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ABSTRACT

Exchange-traded funds (ETFs) are the most prominent financial innovation of the last three decades. Early ETFs offered broad-based portfolios at low cost. As competition became more intense, issuers started offering specialized ETFs that track niche portfolios and charge high fees. Specialized ETFs hold stocks with salient characteristics—high past performance, media exposure, and sentiment—that are appealing to retail and sentiment-driven investors. After their launch, these products perform poorly as the hype around them vanishes, delivering negative risk-adjusted returns. Overall, financial innovation in the ETF space follows two paths: broad-based products that cater to cost-conscious investors and expensive specialized ETFs that compete for the attention of unsophisticated investors.

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1 Introduction

Over the last 30 years, the asset management industry has been disrupted by the growth of exchange-traded funds (ETFs), investment vehicles that passively replicate the performance of some index and can be traded continuously in the stock market. In 2020, the assets managed by ETFs in the U.S. alone surpassed the $5 trillion mark, amounting to about 17% of the total assets in U.S. investment companies. To date, over 3,400 ETFs have been launched, covering all the way 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. Just as easily as they can trade a single stock, investors can now trade large baskets of any asset class (stocks, bonds, commodities, etc) using ETFs.

ETFs embody the current trend of democratization of the investment process.[1] In this new environment, investors have gained direct access to financial markets (e.g., low-cost online brokers and self-managed 401K plans) as well as to real-time financial information through commercial providers and social media. As investors are faced with an abundance of information, suppliers of financial products must compete more strongly for investor attention.[2] However, since most ETFs are transparent investment vehicles that passively replicate indexes, ETF suppliers cannot tout portfolio managers' past performance and skill (as in mutual funds; see Jain and Wu, 2000) or rely on product opaqueness to promise high yields and shroud risk (as in structured products; see Célérier and Vallée, 2017; Vokata, 2021).[3] Instead, they need to device other competitive strategies to make their investment products attractive to investors. Thus, the ETF industry offers a unique opportunity to study how financial innovators design their products to draw investor attention in a space in which products are inherently simple and transparent.

To gain intuition on the dynamics of product innovation in this market, Figure 1 provides a bird's eye view of the evolution of the ETF "species" over time. The left axis shows the annual fees that these products charge their investors, a proxy for their direct cost, and the color of the markers reflects the degree of product differentiation with respect to the existing product offerings 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

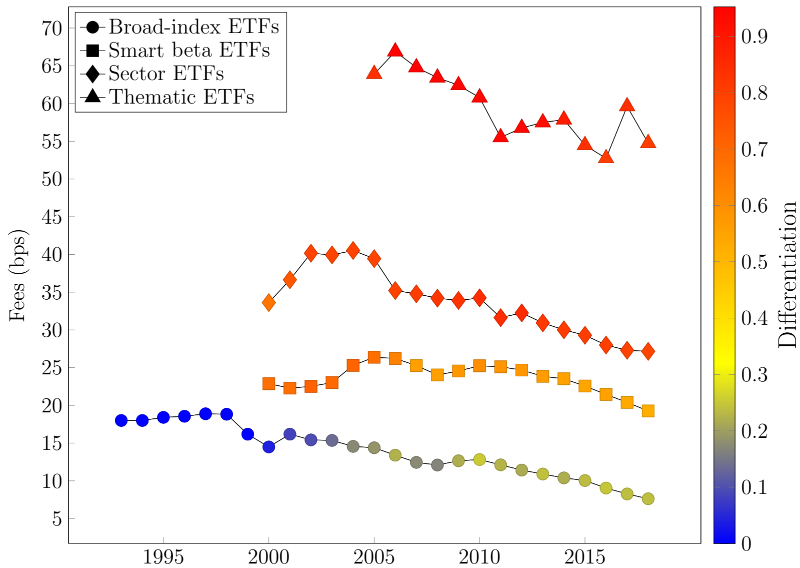
[1] See Barbara Novick (BlackRock's vice chair and co-founder), "How Index Funds Democratize Investing," *Wall Street Journal*, January 8, 2017.

[2] Attention by investors has been shown to be a first-order driver of investor demand, see, e.g., Da, Engelberg, and Gao (2011).

[3] 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 (Greenwood and Hanson, 2013; Gennaioli, Shleifer, and Vishny, 2012), mutual funds (Massa, 1998; Cooper, Gulen, and Rau, 2005; Kostovetsky and Warner, 2020), and equity offerings (Baker and Wurgler, 2007).

Figure 1. The Evolution of the ETF Species

The figure shows the average fees 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 2 provides information about the classification of ETFs.



segment of the market has led to lower fees. To preserve high margins, the response of the ETF industry has been to launch higher priced breeds of ETFs that diverged from existing products, focusing on more specialized indexes. It appears, therefore, that the industry has progressed towards more differentiated products, which have allowed incumbents and new entrants to remain profitable despite tougher competition.

We conjecture that this product evolution can be interpreted within the framework of the Bordalo, Gennaioli, and Shleifer (2016) model of industrial organization, which describes 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. In the context of the ETFs financial innovation, price maps into the management fees while quality translates into product attributes that appeal to some investors—e.g., the expectation of high returns, an opportunity to gamble, or a portfolio selection approach that is socially-responsible or complies with religious values.

Consistent with this framework, we document that as price competition becomes tighter, ETF providers offer new breeds of ETFs that were innovative along the quality dimension. The resulting configuration of the market reflects the two types of competition, with some

ETFs offering low-cost access to broad-based indexes and others charging high fees and offering access to specialized segments of the market that respond to investors' preference for popular themes. Analogously to the evidence for closed-end funds in the 1980s (Lee, Shleifer, and Thaler, 1991), stocks in the portfolios of specialized ETFs are overvalued; consequently, these ETFs deliver negative performance in the years following launch. Overall, our findings suggest that the most important financial innovation of the last three decades, originally designed to promote cost-efficiency and diversification, has also provided a platform to cater to investors' irrational beliefs.

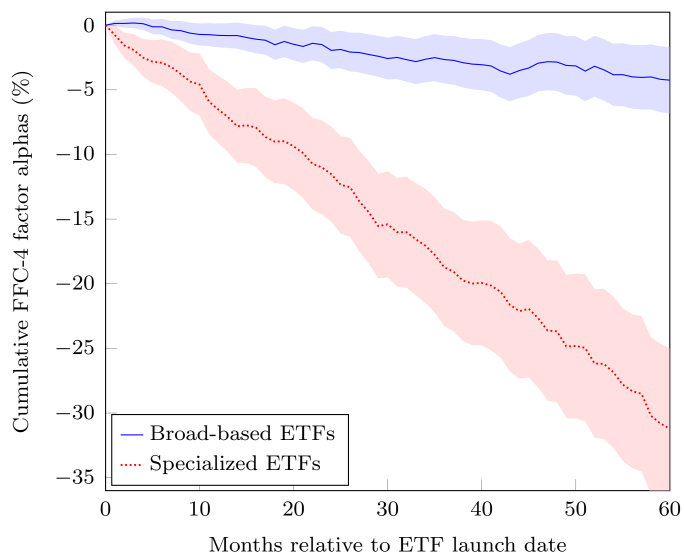
Our study is organized in two parts. In the first part, we describe the segmentation in the ETF industry that corresponds to the price-salient and a quality-salient equilibria in Bordalo, Gennaioli, and Shleifer (2016). Our sample consists of a large majority of the equity ETFs that ever traded in the 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, the two groups differing 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 manage only 18% of the industry's assets yet generate about 36% of the industry's fee revenues. We show that 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 undiversified and differentiated portfolios and charge higher fees.

Further corroborating the evidence of multiple equilibria, 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 positive 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 study, we investigate the purpose of specialized ETFs. In other words, we study the nature of "quality competition" in the ETF space. The obvious conjecture is that specialized ETFs charge high fees because they are able to generate better performance, for example, by picking investment styles that will outperform. Our tests show that this is not the case. In fact, we find that the performance of specialized ETFs is disappointing after adjusting for their risk exposure. A portfolio of all specialized ETFs earns a negative risk-adjusted performance of 3.1% per year, after fees. This underperformance is due mostly to newly launched specialized ETFs, which lose about 6% per year in risk-adjusted terms. In comparison, the performance of broad-based ETFs is slightly negative, though statistically indistinguishable from zero. The absolute size of the underperformance of specialized ETFs is non-negligible in dollar terms given that these funds manage 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.



