	−4.04	33.33***	37.37***
	(−1.28)	(3.19)	(4.29)
Media sentiment	0.22***	0.64***	0.42***
	(4.81)	(4.51)	(3.98)
Earnings surprise	0.02***	0.03***	0.01***
	(9.00)	(10.78)	(2.50)
Market-to-book	2.98***	3.14***	0.15**
	(44.51)	(32.10)	(2.07)
Short interest	0.02***	0.03***	0.01***
	(25.60)	(15.92)	(3.61)

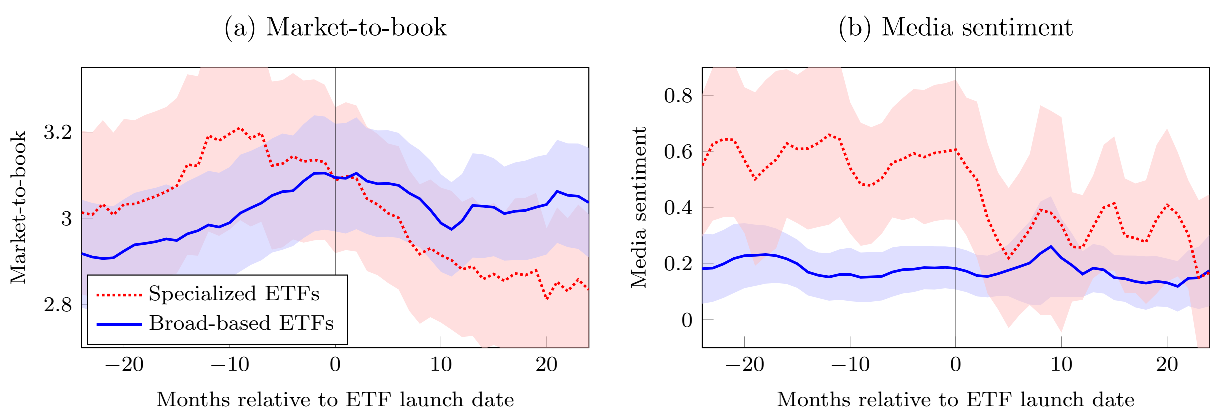
experienced greater media exposure, with more positive sentiment, and higher earnings surprises. The table also suggests that specialized ETFs hold glamour stocks, those with high market-to-book ratios, and those with high short interest. These characteristics are typically associated with lower future returns (Lakonishok, Shleifer, and Vishny, 1994; Daniel and Titman, 1997; Boehmer, Jones, and Zhang, 2008; Ben-David, Drake, and Roulstone, 2015). We also note that turnover is materially larger for specialized products (see Table 1), which is consistent with the conjecture that these products are used for speculative purposes (e.g., Simsek, 2013a).

The characteristics of the securities included in the portfolios of specialized ETFs indicate that they are popular stocks. This finding is also consistent with anecdotal evidence on ETF launches in recent times. In 2019, for example, new ETFs included products focusing on cannabis, cyber security, and video games. In 2020, new specialized ETFs covered stocks related to the Black Lives Matter movement, COVID-19 vaccines, and the work-from-home trend. In 2021, tracking the recovery after the COVID recession, new specialized ETFs covered the travel industry, and space travel as well as real estate and construction.

To see how the popularity of the stocks in specialized ETFs varies around the time of the launch, in Figure 6 we compare the evolution of the market-to-book ratios of the stocks in broad-based and specialized ETFs (Panel (a)) as well as their media sentiment scores (Panel (b)) around their launch. The figure shows that specialized stocks enjoy higher market-to-book ratios and more positive media sentiment prior to launch. In the year after the launch, both market-to-book ratios and the media sentiment of the stocks in specialized ETFs quickly revert.[24]

Figure 6. Dynamics of ETF Portfolio Characteristics

The figure presents the evolution of ETF portfolio characteristics, per ETF category. Panel (a) shows the evolution of the market-to-book ratio, and Panel (b) shows the evolution of media sentiment. For each characteristic of interest, we construct the time series of the ETF–month-level characteristic from month −24 to month +24 using the ETF's portfolio weights. In the pre-launch periods, we use the ETF's initial portfolio weights in the launch month 0. In the post-launch periods, we use the actual portfolio weights. We then calculate the average characteristic across all ETFs in each month, per ETF category. The shaded areas represent 95% confidence intervals.



[24] We note that, while we cannot infer that the two series in Panel (a) of Figure 6 differ at a given point in time for lack of power, the test in Table 6, using data over the entire 24-month period before launch, allows us to conclude that the market-to-book ratio of specialized ETFs is significantly higher than that of broad-based ETFs.

This figure suggests that specialized ETFs are launched in a late stage of the valuation cycle of the underlying portfolios. This pattern is consistent with the fact that it takes six months to a year to launch a new ETF. Thus, there is a substantial delay between when ETF providers spot trends of interest to investors and when ETFs actually reach the market. After launch, valuations start sliding downward.[25]

To provide further evidence that the characteristics in Table 6 and the patterns in Figure 6 reflect overvaluation of specialized ETFs, we return to the calendar-time portfolio approach. Specifically, in Figure 7, we split ETFs based on whether the average characteristics of the stocks in the ETF portfolio are above or below their median. The figure shows that portfolios of the specialized ETFs scoring high on past returns and media sentiment display more negative six-factor alphas after launch. Similar results are obtained with the other risk adjustments that we consider.

Overall, the evidence in this subsection suggests that the underperformance of specialized ETFs is likely related to the overvaluation of the securities in the underlying portfolios at the time of launch. Given that the pre-launch performance of the underlying portfolios of these ETFs, as well as the attention they attract, is high, the negative post-launch alpha suggests that the issuance of specialized ETFs occurs near the peak of valuation of the underlying securities.

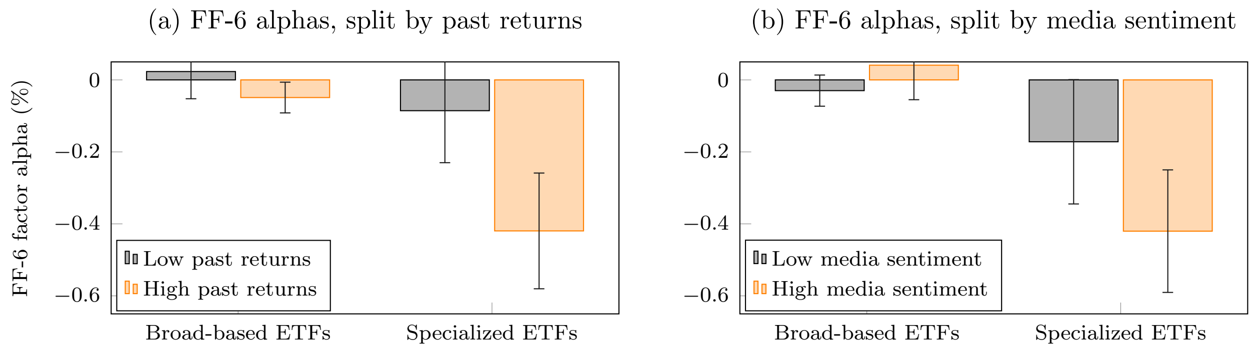
6.2 Evidence on the Nature of Investor Expectations

Given that specialized ETFs hold securities displaying high past returns, high media sentiment, and high valuations prior to launch, it is natural to ask whether the providers of specialized ETFs cater to investors' extrapolative expectations. Following Bordalo et al. (2019), we make the working assumption that analysts' forecasts are reflective of investor

[25] After the end of our sample, the time-to-market for ETFs shortened due to a simplification of the regulatory approval process. Specifically, in December 2019, with compliance date in December 2020, the SEC introduced Rule 6c-11, which "permits exchange-traded funds that satisfy certain conditions to operate without the expense and delay of obtaining an exemptive order." See `https://www.sec.gov/rules/final/2019/33-10695.pdf`. We expect this change to delay the valuation peak in Panel (a) of Figure 6 but not to affect the overall conclusion of underperformance in the five years after launch in Figure 2.

Figure 7. Performance of ETFs, Split by Pre-launch Stock Characteristics

The figure presents the Fama-French six-factor model (FF-6, Fama and French (2018)) alphas of the portfolios of ETFs from 2000 to 2019, split by ETF categories and stock characteristics groups. In Panel (a), we split each ETF category into two subgroups based on the past market-adjusted returns, computed as in Table 6. In Panel (b), we split each ETF category into two subgroups based on the past media sentiment, computed as in Table 6. In each month, we identify *new* ETFs that were launched in the previous five years. We then form portfolios consisting of all *new* ETFs in the same category and the same subgroup. The portfolio returns are value-weighted using one-month-lagged market capitalization. To adjust returns for risk factors, we estimate FF-6 alphas of the portfolios. The alphas are in monthly percentage points. Error bars represent 95% confidence intervals.



beliefs and that they are informative about the expectations shaping market prices.

