Active ETFs as Attention Assets: Retail Trading Meets Managed Funds*

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Abstract

Active exchange-traded funds (AETFs) are booming despite massive outflows from traditional active mutual funds (AMFs). This growth is not driven by performance; AETFs persistently underperform their AMF peers. Instead, AETFs capitalize on their intraday tradability to attract an attention-driven retail clientele. We document a novel U-shaped flow-performance relation where AETF investors chase extreme short-term returns—both positive and negative. Because long-term underperformance is not penalized with outflows, AETF managers are incentivized to rely on elevated risk-taking to generate these attention-grabbing returns. Overall, AETFs function less as skill-based investment products and more as high-risk attention assets.

Keywords: Active Management, Exchange-Traded Funds, Attention, Retail Investors.

JEL Classification: G11, G14, G20

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Abstract

Active exchange-traded funds (AETFs) are booming despite massive outflows from traditional active mutual funds (AMFs). This growth is not driven by performance; AETFs persistently underperform their AMF peers. Instead, AETFs capitalize on their intraday tradability to attract an attention-driven retail clientele. We document a novel U-shaped flow-performance relation where AETF investors chase extreme short-term returns—both positive and negative. Because long-term underperformance is not penalized with outflows, AETF managers are incentivized to rely on elevated risk-taking to generate these attention-grabbing returns. Overall, AETFs function less as skill-based investment products and more as high-risk attention assets.

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1. Introduction

Active management is in sharp decline. Investors have pulled $1.5 trillion from active mutual funds (AMFs) over the past decade, and more than 1,500 funds have closed. Much of this decline has been attributed to investors flocking to passive funds due to their lower fees and the inability of active managers to beat the market consistently. In fact, Fama and French (2010) find that few fund managers have skill. Various industry studies also show that active managers struggle to beat the index consistently (Sommer, 2022).

Yet, one category of active management is not only surviving but thriving: active ETFs (AETFs). These funds have grown their assets under management to over $1 trillion during the same decade (Lee, 2025). To illustrate the stark difference in the AETF and AMF industries, we compare their trajectories in **Figure 1**. Between 2015 and 2023, more than 700 new active ETFs were launched, attracting over $150 billion in fund flows. In contrast, nearly 2,000 active mutual funds shut down and over $2 trillion in flows fled the active mutual fund industry. In this paper, we examine the economics of the AETF industry, including what has driven its growth, what kind of incentives it creates for managers, and how managers have reacted to those incentives. While the concurrent migration from passive mutual funds to passive ETFs is largely driven by the structural tax advantages of the ETF wrapper (Moussawi, Shen, & Velthuis, 2025; Goldenring, 2026), we demonstrate in this paper that the rapid rise of AETFs is driven by a completely different set of economic forces.

In summary, our results suggest that AETFs have taken advantage of the rapid growth of retail trading over the last several years. AETFs do not solve the main issue that has led to the decline of AMFs – underperformance against passive alternatives. In fact, AETFs have worse average performance relative to active mutual funds on both a net-of-fee and gross-of-fee basis. However, long-term performance does not seem to be the primary focus of how AETF investors allocate flows. Rather, retail investors invest in AETFs more like equities than investors in managed funds (AMFs), i.e., chasing extreme performance, in either direction, over short-term horizons. That is, the best and worst AETFs receive more flows than those in the middle, consistent with the rank effect in equity trading documented in Hartzmark (2015). This trading pattern incentivizes managers to take on more risk to capture investors' attention. Indeed, we find that AETFs are significantly riskier.[1]

Specifically, we first examine the performance of active ETFs, given that the relative underperformance of AMFs is a main reason for their decline. Consistent with contemporary work (e.g., Zhang (2024)), we find that performance advantages do not explain the AETF boom. Surprisingly, given their growth, AETFs have significantly negative alphas and perform even *worse* than their AMF peers on both a net-of-fee and gross-of-fee basis. AETFs underperform AMFs even after adjusting for the tax efficiency of AETFs. In addition, we find no evidence of performance persistence in AETFs. Therefore, to understand the stark difference in the trajectories of AETFs and AMFs, we must look beyond traditional performance metrics.

One key difference between AETFs and AMFs is how they trade. AMF orders can be fulfilled only once a day at the end of the trading session. Even then, there are often restrictions on rapid purchases and sales. Given these liquidity constraints, AMF investors tend to allocate capital based on long-term performance (Sirri & Tufano, 1998; Chevalier & Ellison, 1997; Del Guercio & Tkac, 2002; J. Huang, Wei, & Yan, 2007). In contrast, AETFs trade continuously on exchanges like any other stock, which may invite stock-like trading behavior.[2] In addition, AETFs likely attract retail investors who trade more based on behavioral biases ((Barber & Odean, 2008; Hartzmark, 2015; Barber, Huang, Odean, & Schwarz, 2022)). If AETFs are treated similarly to equities by retail investors, we should expect their flows to react to similar attention-grabbing events, such as extreme performance, both positive and negative.

Aggregate descriptive statistics confirm that retail traders are relatively more active in AETFs. First, as shown in **Figure 1b**, there was almost no growth from 2016 to the end of 2019. However, after 2019, AETFs grew rapidly after the start of commission-free trading and the COVID-19 crisis, which corresponds to the explosion in overall retail trading (Ozik, Sadka, & Shen, 2021). In addition, AETFs have an average monthly turnover of 32.7% compared to 2.3% for AMFs, suggesting that AETFs attract particularly impatient

[1] Our analysis focuses exclusively on unlevered AETFs. We explicitly exclude levered or inverse ETFs from our sample because their extreme risk profiles are mechanically engineered through derivatives rather than active portfolio management, and they operate under a distinct regulatory framework.

[2] For example, on all large retail brokers, the procedure for buying a stock and an AETF is the same. However, mutual funds usually have their own trading page.

investors who were likely not part of the AMF clientele (for example, retail day traders). This observation is consistent with Du, Starks, and Xiaolan (2024), who find no cannibalization between AMFs and their AETF clones.

When examining the flow-performance relation, we find that investors trade AETFs more like individual equities than like traditional managed funds. This stock-like behavior is most striking among the worst-performing funds, where AETFs and AMFs move in completely opposite directions. The worst-performing AMFs have a positive, albeit mostly flat, flow-performance sensitivity, consistent with the canonical finding that investors lack attention to underperforming mutual funds (Sirri & Tufano, 1998). In stark contrast, worst-performing AETFs have a *negative* flow-performance sensitivity. That is, among the bottom AETFs, those with the very worst returns actually attract *higher* flows than those with slightly less negative returns. We argue that this pattern is driven by investors paying more attention to AETFs with extreme returns, even if the returns are extremely negative. We provide direct evidence for this attention-based explanation in subsequent analyses.

This attention-driven behavior is also evident when examining the right tail of the performance distribution. Among the best-performing funds, AETFs and AMFs behave qualitatively similarly: both have a positive flow-performance relation. However, the magnitude of the relation is significantly amplified for AETFs. Specifically, a 1% increase in short-term (prior-week) returns is associated with a 0.30% increase in monthly fund flows for AMFs, compared to a 0.88% increase for AETFs. This almost tripled sensitivity demonstrates that the AETF retail clientele is more impatient and chases extreme positive short-term returns much more aggressively than the traditional AMF investor base.

Taken together, the combination of negative sensitivity at the bottom and amplified positive sensitivity at the top results in a distinct U-shape. To the best of our knowledge, we are the first to document this U-shaped flow-performance relation in the managed fund industry. While prior literature establishes that retail investors exhibit attention-driven trading in individual equities (Barber & Odean, 2008; Hartzmark, 2015; Barber et al., 2022), we show that AETFs have successfully imported this behavior into the fund space. We find the same U-shaped pattern in Google Search Volume relative to short-term AETF returns, suggesting that extreme short-term returns — both positive and negative — generate significant spikes in investor attention. We also observe the same U-shaped pattern in retail trading activity using TAQ data (Boehmer, Jones, Zhang, & Zhang, 2021; Barber, Huang, Jorion, Odean, & Schwarz, 2024), suggesting that high attention generated by extreme returns does translate into actual trading activity. These results reveal the underlying economic mechanism – the attention economy among retail investors. In short, AETFs trade like individual stocks and exhibit stock-like behaviors in the short term.

Over longer horizons, however, AETFs behave qualitatively similar to AMFs. While AETFs' flow-performance relation is still more convex than AMFs, the magnitude of the difference declines over longer time horizons, and AETF investors no longer chase extreme underperformance. Importantly, extreme poor performance over these longer time horizons also does not result in meaningful outflows.

While contemporary work observes that AETFs attract a distinct retail clientele, our central contribution is demonstrating how this novel investor base fundamentally alters managerial incentives. It is well-established that managers take greater risks when faced with highly convex, asymmetric payoffs.[3] Because short-term extreme returns result in long-term asset capture (because poor long-term performance does not lead to meaningful outflows), the unique U-shaped flow-performance relation of AETFs provides managers with even stronger incentives to spike volatility than their AMF peers. An environment where flows reward extreme short-term attention but do not penalize long-term underperformance is particularly attractive to unskilled managers, who can rely on generating high volatility rather than demonstrating fundamental stock-picking skill.

Consistent with these skewed incentives, we find that AETF managers' risk-taking is significantly higher than that of AMFs. AETF managers trade more frequently and hold portfolios with higher industry concentration, thereby reducing diversification and amplifying return volatility and the likelihood of extreme returns. Notably, this increased risk-taking is concentrated in funds in both the top and bottom short-term performance quintiles, suggesting that AETF managers actively exploit the attention that extreme returns generate. Over the long term (quarter or year), the pattern reverts to the traditional mutual fund tour-

[3]This dynamic has been documented extensively across mutual funds (K. C. Brown, Harlow, & Starks, 1996; Schwarz, 2012), hedge funds (Goetzmann, Ingersoll Jr, & Ross, 2003; Agarwal, Daniel, & Naik, 2009; Panageas & Westerfield, 2009), and corporate settings (Coles, Daniel, & Naveen, 2006).

nament behavior (K. C. Brown et al., 1996; Schwarz, 2012), where only the worst-performing funds continue to take on high risk to avoid closure.

Next, we investigate the survival outcomes for AETFs and AMFs. Active ETFs face two countervailing forces: the ability to attract rapid inflows via short-term attention, offset by the long-term drag of elevated risk-taking and weaker performance. We find that when examining survival as a function of short-term (past-month) performance, AETFs face a 68% higher unconditional probability of closure than AMFs, reflecting the inherent fragility of their aggressive risk-taking. However, strong short-term performance sharply reduces an AETF's likelihood of closure (Massa & Patgiri, 2009), whereas short-term performance has little impact on AMF survival. Over longer evaluation horizons (such as a quarter or a year), AETF survival dynamics mirror those of AMFs. Holding long-term performance constant, the baseline closure risk is similar across both fund types. Thus, in the long term, AETFs are treated by the market just like traditional mutual funds, and their higher overall closure rate is driven primarily by their inferior performance.

Finally, we provide novel evidence on the human capital driving the AETF industry. If AETFs simply represented traditional managers adopting a new fund wrapper, we would expect similar manager profiles across both fund types. Instead, using Revelio Labs data to track LinkedIn career paths, we find that the vast majority of AETF managers have never managed a mutual fund before. AETFs source from a fundamentally different labor pool: their managers have significantly shorter tenures in the investment industry and less experience as portfolio managers. This relative lack of experience helps explain the economics of the AETF industry as a whole. It provides a cohesive explanation for why AETFs underperform AMFs on average, and why their managers must rely on high risk-taking and attention-driven flows, rather than consistent long-term performance, to survive.

Overall, this paper contributes to our understanding of how the asset management industry is adapting to the decline of its traditional distribution channels and the simultaneous explosion in retail trading. We show that AETFs do not resolve the fundamental issues that have driven investors away from active mutual funds, namely negative alphas and a lack of performance persistence. Instead, by wrapping active management in an equity-like, intraday-tradable vehicle, the industry has successfully imported the behavioral biases of stock market day-traders (Barber & Odean, 2008; Hartzmark, 2015; Barber et al., 2022) into the managed fund space. Ultimately, our results suggest that AETFs function less as a revival of active management skill and more as high-risk attention assets tailored for the modern retail investor.

The rest of the paper is organized as follows. After discussing related literature in the following section, Section 2 discusses the institutional details of the AETF industry and the data. Section 3 shows that AETFs do not offer superior performance relative to AMFs. Section 4 examines the flow-performance relation, while Section 5 shows the resulting incentive shift for AETF managers. Section 6 investigates active ETF survival. Finally, Section 8 concludes.

1.1. Related Literature

We extend the literature on ETFs, which has traditionally focused on passive funds (Pan & Zeng, 2017; Ben-David, Franzoni, & Moussawi, 2018; Da & Shive, 2018; Glosten, Nallareddy, & Zou, 2021; Shim & Todorov, 2023; Koont, Ma, Pastor, & Zeng, 2024; Brogaard, Heath, & Huang, 2023). Zhang (2024) finds that AETFs trade more actively and underperform AMFs but attributes these results to AETFs being new to the market. We distinguish our work by demonstrating that AETF managers face fundamentally different incentives driven by a novel U-shaped flow-performance relation. This dynamic is a direct result of attention-driven trading by a unique retail clientele (Barber et al., 2022; Ben-David, Franzoni, Kim, & Moussawi, 2023; Aragon, Tserlukevich, Keen, & Wymbs, 2024; Du et al., 2024). As a result, AETFs successfully capitalize on the sharp rise of retail participation in the stock market (Ozik et al., 2021; van der Beck & Jaunin, 2021; Eaton, Green, Roseman, & Wu, 2022; Welch, 2022; Bradley, Hanousek Jr., Jame, & Xiao, 2024). Recognizing this dynamic, AETF managers rely on elevated risk-taking to capture flows from these attention-driven retail investors (Sirri & Tufano, 1998; Lynch & Musto, 2003; Ben-David, Li, Rossi, & Song, 2022), rather than competing on fundamental stock-picking skill.

Our findings also contribute to the literature documenting inefficient and inferior investment options in the asset management industry. van der Beck, Bouchaud, and Villamaina (2024) document that some funds hold a concentrated portfolio such that inflows mechanically push up the price of the underlying security, which helps them attract more flows and continue the cycle. They term these funds as "Ponzi funds." Ben-David et al. (2023) find that many ETF providers launch products that track niche, attention-grabbing themes with high fees and poor performance. Similarly, D. C. Brown, Cederburg, and Towner (2024) find that many ETFs charge high fees but offer highly correlated returns compared to much cheaper alternatives. By showing that AETFs deliver worse returns and take higher risks than their AMF counterparts, we provide evidence consistent with D. Huang (2024), who argues that unskilled managers are fleeing the traditional mutual fund space. Ultimately, our results reinforce the notion that AETFs serve as an inferior vehicle for return-maximizing investors.

2. Institutional Background and Data

In this section, we introduce the relevant institutional details of active ETFs. We then describe the data by comparing active ETFs and active mutual funds.

2.1. Institutional Background

History of Active ETFs. The first ETF in the U.S. was the SPDR S&P 500 ETF Trust (ticker: SPY), launched in 1993. As early as 2001, the Securities and Exchange Commission (SEC) expressed interest in exploring the active ETF and solicited public comments in a Concept Release (U.S. Securities and Exchange Commission, 2001). It was not until March 2008 that the U.S. market saw the introduction of the first active ETF, Bear Stearns Current Yield Fund (ticker: YYY). However, YYY was liquidated in September 2008 due to the collapse of Bear Stearns during the financial crisis. The first successful active ETF is often considered to be the PIMCO Enhanced Short Maturity Active ETF (ticker: MINT), which was launched in November 2009 and is still actively traded as of 2023.