We then explore two potential explanations for the severe underperformance of specialized ETFs that we observe. The first possibility is that specialized ETFs are used by rational investors to hedge their exposure to risk factors. According to this interpretation, through these products, investors obtain insurance for risks to which they are exposed and, for this reason, they are willing to bear a cost in terms of lower returns. More broadly, this explanation relates to the view of financial innovation as a way to achieve market completion (Allen and Gale, 1994; Duffie and Rahi, 1995). While in principle ETFs can be replicated using the underlying assets, they can still be interpreted as a form of market completion in that they reduce transaction and search costs for a large swath of investors. However, we do not find evidence consistent with an insurance motive. For example, the portfolio of stocks that are most negatively correlated with the portfolio of all specialized ETFs does not earn abnormally positive returns, which should be the case if it were a risk factor of hedging concern. While an insurance motive predicts that investors willingly sacrifice performance, low returns of specialized ETFs are followed by capital outflows, suggesting that investors are disappointed by the poor performance. Relatedly, we document that stocks that are included in specialized ETFs experience, after launch, a steep drop in their media sentiment relative to the pre-launch period.

The second explanation is that the demand for specialized ETFs comes from investors who chase investment ideas that, in their view, will produce higher expected returns, but—in reality—the underlying assets of these ETFs are overvalued and therefore underperform after issuance. Our results 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), have more positive earnings surprises, and in general display traits that were 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 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. Relatedly, specialized ETFs are very popular among sentiment-driven investors, i.e., those that trade through the online platform Robinhood, which has become famous in recent years for hosting investment frenzies (Barber, Huang, Odean, and Schwarz, 2020). Finally, specialized ETF investors are more prone to positive feedback trading (De Long, Shleifer, Summers, and Waldmann, 1990).

Put together, these results suggest that ETF providers cater to investors with extrapolative beliefs (Barberis and Shleifer, 2003; Greenwood and Shleifer, 2014; Barberis, Greenwood, Jin, and Shleifer, 2018; Da, Huang, and Jin, 2020), i.e., those who view recent performance of a security or a sector as representative of its future performance, or to investors with diagnostic expectations (Bordalo, Gennaioli, and Shleifer, 2018; Bordalo, Gennaioli, La Porta, and Shleifer, 2019) who, after observing good performance realizations of the ETF components, overweight the probability that the new ETF will outperform in the future as well. These investors also tend to neglect the risks that arise from the underdiversification of specialized portfolios, consistent with the theory of Gennaioli et al. (2012).

This description of financial innovation via ETFs also resonates with the model of Simsek (2013a) (also see Simsek, 2013b), in which new financial products are used both by investors seeking risk sharing and by those with different beliefs interested in speculation. In the case of ETFs, it appears that broad-based products are primarily geared toward the risk-sharing goal, while specialized ETFs are preferred by speculators. In the model, innovators endogenously choose to supply products for which the speculative motive is stronger and, consequently, volume is higher. This prediction is consistent with the recent proliferation of specialized ETFs for which the turnover is significantly higher.[4] Moreover, the finding of more intense trading in specialized ETFs, in combination with the evidence that specialized ETFs are relatively more popular with retail investors, suggests that the users of these products are more likely to incur losses from excessive trading relative to investors holding a well-diversified portfolio (Barber and Odean, 2013; Barber et al., 2020).

Overall, our results provide a new narrative for the evolution of the most transformative financial innovation of the last three decades. The original ETFs, which are broad-based products, are beneficial investment platforms, as they reduce transaction costs and provide diversification. Specialized ETFs ride the same wave of financial innovation. However, these products compete for the attention of unsophisticated investors who chase past performance and neglect the risks arising from the underdiversified portfolios. Specialized ETFs, on average, have generated disappointing performance for their investors.

2 Data

2.1 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 to equity-focused ETFs that hold some 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, active.[5] The final sample contains 1,080 distinct U.S. equity ETFs that satisfy all requirements. 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 dataset that includes holdings information on the earliest date (closest to the launch date). We use

[4] While turnover is not a direct source of income for ETF providers, arguably, the supply of products that cater to investors' speculative demand attracts assets under management, which, in turn, generate revenues through fees.

[5] Some active ETFs, notably those issued by the provider ARK, exhibit great performance in the year 2020. Using the newly available return data from CRSP for 2020, we have updated our results and included active ETFs in the specialized category. Using this updated sample, we find that the evidence of underperformance of specialized ETFs is confirmed in the whole sample and in 2020 as well. The reason is that the weight of the ARK ETFs is relatively small within the specialized category, about 3.9% in December 2020.

the other dataset to complement missing data when needed.

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

2.2 Classification of ETFs

We group ETFs based on their investment objective. We classify as *broad-based* all the ETFs that track broad market indexes, i.e., the broad-index and smart-beta categories in Figure 1. 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 the figure.

With regard to the specific categories in Figure 1, the *thematic* group includes ETFs that, according to the data provider Bloomberg, track multiple industries that are tied by a theme. If they track a single industry, they belong to the *sector* category.[6] *Smart-beta* ETFs are identified mainly using the Strategic Beta field in Morningstar. Finally, we identify as *broad-index* ETFs funds for which the Morningstar category Index Selection variable has the value *Market Capitalization* and that are not smart beta funds.[7] We do not create a separate category for ESG products because they cut across multiple classes of ETFs with different degrees of diversification. In particular, ESG ETFs are classified as specialized if they are sector ETFs according to the CRSP Classification codes (e.g., the ALPS Clean Energy ETFs). The remaining ESG ETFs, which are more diversified products (e.g., the iShares ESG Screened S&P 500 ETF), are included in the broad-based category.

Over the sample period, there are 554 broad-based ETFs—i.e., 90 broad-index and 464 smart beta ETFs—and 526 specialized ETFs—i.e., 115 thematic and 411 sector ETFs.

[6]Specifically, we reference the Bloomberg field *FUND_INDUSTRY_FOCUS*. Moreover, ETFs with 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 (AI), clean energy, or gender themes, and as sector ETFs otherwise.

[7]For the remaining equity ETFs, we rely on *LIPPER_CLASS* to classify funds as either broad-index or smart-beta. *LIPPER_CLASS* values of *LCVE*, *MCVE*, *MLVE*, *SCVE*, *LCGE*, *MCGE*, *MLGE*, *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.

3 The "Walmarts" and "Starbucks" of the ETF World

3.1 Theoretical Background

The ETF market has developed substantially since the 1990s. To date, in the U.S. alone, over 3,000 exchange-traded funds have been launched; of these, more than 1,000 invest in U.S. equities. These 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 bps to over 150 bps per year). What are the factors that drive the introduction of new products in this space?

Historically, the first ETFs, launched in the mid-1990s, tracked broad-based indexes, held large portfolios, and charged low fees. These products were viewed as alternative investment vehicles to index futures contracts. Toward the late 1990s, ETFs were marketed as alternative investment vehicles to index mutual funds.[8] Specialized ETFs began to appear around the dot.com boom, 1999; they tracked primarily the technology sector and charged higher fees.

We conjecture that the proliferation of ETF products is the result of issuers competing for investors' attention by emphasizing *either* the low price *or* other unique features of the product that are different from the price. If investors give more weight to a product feature as a function of its salience, i.e., its distinctiveness relative to the competition, then firms have an incentive to attract attention to a specific product characteristic in order to gain market share.

Bordalo, Gennaioli, and Shleifer (2016) use this idea to describe competitive strategies in product markets and extend their analysis to financial markets, looking specifically at financial innovation. Product markets can gravitate around either (*i*) a price-salient equilibrium, in which products are commoditized and producers compete by offering low prices—the "Walmarts"—or (*ii*) a quality-salient equilibrium in which prices are high and producers differentiate themselves by offering distinct product features—the "Starbucks". Paralleling this market structure, in financial markets, there are products that improve transaction efficiency, and there are products that attract investors' attention to specific features, like high promised returns, while shrouding risk, generating "reaching-for-yield" behavior.