In Figure 8, we study analysts' forecasts for the stocks included in broad-based and specialized ETFs. We use data from I/B/E/S on analysts' long-term earnings growth (LTG) forecasts and earnings-per-share (EPS) realizations. In Panel (a), we report the behavior of the average LTG forecasts for the stocks in the broad-based and specialized portfolios around the time of the ETF launch. Mirroring the pattern of the high-LTG portfolio in Bordalo et al. (2019), the portfolio of specialized stocks displays significantly higher forecasts on average. These forecasts become increasingly more positive in the period leading up to the launch. However, after the ETF launch, these stocks experience a marked downward revision in LTG expectations. No such pattern is found for the stocks in the broad-based portfolio. This finding cannot be attributed to attrition in the sample, as we keep only the stocks that have LGT forecasts for all the relevant periods.

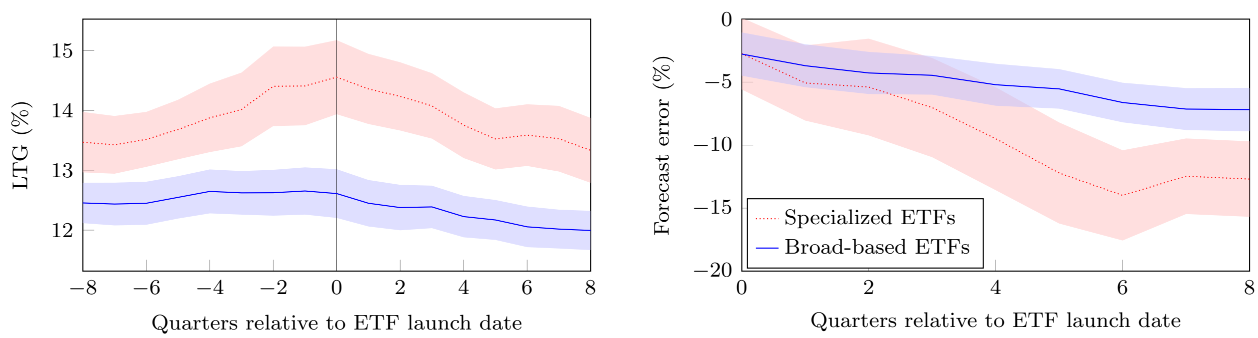
As argued by Bordalo et al. (2019), the mean-reversion in LTG forecasts could result from mean reversion in the underlying process, making Panel (a) compatible with rational expectations or excessively optimistic forecasts. To test the latter alternative, in Panel (b) of Figure 8, we report the average forecast errors for the stocks in the ETF portfolio in the eight quarters following the launch. Forecast errors are computed as the annual change in realized EPS minus the LTG forecast at the time of launch. We find that forecast errors for specialized ETFs grow to be significantly negative and economically large, consistent with strong overoptimism in expectations. We also find slightly negative forecast errors for broad-based ETFs, consistent with analysts' incentives to inflate their forecasts (Easterwood and Nutt, 1999; Michaely and Womack, 1999; Dechow, Hutton, and Sloan, 2000).

Figure 8. Dynamics of Earnings Forecasts Around Launch

The figure presents the evolution of earnings forecasts and forecast errors, per ETF category. Panel (a) shows the evolution of analysts' expectations of long-term annual earnings growth (LTG). Panel (b) shows the evolution of forecast errors, defined as the difference between the realized annual earnings growth ($[\text{EPS}_q/\text{EPS}_{q-4}]-1$) and LTG one quarter before launch (LTG_{-1}). For each variable of interest, we construct the time series of the ETF–quarter-level characteristic from quarters -8 to $+8$ relative to ETF launch quarter 0 using the ETFs portfolio weights. To compute the portfolio-level averages, in the pre-launch periods, we use the ETFs initial portfolio weights in the launch quarter 0. In the post-launch periods, we use the actual portfolio weights. We then calculate the average across all ETFs in each quarter, per ETF category. Shaded areas represent 95% confidence intervals.

(a) LTG

(b) Forecast error



According to Bordalo et al. (2019), such patterns of expectations are inconsistent with a rational model of belief formation. Rather, these patterns can be generated in a model with diagnostic expectations, which represent a specific form of extrapolative beliefs. In particular, investors with diagnostic expectations would consider recent extreme realizations as representative of the prevailing distribution for a group of stocks—in our case the stocks that will be included in the specialized ETFs. Therefore, after positive surprises, expectations about future performance tend to be excessively optimistic.

In sum, the evidence in this subsection supports the hypothesis that the providers of specialized ETFs launch new products in segments of the stock market in which investors hold optimistic beliefs. These stocks likely experience greater investor demand, hence increasing the attractiveness of the new products.

6.3 Who Is Attracted to Specialized ETFs?

To determine whether specialized ETFs are relatively more appealing to unsophisticated investors, we more closely examine the investor composition of the different types of ETFs. In this analysis, we focus on the first year after launch to more closely identify the target clientele of these products when they are created.

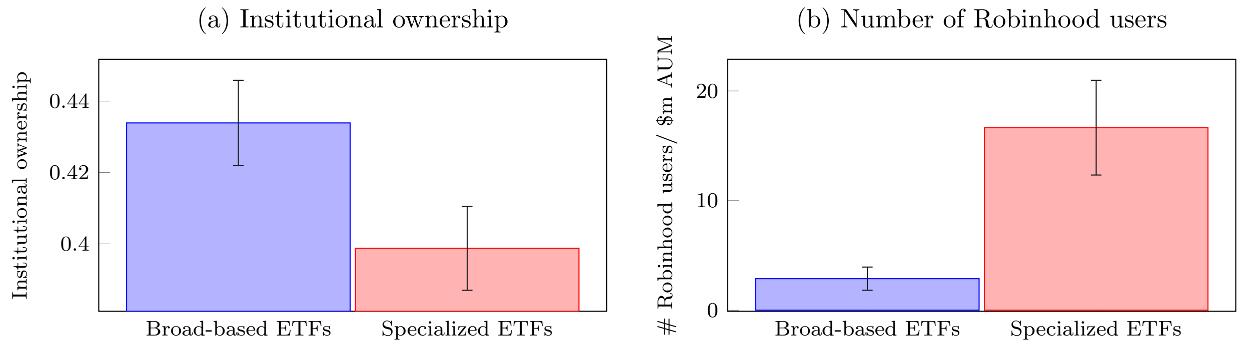
We start by using regulatory filings by institutional investors. In particular, they report their ownership of ETFs on the mandatory SEC 13F forms.[26] Institutional investors include mutual funds, hedge funds, pension funds, banks, insurance companies, endowments, etc. Prior literature suggests that institutions are on average more sophisticated, i.e., their investment decisions are less prone to the systematic biases (e.g., French, 2008; Stambaugh, 2014) that plague retail investors' decisions (Barber and Odean, 2013)

Figure 9, Panel (a), reports the average fraction of shares owned by institutional investors in the first four quarters after launch. The panel shows that institutions own about 43% of the market capitalization of broad-based ETFs in their first year. In contrast, institutions own a significantly lower share of the market capitalization of specialized ETFs, about 39%. Because shares not owned by 13F-reporting institutions are either owned by smaller (nonreporting) institutions, managers, or retail investors, we deduce that retail investors are likely to own a greater share of the specialized ETFs universe than that of the broad-based ETF universe, supporting the view that unsophisticated investors are more likely to be attracted to specialized ETFs.

[26]Only institutions that manage more than $100 million in U.S. equity and which are doing business with U.S. investors are required to file a 13F form. The filers need to report positions exceeding $200,000 or 10,000 shares.

Figure 9. ETF Ownership Soon After Launch

The figure presents the ownership structures of ETFs one year after launch, per ETF category. Over the first 4 quarters after launch, we calculate the average ownership of 13F institutional investors and the number of Robinhood users scaled by AUM ($m). Panel (a) reports 13F ownership, and Panel (b) reports the number of Robinhood users per AUM. Bar charts represent the average ownership, and error bars represent 95% confidence intervals.



We can also gain direct insights into ownership by sentiment-driven investors through user data from the discount brokerage Robinhood. These data are available starting in 2018 and include the number of Robinhood accounts holding each security. The Robinhood platform has recently become known for investment frenzies, characterizing its users.[27] Panel (b) of Figure 9 shows that the number of Robinhood users scaled by ETF market capitalization is substantially higher for specialized ETFs than for the broad-based ETFs in their first year of existence.