A recent regulatory milestone—the passage of the ETF rule (or Rule 6c-11) in late 2019 (U.S. Securities and Exchange Commission, 2019a)—boosted the popularity of active ETFs. The rule standardizes the regulatory framework for ETFs. Before the passage of the rule, all ETFs were required to obtain exemptive relief from the Investment Company Act (the 40 Act) on a case-by-case basis.[4] Following the ETF rule, the standardized approval process not only removed regulatory roadblocks for new products, but also spurred the creation of "ETF white-labelers."[5] These firms provide a so-called ETF-in-a-box service, which includes launching, marketing, and maintaining the operation of the ETF. This service allows managers to launch ETFs as long as they have an investment idea without having to understand the institutional, legal, and logistical details of ETFs.[6] Together, the ETF Rule and the emergence of white-label firms significantly lowered the barriers to entry, paving the way for the recent boom in active ETFs.

Transactions of Active ETFs. Active ETFs trade for two reasons: investor flows and the active management of the portfolio composition. These ETFs handle flows through in-kind transactions between the ETF sponsor and authorized participants (APs). When the buying demand exceeds (falls below) the selling demand in the secondary market during the trading day, APs, who act as market makers for the ETF, create (redeem) shares with the sponsor at the end of the day. In a creation transaction, APs deliver a representative basket of securities from the ETF's holdings to the sponsor and receive ETF shares in exchange, effectively "creating" new ETF shares. A redemption transaction operates similarly, with the basket of securities and ETF shares moving in the opposite direction. Active ETFs' creation and redemption process is the same as that of passive ETFs, which is well-studied in the literature (Pan & Zeng, 2017; Shim & Todorov, 2023; Brogaard et al., 2023; Koont et al., 2024).

Active ETFs also manage their portfolio composition through in-kind transactions, but they use a more complex process involving custom creation and redemption baskets. Consider the following example. Suppose an AETF manager wants to buy stock A while selling stock

[4] For example, ETFs need to obtain exemptive relief from section 22(d) for sales at a negotiated price (i.e., secondary market making), from section 17(a) for transactions with affiliated parties (i.e., creation and redemption with authorized participants), from section 18(f) for issuance of multiple fund classes (i.e., for co-existence of ETF class and mutual fund class of the same fund), from section 24(d) for digital delivery of prospectus, etc.

[5] Most ETFs do not need separate exemptive relief post 6c-11, with some notable exceptions such as inverse ETFs, non-transparent ETFs, and commodity ETFs. These ETFs are still required to obtain separate exemptive reliefs due to their unique features.

[6] We obtained unofficial quotes from several industry experts that the cost of launching the ETF as of 2024 is roughly \$80,000 to \$100,000, and the maintenance cost is roughly \$200,000 per year, excluding marketing expenses, which are charged on a case-by-case basis.

B. The sponsor defines a custom creation basket consisting solely of stock A and a custom redemption basket consisting solely of stock B. Authorized participants facilitate the swap between stock A and stock B by conducting two separate in-kind transactions. They create ETF shares by delivering stock A to the sponsor, and they redeem ETF shares by receiving stock B from the sponsor. This process resembles the "heartbeat trades" employed by passive ETFs, as first documented by Kashner (2017), which are used to change portfolio compositions due to index reconstitution.[7]

Disclosure Requirements for Active ETFs. The hallmark of ETFs is their intraday liquidity, with a market price closely tracking the net asset value (NAV) of their underlying portfolio. This intraday liquidity is in part facilitated by the daily disclosure requirement. Frequent portfolio disclosure is less of an issue for passive funds but could potentially be very burdensome for active funds (S. J. Brown & Schwarz, 2020; Agarwal, Mullally, Tang, & Yang, 2015), especially for skilled ones due to the information content in the portfolio holdings (Agarwal, Jiang, Tang, & Yang, 2013; S. J. Brown & Schwarz, 2020). To address this concern, the industry developed an innovative solution: non-transparent active ETFs, which hide portfolio holdings while maintaining close tracking between intraday prices and the NAV. In 2019, the SEC granted exemptive relief to the first non-transparent active ETF for Precidian Funds (U.S. Securities and Exchange Commission, 2019b), which attracted some interest and concerns (Hu & Morley, 2018; Haeberle, 2021). However, non-transparent active ETFs never gained significant traction in the market. As of the first quarter of 2023, there were 53 active non-transparent ETFs in the U.S. market with total assets under management of $5.6 billion, and the largest one had under $30 million. However, the lack of traction for these non-transparent products suggests that investors—and managers—are less concerned about holding disclosure than initially anticipated. Contemporary studies also show that active ETFs' portfolio disclosure may even benefit them by inducing others to copy their trades and push up the price of their holdings (D. Huang & Nair, 2024). This is consistent with S. J. Brown and Schwarz (2020), who find investors copycat hedge fund

[7] This arrangement of pairs of in-kind transactions originally arose from tax considerations. In-kind transactions allow ETF investors to defer capital gains taxes, which would otherwise be distributed annually, until the sale of ETF shares. This tax efficiency is particularly advantageous for passive ETFs, whose clientele includes buy-and-hold investors with investment horizons spanning years or even decades. However, it is less relevant for active ETFs, as their investors typically hold these funds for much shorter periods.

stocks in hedge fund 13F filings.

2.2. Data

In this section, we describe the sources of our data and compare the key characteristics of active ETFs and mutual funds.

We construct our ETF and mutual fund samples from two data sources. The ETF sample comprises all active, unlevered U.S. equity ETFs from ETF Global, which provides a comprehensive set of fund characteristics. We explicitly exclude leveraged and inverse ETFs from our analysis. While these products exhibit extreme volatility, they achieve this risk mechanically through derivatives rather than active portfolio management, and they operate under a different regulatory approval framework. We merge this dataset with return data from CRSP. The mutual fund sample includes all active U.S. equity funds from the CRSP Mutual Fund Database (MFDB). We exclude funds that charge a management fee greater than 2% to remove outliers. The sample period is from 2015 to 2023. The final sample contains 909 unique active ETFs and 19,910 active mutual fund classes. This massive difference in count is consistent with the fact that active ETFs have only become popular recently, whereas AMFs have a much longer history. We conduct all subsequent analyses at the fund-class level because different fund classes target different clientele (e.g., retail and institutions), and retail investors' attention is a key driver of our results.

Insert **Table 1** About Here

Table 1a and **Table 1b** present the summary statistics for active ETFs and active mutual funds, respectively. Active mutual funds are roughly double the size of active ETFs on average. However, compared to AMFs, AETFs attract more flows, calculated as a percentage of total net assets every month as follows: $(\text{TNA}_t - \text{TNA}_{t-1} \cdot r_t)/\text{TNA}_{t-1}$. On average, AETFs see a 3.3% monthly flow from 2015 to 2019, which increases to 4% after the passage of the ETF Rule at the end of 2019, consistent with the growing popularity of AETFs. In contrast, AMF flows decrease from 0.8% before the ETF Rule to merely 0.2% after 2020. AETFs feature lower average expense ratios, largely because their exchange-traded structure avoids traditional distribution costs like the 12b-1 fees paid by AMFs.[8] Notably, following the ETF rule, AMFs reduced their fees by roughly 10% compared to pre-6c-11 levels, likely in response to growing competition from AETFs. AETFs underperform AMFs on average, but the difference almost entirely comes from the post-6c-11 period, suggesting that the proliferation of active ETFs coincides with a deterioration of skill in the AETF industry.

3. Active ETF Performance

We begin by examining the performance of active ETFs to see whether it explains the stark divergence in the trajectories of the AETF and AMF industries. Given that underperformance against passive alternatives is a primary driver of the AMF industry's decline, one might expect AETFs to offer superior returns. Instead, we find that AETFs underperform AMFs across all return metrics and exhibit no return persistence. Thus, AETFs do not solve the fundamental performance problem facing active management, implying that their rapid growth must be driven by other factors.

3.1. Comparing AETF and AMF Performance

Table 1 shows that AETFs earn an average net-of-fee return of 0.46% per month, whereas AMFs earn 0.63% over the full 2015–2023 sample period. Interestingly, AETFs generated a higher return of 0.58% in the first half of the sample but a lower return of 0.43% in the second half. This deterioration in performance coincides directly with the proliferation of new AETFs, providing initial evidence that performance does not explain the industry's rapid expansion. Furthermore, AETFs underperform AMFs even on a gross-of-fee basis, despite operating with lower average expense ratios.

AETFs also underperform AMFs on an after-tax basis, despite the well-documented tax efficiency of the ETF structure (Moussawi et al., 2025; Goldenring, 2026). Unlike mutual funds, which distribute capital gains annually, ETFs allow investors to defer capital gains

[8] Although brokerage platforms do not directly charge active ETFs the 12b-1 fee, they could still charge a "listing fee" on the fund family level. However, the disclosure is very poor, and this fee is not apportioned to the individual fund. See a detailed discussion in Boyson (2019).

taxes until they sell their shares. However, to reap this tax-deferral benefit, investors must hold the asset for at least a year. In reality, the annual turnover ratio for AETFs (calculated as annual trading volume divided by shares outstanding from CRSP) averages roughly 400%. This implies an average holding period of just three months—far too short for tax efficiency to have any material impact.[9] Consequently, the structural tax advantages of ETFs cannot overcome the funds' severe underperformance.

Finally, we estimate the alphas of AETFs and AMFs to ensure that this underperformance is not simply a result of different systematic risk exposures. We estimate the following equation:

$$r_{i,t} = \alpha_i + \beta_{1,i} \times \text{MktRF}_t + \beta_{2,i} \times \text{SMB}_t + \beta_{3,i} \times \text{HML}_t + \beta_{4,i} \times \text{MOM}_t + \epsilon_{i,t}, \qquad (1)$$

for each fund i and month t using a rolling 12-month estimation window. We calculate alphas using the CAPM, Fama-French 3-Factor model, and Carhart 4-Factor model.[10] **Table 2** presents the results.

Insert **Table 2** About Here

Table 2 shows that active ETFs exhibit significantly lower alphas than active mutual funds on average. Panel (a) compares the full samples of AETFs and AMFs. The net-of-fee monthly alpha of AETFs is 4.9 to 6.8 basis points (60.4 to 84.7 basis points annually) lower than that of AMFs. This is an economically large difference, representing a 37% to 46% reduction in net-of-fee alpha relative to AMFs. These differences are also statistically significant at the 1% level.

Gross-of-fee alphas paint an even starker picture of managerial skill. The gross-of-fee alpha gap is wider still, ranging from 8.1 to 10.0 basis points monthly (101.6 to 126.8 basis points annually), reflecting the fact that AETFs offset some of their poor performance

[9] In **Appendix A**, we provide a detailed after-tax comparison using empirically observed returns and turnover ratios. **Table A.1** shows that an investor would need to hold an AETF for 20 years to break even with an AMF on an after-tax basis, even when assuming a highly generous 15% annual discount rate.

[10] Using 24- and 36-month estimation windows yields qualitatively similar results.

through lower distribution costs. In Panel (b), we verify that these results are not driven by fund characteristics by repeating the comparison on a propensity-score matched sample (matched on objective code, size, and fees). The results remain robust: AETFs significantly underperform AMFs across all risk-adjusted measures.

We conclude that AETFs underperform AMFs by every conventional return metric. Performance simply cannot explain the sharp rise of the AETF industry.

3.2. Active ETF Return Persistence

Next, we evaluate the performance persistence of active ETFs, a standard proxy for managerial skill in the literature (S. J. Brown & Goetzmann, 1995; Carhart, 1997; Bollen & Busse, 2001; Boyson, 2008). Following Bollen and Busse (2005), we sort all AETFs into quintiles at the end of each period (week, month, quarter, and year) based on their abnormal return, defined as the fund return minus the average return of funds within the same style objective. If AETF managers possess skill, funds in the top (bottom) performance quintile should continue to deliver high (low) returns in the subsequent period. To test AETFs return persistence, we calculate the average return for each quintile during both the ranking period and the subsequent period. **Table 3** presents these results across different evaluation horizons.

Insert **Table 3** About Here

Table 3 reveals a complete lack of return persistence for active ETFs across all horizons. For instance, the difference in subsequent-week returns between the best-performing and worst-performing quintiles is a negligible -0.12% (-0.07% minus 0.05%), which stands in stark contrast to their ranking-week return spread of 3.28% (1.66% minus -1.62%). Furthermore, there is no monotonic relationship in subsequent returns across the quintiles. We visualize these dynamics in **Figure 2**, plotting ranking-period returns (dashed blue lines) against subsequent-period returns (solid red lines). While the ranking-period returns slope upward by construction, the subsequent-period return line in Panel (a) is entirely flat, confirming the absence of short-term persistence. This finding holds across longer horizons; Panels (b), (c), and (d) show no upward trend in subsequent returns, confirming that AETF performance does not persist.

Insert **Figure 2** About Here

We formally test for performance persistence using the following panel regression:

$$r_{d,t}^{\text{NP}} = \beta \times r_{d,t}^{\text{RP}} + \lambda_t + \epsilon_{d,t}, \tag{2}$$

where $r_{d,t}^{\text{RP}}$ is the average abnormal return of funds in quintile d during the ranking-period t, and $r_{d,t}^{\text{NP}}$ is the average abnormal return of those same funds in the subsequent period. We include time fixed effects, λ_t, to absorb any market-wide shocks to persistence. The results, reported in **Table 4**, statistically confirm the lack of return persistence. The coefficients on ranking-period returns are economically and statistically indistinguishable from zero at the weekly and monthly horizons. Over quarterly and yearly horizons, the coefficients turn negative and statistically significant, indicating that long-term AETF returns actually exhibit mean reversion. Together, these findings confirm that AETF returns do not persist, suggesting a distinct lack of managerial skill.[11]

Insert **Table 4** About Here

4. Active ETF Flow-Performance Dynamic

In this section, we examine the flow-performance relation of AETFs and AMFs. We first document our main finding: a unique U-shaped short-term flow-performance relation for AETFs. We then show that this pattern is even more pronounced among large AETFs,

[11] Because AETFs underperform and their managers demonstrate no persistent skill, their portfolio holdings contain little proprietary information (Agarwal et al., 2013; S. J. Brown & Schwarz, 2020). This lack of a "secret sauce" explains why the daily portfolio disclosure requirement of ETFs imposes minimal actual costs on these managers, and why non-transparent AETFs failed to gain market traction.

likely because size amplifies investor attention. Finally, we provide direct evidence of the underlying attention mechanism using Google Search Volume and retail trading data from Robinhood.

Our key finding is that AETFs exhibit a U-shaped flow-performance relation over short-term horizons. While well-performing funds attract more flows by performing better, poor-performing funds attract *more* flows by performing *worse*. Over longer horizons, however, the AETF flow-performance relation reverts to a more traditional shape: flat in the poor-performing region and positively sloping in the well-performing region. That is, in the long run, AETFs are rewarded with inflows for good performance but are not severely punished with outflows for poor performance. This long-term dynamic is qualitatively similar to the canonical mutual fund pattern first documented by Sirri and Tufano (1998).

To begin, we non-parametrically investigate these flow-performance relations. Each month, we sort AETFs into 25 bins according to their past performance and calculate the average fund flow in each bin. We repeat this process for active mutual funds and calculate the difference between ETF and MF flows in each performance bin. By netting out the baseline flow behavior of traditional mutual funds, this difference isolates the flow-performance dynamic unique to the AETF structure. We plot this dynamic using performance bins based on the past week, month, quarter, and year to examine heterogeneous effects across different horizons. **Figure 3** presents the results.

Insert **Figure 3** About Here

Panel (a) of **Figure 3** shows that, relative to AMFs, AETFs exhibit a stark U-shaped flow-performance relation based on past-week returns. Compared to mutual funds, AETFs attract significantly more flows when they perform both extremely well and extremely poorly. In fact, the *best*-performing and the *worst*-performing AETFs attract the highest relative inflows. While this result may seem counterintuitive for a managed fund, it aligns perfectly with the behavioral literature on equity trading. For example, the rank effect (Hartzmark, 2015) and attention-induced trading (Barber et al., 2022) both predict this exact U-shaped pattern. In the short term, AETF investors trade these funds exactly like individual stocks.