We argue that these two equilibria provide a fitting description of the situation in the ETF market. The "price" feature is reflected in the fees that ETFs charge. Thus, the inexpensive and broad-based index-tracking ETFs are the commoditized products that could be mapped into the price-salient equilibrium—the Walmarts of the ETF world. This group of ETFs appeals to price-conscious investors who seek exposure to an asset class at the lowest possible cost. In comparison, more expensive, less-diversified ETFs are part of the quality-

[8]For example, Guedj and Huang (2009) explain that because ETFs have liquidity advantages over index funds, they may appeal to a broader clientele.

salient equilibrium—the Starbucks. The latter products correspond to the specialized ETFs. Investors in these ETFs are less concerned about paying a high price or losing diversification as long as they can get exposure to their desired themes. In this segment of the market, ETF issuers attract investor attention by designing products that cater to investors' expectations of high future returns.

In this framework, an ETF's expected return is a measure of product quality.[9] Importantly, some investors may not act rationally when forming expectations about future returns. For example, investors may suffer from representativeness bias and therefore extrapolate past performance into the future (Greenwood and Shleifer, 2014; Barberis et al., 2018; Cosemans and Frehen, 2021) or to have diagnostic expectations (Bordalo et al., 2018, 2019). Catering to this audience, issuers can make the quality characteristic salient by launching ETFs focusing on segments of the market that experienced superior past performance.

One can extend the notion of "quality" beyond subjective expected returns to encompass non-standard preferences. For example, some studies propose that investors have a preference for gambling (Brunnermeier and Parker, 2005; Brunnermeier et al., 2007; Mitton and Vorkink, 2007; Barberis and Huang, 2008; Kumar, 2009). In that case, issuers could attract investors by offering products with a positively skewed payoff profile. Moreover, investors may be interested in investing in themes they fancy, such as responsible and sustainable manufacturing, or in firms that comply with religious values. Some authors argue that an investment that complies with investors' system of beliefs generates nonpecuniary benefits in their utility function (as in Fama and French, 2007; Pástor, Stambaugh, and Taylor, 2021). Therefore, new ETFs could cater to this demand by constructing portfolios around these themes.

3.2 Testable Predictions

The theoretical framework discussed above has some testable implications. The predictions of the Bordalo, Gennaioli, and Shleifer (2016) model that we derive for the ETF space can be tested against the traditional interpretation of financial innovation.

According to the traditional view, financial innovation helps to complete the market, allowing investors to achieve a broader set of payoffs (Allen and Gale, 1994; Duffie and Rahi, 1995). Even though ETFs replicate cash flows profiles of securities that already exist in the market, they increase the accessibility of these portfolios to investors by reducing search and trading costs. The variety of products coming to the market reflects the heterogeneity in

[9]Supporting this view, previous research shows that financial intermediaries tend to emphasize products' promised headline return while shrouding associated risk (Henderson and Pearson, 2011; Célérier and Vallée, 2017; Vokata, 2021).

investors' endowments and their need to insure the risks associated with their exposure—i.e., their hedging demand. Viewed through this lens, financial innovation responds to rational investors' demand and is welfare improving.

The traditional and "competition for attention" frameworks converge on the rationale for inexpensive broad-based ETFs. According to the two views, these products fulfill investors' needs—diversification and hedging—at a low cost.

The frameworks, however, differ in the answer to why specialized ETFs exist. According to the traditional view, these underdiversified products must offer benefits to investors as hedging tools.

In contrast, according to the "competition for attention" view, specialized ETFs are designed to attract consumers' attention to a feature other than their price. In the context of financial innovation, investors' attention could be attracted by offering access to a theme that matches their expectations of future performance. If investors have high sentiment about a specific investment idea, then new ETFs are likely to be launched around this theme.[10]

Given our empirical setting, we introduce an additional conjecture. Specifically, if there are limits to arbitrage and security prices are overvalued because of great demand for an investment theme, it is plausible that the new ETFs that are created to cater to the same demand will also be overpriced. For example, investor demand for cannabis-related ETFs will be high when cannabis stocks are in big demand and, therefore, overvalued. As a consequence, new specialized ETFs will underperform due to the overvaluation of their portfolio holdings.

To summarize, the "competition for attention" framework predicts that newly launched specialized ETFs focus on attention-grabbing themes. Stocks in these ETFs are likely to be overvalued, meaning that these ETFs are likely to deliver negative risk-adjusted performance that is disappointing for investors. In addition, they are likely to attract unsophisticated investors who form expectation in a non-rational way.

4 Empirical Analysis: Segmentation in the ETF Space

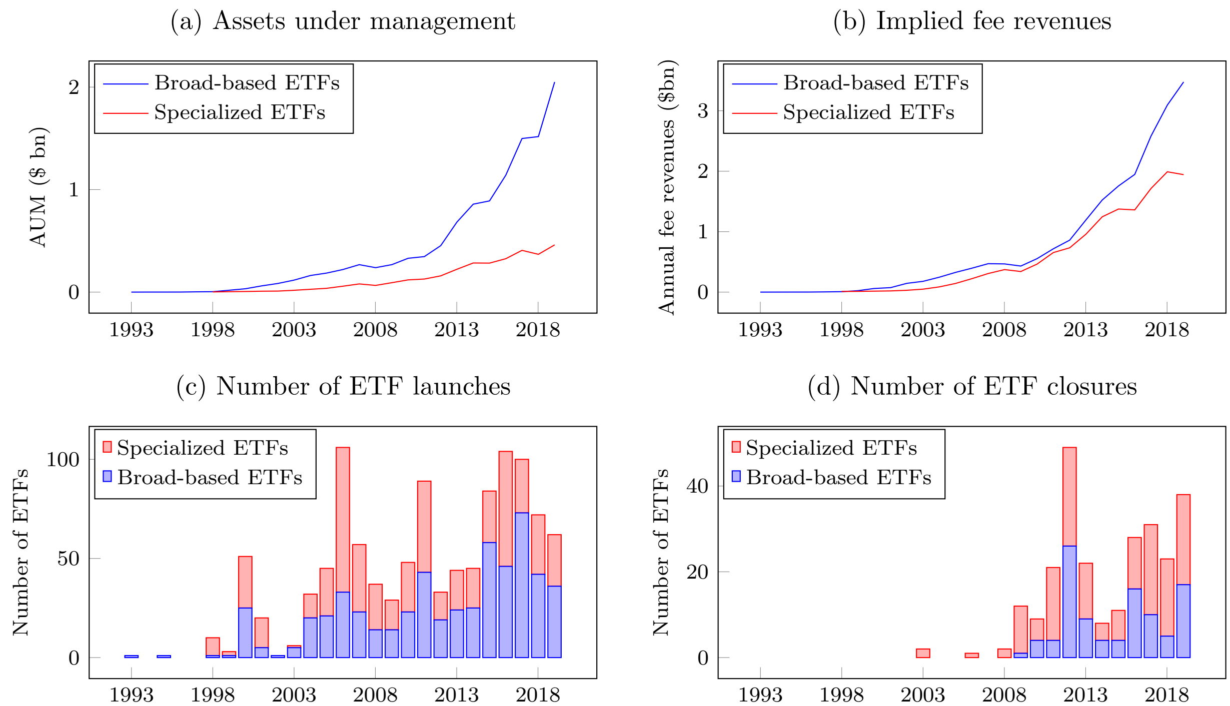
Figure 3 shows the time-series evolution of the assets under management (AUM) and implied revenues (percentage fees $\times$ AUM), as well as the time series of ETF launches and closures.

Panels (a) and (b) show that the assets managed by broad-based ETFs grows exponentially over the years, whereas the growth of the assets in specialized ETFs is less striking.

[10] In a similar vein, Henderson, Pearson, and Wang (2020) find that structured equity products are designed around stocks with high investor sentiment.

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 × AUM. Panel (c) presents the number of ETF launches and Panel (d) shows the number of ETF closures.