The interest of Robinhood traders in specialized ETFs is consistent with the observations of Barber et al. (2020) and Welch (2020), who document that Robinhood investors hold attention-grabbing securities. The authors show that Robinhood traders experience negative returns shortly after they enter their positions.[28]

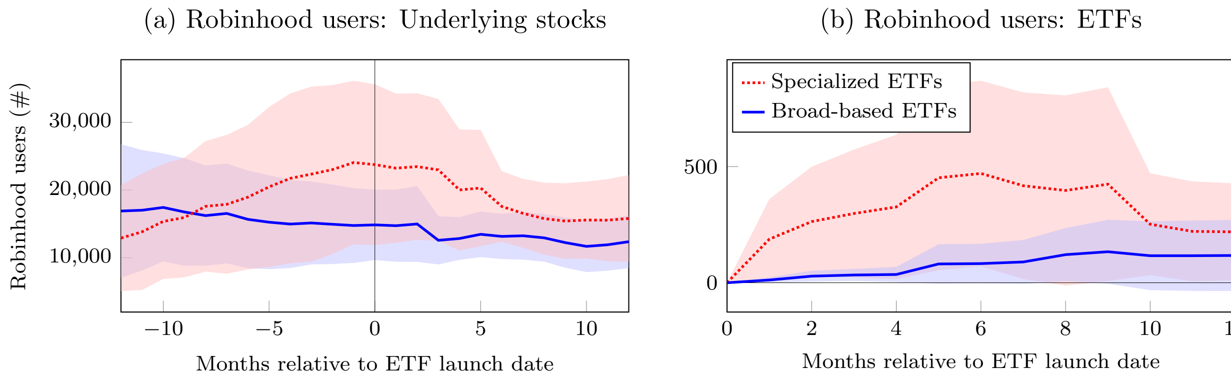
Indeed, examining the portfolios of Robinhood users around the launch of ETFs provides further support for the hypothesis that specialized ETFs are launched in segments of the market that have attracted investor attention. In Figure 10, we use an event study around

[27]See `https://www.nytimes.com/2020/07/08/technology/robinhood-risky-trading.html`.

[28]Welch (2020) also finds that Robinhood traders' strategy, which is concentrated on high-volume and large stocks, delivers a positive alpha over the 1980–2020 period. This evidence, arising from trades in *stocks*, does not contradict our results showing that *specialized ETFs*, which are favored by Robinhood traders, deliver a negative alpha.

Figure 10. Robinhood Users' Investments in the Underlying Stocks and ETFs

The figure presents the number of Robinhood users who hold ETFs or their underlying stocks around ETF launch, per ETF category. We subtract the median of the Robinhood users in each month to filter out time trends. In Panel (a), we construct the time series of the ETF–month-level number of Robinhood users from month −18 to month +18 using the ETF's portfolio weights. In the pre-launch periods, we use the ETF's initial portfolio weights in the launch month 0. In the post-launch periods, we use the actual portfolio weights. We then calculate the average number of Robinhood users across all ETFs in the same category. Panel (b) reports the average number of Robinhood users who directly invest in ETFs. The shaded areas represent 95% confidence intervals.



ETF launches to plot the holdings of stocks in ETF portfolios by Robinhood users. Specifically, we compute the number of users holding the stocks that will be included in the ETF (to be launched in month 0), weighted by their weight in the ETF. Because the Robinhood user base increased significantly over the sample period, we subtract the median stock holding in the relevant calendar month.[29] We also report the number of users holding the ETFs themselves.

The results in Panel (a) of Figure 10 show that the number of users holding the stocks that will be included in specialized ETFs increases and peaks right before the launch. Around the launch time, the number of users starts declining. We observe no similar pattern for broad-based ETFs. These results reiterate the point made in Subsection 6.1 that specialized ETFs are launched in segments of the market about which investors hold positive views; further, these products arrive to the market after the excitement has peaked.

Once new specialized ETFs are launched, they attract some of the Robinhood traders (Figure 10, Panel (b)), though not at the same rate as the underlying stocks do. Investors

[29]Due to the skewness of the holdings data, adjusting user holdings by the mean results in very high cross-sectional variance in some months. Adjusting by the median produces more stable estimates.

who are drawn to new specialized ETFs lose their interest within a few months of the launch. Broad-based ETFs do not exhibit these patterns.

The picture that emerges from the results in this section is that specialized ETFs cater to investors' expectations formed by extrapolating past performance of popular investment themes into the future. These portfolios include attention-grabbing stocks that are overvalued at the time of launch. In the years following the launch, the value of specialized ETFs declines drastically.

7 Conclusion

This paper studies the most prominent financial innovation in the last 30 years: exchange-traded funds (ETFs). Many observers view the growth of ETFs as a positive development that allows ordinary investors to achieve diversification at low cost and to construct payoff profiles that would otherwise be unattainable.

Our evidence shows a more nuanced reality. We identify two segments in the ETF market. Broad-based ETFs hold diversified portfolios and charge low fees. These products respond to investors' motive to achieve diversification and market access at a low cost. Specialized ETFs, in contrast, offer investors exposure to trendy themes at a high cost and low level of diversification. Although the average AUM of these funds are smaller, in the aggregate, they drive over one-third of the revenues of the equity-based ETF industry.

While broad-based ETFs clearly achieve their goal of providing diversification at low cost, we examine whether specialized ETFs provide value in terms of exposure to successful investment ideas or, if that is not the case, in the form of insurance. Our results suggest that specialized ETFs, on average, do not create value for investors. These ETFs tend to hold attention-grabbing and overvalued stocks and therefore underperform significantly: They deliver a negative alpha of about -6% in the five years after their inception, on average. We find no evidence that the negative performance corresponds to the price that investors are willing pay to insure against some relevant risk factor. Instead, our evidence suggests that specialized ETFs are launched just after the very peak of excitement around popular investment themes.

We conclude that the implications of the "democratization of investment" that ETFs bring about are mixed. On the one hand, investors can now access financial markets at low cost, which can be welfare-improving because it allows broader risk sharing. On the other hand, the marketing strategies of specialized ETFs facilitate speculation in overvalued securities, which soon underperform. It is possible that, absent specialized ETFs, these investors would still invest their money inefficiently. However, specialized ETFs likely encourage greater investor participation due to their marketing efforts and competitive strategies. Investors on the extensive margin may be worse off as a result of holding specialized ETFs.

References

Akey, Pat, Adriana Robertson, and Mikhail Simutin, 2021, Closet active management of passive funds, Working paper, University of Toronto.

Allen, Franklin, and Douglas Gale, 1994, *Financial innovation and risk sharing* (MIT press).

Arteaga, Kenneth R, Conrad S Ciccotello, and C Terry Grant, 1998, New equity funds: Marketing and performance, *Financial Analysts Journal* 54, 43–49.

Baker, Malcolm, Robin Greenwood, and Jeffrey Wurgler, 2009, Catering through nominal share prices, *Journal of Finance* 64, 2559–2590.

Baker, Malcolm, and Jeffrey Wurgler, 2000, The equity share in new issues and aggregate stock returns, *Journal of Finance* 55, 2219–2257.

Baker, Malcolm, and Jeffrey Wurgler, 2002, Market timing and capital structure, *Journal of Finance* 57, 1–32.

Baker, Malcolm, and Jeffrey Wurgler, 2004, A catering theory of dividends, *Journal of Finance* 59, 1125–1165.

Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor sentiment in the stock market, *Journal of Economic Perspectives* 21, 129–152.

Barber, Brad M, Xing Huang, Terrance Odean, and Christopher Schwarz, 2020, Attention induced trading and returns: Evidence from Robinhood users, Working paper, University of California at Davis.

Barber, Brad M, and Terrance Odean, 2013, The behavior of individual investors, in *Handbook of the Economics of Finance*, volume 2, 1533–1570 (Elsevier).

Barberis, Nicholas, Robin Greenwood, Lawrence Jin, and Andrei Shleifer, 2018, Extrapolation and bubbles, *Journal of Financial Economics* 129, 203–227.

Barberis, Nicholas, and Ming Huang, 2008, Stocks as lotteries: The implications of probability weighting for security prices, *American Economic Review* 98, 2066–2100.

Barberis, Nicholas, and Andrei Shleifer, 2003, Style investing, *Journal of Financial Economics* 68, 161–199.

Ben-David, Itzhak, Michael S Drake, and Darren T Roulstone, 2015, Acquirer valuation and acquisition decisions: Identifying mispricing using short interest, *Journal of Financial and Quantitative Analysis* 50, 1–32.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2017, Exchange-traded funds, *Annual Review of Financial Economics* 9, 169–189.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2018, Do ETFs increase volatility?, *Journal of Finance* 73, 2471–2535.

Berk, Jonathan B, and Richard C Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269–1295.

Boehmer, Ekkehart, Charles M Jones, and Xiaoyan Zhang, 2008, Which shorts are informed?, *Journal of Finance* 63, 491–527.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer, 2019, Diagnostic expectations and stock returns, *Journal of Finance* 74, 2839–2874.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2016, Competition for attention, *Review of Economic Studies* 83, 481–513.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2018, Diagnostic expectations and credit cycles, *Journal of Finance* 73, 199–227.