This U-shaped relation disappears when we form performance bins based on returns over the past month, quarter, and year, as shown in panels (b), (c), and (d). The long-term flow-performance relation is largely flat across the bottom and middle percentiles and tilts upward in the top percentiles, qualitatively matching the canonical mutual fund pattern (Sirri & Tufano, 1998). This finding is also consistent with Barber et al. (2022), who note that securities with the absolute best performance ultimately attract the most enduring attention.

Taken together, active ETFs behave qualitatively similarly to traditional mutual funds in the long term, but exhibit a unique U-shaped flow-performance relation in the short term. These results support the idea that AETFs attract impatient, short-term-focused retail investors who trade the funds as if they were common equities.

We next formalize this non-parametric evidence by estimating the flow-performance relation in a panel regression framework. Following Sirri and Tufano (1998), we estimate the following piecewise linear specification:

$$\text{Flow}_{i,t} = \sum_{q=1}^{5} \left(\beta_1^q \times r_{i,t-j\to t}^q + \beta_2^q \times r_{i,t-j\to t}^q \times \text{ETF}_i \right) + X_{i,t} + \kappa_i + \tau_t + \epsilon_{i,t}, \tag{3}$$

where $\text{Flow}_{i,t}$ is the percentage flow of fund i in month t, measured as $(\text{TNA}_{i,t} - \text{TNA}_{i,t-1}(1 + r_{i,t}))/\text{TNA}_{i,t-1}$. ETF_i is an indicator variable that equals 1 if the fund is an ETF and 0 otherwise. Control variables $X_{i,t}$ include the log fund size, past return volatility measured as the standard deviation of fund return in the past 12 months, and the average percentage fund flow for all funds in the same objective code. κ_i are fund fixed effects that control for time-invariant fund-specific characteristics such as the reputation effect from the fund family or the catchy-ness of the fund ticker. τ_t are year-month fixed effects that sweep out unobserved effects to the entire market at any point in time. Past return $r_{i,t-j\to t}$ is measured from $-j$ ($j = 1$ week, 1 month, 1 quarter, and 1 year) up to *the day prior to* month t for each fund i. Past returns are further splined into quintiles $r_{i,t-j\to t}^q$ using the following equation (return subscripts are suppressed for clarity):

$$\begin{aligned} r^1 &= \min(r, k^1), \\ r^m &= \max\big(\min(r, k^m), k^{m-1}\big) - k^{m-1} \quad \forall m \in (2, 3, 4), \\ r^5 &= \max(r, k^4) - k^4, \end{aligned} \tag{4}$$

where k^1, k^2, k^3, and k^4 are the 20^{th}, 40^{th}, 60^{th}, and 80^{th} percentiles of the return $r_{i,t-j\to t}$ in the cross section at each point in time. These splines allow us to estimate the flow-performance sensitivity for each performance quintile separately. The coefficients β_1^1 through β_1^5 in **Equation (3)** capture the baseline flow-performance sensitivity of active mutual funds across the performance distribution. The interaction coefficients β_2^1 through β_2^5 capture the *incremental* flow-performance sensitivity of active ETFs relative to their AMF peers. **Table 5** presents the results.

Insert **Table 5** About Here

Table 5, column 1, reports the results using past-week returns. For active mutual funds, a one percentage point increase in past-week return for funds in the bottom-performing quintile is associated with a 0.1% inflow in the subsequent month. In contrast, the sensitivity for funds in the top quintile is triple that of funds in the bottom quintile, consistent with the well-documented convexity in mutual funds' flow-performance relation (Sirri & Tufano, 1998).

Next, we focus on the interaction coefficients β_2^1 to β_2^5, which describe the unique flow-performance dynamic for active ETFs. Compared to active mutual funds, active ETFs attract *more* flows when they deliver *worse* performance, provided they are already in the worst-performing quintile. Conversely, in the best-performing quintile, a one percentage point increase in past-week return is associated with roughly 0.6% *additional* inflow compared to mutual funds. We visually present these point estimates and standard errors in **Figure 4**. The negative sensitivity at the bottom and the positive sensitivity at the top shown in **Figure 4** panel (a) are consistent with the U-shape relation visually presented in **Figure**

3. The results suggest that investors focus on the worst and the best funds, consistent with how the rank effect influences trading behaviors in the equity market (Hartzmark, 2015). The heightened sensitivities on both extremes highlight attention as a strong, short-term motivator for retail investors' trading behavior (Barber & Odean, 2008; Barber et al., 2022). Our results also complement Dannhauser and Pontiff (2024), who find that ETF flow-performance sensitivity is heightened by institutional ownership and mitigated by secondary market trading. We find that in the case of active ETFs as well.

Insert **Figure 4** About Here

We next evaluate these dynamics over longer past-return horizons: months, quarters, and years. For mutual funds, the relation remains qualitatively similar, though the convexity weakens, as indicated by a flatter slope in the best-performing regions of Panels (b), (c), and (d) in **Figure 4**. For active ETFs, the anomalous negative sensitivity among the worst-performing funds completely disappears. In the best-performing quintile, AETFs still exhibit heightened flow-performance sensitivity compared to AMFs, but this difference decays as the evaluation horizon lengthens. These results indicate that investors treat AETFs like individual stocks only in the short term. Over longer horizons, the AETF flow-performance relation reverts to the canonical Sirri-Tufano shape, albeit with a slightly steeper slope in the best-performing region compared to AMFs.

4.1. The U-Shape and Active ETF Fund Size

We next explore how fund size impacts this novel short-term U-shaped flow-performance relation. There are two competing hypotheses. On the one hand, larger funds may attract a higher concentration of rational institutional capital, whose standard performance-chasing behavior could mitigate the retail trading patterns and weaken the U-shape. On the other hand, larger AETFs inherently command more visibility and media coverage, which could amplify retail attention and strengthen the U-shape.

To test these hypotheses, **Table 6** repeats our baseline short-term flow-performance analysis (from **Table 5**, Column 1), but restricts the AETF sample to increasingly larger funds. Specifically, Columns 1 through 4 restrict the AETF sample to those in the top half, tercile, quartile, and quintile of the size distribution, respectively.

We find strong evidence supporting the second hypothesis: large AETFs command more retail attention and exhibit an even more pronounced U-shaped pattern. Focusing on the worst-performing funds, the coefficients for the bottom quintile (β_2^1) are negative, highly statistically significant, and economically larger in magnitude than the baseline results. Whereas the full sample exhibits a sensitivity of -0.21 (**Table 5**, Column 1), the sensitivity for the largest AETFs ranges from -0.27 to -0.35. These more negative coefficients indicate that the tendency for investors to allocate flows into the worst-performing AETFs is significantly amplified among larger funds. We interpret this stronger left-tail sensitivity as evidence that retail attention dominates the AETF flow-performance dynamic: large funds generate more headlines and social media chatter, drawing greater retail attention when they experience extreme negative returns.

For the best-performing funds, the coefficients for the top quintile (β_2^5) remain economically large and positive, ranging from 0.47 to 0.66, comparable to the 0.58 estimate in the full sample. While these estimates lose statistical significance—likely due to the significantly reduced sample size when restricting the AETF universe to the top size quantiles—the point estimates confirm that the right side of the U-shape is preserved among large funds.

Taken together, these results indicate that the unique U-shaped flow-performance relation is not mitigated by traditional institutional capital as fund size grows. Instead, larger AETFs appear to attract even more retail attention, thereby amplifying the short-term return-chasing behavior observed across the entire AETF sample.

4.2. Attention and Google Search Volume

To provide direct evidence of the underlying mechanism, we investigate how retail investor attention responds to past fund performance using daily Google Search Volume data. While our main results document a unique short-term U-shaped flow-performance relation, identifying the exact driver requires a measure that isolates investor interest from actual capital deployment. If the U-shape in flows is driven by the fact that extreme performance attracts retail attention, we should observe a corresponding U-shape in how actively investors search for these funds. By directly measuring the volume of search queries, we can determine whether extreme winners and extreme losers both trigger significant spikes in retail attention.

We obtain daily Google Search Volume for each active ETF ticker, providing a high-frequency, direct proxy for investor attention (Da, Engelberg, & Gao, 2011). To mitigate the potential influence of extreme positive skewness in search popularity, we employ the logarithm of daily search volume as our primary dependent variable. Because retail investors typically use ticker symbols when researching or trading on platforms like Robinhood, tracking ticker-specific searches captures targeted, actionable attention rather than broad topical interest.[12]

We estimate the attention-performance relation by regressing the log of Google Search Volume on a piecewise linear spline of past returns. This specification allows us to isolate the attention effects of extreme outperformance and underperformance. Specifically, we estimate the following panel regression model:

$$\log(\text{Search Volume}_{i,t}) = \beta^1 r^1_{i,t-j\to t-1} + \beta^{2\to 4} r^{2\to 4}_{i,t-j\to t-1} + \beta^5 r^5_{i,t-j\to t-1} + \kappa_i + \tau_t + \epsilon_{i,t},$$

where the dependent variable is the log of Google Search Volume for active ETF i on day t. The independent variables are the fund's past returns measured over horizon j (past week, month, quarter, and year) day $t-1$, splined into three segments: the bottom quintile ($r^1_{i,t-j\to t-1}$), the top quintile ($r^5_{i,t-j\to t-1}$), and the middle three quintiles combined ($r^{2\to 4}_{i,t-j\to t-1}$). The model includes fund fixed effects (κ_i) to control for baseline differences in fund popularity, and day fixed effects (τ_t) to absorb broad market-wide trends in search activity and returns.

We use a three-part spline, rather than the even five-quintile spline, because our focus is

[12] The results we report in the paper use Google Search Volume from single-AETF-ticker queries, which allow a 9-month window at the daily frequency at a time and return search volumes scaled from 0 to 100. We repeatedly query the data with one-month overlaps to "stitch together" a continuous time series for each AETF. Variations in baseline search volume across tickers are absorbed by fund fixed effects in our regressions. While we also explored two-ticker queries using a common benchmark following Da et al. (2011), the vast difference in baseline popularity across AETFs often resulted in AETF search volume being censored at 0 or 100, depending on the benchmark. This "squishing" effect eliminates time-series variation, rendering the benchmarked data less useful for our empirical analysis.

on the top and bottom extremes of the performance distribution. By collapsing the middle 60% of returns into a single segment, the estimates more sharply contrast the behavioral responses at the tails against the middle. This specification ensures that the coefficients for the top and bottom quintiles cleanly capture the attention effect associated with extreme outperformance and underperformance.

Insert **Table 7** about here

Table 7 reports the results, which provide an attention-based explanation for the U-shaped flow-performance relation in our main results. For short evaluation horizons (the past week and past month in Columns 1 and 2), extreme performance clearly attracts retail attention. The coefficient on the bottom quintile (β^1) is negative and statistically significant. Economically, a 1 percentage point drop in past-week returns for the worst-performing funds leads to a 1.79% increase in daily search volume. Conversely, the top quintile coefficient (β^5) is positive and highly significant: a 1 percentage point increase in past-week returns among the best performers leads to a 1.62% increase in searches. Meanwhile, the middle quintiles' coefficient ($\beta^{2\to4}$) is statistically indistinguishable from zero, suggesting that investors' attention is insensitive to fund performance when the performance is ordinary. This U-shaped attention curve directly mirrors our short-term flow-performance results, providing strong empirical evidence that retail attention drives the heavy inflows observed for both the best- and worst-performing active ETFs. Over longer horizons (the past quarter and past year in Columns 3 and 4), the relations are weaker, with coefficients decaying toward zero and losing statistical significance. This pattern indicates that retail attention does not respond strongly to long-term performance trends, consistent with our main findings: in the long term, the U-shape dissipates, and active ETFs behave similarly to traditional mutual funds.

4.3. Retail Trading

Having established that attention drives the short-term U-shaped flow-performance relation, a natural question arises: why are active ETF investors significantly more responsive to short-term signals than traditional active mutual fund investors? We argue that this behavior stems from structural differences that attract a specific retail clientele (Du et al., 2024) prone to attention-driven trading (Barber & Odean, 2008; Hartzmark, 2015; Barber et al., 2022).

The primary structural difference between active ETFs and active mutual funds is how they trade. When investors want to trade mutual fund shares, they can submit orders at any time, but they must wait until the market closes for the trade to be executed at the end-of-day net asset value. In contrast, active ETFs are exchange-traded, meaning their investors can buy and sell shares in real time during regular trading sessions. In other words, investors can day-trade active ETFs, but cannot day-trade active mutual funds.

This intraday liquidity inherently appeals to a more impatient clientele who treat active ETFs more like common equities than traditional funds. Empirical evidence strongly supports this difference in investor behavior: we find that active ETFs exhibit an average monthly turnover of 32.7% (calculated from the CRSP daily file), compared to a mere 2.3% for active mutual funds (Schwarz & Sun, 2023). This clientele sorting is also consistent with Du et al. (2024), who find no cannibalization between active mutual funds and their active ETF clones, implying that the two vehicles serve entirely distinct investor bases.

Figure 5 provides suggestive evidence that the rise in AETFs' popularity is attributable to retail investors. **Figure 5a** plots the cumulative flows into AETFs alongside the cumulative *retail* flows into common equities since 2019.[13] We see that the rise of AETFs largely coincides with the broader growth of retail trading, although AETF inflows lag retail equity flows by about two years—likely due to the time required to launch new AETFs. **Figure 5b** provides further evidence of AETFs' popularity among retail investors by plotting the fraction of retail trading volume (Boehmer et al., 2021; Barber et al., 2024) relative to total AETF trading volume over time. We observe a remarkably high level of retail trading in AETFs, ranging from 40% to 60%, compared to a steady 30% for common equities. To summarize, the proliferation of AETFs aligns with the rise of retail trading, and AETFs attract a disproportionate share of impatient retail investors. These investors exhibit attention-driven behavioral biases, trading AETFs more like individual stocks than traditional managed funds in the short term.

[13] We thank Phil Mackintosh from NASDAQ for sharing the retail flow data.

Insert **Figure 5** About Here

Next, we provide direct evidence that this attention-driven retail trading behavior generates the U-shaped flow-performance relation. We obtain shares purchased by retail investors at the AETF-day level using the TAQ data, following the methodology of Boehmer et al. (2021); Barber et al. (2024). This measure allows us to directly map the spikes in attention (from Google Search Volume) to actual trading behavior. We define our dependent variable as the natural log of retail buy volume (in shares) for active ETF i on day t.[14] We estimate the following panel regression to evaluate how retail purchase responds to past returns:

$$\log(\text{Retail Buy})_{i,t} = \beta^1 r^1_{i,t-j\to t-1} + \beta^{2\to 4} r^{2\to 4}_{i,t-j\to t-1} + \beta^5 r^5_{i,t-j\to t-1} + \kappa_i + \tau_t + \epsilon_{i,t}, \tag{5}$$

The key coefficients of interest are β^1 and β^5, which capture the relation between retail purchase and past returns for the worst- and best-performing funds, respectively. As in previous tests, we combine the middle quintiles since they are not the focus of the analysis and do not attract retail attention (**Table 7**). The model includes fund fixed effects (κ_i) to control for time-invariant differences in baseline trading volume across funds, and day fixed effects (τ_t) to absorb broad market-wide trading trends and returns. **Table 8** reports the results.