By the end of 2019, broad-based ETFs account for about 82% of the assets invested in equity-based ETFs, and specialized ETFs account for the remaining 18%. Despite their relatively small share, specialized ETFs account 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) 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. 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 significantly smaller portfolios 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 (compare medians of 35 versus 58 basis points, respectively). These statistics support the conjecture that providers of specialized ETFs compete on quality by offering portfolios that are concentrated in smaller portions of the market, and hence more risky—e.g., see the difference in standard deviation of abnormal returns—while charging a higher management fee for their service. Turnover is significantly larger for specialized products, consistent with the notion that these products are used for speculative purposes (e.g., Simsek, 2013a).

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 annualized expense ratio. *Turnover* is the average daily turnover over the six months since launch. *Short interest* is the average monthly short interest ratio over the six months since launch. *Abnormal return* is monthly ETF return in excess of CRSP value-weighted return over the 60 months since 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 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 (bp)	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
Short interest (months 1–6; %)	426	4.97	11.04	0.03	0.42	1.17	3.98	24.25
Abnormal 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 (bp)	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
Short interest (months 1–6; %)	406	6.80	15.16	0.10	0.50	1.57	6.01	32.34
Abnormal 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

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).[11] The figure shows that over time two clusters of products have emerged. On the one hand, broad-based ETFs, the early comers to the market, tend to charge lower fees and to be more similar to one another. On the other hand, specialized products, which proliferate in the late sample, are more differentiated and expensive.

Based on the size of the circles in Figure 4, which capture ETFs' relative AUM, we can also conclude that there is more concentration in the broad-based segment of the market. This is probably a consequence of price competition leading to a winner-takes-all equilibrium. Instead, higher fees in the specialized segment allow multiple differentiated products to survive even with smaller assets under management, leading to a more equalized distribution of market share in this part of the industry. Table 1 shows that the distribution of revenues generated by broad-based ETFs largely matches that of specialized ETFs. For example, as of 2019, the median annual fee revenue is nearly \$1m in each group and the revenues at the 75$^{\text{th}}$ percentile are 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) pull higher revenues due to their sheer size.

Further, we note that while in broad-based ETFs competition has driven fees down (see Figure 1), in the specialized segment, fees decline only slightly even though the supply of specialized products increases substantially over time. The reason for this is likely to be that specialized ETFs are very differentiated, so new products entering are not directly competing with existing ones. Arguably, there exists a first-mover advantage that increases the barriers to entry into a specific theme. Specifically, investors appear to value liquidity when choosing ETFs (Khomyn, Putniņš, and Zoican, 2020). Given that the demand for specific themes is limited, it is unlikely that multiple products with the same theme would attract high liquidity. Thus, new ETF providers are discouraged from launching competing products in small niches of the market.[12]

Another set of results demonstrates the segmentation in the ETF market. Table 2 studies

[11]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.

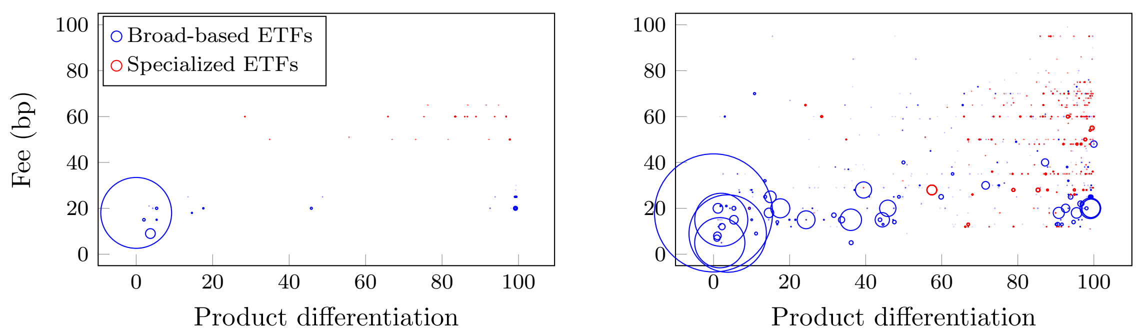
[12]Additional evidence on the bifurcation of the market comes from textual analysis. We use the names of ETFs products to form word clouds, presented in Appendix Figure A.I. These clouds show that names of broad-based ETFs include repeating terms related to general index names, e.g., S&P 500, Russell 1000, etc. In contrast, the cloud that uses specialized ETF names is composed of many more terms, with lower frequency. It includes industry and specialized words, like healthcare, information, and cannabis.

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 bubble represents one ETF and the size of the bubbles represents relative share of assets under management across all ETFs. Blue bubbles represent broad-based ETFs and red bubbles represent specialized ETFs.

(a) Differentiation, Fees, and AUM: 2002

(b) Differentiation, Fees, and AUM: 2019



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 or diagnostic beliefs and, in this sense, are a measure of quality. The results in Panel A suggest that investors in broad-based ETFs pay more attention to price than investors in specialized products, as their sensitivity to fees is significantly more negative. In the late sample, specialized investors' sensitivity to fees is indistinguishable from zero providing clear evidence in support of a quality-salient equilibrium in which consumers neglect price.[13]

In Panel B of Table 2, we study how the salience of an ETF in investors' perception, proxied by media attention for the stocks in its portfolio, modifies investors' response to different product attributes. Again, the evidence suggests that two different equilibria prevail in the market. The investors in ETFs holding stocks that attract 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.

In Figure 5, we examine the flow-performance sensitivity of broad-based and specialized ETFs. In each month t, we compute next-period flows as $100 \times (\text{AUM}_{t+1} - \text{AUM}_t \times$

[13] An additional reason for investors in specialized ETFs to neglect 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. *SP* is a dummy variable that equals 1 if an ETF is a specialized ETF. *HM* 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				**Panel B: Flows and High Media Sentiment**			
Dependent variable:	Flows$_{t+1}$ (%)			Dependent variable:	Flows$_{t+1}$ (%)		
Sample period:	2000–2019	2000–2009	2010–2019	Sample period:	2000–2019	2000–2009	2010–2019
Fee (bp)	−0.04***	−0.07***	−0.03***	Fee (bp)	−0.03***	−0.07***	−0.02***
	(−6.91)	(−4.02)	(−5.89)		(−6.12)	(−3.76)	(−5.04)
Fee × SP	0.01**	−0.01	0.02***	Fee × HM	0.02**	0.01	0.02*
	(2.05)	(−0.30)	(2.76)		(2.08)	(0.41)	(1.91)
Return rank$_t$	0.04***	0.03***	0.04***	Return rank$_t$	0.05***	0.04***	0.05***
	(9.73)	(3.63)	(9.30)		(12.61)	(4.98)	(12.15)
Return rank$_t$ × SP	0.02***	0.02*	0.01***	Return rank$_t$ × HM	0.01	0.02	0.00
	(3.07)	(1.66)	(2.91)		(1.11)	(1.19)	(0.63)
SP	−1.55***	−0.38	−1.86***	HM	−1.12**	−1.83	−0.77
	(−3.23)	(−0.31)	(−3.86)		(−2.10)	(−1.41)	(−1.34)
log(AUM$_t$)	−0.13**	−0.87***	0.01	log(AUM$_t$)	−0.13*	−1.16***	0.03
	(−2.00)	(−3.62)	(0.16)		(−1.79)	(−3.48)	(0.50)
log(Age$_t$)	−1.84***	−1.35***	−1.93***	log(Age$_t$)	−1.84***	−1.11*	−1.98***
	(−12.39)	(−2.90)	(−12.33)		(−11.91)	(−1.89)	(−13.21)
Year FE	Yes	Yes	Yes	Year FE	Yes	Yes	Yes
Observations	80,770	17,821	62,949	Observations	63,828	12,282	51,546
Adj R^2	0.042	0.031	0.047	Adj R^2	0.044	0.035	0.047

ETF return$_{t+1}$)/AUM$_t$. Then, we estimate a nonparametric relation between flows and raw returns using local polynomials approximations.[14]