Brunnermeier, Markus K, Christian Gollier, and Jonathan A Parker, 2007, Optimal beliefs, asset prices, and the preference for skewed returns, *American Economic Review* 97, 159–165.

Brunnermeier, Markus K, and Jonathan A Parker, 2005, Optimal expectations, *American Economic Review* 95, 1092–1118.

Carhart, Mark M, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Célérier, Claire, and Boris Vallée, 2017, Catering to investors through security design: Headline rate and complexity, *Quarterly Journal of Economics* 132, 1469–1508.

Cooper, Michael J, Huseyin Gulen, and P Raghavendra Rau, 2005, Changing names with style: Mutual fund name changes and their effects on fund flows, *Journal of Finance* 60, 2825–2858.

Cosemans, Mathijs, and Rik Frehen, 2021, Salience theory and stock prices: Empirical evidence, *Journal of Financial Economics* Forthcoming.

Da, Zhi, Xing Huang, and Lawrence J Jin, 2020, Extrapolative beliefs in the cross-section: What can we learn from the crowds?, *Journal of Financial Economics* 140, 175–196.

Daniel, Kent, and Sheridan Titman, 1997, Evidence on the characteristics of cross sectional variation in stock returns, *Journal of Finance* 52, 1–33.

Dannhauser, Caitlin D, and Jeffrey Pontiff, 2019, Flow, Working paper, Boston College.

De Long, J Bradford, Andrei Shleifer, Lawrence H Summers, and Robert J Waldmann, 1990a, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703–738.

De Long, J Bradford, Andrei Shleifer, Lawrence H Summers, and Robert J Waldmann, 1990b, Positive feedback investment strategies and destabilizing rational speculation, *Journal of Finance* 45, 379–395.

Dechow, Patricia M, Amy P Hutton, and Richard G Sloan, 2000, The relation between analysts' forecasts of long-term earnings growth and stock price performance following equity offerings, *Contemporary Accounting Research* 17, 1–32.

Duffie, Darrell, and Rohit Rahi, 1995, Financial market innovation and security design: An introduction, *Journal of Economic Theory* 65, 1–42.

Easley, David, David Michayluk, Maureen O'Hara, and Tālis J Putniņš, 2018, The active world of passive investing, Working paper, Cornell University.

Easterwood, John C, and Stacey R Nutt, 1999, Inefficiency in analysts' earnings forecasts: Systematic misreaction or systematic optimism?, *Journal of Finance* 54, 1777–1797.

Egan, Mark, Alexander MacKay, and Hanbin Yang, 2019, Recovering investor expectations from demand for index funds, Working paper, Harvard University.

Elton, Edwin J, Martin J Gruber, and Joel Rentzler, 1989, New public offerings, information, and investor rationality: The case of publicly offered commodity funds, *Journal of Business* 62, 1–15.

Evans, Richard B, 2010, Mutual fund incubation, *Journal of Finance* 65, 1581–1611.

Fama, Eugene F, and Kenneth R French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F, and Kenneth R French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Fama, Eugene F, and Kenneth R French, 2018, Choosing factors, *Journal of Financial Economics* 128, 234–252.

French, Kenneth R, 2008, Presidential address: The cost of active investing, *Journal of Finance* 63, 1537–1573.

Gao, Pengjie, Allen Hu, Peter Kelly, Cameron Peng, and Ning Zhu, 2020, Exploited by complexity, Working paper, University of Notre Dame.

Gennaioli, Nicola, Andrei Shleifer, and Robert Vishny, 2012, Neglected risks, financial innovation, and financial fragility, *Journal of Financial Economics* 104, 452–468.

Ghysels, Eric, Alberto Plazzi, and Rossen Valkanov, 2016, Why invest in emerging markets? The role of conditional return asymmetry, *Journal of Finance* 71, 2145–2192.

Greenwood, Robin, and Samuel G Hanson, 2013, Issuer quality and corporate bond returns, *Review of Financial Studies* 26, 1483–1525.

Greenwood, Robin, and Andrei Shleifer, 2014, Expectations of returns and expected returns, *Review of Financial Studies* 27, 714–746.

Harris, Lawrence E, Samuel M Hartzmark, and David H Solomon, 2015, Juicing the dividend yield: Mutual funds and the demand for dividends, *Journal of Financial Economics* 116, 433–451.

Henderson, Brian J, and Neil D Pearson, 2011, The dark side of financial innovation: A case study of the pricing of a retail financial product, *Journal of Financial Economics* 100, 227–247.

Henderson, Brian J, Neil D Pearson, and Li Wang, 2020, Retail derivatives and sentiment: A sentiment measure constructed from issuances of retail structured equity products, Working paper, University of Illinois at Urbana-Champagne.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015, Digesting anomalies: An investment approach, *Review of Financial Studies* 28, 650–705.

Huang, Shiyang, Maureen O'Hara, and Zhuo Zhong, 2020, Innovation and informed trading: Evidence from industry ETFs, *Review of Financial Studies* 34, 1280–1316.

Huang, Shiyang, Yang Song, and Hong Xiang, 2020, The Smart Beta mirage, Working paper, University of Washington.

Jain, Prem C, and Joanna Shuang Wu, 2000, Truth in mutual fund advertising: Evidence on future performance and fund flows, *Journal of Finance* 55, 937–958.

Khomyn, Marta, Tālis J Putniņš, and Marius Zoican, 2020, The value of ETF liquidity, Working paper, University of Technology Sydney.

Khorana, Ajay, and Henri Servaes, 1999, The determinants of mutual fund starts, *Review of Financial Studies* 12, 1043–1074.

Kostovetsky, Leonard, and Jerold B Warner, 2020, Measuring innovation and product differentiation: Evidence from mutual funds, *Journal of Finance* 75, 779–823.

Kumar, Alok, 2009, Who gambles in the stock market?, *Journal of Finance* 64, 1889–1933.

Lakonishok, Josef, Andrei Shleifer, and Robert W Vishny, 1994, Contrarian investment, extrapolation, and risk, *Journal of Finance* 49, 1541–1578.

Lee, Charles MC, Andrei Shleifer, and Richard H Thaler, 1991, Investor sentiment and the closed-end fund puzzle, *Journal of Finance* 46, 75–109.

Lintner, John, 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* 47, 13–37.

Massa, Massimo, 1998, Why so many mutual funds? Mutual fund families, market segmentation and financial performance, Working paper, Insead.

Michaely, Roni, and Kent L Womack, 1999, Conflict of interest and the credibility of underwriter analyst recommendations, *Review of Financial Studies* 12, 653–686.

Miller, Edward M, 1977, Risk, uncertainty, and divergence of opinion, *Journal of Finance* 32, 1151–1168.

Mitton, Todd, and Keith Vorkink, 2007, Equilibrium underdiversification and the preference for skewness, *Review of Financial Studies* 20, 1255–1288.

Mossin, Jan, 1966, Equilibrium in a capital asset market, *Econometrica* 34, 768–783.

Moussawi, Rabih, Ke Shen, and Raisa Velthuis, 2020, ETF heartbeat trades, tax efficiencies, and clienteles: The role of taxes in the flow migration from active mutual funds to ETFs, Working paper, Villanova University.

Novick, Barbara, 2017, How index funds democratize investing, *Wall Street Journal* (January 08).

Sharpe, William F, 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425–442.

Shleifer, Andrei, and Robert W Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35–55.

Simsek, Alp, 2013a, Speculation and risk sharing with new financial assets, *Quarterly Journal of Economics* 128, 1365–1396.

Simsek, Alp, 2013b, Financial innovation and portfolio risks, *American Economic Review: Papers & Proceedings* 103, 398–401.

Stambaugh, Robert F, 2014, Presidential address: Investment noise and trends, *Journal of Finance* 69, 1415–1453.

Vokata, Petra, 2021, Engineering lemons, *Journal of Financial Economics* forthcoming.

Welch, Ivo, 2020, Retail raw: Wisdom of the Robinhood crowd and the Covid crisis, Working paper, National Bureau of Economic Research.

Appendix A A Primer on ETFs

Exchange-traded products (ETPs) are investment companies whose objective is to replicate the performance of an index, in a similar manner to index mutual funds. Unlike index funds, however, ETPs are listed on an exchange and are traded throughout the day. These funds are organized in several legal structures, such as exchange-traded funds (ETFs), exchange-traded notes (ETNs), exchange-traded commodities, and index participation units (IPU). In this article, we focus exclusively on ETFs.

The first U.S. ETF was launched in January 1993. It tracked the S&P 500 (ticker: SPY). SPY is currently the largest ETF in the world, with nearly $300 billion in assets. As of the end of 2019, the number of ETFs has grown to over 3,000 in the United States and nearly 7,000 globally, with these products spanning various asset classes.

ETFs can reproduce the performance of the relevant index in two distinct ways. First, they can hold a basket of securities that, more or less, replicates the index ("physical replication"). Second, they can enter into swap agreements with financial institutions to have the performance of the index delivered by these counterparties in exchange for a fee ("synthetic replication"). The physical structure is prevalent in the United States, and it characterizes all the ETFs in our sample.