Insert **Table 8** About Here

Column 1 of **Table 8** reports how the daily retail buy volume of a specific AETF responds to its past-week performance. We observe a highly significant U-shaped pattern: extreme returns in either direction are associated with increased retail buying. Among the worst-performing AETFs, a 1 percentage point *decrease* in the past-week return is associated with a 7.14% *increase* in retail buying activity. Conversely, for the best-performing AETFs, a 1 percentage point increase in past-week return is associated with an 11.27% increase in

[14] We use retail buy volume to map trading activity to attention generated by extreme returns, whereas the net flow effect is captured in the main results in **Table 5**. We conduct additional robustness checks on net retail activities in **Appendix B.1** and show qualitatively similar, albeit statistically weaker, results.

retail buys. The U-shape in retail trading activity, along with the U-shape in Google Search Volume, provides direct evidence that retail investors trade AETFs based on the attention generated by extreme returns. That is, the U-shaped flow-performance relation observed in **Table 5** is driven by retail investors' attention-driven trading behavior.

Columns 2 through 4 evaluate these dynamics over longer horizons. While retail investors continue to chase past-month returns among the best-performing AETFs over longer horizons (positive and statistically significant β^5 in Columns 2 to 4), the left-tail coefficient (β^1) decays and ultimately loses statistical significance using the 1-year past return (Column 4). This decaying effect in retail trading, along with the decaying effect in attention in the Google Search Volume results in **Table 7**, explains why the flow-performance relation flattens out for worst-performing funds in the long term. After the initial short-term attention fades, investors simply stop paying attention to these holdings when they perform poorly.

Finally, we supplement these regression results by directly observing how retail investors react to high-attention events. Following Barber et al. (2022), we define high-attention events as days on which Robinhood users herd into establishing new positions, observed using the Robintrack data. Specifically, we define stocks in the top 0.5% of the daily user change distribution (with a minimum of 100 users on the prior day) as experiencing a high-attention herding event. In **Figure 6**, the solid red line plots the cumulative user change from 10 days before to 21 days after the high-attention event, while the dashed blue line plots the buy-and-hold cumulative returns over the same period.[15] We observe that the initial herding is clearly driven by a massive spike in returns, which generates intense short-term attention. However, as returns revert and decline, retail users do not divest from these initially high-attention assets. **Figure 6** provides clear visual evidence that retail investors strongly react to short-term attention shocks, but do not pay attention to their positions in the long term. This behavioral attention mechanism confirms the regression results for Google Search Volume (**Table 7**) and retail trading activity (**Table 8**), and perfectly underpins the U-shaped flow-performance dynamics documented in **Tables 5**.

Insert **Figure 6** About Here

[15]We thank Barber et al. (2022) for sharing their data.

To summarize, we show that AETFs exhibit a U-shaped flow-performance relation in the short run and the canonical Sirri-Tufano convex relation in the long run due to retail investors' attention-driven trading behavior. This combination is a big advantage for AETFs because short-term extreme (both positive and negative) returns result in long-term asset capture for the AETF, even if it is ultimately among the worst-performing ones in the long term. We next investigate how this unique flow-performance dynamic in AETFs shapes the risk-taking incentive for the managers.

5. Active ETF Risk-Taking

In this section, we investigate how AETF managers take risks in response to the unique flow-performance dynamics of their vehicle. We find that they take systematically higher risks to increase portfolio volatility and generate extreme returns. Importantly, this elevated risk-taking is present among both the best-performing and worst-performing funds. In contrast, the canonical literature on mutual fund tournaments (K. C. Brown et al., 1996; Schwarz, 2012) and managerial compensation (Goetzmann et al., 2003; Panageas & Westerfield, 2009) predicts elevated risk-taking primarily among the worst-performing funds. Thus, the higher risk-taking by AETF managers that we observe cannot be fully explained by traditional tournament incentives. Instead, it is driven by the incentive to generate extreme returns—in either direction—to capture investor attention.

We first examine whether AETF managers take systematically higher risks compared to their AMF counterparts. We calculate several return volatility measures for both vehicles and compare them in **Table 9**, using both the full sample (**Table 9a**) and a propensity-score matched sample based on objective code, size, and fees (**Table 9b**). Total volatility, defined as the standard deviation of daily returns over the entire sample period, is significantly higher for AETFs. Specifically, AETF total volatility is 7.6 percentage points higher in the full sample (4.1 percentage points higher in the matched sample) compared to AMFs.

However, higher total risk could come from higher factor loadings due to structural constraints rather than active managerial risk-taking. To address this, we calculate idiosyncratic risk using the CAPM, Fama-French three-factor, and Carhart four-factor models. We estimate these models using daily returns over the entire sample period and define idiosyncratic volatility as the standard deviation of the residualized returns. Here, the difference between the vehicles is even more pronounced: AETF idiosyncratic risk is roughly 20% to 25% higher (34% to 39% higher in the matched sample) than that of AMFs across all factor specifications.

Insert **Table 9** About Here

Having established that AETF managers take systematically higher risks, we investigate *how* they generate this excess volatility. We document two primary ways in which they increase portfolio volatility. First, they hold significantly less diversified portfolios. We calculate the Herfindahl-Hirschman Index (HHI) of industry concentration based on the portfolio holdings of AETFs and AMFs. The HHI for AETFs is approximately 18% higher in the full sample (16% higher in the matched sample) than for AMFs, suggesting that AETF managers could be concentrating their sector bets to amplify the probability of extreme return outcomes. Second, AETF managers trade more aggressively. AETFs exhibit an average monthly portfolio turnover of 6.5% (6.2% in the matched sample), whereas AMFs turn over just 5.2% (3.8% in the matched sample) of their portfolios monthly. This represents a 27% increase in trading activity for the full sample (66% increase in the matched sample).[16]

As part of this more aggressive trading behavior, AETF managers also trade heavily throughout the day. To illustrate this intraday activity, we compare the realized daily returns of AETFs (which incorporate the managers' intraday trades) against hypothetical holding-based returns, assuming the manager did not trade during the day. We calculate the hypothetical return for day t based on the fund's reported holdings at the end of day $t-1$ and the subsequent returns of those constituents on day t. The difference between these realized and hypothetical returns represents the "return gap" (Kacperczyk, Sialm, & Zheng, 2008), cleanly capturing the impact of intraday trades hidden from investors until the end-of-day portfolio disclosure. If these hidden intraday trades are aggressive (conservative), the

[16] For additional robustness, see **Appendix B.2** where we confirm these comparison results in a regression framework with controls and fixed effects in **Table B.3**.

distribution of realized returns will be wider (narrower) than the distribution of hypothetical returns. As shown in **Figure 7**, while both return distributions share a nearly identical mean (differing by just 0.2 basis points per day), the realized returns exhibit a substantially wider dispersion. This wider dispersion confirms that, on average, intraday trading by AETF managers does not generate better returns; rather, it spreads out the return distribution, which is more likely to lead to extreme return outcomes. In summary, AETF managers systematically elevate risk relative to their AMF peers by holding concentrated portfolios and executing frequent, aggressive trades.

Insert **Figure 7** About Here

Lastly, we distinguish the risk-taking behavior in the cross-section between AETF managers motivated by retail attention and AMF managers motivated by the traditional tournament incentive. Asymmetric payoffs created by traditional fund tournaments or compensation contracts are known to incentivize high risk-taking (K. C. Brown et al., 1996; Schwarz, 2012; Goetzmann et al., 2003; Panageas & Westerfield, 2009). However, under these traditional frameworks, elevated risk-taking typically occurs only among underperforming managers. We show that both underperforming and outperforming AETF managers take higher risk in **Table 10**, consistent with the attention motive.

Insert **Table 10** About Here

In the first two rows of **Table 10**, we sort AETFs into quintiles based on their performance in the past week and past year and report each quintile's total volatility. We see that AETFs in both performance extremes based on past week returns have higher volatility. Specifically, the bottom and top funds over the past week have total volatility of 1.22% and 1.19% in the subsequent month, respectively. AETFs in the middle quintiles exhibit a much lower volatility, ranging from 0.92% to 0.98%. The volatility at both extremes is statistically significantly higher than the unconditional sample mean of 1.05%. This elevated risk-taking on both performance extremes cannot be explained by the traditional tournament theory, which predicts risk-seeking behavior only among funds with extreme underperformance. Instead, it is more consistent with the explanation that AETF managers understand the "attention economy" and spike volatility at both performance extremes to maximize their attention among retail traders.

When we sort AETFs based on past-year performance, a different pattern emerges. Only the bottom-quintile funds continue to take higher risks, while top-performing funds have volatility that is statistically indistinguishable from the sample mean. This long-term behavior mirrors the traditional risk-taking dynamics documented in the canonical mutual fund tournament literature (K. C. Brown et al., 1996; Schwarz, 2012). We also repeat this analysis using idiosyncratic volatility measures and show that they exhibit the same patterns.

In summary, AETF managers dynamically adjust their risk-taking in response to their investor base. In the short term, they elevate risk at both performance extremes to capitalize on stock-like retail attention. In the long term, when the attention economy no longer dominates the flow dynamic, their behavior reverts to canonical mutual fund tournament incentives.

6. Active ETF Survival

Active ETFs face two countervailing forces regarding their survival. On the one hand, they can rapidly attract flows by generating extreme short-term returns. On the other hand, they take systematically greater risks and deliver weaker performance over the long run. In this section, we reconcile these competing forces by examining fund closure patterns in a Cox Proportional Hazard framework.

Insert **Table 11** About Here

Table 11, Column 1, examines fund survival as a function of short-term past-month returns.[17] We find that AETFs face an unconditional baseline probability of closure that

[17] Although we define "short term" as the past week in all previous analyses on fund flow and risk-taking,

is 68% higher than that of AMFs, reflecting the fragility of their high-risk strategies. However, this closure risk declines rapidly following strong past-month returns, whereas AMFs' survival probability does not respond to short-term performance. This pattern is consistent with our hypothesis that AETFs attract investors' attention in the short run to capture flows and stay afloat.

Columns 2 and 3 examine fund survival as a function of longer-term past quarterly and yearly returns. There are two key differences compared to the short-term results. First, the coefficient on the standalone ETF indicator is much smaller, indicating that the baseline probability of closure for AETFs and AMFs converges when holding long-term past returns constant. In fact, in Column 3, the ETF indicator does not have any material impact on the fund's survival probability. Second, the "closure-performance sensitivity" is nearly identical between AETFs and AMFs. Put together, these results demonstrate that in the long run, AETFs are evaluated by the market just like traditional managed funds. Their overall higher closure rate is explained mainly by their inferior performance relative to AMFs.

This elevated baseline probability of closure naturally raises the question of whether this high-risk strategy is economically sustainable for AETF sponsors. As discussed in Section 2, the proliferation of "ETF white-labelers" has drastically lowered the cost of launching a new fund. Because the flow-performance relation is highly convex in the right tail, an ETF sponsor can afford to launch multiple highly volatile AETFs at a relatively low cost. Even if many of these funds ultimately close due to poor long-term performance, the few that land in the extreme right tail will capture massive, sticky AUM from attention-driven retail investors. Thus, from the perspective of the fund sponsor, an elevated closure rate among individual funds is an acceptable cost, provided that a few funds successfully land in the right tail and gather outsized attention and flows.

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we consider the past month as "short term" in the context of fund closure since the decision to close out a fund cannot be made based on a single week's performance. For the same reason, we omit the past week's return as an independent variable in the survival analysis.

7. Active ETF Managers

Lastly, we investigate the human capital driving the AETF industry by comparing the professional backgrounds of AETF and AMF managers. Given the structural underperformance and elevated risk-taking of AETFs, we hypothesize that the two vehicles attract managers with distinct professional profiles. To test this hypothesis, we examine managerial career histories derived from LinkedIn profiles, provided by Revelio Labs. Specifically, we measure total years of work experience in the investment industry and the fraction of a manager's career spent specifically as a portfolio manager. The rationale is straightforward: longer industry tenure indicates a more seasoned manager, while a higher proportion of time spent as a portfolio manager serves as a proxy for specialized, relevant experience.

The Revelio Labs data contains comprehensive LinkedIn profiles, including historical positions, companies, position durations, and education. We link the managers from our CRSP MFDB and ETFG datasets to the Revelio Labs data using exact matches on last name and industry (requiring a two-digit NAICS code of 52), followed by fuzzy matching on first name and company name. This process yields a sample of 341 AETF managers and 800 AMF managers whose entire career trajectories we can observe. Notably, there is very little overlap between the two sets of managers (only 25 individuals manage both types of funds), suggesting that the AETF and AMF industries source talent from fundamentally different labor pools.

For each manager, we calculate their total years of work experience in the investment industry (identified by the first three digits of the NAICS code equaling 523) as of 2023. **Figure 8a** plots the density distribution of industry experience for both groups. The distribution for AMF managers is clearly shifted to the right relative to AETF managers. Specifically, the average AETF manager has 17.5 years of experience, compared to 19.4 years for the average AMF manager. This difference is highly statistically significant ($t = 3.2$), confirming that AETF managers are systematically less experienced than their mutual fund counterparts.

Insert **Figure 8** About Here

We also calculate the fraction of each manager's career spent specifically as a portfolio manager. The underlying rationale is that, holding total experience constant, an individual who has spent a larger proportion of their career managing portfolios is likely to possess more specialized expertise than someone with less direct portfolio management experience. We observe a similar pattern in **Figure 8b**: the distribution for AMF managers is once again shifted to the right. The average difference between the two groups is roughly 3% (with a t-stat of 1.5). Although not statistically significant at conventional levels, this difference provides further suggestive evidence that AETF managers possess less specialized experience than AMF managers, a finding that aligns with the severe underperformance and elevated risk-taking patterns documented earlier.

To summarize, there is almost no overlap between AMF and AETF managers, indicating that the two vehicles hire from fundamentally different talent pools. Compared to their AMF peers, AETF managers are systematically less experienced, which helps explain their reliance on attention-driven risk-taking rather than fundamental stock selection.

8. Conclusion

Active ETFs have emerged as an unlikely success story amid the broader decline of active management. Despite delivering weaker performance than active mutual funds on both a gross and net-of-fee basis, AETFs have grown rapidly in recent years. Our analyses suggest that this growth is driven not by a superior investment product, but by a fundamental shift in the investor base and the mechanics of fund trading. By mimicking the form and trading convenience of individual stocks, AETFs tap into the surge of retail activity and behavioral patterns shaped by attention-driven trading. In doing so, they attract a clientele who are less concerned with long-term alpha and more responsive to short-term, extreme returns—whether positive or negative.

This dynamic gives rise to a unique incentive environment. AETF managers benefit from a U-shaped flow-performance relation over short horizons, where both large gains and large losses attract attention and subsequent inflows. This structural reality creates a powerful incentive for less experienced managers to spike portfolio volatility to increase the likelihood that they end up on either extreme of the performance distribution. Consistent with this, we show that AETFs take on significantly more risk than their mutual fund counterparts, primarily driven by managers holding highly concentrated, high-turnover portfolios. While this volatility-seeking strategy may attract short-term flows, it remains fragile: AETFs face a substantially higher baseline closure risk because they ultimately deliver inferior performance in the long run.

Taken together, our results show that AETFs suffer from the exact same shortcomings that have driven the decline of traditional mutual funds: they persistently underperform passive benchmarks and display no evidence of managerial skill. Rather than addressing the structural issues of active management, we find that AETFs are simply a clever adaptation designed to exploit the behavioral biases of the modern retail investor. Their rapid rise of active ETFs illustrates how product packaging and ease of trading can attract capital despite poor underlying investment quality.