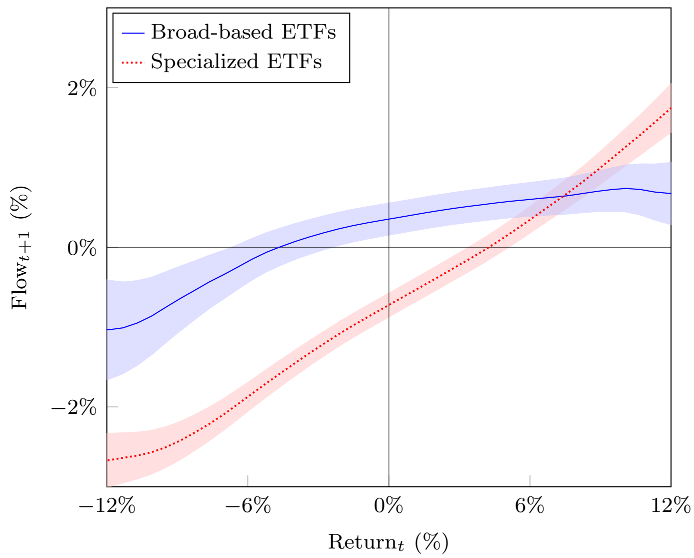
Consistent with the results in Table 2, the figure shows that the return-chasing behavior of investors in broad-based ETF differs from that of investors in specialized ETFs. Dannhauser and Pontiff (2019) document return chasing in ETFs in general; however, here we find that the sensitivity of flows to past returns is significantly higher for specialized ETFs, consistent with more attention to quality-salient features, i.e., past returns, in this segment of the

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

market.[15]

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. The shaded areas represent 95% confidence intervals.



5 The "Quality" of Specialized ETFs

In contrast to the clear value created by broad-based ETFs, the case for value creation by specialized ETFs is less obvious. Given the high fees that investors are willing to pay to invest in these products, the first conjecture we make is that investors benefit from investing in specialized ETFs along some pecuniary dimension.

The first possibility we entertain 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. Specialized ETFs, therefore, would provide a low-cost tool for accessing these investment ideas.

[15]One might interpret these results as consistent with an extended version of the Berk and Green (2004) model, in which Bayesian investors learn the risk-adjusted performance of the strategies underlying specialized ETFs and flows are the result of this inference. This is not likely to be the explanation for the observed return chasing in the case of specialized ETFs for two reasons. First, these products, on average, display a significantly negative alpha compared to broad-based ETFs (see Section 5), while, according to Berk and Green (2004), competition among investors should drive performance to zero. Second, as we show later, the investor base in specialized ETFs is tilted towards retail investors, which are considered to be less sophisticated than institutional investors and, therefore, are less likely to engage in Bayesian learning.

The second possibility is that specialized ETFs create value by providing hedging against some risks that investors care about. In other words, these products might operate like an insurance policy. For this reason, their risk-adjusted performance would not have to be positive, to the extent that it negatively correlates with some risk factor that is of hedging concern to investors. We emphasize that the risk factor has to be common across investors, as opposed to investor-specific, because idiosyncratic hedging demand would be washed out in the aggregation of demand across investors and we would not observe an effect on equilibrium prices.

Thus, the first test that discriminates between these two possibilities relies on measuring the risk-adjusted performance of specialized ETFs. The next subsection describes this analysis and the results.

5.1 The Performance of Specialized ETFs

To measure the performance of specialized ETFs, we use a standard approach in the asset pricing literature. We form a monthly portfolio that holds all the available ETFs in the market. We separately consider the universes of broad-based and specialized products. The portfolios are re-formed each month and are market-capitalization-weighted.[16] Then, we run regressions of ETF returns (net of fees) of these portfolios in excess of the risk-free rate on commonly used risk factors,[17] as is customary in the asset pricing literature.

In Table 3, we present the intercept from these regressions, which reflects the risk-adjusted performance of the portfolios, and is commonly labeled "alpha." The table shows that specialized ETFs persistently generate negative alphas of about -3.1% per year (i.e., $-0.27\% \times 12$) for the Fama-French-Carhart four factors (Fama and French, 1993; Carhart, 1997). Underperformance is smaller (but still negative) when using more elaborate factor models. The underperformance of specialized ETFs cannot be attributed to their high fees (0.55% on average on annual basis; see Table 1). In comparison, using the same risk model, broad-based ETFs generate negative alpha of about -0.5% a year (i.e., $-0.04\% \times 12$), which is closer to the fees they charge. Importantly, the difference in alphas of specialized and broad-based ETFs (about -2.9% per year) is an order of magnitude larger than the difference in fees between the two groups. Hence, the relative underperformance of specialized ETFs cannot be accounted for by the higher fees that they charge.

To summarize, this analysis suggests that specialized ETFs do not create value for their

[16] The results with equal-weighted portfolios are similar as shown in Appendix Table A.I.

[17] 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`.

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. In Panel C, we identify *old* ETFs that were launched more than five years prior in each month. We then form portfolios consisting of all *old* 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*, *FFC6*, 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-Carhart 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	FFC6	Q
Panel A: All Months							
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	FFC6	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)
Panel C: Months > 60							
	Excess return	CAPM	FF3	FFC4	FF5	FFC6	Q
Broad-Based ETFs	0.45	−0.01	−0.02	−0.01	−0.09**	−0.09**	−0.05
	(1.62)	(−0.30)	(−0.64)	(−0.36)	(−2.56)	(−2.56)	(−1.20)
Specialized ETFs	0.66**	−0.11	−0.11	−0.12	−0.10	−0.11	−0.07
	(2.04)	(−1.57)	(−1.57)	(−1.57)	(−1.37)	(−1.38)	(−0.99)
SP minus BB	−0.08	−0.06	−0.07	−0.08	−0.05	−0.05	−0.03
	(−1.19)	(−0.95)	(−1.10)	(−1.11)	(−0.69)	(−0.71)	(−0.45)

investors by providing outperforming investment strategies. Consequently, the high fees and lack of diversification of these products remain a puzzle. For this reason, we entertain more closely the hypothesis that specialized ETFs provide insurance against some risk factors.

5.2 Hedging Properties of Specialized ETFs

Our results suggest that specialized ETFs deliver negative risk-adjusted performance, on average. To explain investors' demand for these products in spite of their underperformance, we conjecture that specialized ETFs deliver value as a form of insurance.

In the asset-pricing language, it is possible that our earlier tests fail to capture some unobserved risk factor that investors care about—often called "a hedging concern." Specialized ETFs might be the right vehicle that allows these investors to hedge against this unobserved risk factor. For this reason, investors are willing to accept lower returns.[18]

The 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 pays a positive risk premium. To test this prediction, we construct a portfolio of stocks that have negative correlation with the portfolio of all specialized ETFs. We emphasize that, for this test, we pool all specialized ETFs together because 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 single specialized ETFs serve as a hedging tool for some groups of investors. However, this fact would not explain the negative performance of specialized ETFs in the aggregate, as it would be an idiosyncratic property.

Every month, we form five portfolios of stocks sorted on their beta on the excess return of the market-capitalization-weighted portfolio of specialized ETFs, controlling for the market factor.[19] Portfolio 1 (5) has the stocks with the lowest (highest) correlation with the specialized portfolio.

Table 4 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. This evidence, therefore, does not support the conjecture that specialized ETFs provide hedging for an underlying risk factor.

Another way to investigate whether investors hold specialized ETFs for hedging purposes is to study investors' loyalty to these products as they experience negative performance. Specifically, if the negative performance of specialized ETFs reflects an insurance premium, investors should not be disappointed, and they should stick with them in spite of the low returns.

[18] Note that the hedging motive we discuss here is different from the more narrow notion that arbitrageurs use industry ETFs as hedging tools within long-short strategies (Huang, O'Hara, and Zhong, 2020a). 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).

[19] The beta is estimated using 60-month-rolling-window regressions, requiring each stock to have at least 36 months of observations with returns. Then, we form five portfolios corresponding to the quintiles of the estimated betas based on the breakpoints of the distribution of NYSE-listed stocks, to avoid giving disproportionate influence to smaller stock listed on other exchanges (Fama and French, 1992).