The focus in this article is on "plain vanilla" equity ETFs that hold portfolios of stocks that track an index. The index can be an existing index, such as the S&P 500 or Russell 2000, or an index that is designed by the issuers expressly for the ETF, e.g., the index tracked by the work-from-home ETF, launched in June 2020.

The innovation in the ETF structure revolves around the creation and redemption mechanism that takes place on a daily basis and keeps the market price of the ETF in close proximity to the value of the basket of securities in the index it tracks. Because ETFs hold securities that are, themselves, traded on the market, there is a possibility of temporary misalignment between the price of ETF shares and the value of the basket of securities. For example, when there is high demand for the ETF, but not yet for the underlying securities, the ETF will trade at a premium relative to the underlying index. To ensure that significant deviations are not created between the ETF and the underlying securities portfolio, ETFs continuously issue new shares when investor demand is high or redeem shares when investor demand is low. The creation or redemption of ETF shares is called *flows*, which can be positive or negative, and can indicate the demand for the ETF in excess of the demand for the underlying securities.

For further reading about ETFs, please see Ben-David, Franzoni, and Moussawi (2017) and Ben-David, Franzoni, and Moussawi (2018).

Appendix B Data Sources

B.1 ETF Data

We use information from the Center for Research in Security Prices (CRSP) to identify a comprehensive and survivorship-bias-free list of all U.S. equity ETFs. We first select securities with share code of 73 from CRSP, or a nonmissing ETF flag in the CRSP Mutual Fund Database. Because we are interested in ETFs that hold U.S. equities, we drop ETFs focusing on the bond market (that have a CRSP style of fixed income, mixed holdings, or other—style codes: I, M, O, or names that contain the word "bond"). We also drop inverse and leveraged ETFs (that have a Lipper classification code of DSB,[30] or CRSP style code $EDYS$ or $EDYH$,[31] or the name contains any of the following: 2×, 3×, bear, or bull). We exclude ETFs that are classified as foreign equity ETFs (CRSP style code F). The final sample contains 1,080 distinct U.S. equity ETFs that satisfy all requirements.

CRSP is our primary source for daily trading data. We rely on Bloomberg for ETF shares outstanding information, and supplement it with Compustat when the Bloomberg data are not available. Furthermore, we use CRSP's end-of-month information about returns and prices, and supplement it with Bloomberg's and Compustat's total shares outstanding to calculate month-end assets under management (AUM). Compustat is our primary source for monthly short interest data.

B.2 ETF Holdings Data

We obtain ETF holdings information from two sources: the Thomson Reuters Global Mutual Fund Ownership and CRSP Mutual Fund Holdings databases. For many ETFs, both sources contain holdings information; for others, holdings information is only available

[30] DSB: dedicated short bias funds. More information about Lipper classification codes is provided in: `http://www.crsp.org/products/documentation/lipper-objective-and-classification-codes`.

[31] $EDYS$: Dedicated Short Bias Funds. $EDYN$: long/short equity funds, equity market neutral funds, absolute return funds, and equity leverage funds. More information about CRSP style codes is provided in: `http://www.crsp.org/products/documentation/crsp-style-code`.

in one of the sources. In many cases, first report dates of portfolio holdings differ between the two. Our approach is to take one source per ETF as the reference for its holdings. If an ETF has holdings information in both sources, we use the one with the start date that is closer to the launch date in CRSP. We notice that CRSP holdings data are relatively more reliable and timely after June 2010 and those in the earlier period of the sample, the Thomson Reuters Global Ownership data are more reliable to track ETF ownership soon after launch dates.

B.3 Firm-Level Data

We use Compustat for firm-level accounting information and obtain the analysts-forecast-based measure of earnings surprises from I/B/E/S. Firm-level news data are from RavenPack News Analytics. We aggregate daily-level news items into monthly-level news counts. 13F institutional ownership data are from Thomson Reuters, and Robinhood users data are from Robintrack.

B.4 Financial Markets Data

We calculate risk-adjusted returns using six different risk models: the CAPM (Sharpe, 1964; Lintner, 1965; Mossin, 1966), the Fama-French three-factor (Fama and French, 1993), the Fama-French-Carhart four-factor (Carhart, 1997), the Fama-French five-factor (Fama and French, 2015), and the Fama-French six-factor (Fama and French, 2018) models.[32]

[32]Risk factor returns are downloaded from Professor French's website: `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html` and Professors Hou, Xue, and Zhang's website: `http://global-q.org/factors.html`.

Appendix C Variable Definitions

Variable	Definition	Source
ETF-level variables		
Active share	The sum of the absolute value of the difference between the fund portfolio weight and the weight in the market portfolio.	Thomson Reuters Global, CRSP Mutual Fund
# of holdings	The number of stocks in an ETF's portfolio.	Thomson Reuters Global, CRSP Mutual Fund
Fee	Fiscal year-end expense ratio.	Bloomberg
Turnover	The average daily trading volume scaled by the total shares outstanding.	CRSP
Market-adjusted return	ETF monthly returns in excess of CRSP value-weighted returns.	CRSP
Delisted	An indicator for whether an ETF is liquidated as of the end of the sample.	CRSP
AUM	The total market value of the investments ($b).	CRSP
Implied revenues	Fees multiplied by the average AUM ($m) in each year.	Bloomberg, CRSP
Differentiation	One minus the cosine similarity between the ETF portfolio weights and the weights of the aggregate portfolio of all ETFs in the same category that exist in the market at that point in time.	Thomson Reuters Global, CRSP Mutual Fund
Flows	Flows in month $t+1$ are computed as $100 \times (\text{AUM}_{t+1} - \text{AUM}_t \times \text{ETF return}_{t+1})/\text{AUM}_t$.	CRSP
Age	Age in each month t is an ETF's age in months since the launch month 0.	CRSP
13F ownership	The total ownership of 13F institutional investors.	Thomson Reuters
# of Robinhood users	The number of Robinhood users holding an ETF.	Robintrack
Firm-level variables		
Market-adjusted return	Monthly returns in excess of CRSP value-weighted returns.	CRSP
Return skewness	The skewness of returns following Ghysels et al. (2016). We use the 25^{th} and 75^{th} percentiles as cutoffs.	CRSP
Media exposure	The number of monthly news articles scaled by market capitalization.	RavenPack
Media sentiment	Sum of each news article's composite sentiment score scaled by market capitalization.	RavenPack
Earnings surprise	The average earnings-per-share (EPS) surprises scaled by the one-quarter-lagged stock price.	I/B/E/S, CRSP
Market-to-book	Market equity divided by book equity.	Compustat, CRSP
Short interest	The ratio of the number of shares shorted to the total shares outstanding.	Compustat
LTG	Analysts' expectation of long-term annual earnings growth.	I/B/E/S
Forecast error	The difference between the realized annual earnings growth and LTG.	I/B/E/S
# of Robinhood users	The number of Robinhood users holding a stock.	Robintrack

Appendix D Additional Empirical Results

Table D.1. ETF Summary Statistics

The table shows summary statistics at the ETF level. Panels A, B, C, and D report summary statistics for broad-based ETFs, smart-beta ETFs, sector ETFs, and thematic ETFs, respectively. *Number of holdings* represents the average number of stocks in the portfolios of ETFs. *Fee* refers to annualized expense ratio. *Turnover* is the average daily turnover over the six months after launch. *Market-adjusted return* is monthly ETF return in excess of CRSP value-weighted return over the 60 months after launch. *Delisted* is an indicator for whether the ETF was liquidated as of the end of 2019. *Assets under management* (AUM) is the total market value of the investments in 2019. Implied revenues are calculated by multiplying fee by average AUM in 2019.