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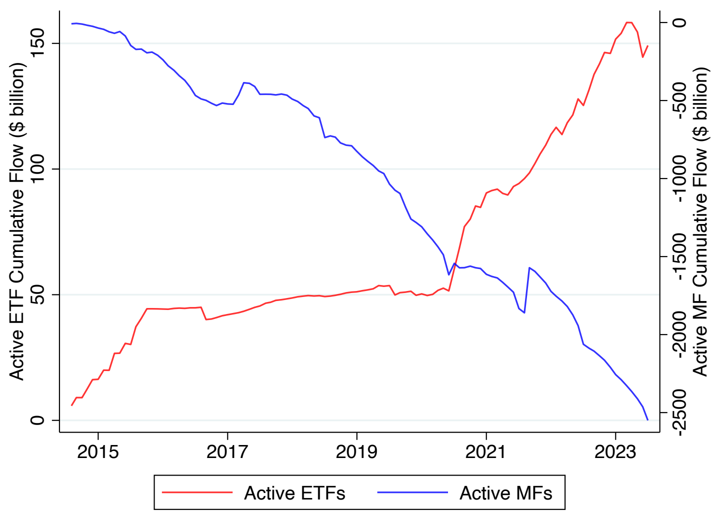
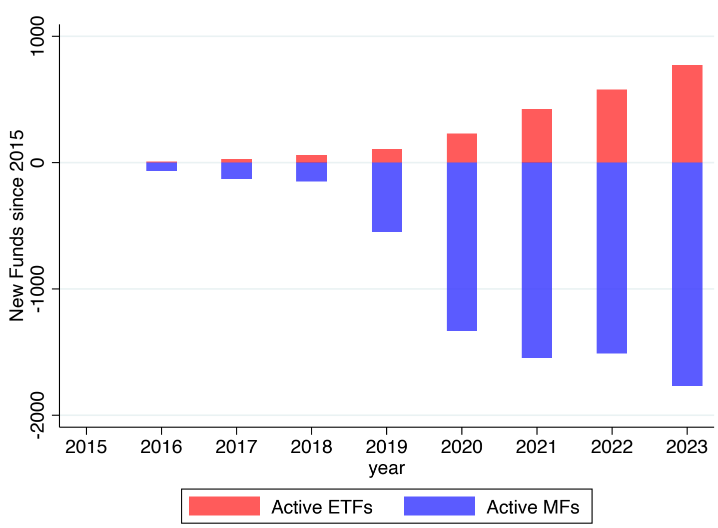
Figure 1. Popularity of Active ETFs and Mutual Funds

(a) Fund Flows

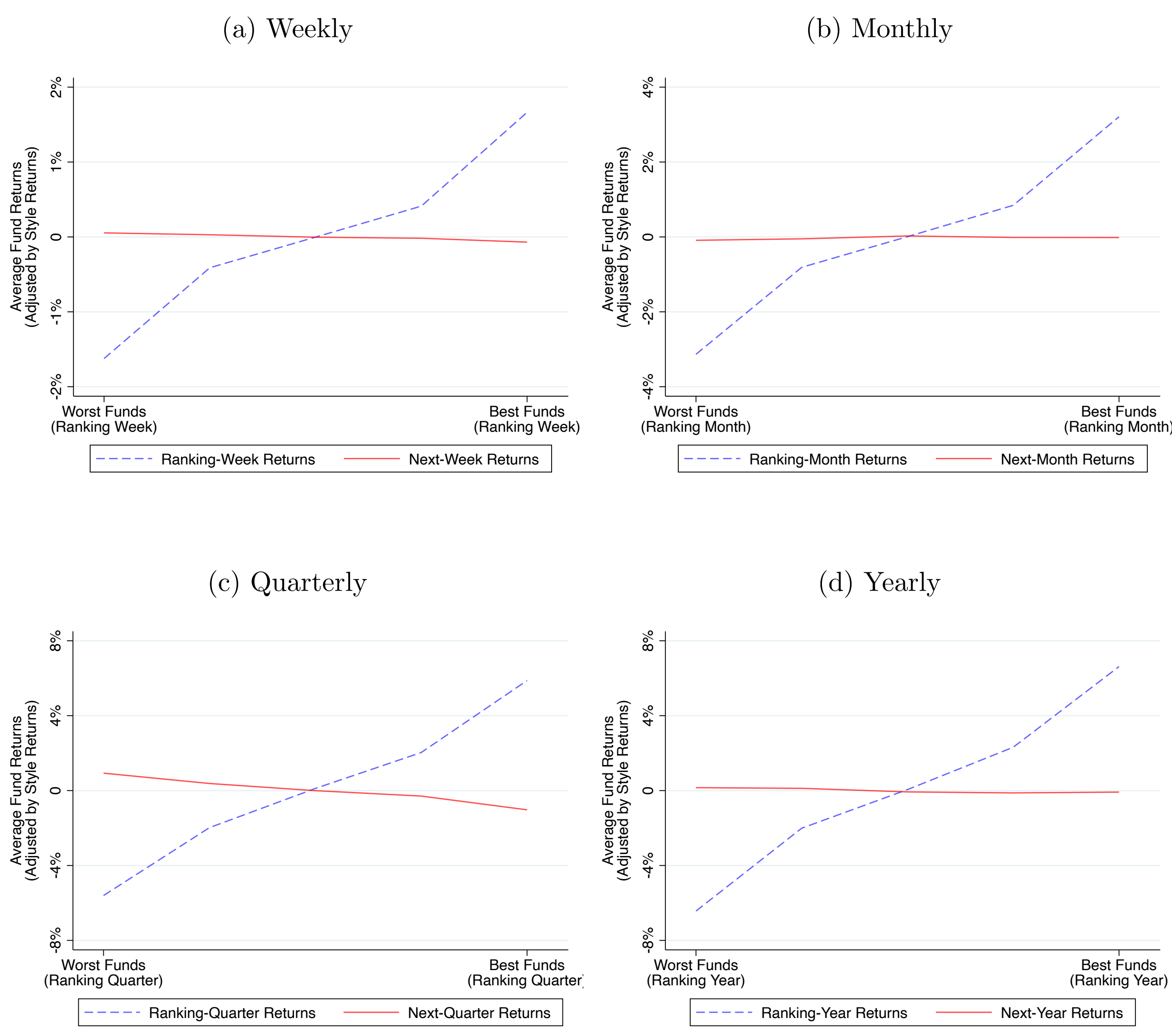


(b) New Funds



The figure plots the popularity trend in active ETFs and mutual funds from 2015 to 2023. Panel (a) plots the cumulative flow and panel (b) plots the cumulative new funds.

Figure 2. Active ETF Return Persistence

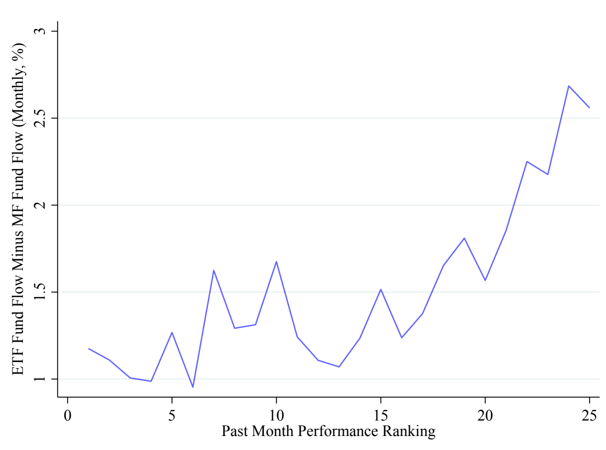


The figure plots active ETFs' ranking period returns and the next period returns by performance quintile reported in **Table 3**. All active ETFs are sorted into quintiles by their performance weekly, monthly, quarterly, and yearly. The average returns of the ETFs in each quintile during the ranking period are reported under columns labeled "Ranking Period." The average returns of the ETFs in the same quintile during the next period are reported under columns labeled "Next Period."

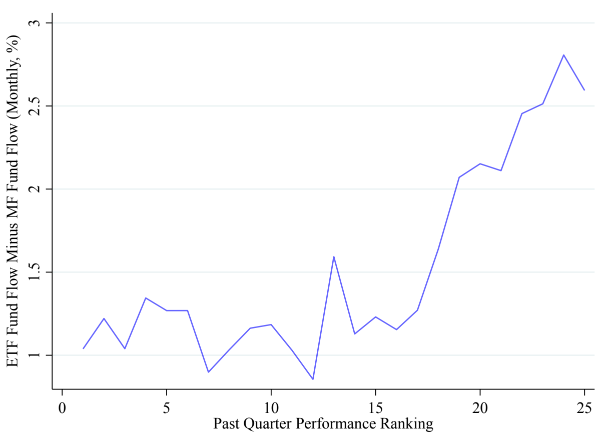
Figure 3. Active ETF Fund Flow Relative to Active MF Fund Flow by Past Performance

(a) Sort on Last-Week Return

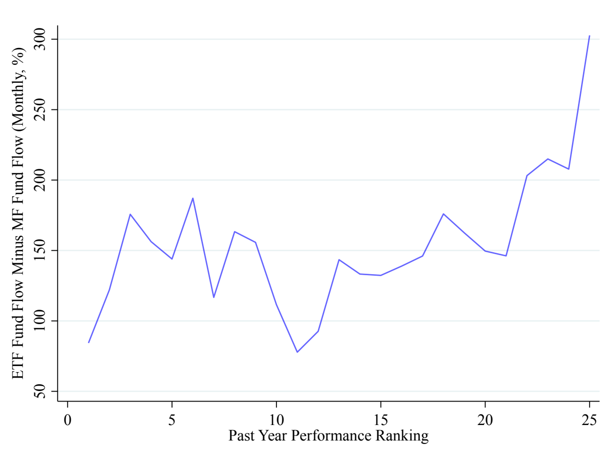
(b) Sort on Last-Month Return



(c) Sort on Last-Quarter Return

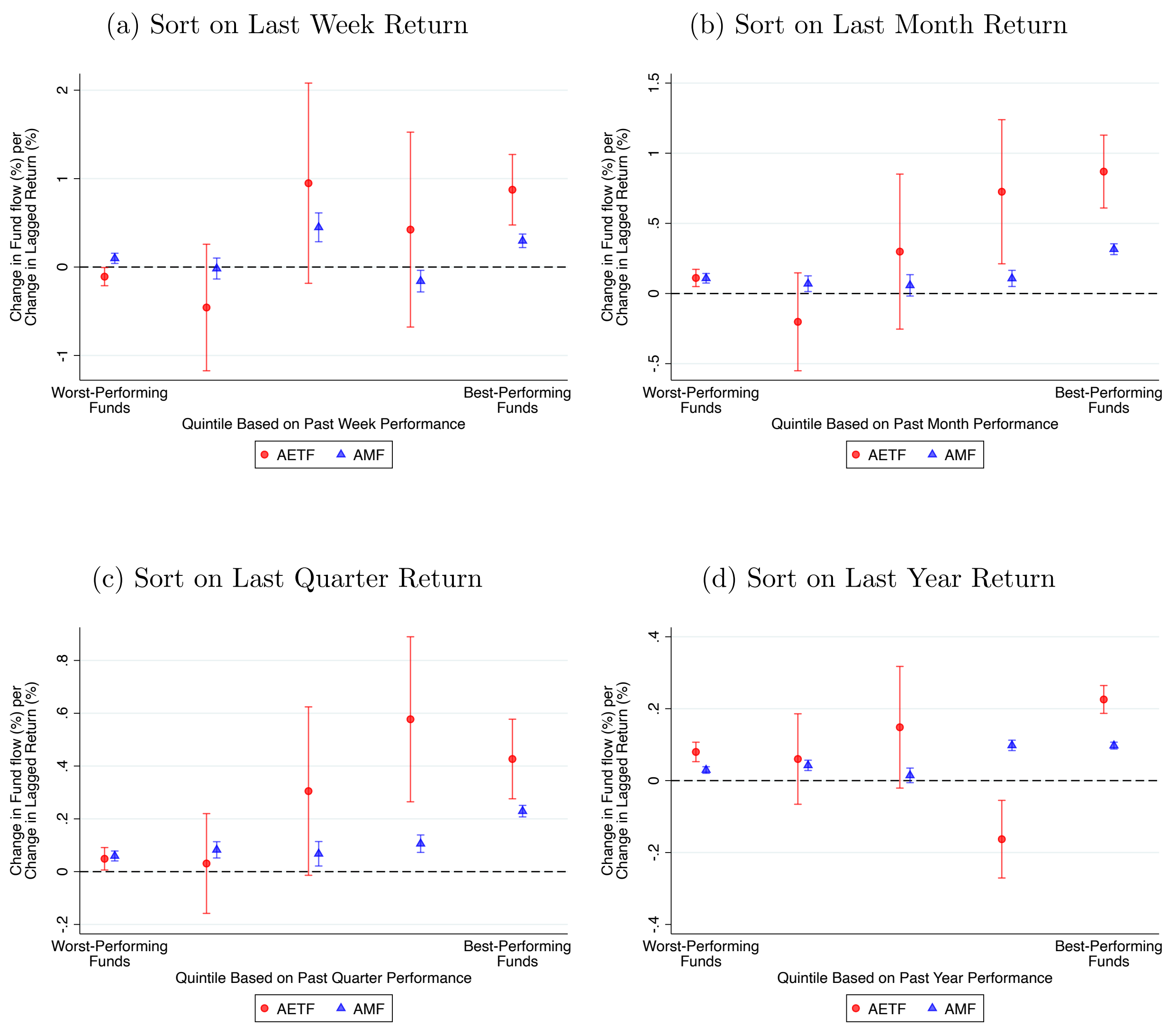


(d) Sort on Last-Year Return



The figure plots the monthly active ETF fund flows relative to active mutual fund flows, sorted into 25 bins based on past performance. Panels (a), (b), (c), and (d) sort the funds into bins by past week, month, quarter, and year performance, respectively.

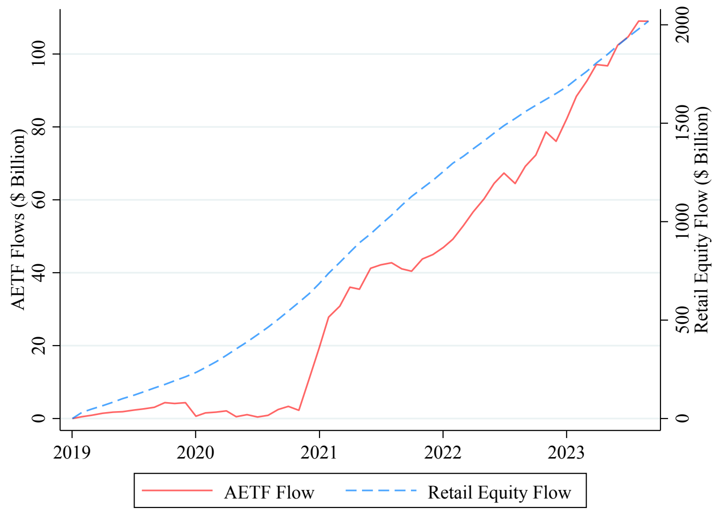
Figure 4. Active ETF and MF Flow-Performance Sensitivity



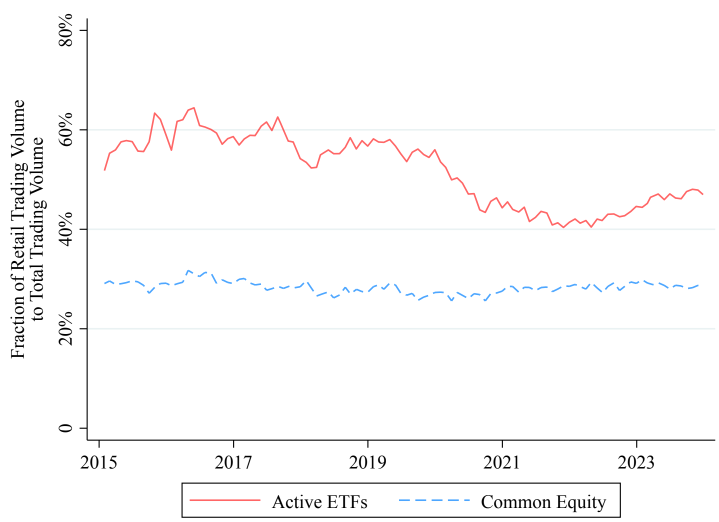
The figure plots the piecewise linear flow-performance sensitivity by performance quintile based on estimates in **Table 5**. Panels (a), (b), (c), and (d) present the coefficients of the regression using past week, month, quarter, and year returns, respectively. In each panel, AETF point estimates correspond to $\beta_1^q + \beta_2^q$ and AMF point estimates correspond to β_1^q in **Equation (3)**. The error bar represents the 95% confidence interval calculated using robust standard errors clustered at the fund level (the standard errors of the AETF estimates are calculated using the delta method).