Table 4. Hedging Motive

The table presents the risk-adjusted monthly performance of stocks from 2000 to 2019, per loading on the portfolio returns of 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 alpha, FF3 alpha, FFC4 alpha, FF5 alpha, FFC6 alpha, 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-Carhart 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)

To shed light on investor behavior, in Table 5, we study investor capital flows over the life of an ETF. We ask whether investors' likelihood to put new money into specialized ETFs changes over the life cycle of the product. Because there can be life-cycle patterns in flows that do not depend on the performance of the product, we benchmark specialized ETFs to the broad-based ETFs. The estimates suggest that investors are very enthusiastic about specialized ETFs at their inception, as they are more likely to put money in these products than in broad-based ETFs in the early stages of their life cycle (i.e., the positive slope on the specialized dummy). However, as time passes, investors are also more likely to lose affection for specialized products (i.e., the negative slope on the interaction between age and the specialized dummy). This disenchantment manifests itself soon after the inception of the ETFs, as suggested by the estimates in the second column, where we condition on ETFs that are less than five years old. We interpret these results 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 purchase specialized ETFs for insurance purposes. We, therefore, turn to a different hypoth-

Table 5. Disappointment in Flows

The table presents flow dynamics of 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:	Positive flow dummy	
Sample:	Full Sample	Age $\leq$ 60 months
Specialized	0.08***	0.06***
	(3.68)	(2.72)
log(Age)	−0.06***	−0.05***
	(−10.37)	(−8.35)
Specialized × log(Age)	−0.03***	−0.03***
	(−5.76)	(−3.87)
Year FE	Yes	Yes
Observations	86,465	46,362
R^2	0.040	0.023

esis to explain the demand for specialized products. The results in Table 5 reveal that these products attract a lot of investor interest around their inception. This finding may indicate that they are launched at times of positive investor sentiment for a specific investment style. Therefore, in the next section, we investigate the hypothesis that specialized ETFs are issued in response to the demand for trendy investment themes.

6 Do Specialized ETFs Cater to Irrational Investors?

The hypothesis that we test in this section is that specialized ETFs are launched in response to investors' demand that is driven by irrational expectations or non-standard preferences, such as a preference for gambling. In other words, some industries or themes are more popular among investors and achieve high valuations. Based on their extrapolative or diagnostic beliefs, investors expect past performance to continue into the future and demand securities in these segments of the market. ETF providers identify the current popular trends in the market and design ETF portfolios that satisfy this demand.[20]

Several predictions arise from this conjecture. First, if specialized ETFs ride recent

[20] 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).

trends, then the securities they hold in their portfolios should (*i*) have attracted investors' attention, and (*ii*) display traits of overvaluation. Second, because this overvaluation should at some point revert, specialized ETFs should have disappointing performance after their launch. Third, investors in specialized ETFs are likely to be unsophisticated and prone to form beliefs in a non-rational way. In the following subsections, we test these predictions.

6.1 Characteristics of the Holdings of Specialized ETFs

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

For each stock in an ETF portfolio, we measure a relevant 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.

Stocks in specialized ETFs display significantly higher pre-launch abnormal returns. This fact makes them attractive to investors with extrapolative or diagnostic believes (e.g., Greenwood and Shleifer, 2014; Barberis et al., 2018; Bordalo et al., 2018). Moreover, specialized stocks display more positive skewness, which is appealing for investors who have a preference for gambling (Brunnermeier and Parker, 2005; Brunnermeier et al., 2007; Mitton and Vorkink, 2007; Barberis and Huang, 2008; Kumar, 2009).

Incidentally, we note that also the stocks in broad-based products experience positive pre-launch returns. This finding raises the possibilities 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.[21]

Next, the table shows that stocks included in the portfolios of specialized ETFs were recently under the spotlight. Relative to broad-based portfolios, stocks in specialized ETFs experienced greater media exposure, with positive sentiment, and larger earnings surprises. Overall, specialized stocks were more likely to attract investors' attention.

Table 6 also suggests that specialized ETFs hold glamour stocks that are likely to be overvalued (Lakonishok, Shleifer, and Vishny, 1994). Specifically, stocks in specialized ETFs have a high market-to-book ratio and high short interest. These characteristics are typically

[21] For example, smart-beta ETFs are classified as broad-based because they do not have a theme or a sector focus. These ETFs hold, on average, stocks that outperformed in the pre-launch period. After launch, these funds generate negative returns. See an analysis of the performance of smart-beta stocks in Huang, Song, and Xiang (2020b).

Table 6. Portfolio Characteristics of ETFs Around Launch

The table reports the portfolio characteristics of ETFs in the two-year period before the 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. *Abnormal return* represents return in excess of CRSP value-weighted return. *Return skewness* is the skewness of returns following Ghysels et al. (2016). We use the 25^{th} and 75^{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. *Earnings surprise* denotes the average EPS surprise scaled by 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
Abnormal 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)

associated with lower future returns (Daniel and Titman, 1997; Boehmer, Jones, and Zhang, 2008; Ben-David, Drake, and Roulstone, 2015).

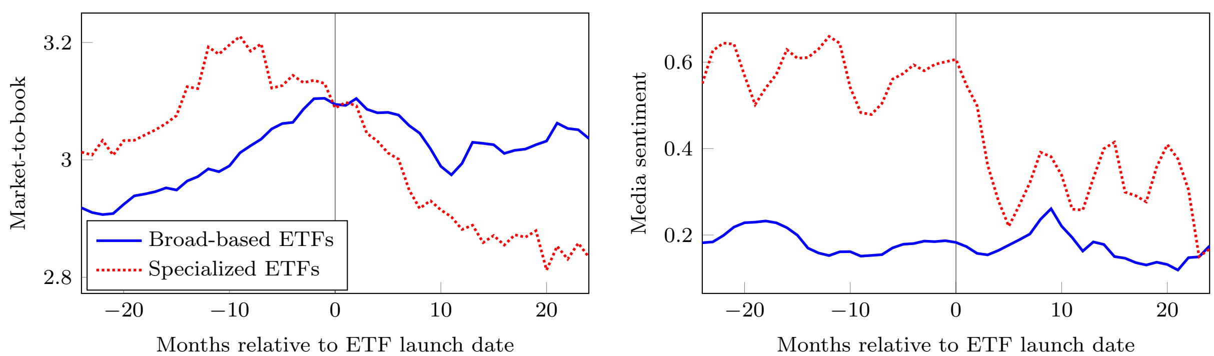
Overall, the characteristics of the securities included in the portfolios of specialized ETFs indicate that they are "hot" stocks. This evidence is also consistent with a casual observation of ETF launches in recent times. In 2019, for example, the new ETFs included products focusing on cannabis, cyber 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.

Figure 6 provides further evidence of excessive optimism around specialized stocks before the corresponding ETF launch. Consistent with Table 6, we find that specialized stocks enjoy higher market-to-book ratios (Panel A) and positive media sentiment (Panel B) prior to their launch. Second, the figure shows that the positive sentiment around specialized stocks quickly reverts in the year after launch. The 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 the time ETF provider spots a hot trend and the time the ETF reaches the market. At that point, the valuation is likely to revert to more normal levels. We study the after-launch performance in the next subsection.[22]

Figure 6. Dynamics of ETF Portfolio Characteristics

The figure presents dynamics of ETF portfolio characteristics, per ETF category. Panel (a) shows the dynamics of the market-to-book ratio, and Panel (b) shows the dynamics 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.