Panel A: Broad-Based ETFs								
	N	Mean	SD	P5	P25	P50	P75	P95
Number of holdings (at launch)	90	865	823	50	266	538	1262	2938
Fee (bps)	77	28	23	5	15	20	28	75
Turnover (months 1–6; %)	87	3.64	3.99	0.33	0.94	1.88	5.84	9.82
Market-adjusted return (months 1–60, %)	88	−0.01	0.30	−0.37	−0.17	−0.02	0.15	0.42
Delisted	90	0.17	0.37	0	0	0	0	1
2019 statistics								
Assets under management ($bn)	75	17.49	47.70	0.00	0.11	1.00	10.17	130.54
Implied revenues ($m)	63	27.82	70.50	0.02	0.55	2.31	19.27	134.15

Panel B: Smart-Beta ETFs								
	N	Mean	SD	P5	P25	P50	P75	P95
Number of holdings (at launch)	463	313	336	36	99	199	437	954
Fee (bps)	418	44	24	13	26	38	60	85
Turnover (months 1–6; %)	460	2.73	3.11	0.19	0.90	2.06	3.42	7.77
Market-adjusted return (months 1–60, %)	463	−0.18	0.40	−0.90	−0.35	−0.12	0.03	0.30
Delisted	464	0.18	0.39	0	0	0	0	1
2019 statistics								
Assets under management ($bn)	357	2.31	6.83	0.01	0.05	0.18	0.96	11.62
Implied revenues ($m)	327	5.68	13.92	0.03	0.20	0.79	4.06	28.37

Panel C: Sector ETFs								
	N	Mean	SD	P5	P25	P50	P75	P95
Number of holdings (at launch)	401	80	80	20	32	50	93	238
Fee (bps)	366	52	20	17	35	55	68	82
Turnover (months 1–6; %)	411	4.04	7.04	0.37	1.09	2.14	4.22	13.63
Market-adjusted return (months 1–60, %)	411	−0.32	0.94	−1.98	−0.68	−0.18	0.27	0.80
Delisted	411	0.28	0.45	0	0	0	1	1
2019 statistics								
Assets under management ($bn)	281	1.55	4.13	0.01	0.05	0.23	1.02	7.87
Implied revenues ($m)	272	6.68	17.17	0.05	0.29	1.02	4.37	37.30

(continued below)

Table D.1. ETF Summary Statistics (Continued)

(continued from the previous page)

Panel D: Thematic ETFs								
	N	Mean	SD	P5	P25	P50	P75	P95
Number of holdings (at launch)	114	108	106	27	39	75	106	350
Fee (bps)	85	67	20	35	50	65	75	95
Turnover (months 1–6; %)	115	2.93	2.87	0.37	1.05	2.04	3.69	9.08
Market-adjusted return (months 1–60, %)	115	−0.87	2.43	−5.04	−0.83	−0.30	0.02	0.50
Delisted	115	0.37	0.48	0	0	0	1	1
2019 statistics								
Assets under management ($bn)	73	0.33	0.66	0.00	0.01	0.06	0.20	1.84
Implied revenues ($m)	57	2.22	3.77	0.02	0.14	0.43	2.10	12.35

Table D.2. Difference in Fees

The table reports the difference in fees across ETF categories from 2000 to 2019. The dependent variable *Fee* is the annualized expense ratio of an ETF in each month. *Specialized* is a dummy variable that equals 1 if an ETF is a specialized ETF. *Thematic* is a dummy variable that equals 1 if an ETF is a theamtic ETF. *Sector* is a dummy variable that equals 1 if an ETF is a sector ETF. *Smart-beta* is a dummy variable that equals 1 if an ETF is a smart-beta ETF. Standard errors are clustered at the ETF, the management company, and the calendar-month levels. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Fee$_t$ (bps)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specialized	14.17***	12.52***	13.72***	11.82***				
	(3.98)	(3.20)	(4.87)	(3.61)				
Thematic					41.77***	19.96***	29.77***	18.45***
					(10.50)	(6.01)	(7.56)	(9.16)
Sector					26.98***	16.65***	22.03***	15.94***
					(9.94)	(4.26)	(10.51)	(4.58)
Smart-beta					18.71***	5.79***	11.81***	5.62***
					(4.82)	(4.35)	(4.25)	(4.10)
Constant	35.50***	36.35***	35.73***	36.71***	20.97***	31.84***	26.54***	32.33***
	(6.53)	(18.01)	(10.12)	(21.79)	(7.14)	(15.59)	(9.52)	(17.09)
Mgmt company FE	No	Yes	No	Yes	No	Yes	No	Yes
Launch year FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	81,594	81,594	81,594	81,594	81,594	81,594	81,594	81,594
R-squared	0.100	0.710	0.353	0.757	0.182	0.715	0.378	0.762

Table D.3. Concentration Among Issuers

The table presents the number of ETFs and issuers across ETF categories from 1993 to 2019. We also report the concentration among issuers within each ETF category in 2019. We proxy the concentration level by computing the Herfindahl-Hirschman Index (HHI) of issuers' market shares in 2019.

	# ETFs	# Issuers	# Issuers/# ETFs	HHI (2019)
Broad-based	90	26	0.289	0.31
Smart-beta	464	86	0.185	0.28
Sector	411	50	0.122	0.24
Thematic	115	44	0.383	0.20

Figure D.1. Number of ETF Issuers

The Venn diagram presents the number of issuers per ETF category.

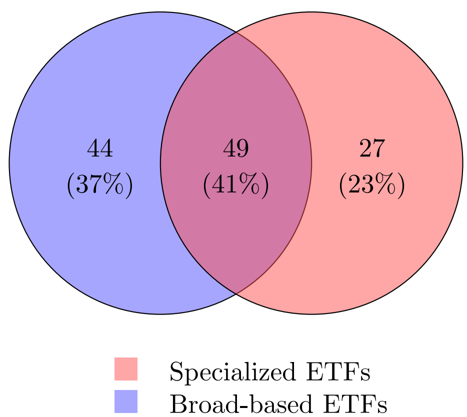


Table D.4. Sensitivity of ETF Flows to Fees (Robustness)

The table reports the flow sensitivity of ETFs to their fees. The observations are at the ETF level. The dependent variable is cumulative flows over a 12-month or 24-month window after the launch of each ETF. *Fee* is the average annualized expense ratio of an ETF over the 12-month or 24-month time window. *Return rank* is the average percentile rank of returns within each month over the 12-month or 24-month time window. *Specialized* is a dummy variable that equals 1 if an ETF is a specialized ETF. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Cumulative flows (%) over	
	12 months since launch	24 months since launch
Fee (bps)	−0.58***	−0.92***
	(−2.67)	(−3.63)
Fee × Specialized	0.70**	0.76*
	(2.08)	(1.92)
Return rank	1.10	2.57**
	(1.55)	(2.34)
Return rank × Specialized	0.60	−1.34
	(0.69)	(−1.00)
Specialized	−82.03*	17.32
	(−1.65)	(0.23)
Launch year FE	Yes	Yes
Observations	931	931
R^2	0.084	0.100

Appendix E Robustness Analysis of ETF Performance

E.1 ETF Performance with Equally Weighted Returns

In Table E.1, we report the performance of ETFs with equal-weighted returns. The results are similar to those reported in Table 3.

Table E.1. Calendar-Time Portfolios of ETFs (Equally-Weighted)

The table presents the risk-adjusted performance of ETFs from 2000 to 2019. In Panel A, we form portfolios consisting of all ETFs in the same category. In Panel B, we identify *new* ETFs that were launched in the previous five years in each month. We then form portfolios consisting of all *new* ETFs in the same category. The portfolio returns are equal-weighted. *Excess return* refers to the average monthly return in excess of the risk-free rate. *CAPM*, *FF3*, *FFC4*, *FF5*, *FF6*, and *Q* denote alphas with respect to the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; Mossin, 1966), the Fama-French three-factor model (Fama and French, 1993), the Fama-French-Carhart four-factor model (Carhart, 1997), the Fama-French five-factor model (Fama and French, 2015), the Fama-French six-factor model (Fama and French, 2018), and the Q-factor model (Hou et al., 2015), respectively. The portfolios of all broad-based (specialized) ETFs comprise 171 (189) ETFs on average. *SP minus BB* denotes the specialized ETF portfolio minus the broad-based ETF portfolio. The excess return and alphas are in percentage points, and t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Excess return	CAPM	FF3	FFC4	FF5	FF6	Q
Panel A: All Months							
Broad-based ETFs	0.50*	0.02	−0.03	−0.02	−0.05	−0.05	−0.03
	(1.73)	(0.41)	(−0.77)	(−0.48)	(−1.47)	(−1.38)	(−0.90)
Specialized ETFs	0.29	−0.25***	−0.25***	−0.20***	−0.19**	−0.17**	−0.11
	(0.89)	(−3.02)	(−3.06)	(−2.72)	(−2.27)	(−2.25)	(−1.50)
SP minus BB	−0.20**	−0.26***	−0.22***	−0.18**	−0.14*	−0.12*	−0.08
	(−2.37)	(−3.31)	(−2.92)	(−2.58)	(−1.79)	(−1.71)	(−1.15)
Panel B: Months $\leq$ 60							
	Excess return	CAPM	FF3	FFC4	FF5	FF6	Q
Broad-based ETFs	0.47	−0.00	−0.05	−0.04	−0.05	−0.05	−0.05
	(1.65)	(−0.07)	(−1.27)	(−1.03)	(−1.38)	(−1.29)	(−1.20)
Specialized ETFs	0.21	−0.34***	−0.34***	−0.29***	−0.28***	−0.26***	−0.19**
	(0.62)	(−3.49)	(−3.58)	(−3.29)	(−2.85)	(−2.85)	(−2.13)
SP minus BB	−0.26**	−0.33***	−0.29***	−0.25***	−0.23**	−0.21**	−0.15*
	(−2.53)	(−3.53)	(−3.20)	(−2.89)	(−2.39)	(−2.34)	(−1.70)

E.2 ETF Performance: Seasoned ETFs

In Appendix Table E.2, we report the performance of portfolios containing ETFs that have been in existence for more than 60 months to complement the results in Table 3. We note that the underperformance of specialized ETFs is no longer significant.

