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ETFs as a disciplinary device*

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Abstract

We document a novel feature of active exchange-traded funds (AETFs): they serve as a disciplinary tool for investors to remove underperforming portfolio managers. Unlike mutual fund shares, ETF shares can be shorted, which enables investors to bet against manager performance. We show that AETFs exhibit over five times greater flow-performance sensitivity than mutual funds, indicating that AETF managers face harsher penalties for poor performance. When an underperforming manager joins an AETF, investors respond by shorting more shares of the fund. Consequently, this manager is more likely to exit the fund management industry, thereby enhancing overall sector efficiency and allowing more high-performing managers to remain. Moreover, the stocks held within AETFs exhibit improved price informativeness. We also find that AETF managers outperform both mutual fund and passive fund managers. In summary, the short-selling feature of AETFs serves as a disciplining device and enhances market efficiency by facilitating the removal of underperforming managers.

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1 Introduction

"Short sellers have ramped up bets against Cathie Wood's flagship Ark innovation fund as belief in its [active] strategy shows signs of faltering. A record 12 per cent of the ARKK exchange traded fund's shares are being shorted by investors betting on a decline — a bet worth more than US$2.7 billion on August 3."

Financial Times reported on Cathie Wood who later resigned from ARKK as portfolio manager on September 16th, 2022.

A recent trend in the asset management industry is the rise of active exchange traded funds (AETFs). The assets of equity AETFs have increased more than *15 times* over the past four years, growing from less than US$20 billion in 2020 to about US$300 billion in 2024 (Figure 1).[1] This exponential growth has raised questions about the factors driving the popularity of these instruments, as well as the costs and benefits of AETFs compared to more traditional investment vehicles like active mutual funds (MFs) or passive ETFs (PETFs). In this paper, we aim to illuminate these questions using a novel dataset on AETFs.

We demonstrate that the AETF structure offers a previously undocumented benefit for investors: it can serve as a disciplinary device to remove poorly performing managers, thereby enhancing market efficiency. Several clear advantages of AETFs compared to MFs are related to their ability to charge lower costs and may explain their rising popularity. These advantages include tax efficiency due to in-kind creations and redemptions and greater liquidity from intra-day trading of ETF shares. While these benefits make ETFs more appealing to both managers and investors, our paper uncovers a novel feature of AETFs: they provide a mechanism for investors to discipline poorly performing managers.

Unlike shares of MFs, ETF shares can be sold short. This allows investors to utilize short-selling as a disciplinary tool. In contrast to MF shares that do not trade on the

[1] The whole AETFs universe exceeded US$1 trillion at the end of 2024: https://finance.yahoo.com/news/active-etf-assets-surge-past-214500207.html, last accessed December 22, 2024.

open market, ETF shares can easily be shorted, similar to shares of individual companies. Consequently, any market participant can short an ETF, ultimately creating outflows from the fund, whereas only existing fund investors can do so in an MF.[2] This feature allows investors to discipline poorly performing AETF managers. Our paper is the first to provide empirical evidence supporting this notion in practice. A prominent example is the ARKK AETF (mentioned in the quote above), which was heavily sold short, ultimately leading to the manager's departure.

We illustrate that AETFs function as a disciplinary device to penalize poorly performing managers. Specifically, we focus on covered shorts that involve physical borrowing of AETF shares from other market participants, and exclude uncovered shorts that are used for mechanical or operational purposes by authorized participants (APs) as suggested by Evans et al. (2022).[3] To assess whether AETFs can effectively discipline managers, we examine the difference in flow-performance sensitivity of AETFs relative to similar MFs. Our first main result reveals that AETFs exhibit significantly more pronounced flow-performance sensitivity than MFs, with sensitivity for AETFs being over five times greater than that of MFs. This higher sensitivity indicates that poorly performing ETFs experience larger outflows than similar MFs, reinforcing the idea that the ETF structure enables investors to more effectively punish poorly performing managers.[4]

In light of this enhanced sensitivity, our second main result shows that covered shorts of an AETF increase when a poorly performing manager joins the fund and decrease

[2]Short selling exerts downward pressure on the price of the ETF but not its net asset value (NAV). Effectively, this makes the ETF trade at a discount and creates outflows as authorized participants (APs) correct the mispricing by redeeming ETF shares.

[3]Evans et al. (2022) show that uncovered shorts are primarily driven by liquidity provision purposes or arbitrage opportunities exploited by APs. In a covered short, the short seller must physically borrow the underlying assets, whereas in an uncovered short, the short seller (i.e., the AP) does not need to borrow the underlying asset. Typically, APs are allowed to short-sell an ETF without borrowing it to provide more liquidity. Evans et al. (2022) provide more details on when APs may rely on uncovered shorts for strategic purposes.