(a) Market-to-book (b) Media sentiment



6.2 Performance After Launch

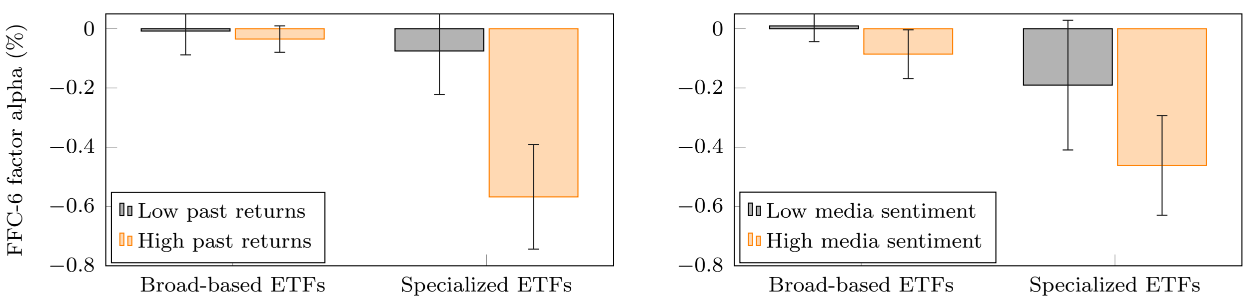
To investigate the performance dynamics of broad-based and specialized ETFs, we focus on the first five years after launch. As in subsection 5.1, we use the calendar-time portfolio approach and estimate risk-adjusted returns (alphas). In greater detail, we form calendar-time portfolios that hold all the ETFs in each of the two categories that were launched in the prior five years. Each month, new ETFs that are just launched enter the portfolio and ETFs that are delisted or were launched more than five years prior are removed from the portfolio. The ETFs in the portfolios are weighted by their lagged AUMs.

[22]After the end of our sample, a regulation change shortened the time-to-market for ETFs through 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 retard 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-Carhart six-factor model (FFC-6) alphas of the portfolios of ETFs from 2000 to 2019, split by ETF categories and stock characteristics groups (Fama and French, 1993; Carhart, 1997; Fama and French, 2015, 2018). In Panel (a), we split each ETF category into two sub-groups based on the past abnormal returns with respect to the market factor, computed as in Table 6, and in Panel (b) we split each ETF category into two sub-groups 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 sub-group. The portfolio returns are value-weighted using one-month-lagged market capitalization. To adjust returns for risk factors, we estimate FFC-6 alphas of the portfolios. The alphas are in percentage points. Error bars represent 1.96 standard error confidence intervals.

(a) FFC-6 alphas, split by past returns (b) FFC-6 alphas, split by media sentiment



The estimates are presented in the earlier Table 3. Similar to our previous findings, Panel B of Table 3 shows that specialized ETFs display negative risk-adjusted performance. Moreover, the performance of specialized ETFs is significantly lower than that of broad-based products. Importantly, the new evidence is that this underperformance is concentrated in the five-year period after launch. For completeness, Panel C shows that, after the first five years, the risk-adjusted underperformance of specialized ETFs is substantially smaller and statistically indistinguishable from zero.[23]

Figure 2 in the Introduction provides a graphical description of this evidence. In this setting, each point in the chart is produced by one regression. 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 existed for only one month; the alpha associated with month two is produced by a portfolio that includes ETFs that have a two-month lifespan. We repeat the process up to the 60-month life span.

Using double-sorted portfolios, we find support for the claim that the characteristics in Table 6 capture overvaluation of specialized ETFs. Specifically, in Figure 7, we further split ETFs based on whether the average characteristic of the stocks in the ETF portfolio is above or below the median. The figure shows that portfolios of the specialized ETFs scoring high

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

on the metrics of investor attention—i.e., past returns—and sentiment display more negative performance after launch.

Overall, our results show that specialized ETFs start underperforming right after 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 launch of specialized ETFs occurs near the peak of valuation for the underlying securities. In order words, it appears that ETF providers cater to excessive optimism for the investment themes to which the underlying stocks relate.

6.3 Who Invests in Specialized ETFs?

To study more directly if ETF providers cater to unsophisticated investors, in the last part of our analysis, we investigate the investor clienteles of the two categories of ETFs. We focus on the period right after the launch of the products, as these early investors are the likely targets of ETF providers.

We start by using regulatory filings by institutional investors. In particular, the SEC 13F form reports the institutional owners of an ETF.[24] Institutional investors include mutual funds, hedge funds, pension funds, banks, insurance companies, endowments, etc. Our working assumption is that institutions are on average more sophisticated than retail investors, i.e., their investment decisions are less prone to systematic biases (e.g., French, 2008; Stambaugh, 2014).

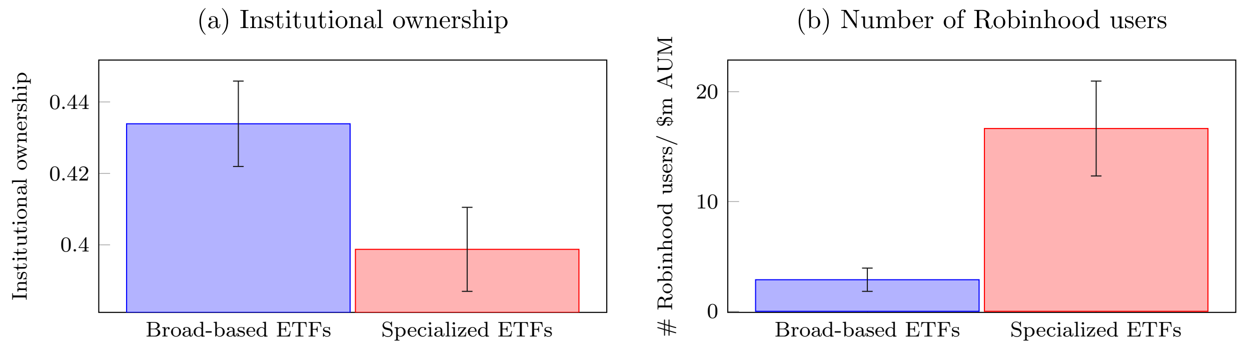
Figure 8, Panel (a), reports the average fraction of shares owned by institutional investors in the first four quarters after launch. The panel shows that institutions own about 43% of the market capitalization of broad-based ETFs in their first year. In contrast, institutions own a significantly lower share of the market capitalization of specialized ETFs, at about 39%. Because shares not owned by 13F-reporting institutions are either owned by smaller (non-reporting) institutions 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 ETFs universe, supporting the view that unsophisticated investors are more likely to populate the clientele of specialized ETFs.

We can also gain direct insights into ownership by retail investors through user data from the discount brokerage Robinhood. These data are available starting in 2018 and include the number of Robinhood users holding each security. The Robinhood platform has

[24] 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 8. ETF Ownership Around Launch

The figure presents the ownership structures of ETFs around 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 assets under management ($m). Panel (a) reports the 13F ownership, and Panel (b) reports the number of Robinhood users per AUM. Bar charts represent the average ownership, and error bars represent 1.96 standard error confidence intervals.



recently become popular for the investment frenzies characterizing its users.[25] Panel (b) of Figure 8 shows that the number of Robinhood users scaled by ETF market capitalization is substantially higher for specialized ETFs than for the broad-based ones 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.[26]

Indeed, examining the portfolios of Robinhood users around the launch of ETFs provides further support for the hypothesis that specialized ETFs are launched in trendy segments of the market. In Figure 9, we plot the holdings of stocks in ETF portfolios by Robinhood users in an event study around ETF launches. 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.[27] We repeat a similar analysis for the number of users holding the ETFs themselves.

The results in Panel (a) of Figure 9 show that the number of users holding the stocks that

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

[26]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.

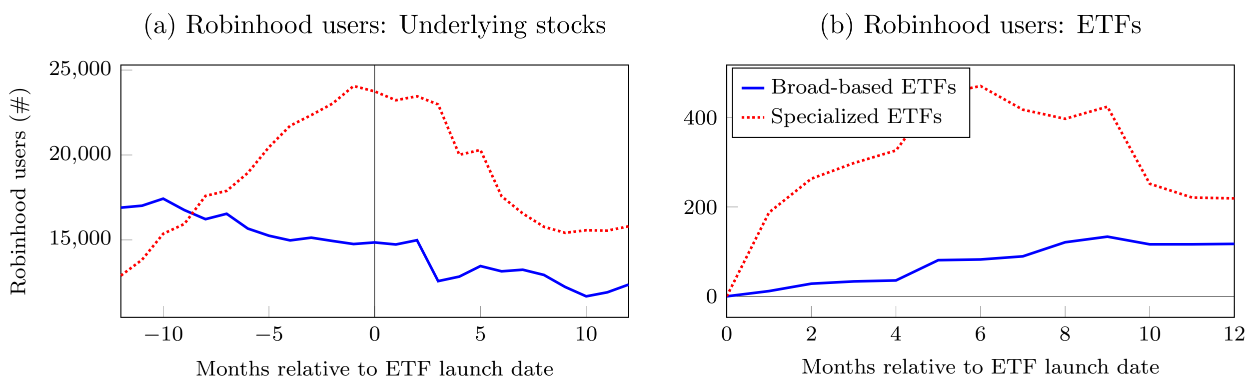
[27]Due to the skewness of the holdings data, adjusting user holdings by the mean results in very high cross-sectional variance in some months. Adjusting by the median produces more stable estimates.