Table E.2. Calendar-Time Portfolios of Seasoned ETFs

The table presents the risk-adjusted performance of *seasoned* ETFs. We identify *seasoned* ETFs that were launched more than five years prior in each month. We then form portfolios consisting of all *seasoned* ETFs in the same category. The portfolio returns are value-weighted using one-month-lagged market capitalization. *Excess return* refers to the average monthly return in excess of the risk-free rate. *CAPM*, *FF3*, *FFC4*, *FF5*, *FF6*, and *Q* denote alphas with respect to the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; Mossin, 1966), the Fama-French three-factor model (Fama and French, 1993), the Fama-French-Carhart four-factor model (Carhart, 1997), the Fama-French five-factor model (Fama and French, 2015), the Fama-French six-factor model (Fama and French, 2018), and the Q-factor model (Hou et al., 2015), respectively. *SP minus BB* denotes the specialized ETF portfolio minus the broad-based ETF portfolio. The excess return and alphas are in percentage points, and t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Excess return	CAPM	FF3	FFC4	FF5	FF6	Q
Broad-based ETFs	0.70**	−0.03	−0.03	−0.03	−0.04*	−0.04*	−0.03
	(2.38)	(−1.32)	(−1.28)	(−1.26)	(−1.91)	(−1.89)	(−1.13)
Specialized ETFs	0.60**	−0.11	−0.11	−0.12	−0.12	−0.12	−0.07
	(2.04)	(−1.57)	(−1.56)	(−1.56)	(−1.54)	(−1.55)	(−1.00)
SP minus BB	−0.10	−0.08	−0.08	−0.09	−0.07	−0.07	−0.05
	(−1.49)	(−1.19)	(−1.25)	(−1.25)	(−1.02)	(−1.05)	(−0.67)

E.3 ETF Performance: U.S. Portfolio ETFs

In Appendix Table E.3, we restrict the sample of broad-based and specialized ETFs to those that include at least 80% of their market capitalization invested in stocks traded in the United States, and estimate risk-adjusted returns using the calendar-time portfolio approach as in Table 3. The results of the analysis are similar to those reported in Table 3.

Table E.3. Calendar-Time Portfolios Around ETF Launches (U.S. ETFs)

The table presents risk-adjusted performance of ETFs from 2000 to 2019. We require ETFs to hold at least 80% of their AUM in U.S. stocks. In each month, we identify *new* ETFs that were launched within the previous five years. We then form a portfolio consisting of all *new* ETFs in the same category. The portfolio returns are value-weighted using one-month-lagged market capitalization. *Excess return* refers to the average monthly return in excess of the risk-free rate. *CAPM*, *FF3*, *FFC4*, *FF5*, *FF6*, and *Q* alpha denote alphas with respect to the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; Mossin, 1966), the Fama-French three-factor model (Fama and French, 1993), the Fama-French-Carhart four-factor model (Carhart, 1997), the Fama-French five-factor model (Fama and French, 2015), the Fama-French six-factor model (Fama and French, 2018), and the Q-factor model (Hou et al., 2015), respectively. The portfolios of broad-based (specialized) ETFs include 89 (79) ETFs on average. *SP minus BB* denotes the specialized ETF portfolio minus the broad-based ETFs portfolio. The alphas are in percentage points, and t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Broad-based ETFs	Specialized ETFs	SP minus BB
Excess return	0.31	−0.07	−0.38**
	(0.90)	(−0.19)	(−2.11)
CAPM alpha	−0.22*	−0.62***	−0.40**
	(−1.67)	(−3.78)	(−2.19)
FF3 alpha	−0.18	−0.60***	−0.42**
	(−1.55)	(−3.85)	(−2.32)
FFC4 alpha	−0.13	−0.58***	−0.45**
	(−1.20)	(−3.72)	(−2.47)
FF5 alpha	0.10	−0.42***	−0.53***
	(1.00)	(−2.65)	(−2.78)
FF6 alpha	0.11	−0.42***	−0.54***
	(1.10)	(−2.63)	(−2.81)
Q alpha	0.06	−0.42***	−0.48**
	(0.53)	(−2.72)	(−2.54)

E.4 ETF Performance: Alternative Classification

In Appendix Table E.4, we confirm the underperformance of specialized ETFs when we identify them as those with either a large active share, a small number of portfolio holdings, or those charging high fees.

In Appendix Table E.5, we show that both sector and thematic ETFs exhibit significant underperformance. The sample period starts in 2010 since few new thematic ETFs are available to form portfolios before 2010.

Table E.4. New ETFs' Performance (Alternative Classification)

The table presents risk-adjusted performance of ETFs from 2000 to 2019. We identify *new* ETFs that were launched within the previous five years. In each month, we form 5 portfolios by sorting *new* ETFs on active share (Panel A), the number of holdings (Panel B), or fee (Panel C). The three variables are measured within the first six months after the launch of ETFs. The portfolio returns are value-weighted using one-month-lagged market capitalization. We exclude ETFs' first six months of returns to avoid a look-ahead bias. *Excess return* refers to the average monthly return in excess of the risk-free rate. *CAPM*, *FF3*, *FFC4*, *FF5*, *FF6*, and *Q* denote alphas with respect to the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; Mossin, 1966), the Fama-French three-factor model (Fama and French, 1993), the Fama-French-Carhart four-factor model (Carhart, 1997), the Fama-French five-factor model (Fama and French, 2015), the Fama-French six-factor model (Fama and French, 2018), and the Q-factor model (Hou et al., 2015), respectively. The alphas are in percentage points, and t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios Sorted by Active Share							
	Excess return	CAPM	FF3	FFC4	FF5	FF6	Q
Low active share	0.52*	−0.02	−0.01	−0.00	−0.03	−0.03	−0.02
	(1.94)	(−0.57)	(−0.22)	(−0.11)	(−0.73)	(−0.74)	(−0.64)
Q2	0.45	−0.14*	−0.14*	−0.12	−0.08	−0.09	−0.09
	(1.49)	(−1.92)	(−1.92)	(−1.63)	(−1.08)	(−1.10)	(−1.17)
Q3	0.56*	−0.02	−0.08	−0.07	−0.07	−0.07	−0.04
	(1.86)	(−0.18)	(−1.00)	(−0.87)	(−0.83)	(−0.84)	(−0.51)
Q4	0.46	−0.14	−0.20	−0.20	−0.23*	−0.23*	−0.13
	(1.42)	(−0.99)	(−1.61)	(−1.55)	(−1.76)	(−1.76)	(−1.00)
High active share	−0.05	−0.62**	−0.67***	−0.66***	−0.63**	−0.63**	−0.55**
	(−0.14)	(−2.43)	(−2.69)	(−2.61)	(−2.38)	(−2.38)	(−2.15)
High minus low	−0.57**	−0.60**	−0.67***	−0.66**	−0.60**	−0.60**	−0.52**
	(−2.23)	(−2.31)	(−2.64)	(−2.58)	(−2.27)	(−2.27)	(−2.05)

(continued below)

Table E.4. New ETFs' performance (Alternative Classification)

(continued from the previous page)

Panel B: Portfolios Sorted by # of Holdings							
	Excess return	CAPM	FF3	FFC4	FF5	FF6	Q
Low # holdings	0.17	−0.44***	−0.47***	−0.42***	−0.35**	−0.35**	−0.32**
	(0.52)	(−3.22)	(−3.52)	(−3.21)	(−2.51)	(−2.57)	(−2.46)
Q2	0.05	−0.49**	−0.51**	−0.50**	−0.53**	−0.53**	−0.45**
	(0.14)	(−2.36)	(−2.43)	(−2.37)	(−2.44)	(−2.44)	(−2.13)
Q3	0.48*	−0.07	−0.08	−0.09	−0.09	−0.09	−0.08
	(1.69)	(−0.83)	(−0.97)	(−1.05)	(−0.97)	(−0.97)	(−0.95)
Q4	0.54*	−0.05	−0.06	−0.04	−0.10	−0.10	−0.04
	(1.82)	(−0.62)	(−0.91)	(−0.63)	(−1.41)	(−1.46)	(−0.49)
High # holdings	0.65**	0.05	−0.00	0.01	0.01	0.00	0.02
	(2.13)	(0.67)	(−0.03)	(0.18)	(0.10)	(0.09)	(0.36)
Low minus high	−0.47***	−0.49***	−0.47***	−0.43***	−0.35**	−0.35**	−0.34**
	(−3.51)	(−3.60)	(−3.49)	(−3.22)	(−2.52)	(−2.56)	(−2.58)