Figure 5. Retail Trading by Security Types

(a) AETF Flow and Retail Equity Flow

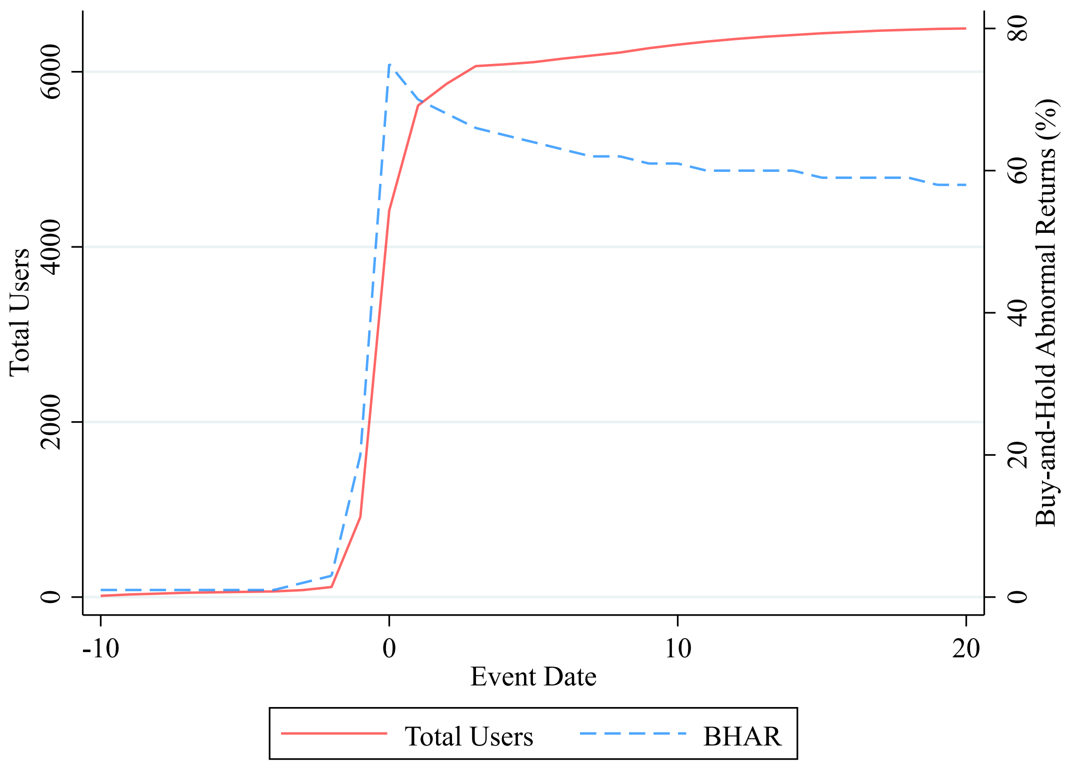


(b) Retail Participation in AETFs and Stocks



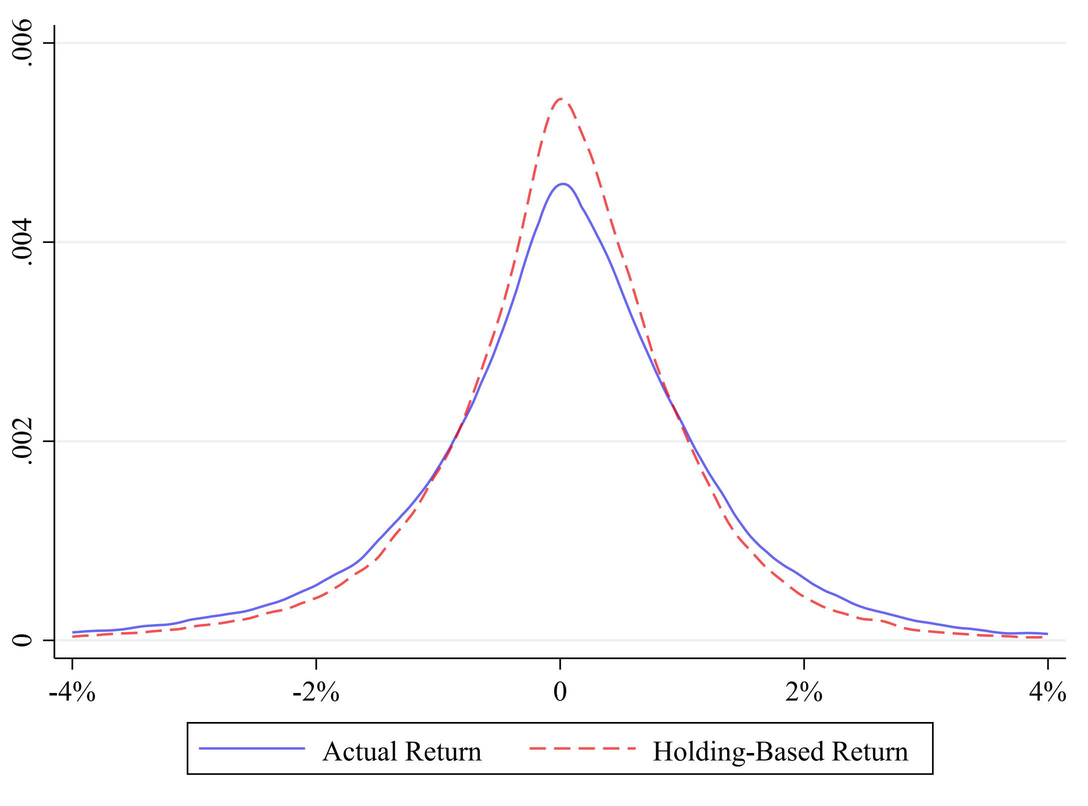
This figure shows the relation between retail trading and active ETFs. Panel (a) shows the cumulative flows into AETFs and the cumulative retail flows into equities in general, obtained from NASDAQ. Panel (b) shows the retail trading volume as a fraction of the total trading volume in AETFs and common equities. The total trading volume is obtained from the CRSP daily file, and the retail trading volume is calculated using the TAQ data following Boehmer et al. (2021) and Barber et al. (2024).

Figure 6. Robinhood Users and High-Attention Events



This figure plots the cumulative user change from 10 days before to 21 days after high-attention herding events in the red solid line. The blue dashed line plots the buy-and-hold abnormal returns (BHAR) for stocks that experienced high-attention herding events. High-attention herding events are defined as the stock-day on which the stock is in the top 0.5% in the user change ratio distribution and has a minimum of 100 users on the prior day.

Figure 7. Active ETF Price-Based and Holding-Based Return



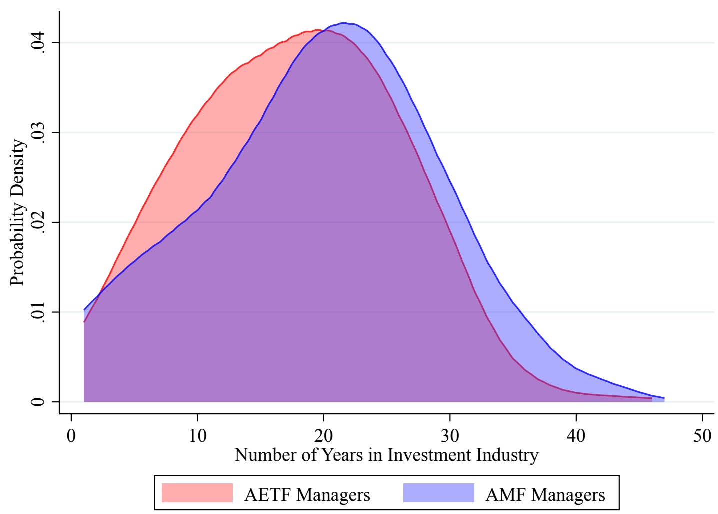
This figure shows the distribution of active ETFs' price-based returns and holding-based returns. The price-based return is the actual realized return of the ETFs. The holding-based return for ETF i on day t is calculated as

$$r_{i,t}^{\text{Holding}} = \sum_j w_{i,j,t-1} \cdot r_{j,t},$$

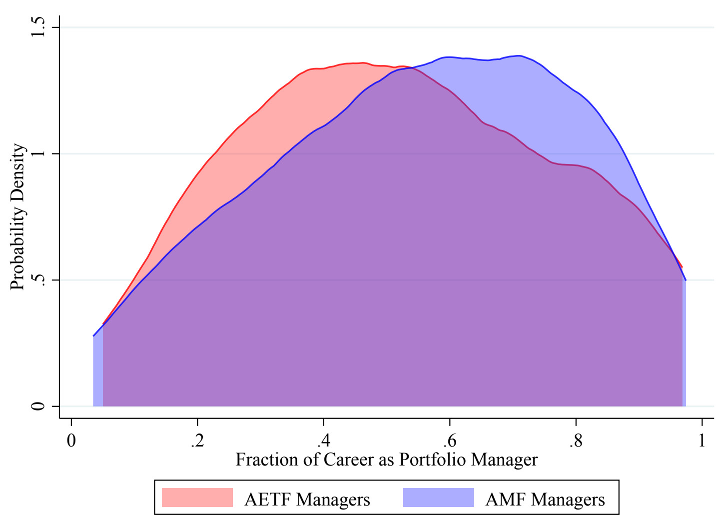
where $w_{i,j,t-1}$ is the portfolio weight of stock j in ETF i on day $t-1$ and $r_{j,t}$ is the return of stock j on day t.

Figure 8. AETF and AMF Managers

(a) Years Spent in the Investment Industry



(b) Fraction of Career as a Portfolio Manager



The figure plots the empirical density distribution of years spent in the investment industry in panel (a) and the fraction of the career as a portfolio manager in panel (b) by AETF and AMF managers.

Table 1
Summary Statistics

The table presents the summary statistics. The percentage monthly fund flow is calculated as the dollar value of fund flow divided by the total net assets at the end of the previous month. Fund returns are net of fees. The sample contains all active U.S. equity ETFs and mutual funds from 2015 to 2023.

(a) Active ETFs

	Mean	StDev	p10	p50	p90	N
Full Sample:						
Size ($ Million)	280.9	1,267.4	5.9	45.2	370.8	23,378
Monthly Flow (%)	3.9	15.5	–5.9	0.1	16.1	22,545
Expense Ratio (bps)	70	25	31	75	96	24,292
Monthly Return (%)	0.46	5.34	–6.10	0.60	6.95	23,466
2015 – 2019 (Pre 6c-11):						
Size ($ Million)	132.3	401.4	6.3	42.4	173.1	4,062
Monthly Flow (%)	3.3	13.6	–5.1	0.0	15.0	3,910
Expense Ratio (bps)	74	28	36	79	105	4,068
Monthly Return (%)	0.58	4.17	–4.59	0.87	5.30	3,947
2020 – 2023 (Post 6c-11):						
Size ($ Million)	312.2	1,380.1	5.7	45.8	412.0	19,316
Monthly Flow (%)	4.0	15.9	–6.1	0.1	16.4	18,635
Expense Ratio (bps)	69	25	30	75	93	20,224
Monthly Return (%)	0.43	5.55	–6.35	0.52	7.26	19,519

(b) Active Mutual Funds

	Mean	StDev	p10	p50	p90	N
Full Sample:						
Size ($ Million)	582.3	3,091.3	1.3	32.9	938.8	1,445,328
Monthly Flow (%)	0.6	10.3	–4.7	–0.5	4.9	1,439,831
Expense Ratio (bps)	109	57	40	104	189	1,248,415
Monthly Return (%)	0.63	4.68	–5.39	0.83	6.41	1,438,616
2015 – 2019 (Pre 6c-11):						
Size ($ Million)	496.0	2,567.5	1.3	28.6	837.3	819,662
Monthly Flow (%)	0.8	11.0	–4.6	–0.5	5.3	815,882
Expense Ratio (bps)	114	58	43	109	193	773,109
Monthly Return (%)	0.60	3.79	–4.23	0.80	5.13	814,979
2020 – 2023 (Post 6c-11):						
Size ($ Million)	695.4	3,662.9	1.4	39.0	1,087.3	625,666
Monthly Flow (%)	0.2	9.2	–4.9	–0.5	4.4	623,949
Expense Ratio (bps)	103	54	36	98	179	475,306
Monthly Return (%)	0.67	5.63	–6.77	0.93	7.92	623,637

Table 2
Active ETF and MF Alpha

The table presents the average monthly alpha of active mutual funds and ETFs. The alpha is estimated for each fund using the following equation:

$$r_{i,t} = \alpha_i + \beta_{1,i} \times \text{MktRF}_t + \beta_{2,i} \times \text{SMB}_t + \beta_{3,i} \times \text{HML}_t + \beta_{4,i} \times \text{MOM}_t + \epsilon_{i,t},$$

where $r_{i,t}$ is the return for fund i over the risk free rate in month t. MktRF_t, SMB_t, HML_t, and MOM_t are the market, size, value, and momentum factors, respectively. Alphas are calculated for each fund-month using an estimation window over the past 12 months. Panel (a) reports the comparison using the full sample, and panel (b) reports the comparison using a matched sample on dimensions including objective code, size, and fees. The reported values are the average of the alpha estimates across all fund-months from 2015 to 2023. Standard errors of the t-tests are reported in parentheses. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

(a) Full Sample

Monthly Alpha	ETFs	MFs	Difference	
Net-of-fee alpha (bps):				
CAPM	–20.9	–15.2	–5.7***	(0.9)
Fama-French 3-Factor	–18.7	–13.8	–4.9***	(0.8)
Carhart 4-Factor	–21.5	–14.8	–6.8***	(1.0)
Gross-of-fee alpha (bps):				
CAPM	–15.1	–6.1	–9.0***	(0.9)
Fama-French 3-Factor	–12.8	–4.7	–8.1***	(0.8)
Carhart 4-Factor	–15.7	–5.7	–10.0***	(1.0)

(b) Matched Sample

Monthly Alpha	ETFs	MFs	Difference	
Net-of-fee alpha (bps):				
CAPM	–20.7	–14.3	–6.4***	(0.3)
Fama-French 3-Factor	–21.0	–19.2	–1.8***	(0.3)
Carhart 4-Factor	–24.0	–18.4	–5.6***	(0.4)
Gross-of-fee alpha (bps):				
CAPM	–14.2	–7.6	–6.6***	(0.3)
Fama-French 3-Factor	–14.4	–12.5	–1.9***	(0.3)
Carhart 4-Factor	–17.4	–11.7	–5.7***	(0.4)

Table 3
Active ETF Return Persistence

This table presents the persistence of active ETF returns. All active ETFs are sorted into quintiles by their performance weekly, monthly, quarterly, and yearly. The average returns of the ETFs in each quintile during the sorting period are reported under columns labeled "Sorting Period." The average returns of the ETFs in the same quintile during the next period are reported under columns labeled "Next Period." All returns are reported in percentage points.