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 9, Panel (b)), though not at the same rate as the underlying stocks do. Investors 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.

Figure 9. 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 launches, 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.



Another way to learn about the sophistication of the clienteles of broad-based and specialized ETFs is to study their demand for these securities in response to past performance. Prior research shows that investors in ETFs chase past performance (Dannhauser and Pontiff, 2019). Here, we find that this tendency is far stronger in specialized ETFs than in broad-based ETFs (see Figure 5 shown earlier). This empirical pattern is consistent with positive feedback trading (De Long et al., 1990) and further suggests that investors in specialized ETFs are less sophisticated than those in broad-based ETFs. While this behavior could make sense in actively managed funds—because investors in such funds can learn about the ability of managers from their past performance (a la Berk and Green, 2004)—it is likely inconsistent with rationality when it comes to passive investment vehicles, such as ETFs. Indeed, Ben-David, Franzoni, and Moussawi (2018) and Brown, Davies, and Ringgenberg

(2021) find that high flows into ETFs are followed by negative returns.

The narrative that emerges from the results in this section is that specialized ETFs cater to retail investors that form expectations extrapolating the performance of trendy 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 wave of financial innovation in the last 30 years: the explosion of 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.

This paper shows that the lens through which one ought to interpret the ETF market is the model developed by Bordalo, Gennaioli, and Shleifer (2016), which argues that producers can compete along either the price ("Walmart") or the quality ("Starbucks") dimensions of a product. In this spirit, two equilibria prevail in the ETF market corresponding to two types of products. Broad-based ETFs hold diversified portfolios and charge low fees. These products appeal to investors seeking a low-cost vehicle to invest in diversified portfolios. 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 is smaller, in the aggregate, they drive over a 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 fail to 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 -3% a year. This underperformance is stronger right after launch, at about -6%, and persists for at least five years after their inception. 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 an investment theme, on average.

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 attract speculation-prone investors to underperforming investment propositions. 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.

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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 U.S. and nearly 7,000 globally, with these products spanning various asset classes.

ETFs can reproduce the performance of the relevant index in two alternative 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 U.S., 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 that 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 could serve as an indication for 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 et al. (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 non-missing ETF flag in the CRSP Mutual Fund Database. Because we are interested in ETFs that hold U.S. equities only, 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,[28] or CRSP style code $EDYS$ or $EDYH$,[29] 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 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

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

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

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: CAPM, and the Fama-French three-factor (Fama and French, 1993), Fama-French-Carhart four-factor (Carhart, 1997), Fama-French five-factor (Fama and French, 2015), -French-Carhart six-factor (Fama and French, 2018),[30] and the Hou-Xue-Zhang q-factor models (Hou et al., 2015).[31]

[30] Fama-French factor data are from Kenneth French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

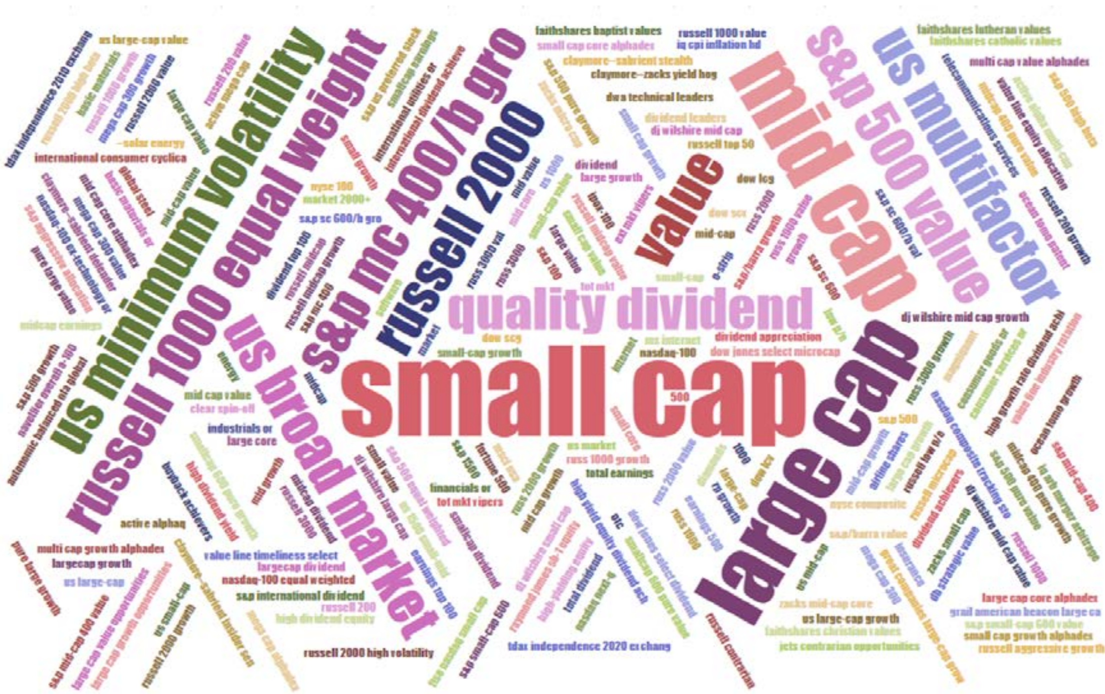
[31] Q-factors data library website: http://global-q.org/index.html.

Appendix C Variable Definitions

Variable	Definition	Source
ETF-Level Variables		
# 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
Short interest	The ratio of the number of shares shorted to the total shares outstanding.	Compustat
Abnormal 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 ($b).	CRSP
Implied revenues	Fee multiplied by the average AUM ($m) in each year.	Bloomberg, CRSP
Product differentiation	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.	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 scaled by market capitalization ($m).	Robintrack
Firm-Level Variables		
Abnormal 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 one-quarter-lagged stock price.	Compustat, 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. We subtract the median of the short interest ratio in each month to filter out time components.	Compustat

Figure A.I. ETF Names: Word Cloud

(a) Broad-based ETFs



(b) Specialized ETFs

Appendix D Robustness Analysis on ETF Performance

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

Table A.I. Calendar-Time Portfolios of ETFs (EW)

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. In Panel C, we identify *old* ETFs that were launched more than five years prior in each month. We then form portfolios consisting of all *old* 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*, *FFC6*, 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-Carhart 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	FFC6	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	FFC6	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)
Panel C: Months $>$ 60							
	Excess return	CAPM	FF3	FFC4	FF5	FFC6	Q
Broad-Based ETFs	0.52*	0.05	0.01	0.02	-0.09**	-0.08**	-0.04
	(1.83)	(0.90)	(0.13)	(0.36)	(-2.10)	(-2.02)	(-0.68)
Specialized ETFs	0.65**	-0.10	-0.09	-0.07	-0.08	-0.06	-0.02
	(2.12)	(-1.55)	(-1.46)	(-1.24)	(-1.20)	(-0.95)	(-0.38)
SP minus BB	-0.05	-0.04	-0.06	-0.04	-0.02	-0.00	0.00
	(-0.86)	(-0.67)	(-1.00)	(-0.79)	(-0.31)	(-0.05)	(0.07)

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 U.S., 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 A.II. 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 alpha, FF3 alpha, FFC4 alpha, FF5 alpha, FFC6 alpha, 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-Carhart 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)
FFC6 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)

Appendix E Robustness Analysis on Flow-Performance Sensitivity

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.

Figure A.II. 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 polynomials. The shaded areas represent 95% confidence intervals.