[4]Although investors may simply exit an active MF or AETF if they believe the manager is underperforming, the short-selling feature of AETFs provides them with an *additional* tool to further penalize poorly performing managers, as short-selling leads to an even greater reduction in flows (i.e., compared to a situation where investors can only exit). In other words, only existing investors can cause outflow from a mutual fund by divesting while any market participant can cause outflow from a AETF by short-selling.

when that manager leaves and is replaced by a better-performing one. This finding holds after controlling for both time-varying factors and time-invariant fund characteristics and supports the notion that investors actively discipline poorly performing managers.

Building on the relationship between short selling and managerial turnover, our third main result indicates that heavily shorted managers are more likely to exit the industry. As these poorly performing managers leave, the overall efficiency of the fund management industry improves, with more high-performing managers remaining. We also find a separation of manager types based on their quality: the best-performing managers manage either an AETF or both an AETF and a mutual fund (MF), while MF-only managers and passive fund managers are the worst-performing types.

Finally, we examine the implications of these findings for funds' investment strategies, demonstrating that funds converted from a MF structure to an AETF structure tend to load more on momentum stocks and stocks with higher idiosyncratic risk. This evidence may suggest a greater propensity for risk-taking among AETFs. We next elaborate on each of these empirical findings.

Our results indicate that AETFs exhibit a more pronounced flow-performance relationship compared to similar MFs. Specifically, we find that the difference in flow-performance sensitivity between the top and bottom quintiles of return performance is, on average, over five times greater for AETFs than for MFs. This result holds true for risk-adjusted returns as reflected in CAPM alphas and the Carhart (1997) 4-factor alphas. To address concerns regarding systematic differences between AETFs and MFs, we control for various fund characteristics (e.g., fund size, age, fees, premium, lagged flows, institutional ownership), as well as fund and time fixed effects, and focus on a subset of AETFs that were converted from MFs to AETFs. We employ propensity score matching to align these AETFs with similar non-converted MFs prior to their conversion and compare their flow-performance sensitivities before and after the conversion. The regression results reveal that more highly shorted ETFs exhibit stronger flow-return sensitivity. These findings suggest that converting MFs to AETFs enhances managers' incentives to perform well and imposes harsher penalties on poorly performing managers, as they experience larger outflows in an ETF structure compared to a MF structure.

We demonstrate that investors actively discipline underperforming managers by short-selling AETF shares. We conduct an event study analysis around manager turnover events. Our findings indicate that short interest is low prior to the arrival of a poorly performing manager, but increases immediately after that. Additionally, short interest decreases when a poorly performing manager leaves the fund and is replaced by a better manager. These patterns support the idea that investors ramp up short sales in a fund managed by a poorly performing manager, betting against their skills. Similarly, when a high-performing manager joins a fund, investors decrease their short-sales. These results confirm that investors actively discipline the performance of funds managed by poorly performing managers. We validate these effects using difference-in-differences (DID) regressions and a series of robustness tests, including the analysis of uncovered shorts.

Building on these findings, we provide evidence that a higher volume of covered shorts predicts worse fund performance and larger fund outflows, aligning with an information-based explanation for covered shorts. This result suggests that investors betting against poorly performing AETF managers are, on average, correct, as more-shorted AETFs tend to perform worse in the future and incur losses.

We document that heavily shorted managers are more likely to exit the industry, thereby improving the overall quality of the remaining fund managers. Specifically, we estimate a conditional logit regression with fixed effects, demonstrating that heavily shorted managers are indeed more likely to leave the fund management industry. This finding suggests that AETFs may enhance the overall efficiency of the fund manager pool by giving investors a tool to discipline poorly performing managers, leading to their exit.

Relatedly, we find evidence of sorting among managers, where the types of funds they manage reflect a hierarchy of manager quality: the best-performing managers oversee AETFs and MFs or AETFs only, while the worst-performing managers manage only MFs or passive funds. To the best of our knowledge, our paper is the first to empirically document that the best-performing managers are those who manage AETFs (or both AETFs and MFs), whereas those who manage only passive ETFs or passive MFs are the worst performers.