	Weekly		Monthly		Quarterly		Yearly	
Performance Quintile	Sorting Week	Next Week	Sorting Month	Next Month	Sorting Quarter	Next Quarter	Sorting Year	Next Year
1 (Lowest)	–1.62	0.05	–3.13	–0.09	–5.60	0.93	–6.43	0.16
2	–0.41	0.03	–0.81	–0.05	–1.98	0.38	–2.01	0.12
3	–0.00	–0.00	0.01	0.03	0.11	–0.00	0.06	–0.07
4	0.41	–0.02	0.84	–0.01	2.03	–0.29	2.32	–0.12
5 (Highest)	1.66	–0.07	3.21	–0.02	5.88	–1.03	6.62	–0.08
Q5 - Q1	3.29***	–0.12*	6.34***	0.07	11.48***	–1.96***	13.05***	–0.24
	(0.06)	(0.07)	(0.19)	(0.22)	(0.80)	(0.38)	(1.40)	(0.17)

Table 4
Active ETF Return Persistence Regression

This table presents the estimates of the following equation:

$$r^{\mathrm{NP}}_{d,t} = \beta \times r^{\mathrm{SP}}_{d,t} + \lambda_t + \epsilon_{d,t},$$

where $r^{\mathrm{SP}}_{d,t}$ is the average sorting-period return of all funds in quintile d during the sorting-period t. $r^{\mathrm{NP}}_{d,t}$ is the average next-period return of the same funds in quintile d sorted during period t. λ_t is the time fixed effects. Robust standard errors are clustered at the time level corresponding to the return period and are reported in parentheses. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Weekly		Monthly		Quarterly		Yearly	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sorting-Period Return	-0.05*	-0.05*	0.02	0.03	-0.19***	-0.19***	-0.03*	-0.03*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)
Time FE	None	Year-Week	None	Year-Month	None	Year-Quarter	None	Year
Adjusted R-squared	0.007	0.085	-0.000	0.236	0.436	0.489	0.069	0.056
Observations	2,332	2,332	530	530	179	179	45	45

Table 5
Active ETF and MF Flow Performance Relation

The table presents the results from the following regression:

$$\text{Flow}_{i,t} = \sum_{q=1}^{5} \left(\beta_1^q \times r_{i,t-j\to t}^q + \beta_2^q \times r_{i,t-j\to t}^q \times \text{ETF}_i \right) + X_{i,t} + \kappa_i + \tau_t + \epsilon_{i,t},$$

where $\text{Flow}_{i,t}$ is the percentage flow of fund i in month t, measured as $(\text{TNA}_{i,t} - \text{TNA}_{i,t-1}(1 + r_{i,t}))/\text{TNA}_{i,t-1}$. Past return $r_{i,t-j\to t}$ is measured from $-j$ ($j = 1$ week, 1 month, 3 months, and 1 year) up to *the day prior to* month t for each fund i. Past returns are further splined into quintiles $r_{i,t-j\to t}^q$. ETF_i is an indicator variable that equals 1 if the fund is an ETF and 0 otherwise. Control variables $X_{i,t}$ include the log fund size, past return volatility measured as the standard deviation of fund return in the past 12 months, and the average percentage fund flow for all funds in the same objective code. κ_i and τ_t are fund and year-month fixed effects. The sample contains all equity funds focusing on the broad market or a sector from 2015 to 2023. Robust standard errors clustered at the fund level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
$\text{Return}_{i,t-j\to t-1}$				
Bottom Quintile (β_1^1)	0.10***	0.11***	0.06***	0.03***
	(0.03)	(0.02)	(0.01)	(0.00)
	-0.02	0.07**	0.08***	0.04***
	(0.06)	(0.03)	(0.02)	(0.01)
	0.45***	0.06	0.07***	0.01
	(0.08)	(0.04)	(0.02)	(0.01)
	-0.16***	0.11***	0.11***	0.10***
	(0.06)	(0.03)	(0.02)	(0.01)
Top Quintile (β_1^5)	0.30***	0.32***	0.23***	0.10***
	(0.04)	(0.02)	(0.01)	(0.00)
$\text{Return}_{i,t-j\to t-1} \times \text{ETF}_i$				
Bottom Quintile (β_2^1)	-0.21***	0.00	-0.01	0.05***
	(0.04)	(0.03)	(0.02)	(0.01)
	-0.44	-0.27	-0.05	0.02
	(0.36)	(0.18)	(0.10)	(0.06)
	0.50	0.24	0.24	0.13
	(0.58)	(0.28)	(0.16)	(0.09)
	0.58	0.62**	0.47***	-0.26***
	(0.56)	(0.26)	(0.16)	(0.05)
Top Quintile (β_2^5)	0.58***	0.55***	0.20**	0.13***
	(0.21)	(0.13)	(0.08)	(0.02)
Return Period	Weekly	Monthly	Quarterly	Yearly
Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.069	0.070	0.071	0.072
Observations	1,454,467	1,454,467	1,454,467	1,454,467

Table 6
U-Shaped Short-Term Flow-Performance Relation and Active ETF Size

The table repeats the analysis in **Table 5** using a subsample containing only large active ETFs (and all active mutual funds). The active ETFs in columns 1, 2, 3, and 4 are those in the top half, tercile, quartile, and quintile, respectively. The sample contains all equity funds focusing on the broad market or a sector from 2015 to 2023. Robust standard errors clustered at the fund level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

AETF included	Top Half (1)	Top Tercile (2)	Top Quartile (3)	Top Quintile (4)
$\text{Return}_{i,t-j\to t-1}$				
Bottom Quintile (β_1^1)	0.09***	0.10***	0.10***	0.10***
	(0.03)	(0.03)	(0.03)	(0.03)
	-0.01	-0.02	-0.02	-0.02
	(0.06)	(0.06)	(0.06)	(0.06)
	0.45***	0.45***	0.45***	0.45***
	(0.08)	(0.08)	(0.08)	(0.08)
	-0.16**	-0.16**	-0.15**	-0.16**
	(0.06)	(0.06)	(0.06)	(0.06)
Top Quintile (β_1^5)	0.30***	0.30***	0.30***	0.30***
	(0.04)	(0.04)	(0.04)	(0.04)
$\text{Return}_{i,t-j\to t-1} \times \text{ETF}_i$				
Bottom Quintile (β_2^1)	-0.27***	-0.35***	-0.32***	-0.28***
	(0.07)	(0.08)	(0.08)	(0.09)
	0.94*	0.87	0.93	0.42
	(0.51)	(0.56)	(0.58)	(0.63)
	-1.17	-0.48	0.39	1.51*
	(0.74)	(0.77)	(0.73)	(0.91)
	1.45**	1.67**	1.25*	0.07
	(0.66)	(0.68)	(0.69)	(0.71)
Top Quintile (β_2^5)	0.55	0.66	0.47	0.63
	(0.35)	(0.44)	(0.44)	(0.54)
Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.068	0.068	0.068	0.067
Observations	1,443,574	1,439,712	1,437,779	1,436,593

Table 7
Active ETF Google Search Volume and Performance Relation

The table presents the results from a panel regression of Google Search Volume for Active ETFs on their past returns:

$$\log(\text{Google Trends})_{i,t} = \beta^1 r^1_{i,t-j\to t-1} + \beta^{2\to 4} r^{2\to 4}_{i,t-j\to t-1} + \beta^5 r^5_{i,t-j\to t-1} + X_{i,t} + \kappa_i + \tau_t + \epsilon_{i,t},$$

where the dependent variable is the logarithm of the Google Search Volume for active ETF i on day t. Past return $r_{i,t-j\to t-1}$ is measured from $-j$ (j = 1 week, 1 month, 3 months, and 1 year) up to day $t-1$ for each fund i. Past returns are further splined into bottom quintile $r^1_{i,t-j\to t-1}$, top quintile $r^5_{i,t-j\to t-1}$, and middle quintiles $r^{2\to 4}_{i,t-j\to t-1}$. κ_i and τ_t represent fund fixed effects and day fixed effects, respectively. Robust standard errors clustered at the fund level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Bottom Quintile (β^1)	-1.79**	-1.21**	-0.73*	-0.40
	(0.73)	(0.47)	(0.39)	(0.30)
Middle Quintiles ($\beta^{2\to 4}$)	-0.19	0.02	-0.05	-0.04
	(0.20)	(0.18)	(0.14)	(0.12)
Top Quintile (β^5)	1.62***	0.86**	0.77***	0.40
	(0.61)	(0.34)	(0.28)	(0.25)
Return Period	Past Week	Past Month	Past Quarter	Past Year
Fund FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.786	0.786	0.786	0.787
Observations	398,209	398,210	398,210	398,210

Table 8
Active ETF Absolute Retail Buying Volume and Performance Relation

The table presents the results from the following panel regression:

$$\log(\text{Retail Buy})_{i,t} = \beta^1 r^1_{i,t-j\to t-1} + \beta^{2\to 4} r^{2\to 4}_{i,t-j\to t-1} + \beta^5 r^5_{i,t-j\to t-1} + \kappa_i + \tau_t + \epsilon_{i,t},$$

where the dependent variable is the natural logarithm of shares purchased by retail investors for active ETF i on day t, measured using the Boehmer et al. (2021) methodology applied to TAQ data. Past return $r_{i,t-j\to t-1}$ is measured from $-j$ ($j = 1$ week, 1 month, 3 months, and 1 year) up to day $t-1$ for each fund i. Past returns are further splined into bottom quintile $r^1_{i,t-j\to t}$, top quintile $r^5_{i,t-j\to t}$, and middle quintiles $r^{2\to 4}_{i,t-j\to t}$. κ_i and τ_t represent fund fixed effects and day fixed effects, respectively. Robust standard errors clustered at the fund level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Bottom Quintile (β^1)	-7.14***	-3.64***	-2.41**	-0.76
	(1.78)	(1.11)	(1.00)	(0.93)
Middle Quintiles ($\beta^{2\to 4}$)	-2.86***	-0.97**	0.37	1.66***
	(0.62)	(0.49)	(0.43)	(0.27)
Top Quintile (β^5)	11.27***	6.33***	4.90***	2.33***
	(1.43)	(0.86)	(0.64)	(0.28)
Return Period	Past Week	Past Month	Past Quarter	Past Year
Fund FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.456	0.456	0.457	0.460
Observations	414,703	414,703	414,703	414,703

Table 9
Active ETF and MF Risk-Taking

This table presents the risk-taking measures for active ETFs (AETFs) and active mutual funds (AMFs). Return-based risk-taking measures include total fund return volatility and idiosyncratic volatility of fund returns residualized against factor models such as CAPM, the Fama-French three-factor model, and the Carhart four-factor model. Holdings-based risk-taking measures include monthly portfolio turnover and the Herfindahl–Hirschman Index (HHI) of the fund portfolio's industry (two-digit SIC) concentration. Standard errors are reported in parentheses. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

(a) Full Sample

	AETFs	AMFs	Difference	
Return-based measure (%)				
Total volatility	1.051	0.974	0.076***	(0.004)
Idiosyncratic volatility (CAPM)	0.563	0.464	0.099***	(0.002)
Idiosyncratic volatility (FF3)	0.492	0.392	0.100***	(0.002)
Idiosyncratic volatility (Carhart)	0.485	0.388	0.097***	(0.002)
Holdings-based measure				
Portfolio's industry concentration (HHI)	0.320	0.270	0.049***	(0.016)
Portfolio turnover	0.065	0.052	0.014***	(0.001)

(b) Matched Sample

	AETFs	AMFs	Difference	
Return-based measure (%)				
Total volatility	1.061	1.020	0.041***	(0.0020)
Idiosyncratic volatility (CAPM)	0.572	0.428	0.144***	(0.0012)
Idiosyncratic volatility (FF3)	0.507	0.366	0.142***	(0.0010)
Idiosyncratic volatility (Carhart)	0.498	0.362	0.135***	(0.0010)
Holdings-based measure				
Portfolio's industry concentration (HHI)	0.314	0.270	0.044***	(0.003)
Portfolio turnover	0.062	0.038	0.025***	(0.000)

Table 10
Active ETF Return Volatility Based on Past Performance

This table presents volatility measures for active ETFs based on their performance over the past week, month, quarter, and year. The volatility measures include total volatility and idiosyncratic volatility of returns orthogonalized against the CAPM, Fama-French Three-Factor, and Carhart Four-Factor models. The table also reports the difference between the Q1 mean and the unconditional sample mean and the difference between the Q5 mean and the unconditional sample mean. Standard errors are reported in parentheses. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Quintiles Sorted on Past Performance						
Sorting Period	Q1 (Lowest)				Q5 (Highest)	Q1 - Mean	Q5 - Mean
Total Volatility (mean = 1.05):							
Past Week	1.22	0.92	0.94	0.98	1.19	0.17***	0.14**
						(0.06)	(0.06)
Past Year	1.39	0.95	0.91	0.91	1.10	0.34***	0.05
						(0.06)	(0.04)
CAPM Idiosyncratic Volatility (mean = 0.56):							
Past Week	0.77	0.45	0.43	0.46	0.71	0.20***	0.14***
						(0.03)	(0.03)
Past Year	0.85	0.49	0.44	0.43	0.60	0.29***	0.03
						(0.03)	(0.02)
Fama-French Three-Factor Idiosyncratic Volatility (mean = 0.49):							
Past Week	0.68	0.40	0.38	0.40	0.60	0.19***	0.11***
						(0.03)	(0.02)
Past Year	0.74	0.44	0.40	0.38	0.50	0.25***	0.01
						(0.03)	(0.02)
Carhart Four-Factor Idiosyncratic Volatility (mean = 0.49):							
Past Week	0.67	0.39	0.37	0.40	0.59	0.18***	0.11***
						(0.03)	(0.02)
Past Year	0.73	0.43	0.39	0.38	0.50	0.24***	0.01
						(0.03)	(0.02)

Table 11
Active ETF and MF Survivals

The table presents estimates from the Cox Proportional Hazards model assessing the likelihood of fund closure. All continuous variables are scaled to a standard deviation of 1. The table reports the marginal effect for ease of interpretation. Z-scores are displayed in parentheses below each estimate. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
ETF	0.68***	0.15***	0.05
	(0.07)	(0.02)	(0.04)
ETF × Lagged Return	-0.25***	-0.20***	-0.31***
	(0.04)	(0.07)	(0.06)
MF × Lagged Return	0.00	-0.20***	-0.40***
	(0.02)	(0.03)	(0.02)
Control	Yes	Yes	Yes
Strata by Fund Style	Yes	Yes	Yes
Return Period	Monthly	Quarterly	Yearly
Observations	1,264,704	1,265,708	1,265,799

Internet Appendix

A. AETF Tax Advantage Analysis

This appendix analyzes the tax advantage of AETFs in detail and shows that AETFs still underperform AMF on an after-tax basis, considering the tax efficiency documented in Moussawi et al. (2025) and Goldenring (2026).

To demonstrate this point, we construct a hypothetical scenario where a buy-and-hold investor invests $10,000 in an AMF and an AETF. **Table A.1** traces out the after-tax return each year. We assume the active mutual fund earns 7.83% annually (i.e., 0.63% monthly in **Table 1b**) and show the investment value each year in **Table A.1a** column 1. We then assume an annual portfolio turnover ratio of 60% (the mean turnover observed in data), which means approximately 60% of the capital gain is distributed to the investor annually. With a 20% capital gains tax rate, we can calculate the annual capital gains taxes (column 2) and update the tax base (column 4). If the investor holds the mutual fund for N years, we calculate the future value (FV) of all annual capital gain tax payments (in column 2) from year 1 to year N using a 15% discount rate and tabulate the FV in column 3. We intentionally choose an unreasonably high discount rate to amplify AETF's tax advantage for the purpose of this demonstration. We also calculate the tax owed when the investor redeems the AMF shares (using the investment value in column 1 and the tax base in column 4) and report it in column 5. The total capital gain taxes for the investor (column 6) at the end of year N is the sum of the FV of annual capital gain taxes and the taxes paid at redemption. Finally, we can calculate the after-tax annual return in column 7 for each investment horizon N from year 1 to year 20.

Table A.1b reports the scenario where the investor buys and holds an AETF that earns 5.66% annually (i.e., 0.46% in **Table 1a**). The calculation is much easier since ETFs use in-kind creation and redemption to manage their positions such that no tax events are triggered and capital gain taxes are only paid once at redemption. We see that the after-tax returns of the AMF and AETF at 20 years are both around 5%. In other words, the investor needs to hold the fund for 20 years for the ETF's tax advantage (which is highly overstated by the 15% discount rate) to make up for the inferior return. In reality, the annual turnover of AETFs (calculated as annual trading volume divided by shares outstanding from CRSP) is roughly 400% on average. That is, average AETF investors hold the position for three months, which is way too short for any tax efficiency to have a material impact. Therefore, we conclude that AETFs underperform AMFs on an after-tax basis.