Panel C: Portfolios Sorted by Fee							
	Excess return	CAPM	FF3	FFC4	FF5	FF6	Q
Low fee	0.36	−0.20	−0.14	−0.11	0.12	0.13	0.08
	(0.99)	(−1.48)	(−1.24)	(−0.94)	(1.11)	(1.22)	(0.74)
Q2	0.61*	0.06	0.01	0.06	0.08	0.09	0.11
	(1.89)	(0.45)	(0.11)	(0.48)	(0.58)	(0.66)	(0.81)
Q3	0.34	−0.13	−0.08	−0.01	−0.08	−0.05	0.00
	(0.98)	(−0.62)	(−0.41)	(−0.05)	(−0.37)	(−0.24)	(0.02)
Q4	0.16	−0.44***	−0.47***	−0.45***	−0.47***	−0.47***	−0.40***
	(0.49)	(−3.42)	(−3.68)	(−3.54)	(−3.51)	(−3.52)	(−3.08)
High fee	0.03	−0.58***	−0.60***	−0.57***	−0.76***	−0.73***	−0.68***
	(0.09)	(−3.10)	(−3.32)	(−3.14)	(−4.30)	(−4.13)	(−3.56)
High minus low	−0.43*	−0.40	−0.46*	−0.44*	−0.83***	−0.80***	−0.75***
	(−1.69)	(−1.57)	(−1.94)	(−1.85)	(−3.84)	(−3.70)	(−3.04)

Table E.5. New ETFs' Performance by Categories

The table presents risk-adjusted performance of ETFs from 2010 to 2019. In each month, we identify *new* ETFs that were launched within the previous five years. We then form a portfolio consisting of all *new* ETFs in the same category. The portfolio returns are value-weighted using one-month-lagged market capitalization. *Excess return* refers to the average monthly return in excess of the risk-free rate. *CAPM*, *FF3*, *FFC4*, *FF5*, *FF6*, and *Q* denote alphas with respect to the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; Mossin, 1966), the Fama-French three-factor model (Fama and French, 1993), the Fama-French-Carhart four-factor model (Carhart, 1997), the Fama-French five-factor model (Fama and French, 2015), the Fama-French six-factor model (Fama and French, 2018), and the Q-factor model (Hou et al., 2015), respectively. The alphas are in percentage points, and t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Excess return	CAPM	FF3	FFC4	FF5	FF6	Q
Broad-based	1.01***	−0.04	−0.03	−0.03	−0.03	−0.03	−0.03
	(3.04)	(−1.07)	(−0.72)	(−0.69)	(−0.79)	(−0.77)	(−0.64)
Smart-beta	0.92***	0.04	0.03	0.04	−0.03	−0.01	−0.01
	(3.21)	(0.47)	(0.34)	(0.51)	(−0.34)	(−0.16)	(−0.09)
Sector	0.36	−0.69***	−0.65***	−0.60***	−0.60***	−0.55***	−0.46**
	(0.95)	(−3.39)	(−3.21)	(−2.99)	(−2.93)	(−2.73)	(−2.38)
Thematic	0.55	−0.71***	−0.79***	−0.75***	−0.73***	−0.70***	−0.71***
	(1.26)	(−3.77)	(−4.18)	(−3.99)	(−3.88)	(−3.72)	(−3.79)

Appendix F Robustness Analysis on Flow-Performance Sensitivity

In Appendix Figure F.1, we replicate the analysis in Figure 5 using market-adjusted returns and the percentile rank of returns within each month. We confirm that the inferences remain unchanged. In Appendix Figures F.2 and F.3, we show that the same flow-performance sensitivity pattern is present when we measure the performance at the quarterly and annual frequencies.

Figure F.1. Flow-Performance Sensitivity

The figure presents the flow-performance sensitivity of ETFs per ETF category. Flows are computed as $100 \times (\text{AUM}_{t+1} - \text{AUM}_t \times \text{ETF return}_{t+1})/\text{AUM}_t$. Market-adjusted returns are raw ETF returns in excess of CRSP value-weighted returns. Return percentile rank is the percentile rank of returns within each month. We estimate a nonparametric relation between flows and returns using local polynomial approximations obtained with Stata's `-lpoly-` command with bandwidth of 0.04. The shaded areas represent 95% confidence intervals.

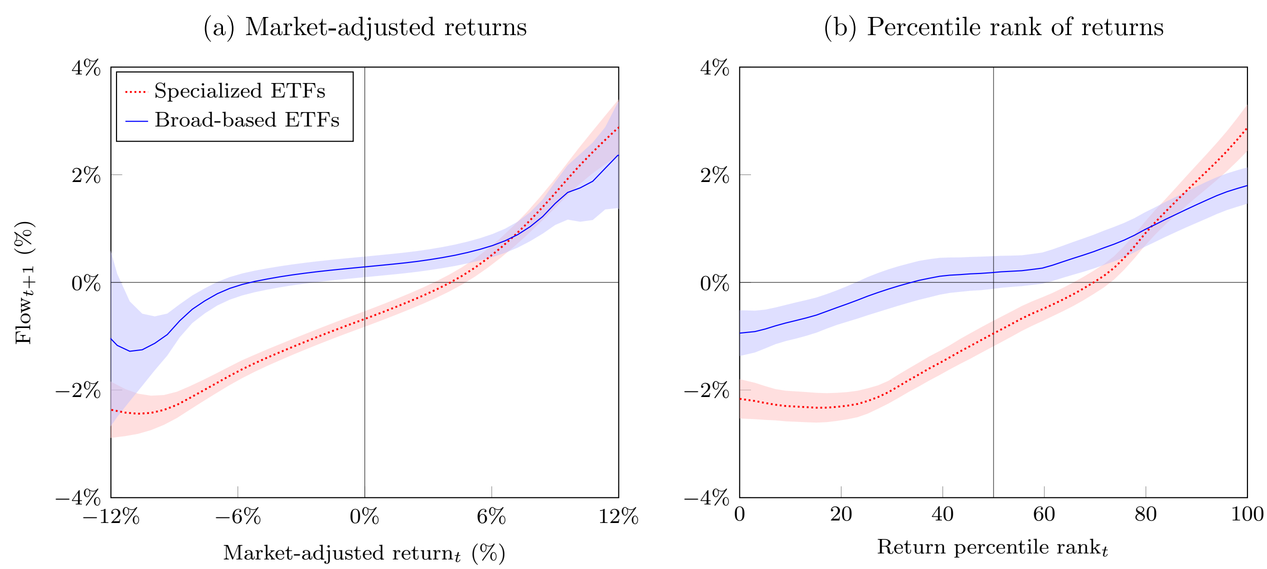


Figure F.2. Flow-Performance Sensitivity (Quarterly)

The figure presents the flow-performance sensitivity of ETFs per ETF category. Flows are computed as $100 \times (\text{AUM}_{q+1} - \text{AUM}_q \times \text{ETF return}_{q+1})/\text{AUM}_q$. Returns are raw ETF returns. We estimate a nonparametric relation between flows and returns using local polynomial approximations obtained with Stata's `-lpoly-` `command with bandwidth of 0.04. The shaded areas represent 95% confidence intervals.`

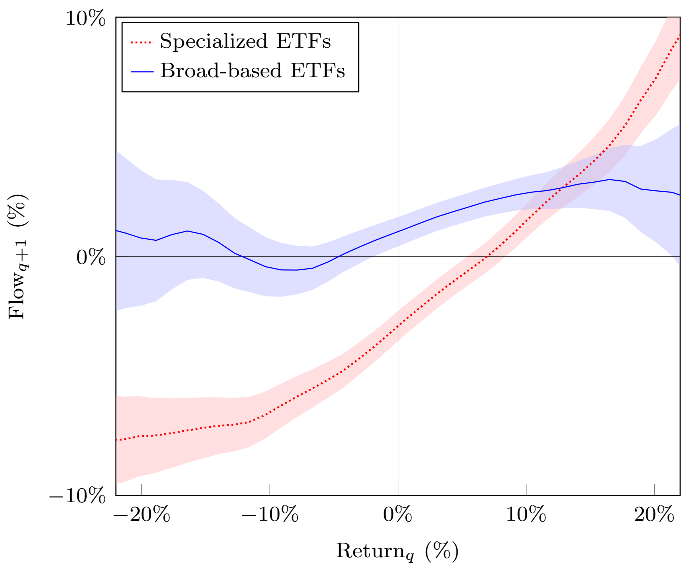


Figure F.3. Flow-Performance Sensitivity (Yearly)

The figure presents the flow-performance sensitivity of ETFs per ETF category. Flows are computed as $100 \times (\text{AUM}_{y+1} - \text{AUM}_y \times \text{ETF return}_{y+1})/\text{AUM}_y$. Returns are raw ETF returns. We estimate a nonparametric relation between flows and returns using local polynomial approximations obtained with Stata's `-lpoly-` `command with bandwidth of 0.04. The shaded areas represent 95% confidence intervals.`