Table A.1
Active MF and ETF After-Tax Performance

The table presents the hypothetical investment in AMFs and AETFs and the corresponding after-tax returns. We assume AMFs earn 7.83% per annum, AETFs earn 5.66% per annum, and AMFs have 60% portfolio turnover per annum (such that 60% of capital gains are distributed), all of which are directly obtained from empirical data. We assume a capital gain tax rate of 20% and a discount rate of 15%, both of which are intentionally chosen to be high to amplify AETF's tax advantage. If an investor holds the active mutual fund (active ETF) for 20 years, her after-tax return would be 5.05% (4.91%).

(a) Active Mutual Funds

Year	(1) Investment Value	(2) Annual Capital Gain Taxes	(3) FV of Annual Taxes	(4) Tax Base	(5) Taxes at Redemption	(6) Total Taxes	(7) After-Tax Return
0	$10,000.00			$10,000.00			
1	$10,782.75	$93.93	$93.93	$10,469.65	$62.62	$156.55	6.26%
2	$11,626.78	$101.28	$209.30	$10,976.07	$130.14	$339.44	6.24%
3	$12,536.87	$109.21	$349.91	$11,522.12	$202.95	$552.86	6.22%
4	$13,518.19	$117.76	$520.15	$12,110.92	$281.46	$801.61	6.19%
5	$14,576.34	$126.98	$725.15	$12,745.80	$366.11	$1,091.26	6.16%
6	$15,717.30	$136.92	$970.84	$13,430.38	$457.38	$1,428.23	6.13%
7	$16,947.58	$147.63	$1,264.10	$14,168.55	$555.81	$1,819.91	6.09%
8	$18,274.16	$159.19	$1,612.91	$14,964.49	$661.93	$2,274.84	6.05%
9	$19,704.57	$171.65	$2,026.50	$15,822.74	$776.37	$2,802.86	6.00%
10	$21,246.96	$185.09	$2,515.56	$16,748.17	$899.76	$3,415.31	5.95%
11	$22,910.07	$199.57	$3,092.46	$17,746.04	$1,032.81	$4,125.27	5.90%
12	$24,703.36	$215.20	$3,771.53	$18,822.02	$1,176.27	$4,947.80	5.84%
13	$26,637.03	$232.04	$4,569.30	$19,982.22	$1,330.96	$5,900.26	5.77%
14	$28,722.05	$250.20	$5,504.89	$21,233.23	$1,497.76	$7,002.66	5.70%
15	$30,970.28	$269.79	$6,600.41	$22,582.17	$1,677.62	$8,278.04	5.61%
16	$33,394.49	$290.91	$7,881.38	$24,036.69	$1,871.56	$9,752.94	5.52%
17	$36,008.45	$313.68	$9,377.26	$25,605.07	$2,080.68	$11,457.94	5.43%
18	$38,827.02	$338.23	$11,122.08	$27,296.21	$2,306.16	$13,428.24	5.31%
19	$41,866.22	$364.70	$13,155.10	$29,119.73	$2,549.30	$15,704.40	5.19%
20	$45,143.31	$393.25	$15,521.61	$31,085.99	$2,811.47	$18,333.08	5.05%

(b) Active ETFs

Year	(1) Investment Value	(2) Annual Capital Gain Taxes	(3) FV of Annual Taxes	(4) Tax Base	(5) Taxes at Redemption	(6) Total Taxes	(7) After-Tax Return
0	$10,000.00			$10,000.00			
1	$10,566.18	$0.00	$0.00	$10,000.00	$113.24	$113.24	4.53%
2	$11,164.42	$0.00	$0.00	$10,000.00	$232.88	$232.88	4.55%
3	$11,796.53	$0.00	$0.00	$10,000.00	$359.31	$359.31	4.58%
4	$12,464.43	$0.00	$0.00	$10,000.00	$492.89	$492.89	4.60%
5	$13,170.14	$0.00	$0.00	$10,000.00	$634.03	$634.03	4.62%
6	$13,915.81	$0.00	$0.00	$10,000.00	$783.16	$783.16	4.65%
7	$14,703.70	$0.00	$0.00	$10,000.00	$940.74	$940.74	4.67%
8	$15,536.20	$0.00	$0.00	$10,000.00	$1,107.24	$1,107.24	4.69%
9	$16,415.83	$0.00	$0.00	$10,000.00	$1,283.17	$1,283.17	4.71%
10	$17,345.26	$0.00	$0.00	$10,000.00	$1,469.05	$1,469.05	4.73%
11	$18,327.32	$0.00	$0.00	$10,000.00	$1,665.46	$1,665.46	4.75%
12	$19,364.98	$0.00	$0.00	$10,000.00	$1,873.00	$1,873.00	4.77%
13	$20,461.39	$0.00	$0.00	$10,000.00	$2,092.28	$2,092.28	4.79%
14	$21,619.88	$0.00	$0.00	$10,000.00	$2,323.98	$2,323.98	4.81%
15	$22,843.95	$0.00	$0.00	$10,000.00	$2,568.79	$2,568.79	4.82%
16	$24,137.34	$0.00	$0.00	$10,000.00	$2,827.47	$2,827.47	4.84%
17	$25,503.95	$0.00	$0.00	$10,000.00	$3,100.79	$3,100.79	4.86%
18	$26,947.94	$0.00	$0.00	$10,000.00	$3,389.59	$3,389.59	4.88%
19	$28,473.68	$0.00	$0.00	$10,000.00	$3,694.74	$3,694.74	4.89%
20	$30,085.81	$0.00	$0.00	$10,000.00	$4,017.16	$4,017.16	4.91%

B. Robustness Checks

This appendix presents additional robustness results that supplement the analyses in the main paper.

B.1. Robustness: Net Retail Trading Activity

In section 4.3 of the main paper, we show that the retail buying activities in response to short-term performance exhibit a strong U-shape that closely mirrors the U-shape in fund flow and investors' attention. This result provides direct evidence of the underlying mechanism: retail investors pay attention to extreme AETF returns in the short term and make trading decisions based on the attention effect. In this section, we provide supplementary evidence that the net retail trading activity, rather than retail buying activity, also exhibits a similar U-shape. We show this pattern in the following two ways.

First, we also run the same specification as in Table 8, but with retail selling volume as the dependent variable. **Table B.1** presents the results. We see that selling activities also follow a U-shaped pattern, providing further evidence that retail trading is largely driven by attention. Importantly, in column 1, the coefficient that captures investors' short-term attention-driven sell (-6.55) has a smaller magnitude than the coefficient that captures investors' attention-driven buy (-7.14, in **Table 8**). That is, extreme short-term underperformance results in net buying activities from retail investors. Similarly, the coefficient for the top quintile AETFs for retail selling activities (9.16) has a smaller magnitude than that for retail buying activities (11.27, in **Table 8**). Taken together, extreme short-term performance in both directions leads to net buying by retail investors, even though the difference between the coefficients in **Table B.1** and **Table 8** is statistically weaker due to the high correlation between retail trading in both directions.

Second, we also capture retail investors' trading behavior using data from Robintrack, a platform that recorded the number of users holding a specific ticker on Robinhood (a popular retail brokerage). We define the *net* change in Robinhood users holding active ETF i from period $t-1$ to period t as:

$$\Delta \text{RhUser}_{i,t} = \frac{\text{RhUser}_{i,t} - \text{RhUser}_{i,t-1}}{\text{RhUser}_{i,t-1}}. \tag{6}$$

We estimate the same piecewise linear panel regression model as in the main text to capture the user flow-performance relation for the best- and worst-performing funds. There are several limitations of the Robintrack data. First, it is a noisy proxy for aggregate retail fund flow: because it only tracks the number of unique accounts holding a ticker, existing investors scaling up or partially paring down their positions will not affect $\Delta \text{RhUser}_{i,t}$. It only captures new investors initiating a position or existing investors completely divesting. Second, while Robinhood is highly popular due to its commission-free model, it does not represent the entire universe of retail investors. Third, the Robintrack dataset only spans from June 2018 to August 2020, missing the bulk of the post-6c-11 AETF boom and the height of pandemic-era retail trading. Consequently, utilizing $\Delta \text{RhUser}_{i,t}$ to estimate retail flow sensitivity likely understates the true magnitude of the effect. Despite these limitations, we use the Robintrack data to provide supplemental evidence to validate the results in the main paper.

Table B.2 reports the results. Consistent with the U-shape we document in AETF fund flow (**Table 5**) and retail attention (**Table 7**), we observe a similar U-shaped pattern in daily user growth. In column 1 of panel (a), the results show that the best-performing AETFs attract significantly more users as returns increase, whereas the worst-performing AETFs attract more users as returns become *even worse*. Columns 2 through 4 show that this behavior decays over longer horizons, reinforcing the idea that retail investor attention is highly transient (Barber & Odean, 2008; Kaniel, Saar, & Titman, 2008). Panel B reports monthly user changes, which mirror the baseline flow patterns in **Table 5** despite lower precision due to the small sample size.

Table B.1
Active ETF Absolute Retail Buying Volume and Performance Relation

The table presents the results from the following panel regression:

$$\log(\text{Retail Sell})_{i,t} = \beta^1 r^1_{i,t-j\to t-1} + \beta^{2\to 4} r^{2\to 4}_{i,t-j\to t-1} + \beta^5 r^5_{i,t-j\to t-1} + \kappa_i + \tau_t + \epsilon_{i,t},$$

where the dependent variable is the natural logarithm of shares purchased by retail investors for active ETF i on day t, measured using the Boehmer et al. (2021) methodology applied to TAQ data. Past return $r_{i,t-j\to t-1}$ is measured from $-j$ ($j = 1$ week, 1 month, 3 months, and 1 year) up to day $t-1$ for each fund i. Past returns are further splined into bottom quintile $r^1_{i,t-j\to t}$, top quintile $r^5_{i,t-j\to t}$, and middle quintiles $r^{2\to 4}_{i,t-j\to t}$. κ_i and τ_t represent fund fixed effects and day fixed effects, respectively. Robust standard errors clustered at the fund level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Bottom Quintile (β^1)	-6.55***	-3.16***	-2.18**	-0.51
	(1.75)	(1.10)	(0.95)	(0.90)
Middle Quintiles ($\beta^{2\to 4}$)	-3.61***	-2.03***	-0.41	1.45***
	(0.62)	(0.46)	(0.43)	(0.27)
Top Quintile (β^5)	9.16***	5.64***	4.50***	2.25***
	(1.31)	(0.77)	(0.60)	(0.27)
Return Period	Past Week	Past Month	Past Quarter	Past Year
Fund FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.463	0.463	0.464	0.467
Observations	414,703	414,703	414,703	414,703

Table B.2
Active ETF Robinhood Account Holding and Performance Relation

The table presents the results from the following regression:

$$\Delta \text{RhUser}_{i,t} = \beta^1 r^1_{i,t-j\to t} + \beta^{2\to 4} r^{2\to 4}_{i,t-j\to t} + \beta^5 r^5_{i,t-j\to t} + X_{i,t} + \kappa_i + \tau_t + \epsilon_{i,t},$$

where $\Delta\text{RhUser}_{i,t}$ is the percentage change in Robinhood users holding active ETFs i in period t (daily or monthly), measured as $(\text{RhUser}_{i,t} - \text{RhUser}_{i,t-1})/\text{RhUser}_{i,t-1}$. Past return $r_{i,t-j\to t}$ is measured from $-j$ (j = 1 week, 1 month, 3 months, and 1 year) up to day $t-1$ in panel (a) and up to the day before month t in panel (b) for each AETF i. Past returns are further splined into bottom quintile $r^1_{i,t-j\to t}$, top quintile $r^5_{i,t-j\to t}$, and middle quintiles $r^{2\to 4}_{i,t-j\to t}$. Control variables $X_{i,t}$ include the log fund size, past return volatility measured as the standard deviation of fund return in the past 12 months, and the average percentage fund flow for all funds in the same objective code. κ_i and τ_t are fund and day or year-month fixed effects. The sample contains all equity funds focusing on the broad market or a sector from 2015 to 2023. Robust standard errors clustered at the fund level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(a) Daily Retail Trader Changes

	(1)	(2)	(3)	(4)
Bottom Quintile (β^1)	-0.06	0.01	0.01	0.01
	(0.06)	(0.03)	(0.02)	(0.02)
Middle Quintiles ($\beta^{2\to4}$)	0.10	0.01	-0.00	-0.01
	(0.07)	(0.03)	(0.01)	(0.01)
Top Quintile (β^5)	0.22***	0.22***	0.05	0.01
	(0.07)	(0.08)	(0.03)	(0.02)
Return Period	Past Week	Past Month	Past Quarter	Past Year
Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.018	0.019	0.018	0.018
Observations	60,259	60,259	60,259	60,259

(b) Monthly Retail Trader Changes

	(1)	(2)	(3)	(4)
Bottom Quintile (β^1)	-0.34	0.45	0.21	0.33
	(1.12)	(0.73)	(0.26)	(0.30)
Middle Quintiles ($\beta^{2\to4}$)	0.50	0.40	0.22	-0.06
	(0.85)	(0.55)	(0.32)	(0.22)
Top Quintile (β^5)	1.29	3.21***	2.34***	0.59*
	(1.22)	(1.05)	(0.68)	(0.31)
Return Period	Past Week	Past Month	Past Quarter	Past Year
Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.115	0.124	0.124	0.116
Observations	2,474	2,474	2,474	2,474

B.2. Robustness: Regression Results for Managers' Risk-Taking

In this section, we compare AETF and AMF managers' risk-taking behavior in a regression framework with fixed effects and controls. The results are qualitatively similar to the t-test results in **Table 9**.

Table B.3
Active ETF and MF Risk-Taking

The table presents the results from the following regression:

$$Y_{i,t} = \beta \times \text{ETF}_{i,t} + X_{i,t} + \kappa_i + \tau_t + \epsilon_{i,t},$$

where $Y_{i,t}$ represents return and holdings-based risk measures for fund i in month t. Return-based risk-taking measures include total volatility of fund returns and idiosyncratic volatility of fund returns residualized against factor models such as CAPM, the Fama-French three-factor model, and the Carhart four-factor model. Holdings-based risk-taking measures include monthly portfolio turnover and the Herfindahl–Hirschman Index (HHI) of the fund portfolio's industry (two-digit SIC) concentration. Control variables $X_{i,t}$ include the log fund size, expense ratio, and the past 12-month return for fund i. ETF is an indicator variable that equals 1 if the fund is an ETF and 0 otherwise. κ_i and τ_t represent objective code and year-month fixed effects. Standard errors, clustered by fund and year-month are reported in parentheses. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	Return-based measures				**Holdings-based measures**	
	Total Volatility	Idiosyncratic Volatility			Turnover	HHI
		CAPM	FF3	Carhart		
ETF	0.024	0.089***	0.078***	0.074***	0.028***	0.045***
	(0.022)	(0.016)	(0.014)	(0.014)	(0.003)	(0.010)
Expense Ratio	12.504***	11.679***	9.148***	8.975***	1.148***	-1.864***
	(0.728)	(0.574)	(0.436)	(0.429)	(0.060)	(0.170)
Fund Size	0.012***	0.006***	0.003***	0.003***	0.000***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Lagged Return	0.095	-0.067	-0.122***	-0.109**	0.006*	-0.044***
	(0.131)	(0.066)	(0.046)	(0.045)	(0.004)	(0.017)
Objective Code FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.684	0.468	0.493	0.498	0.242	0.367
Observations	1,265,799	1,265,799	1,265,799	1,265,799	729,291	729,291