We next analyze the investment style of AETFs and find that they tend to favor momentum stocks and those with higher idiosyncratic risk, indicating a propensity for higher risk-taking behavior. Given that AETFs have stronger incentives to perform well compared to otherwise similar MFs – due to their higher performance-to-flow sensitivity – AETF managers may take on additional risks to end in the top quintile of performance and attract more flows. Consistent with this increased risk-taking, we observe that after an MF is converted to an AETF, managers begin to load more heavily on the momentum factor. Additionally, AETFs invest in stocks with higher idiosyncratic risk, as indicated by Roll's information measure (Roll, 1988). Furthermore, AETFs exhibit a higher turnover ratio of stocks, suggesting more frequent changes in portfolio composition. Finally, we find that AETFs facilitate a quicker incorporation of information about the underlying stocks because higher AETF ownership correlates with increased price efficiency of a stock.

Taken together, our main results have significant implications for ETF markets and the active fund management industry. While our paper highlights the benefits of AETFs—such as lower costs and greater transparency—it also suggests that AETFs can be costly for managers, as they provide investors with a tool to discipline managerial performance. To the best of our knowledge, our paper is the first to document this novel feature of AETFs, which allows them to act as a disciplining device. Our findings indicate that poorly performing managers are more likely to exit the fund management industry in an ETF structure than in an MF one, which means that converting all MFs to AETFs could improve the overall efficiency of the active fund management industry.

Related Literature

Our study contributes to several strands of research. First, we contribute to the relatively new literature on active ETFs. Du, Starks, and Xiaolan (2023) examines the impact of the recent rise in AETFs on the competition for fund flows by identifying forty active MFs that launch a similar AETF. The authors find that these MFs do not suffer from cannibalization of flows and that cloned AETFs attract flows from new clientele.

We provide new evidence that is consistent with the findings of Du, Starks, and Xiaolan (2023). We document that poorly managed AETFs are heavily shorted by market participants, which serves as a disciplinary mechanism. Moreover, these short-selling activities of AETFs are accompanied by a rise in flow-performance sensitivity. Importantly, we do not find such results for managers of better-performing AETFs, which aligns with the findings of Du, Starks, and Xiaolan (2023), as cloned AETFs typically originate from MFs that perform better. Consequently, given that short-selling is used to discipline poorly performing AETFs, it is less likely that this tool is employed against cloned AETFs, as they are generally managed by better-performing managers. Supporting this notion, we find that short-selling is predominantly utilized as a disciplinary tool for newly established and converted AETFs, which collectively constitute 81% of the total AUM of all AETFs in 2023.

While our study and Du, Starks, and Xiaolan (2023) are among the first to explore the AETF literature, it is important to note that our papers focus on different aspects of AETFs. Specifically, while we investigate the short-selling activities of AETFs and their role as a disciplinary device, Du, Starks, and Xiaolan (2023) focus on a different aspect and examine the competition for fund flows among MFs and cloned AETFs.

We also contribute to the literature on short-selling of ETFs. Prior research on this topic has primarily focused on passive ETFs, as AETFs are a relatively new investment vehicles in the fund management industry. Investors typically short-sell passive ETFs to mitigate short-selling bans or to conveniently gain exposure to the underlying stocks that are part of the passive ETF's benchmark index. Li and Zhu (2022) document that investors short-sell passive ETFs to bypass short-sale constraints on individual stocks, suggesting that ETFs play a significant role in facilitating short-selling activities. Furthermore, Karmaziene and Sokolovski (2021) show that investors were able to circumvent the 2008 short-sale ban by short-selling the largest and most liquid ETF, the SPY. In contrast, we complement the work of Li and Zhu (2022) and Karmaziene and Sokolovski (2021) by demonstrating that short-selling of AETFs can be employed to discipline managers rather than merely to obtain exposure to the underlying stocks in the AETF's portfolio. Unlike the case of short-selling passive ETFs, when investors short-sell AETFs, they do so to discipline the manager. This observation is similar to Massa et al. (2015), who show that short-selling of individual stocks may be used as a means to discipline managers. Our results illustrate that this effect also applies to the active asset management industry with the introduction of AETFs.

By focusing on the short-selling aspect of AETFs, our paper further contributes to the literature that studies the effects of short-selling on financial markets. Relevant studies include Asquith et al. (2005) and Diether et al. (2008), who show that short-selling negatively predicts future stock performance. Hwang et al. (2019) and Huang et al. (2020) document that short-selling individual stocks or industry ETFs, respectively, may also be used for hedging purposes. Other related studies include Saffi and Sigurdsson (2010), Beber and Pagano (2013), Boehmer et al. (2013), Fang et al. (2016), Wang et al. (2020), and Dixon (2020). We complement this line of research by showing that short-selling may also be employed to discipline managers in the case of AETFs.

Furthermore, our paper contributes to the literature on market efficiency by demonstrating that there is a positive association between higher AETF ownership of stocks and improved stock price informativeness. In this context, Boehmer et al. (2013), Huang et al. (2020), Glosten et al. (2020), Filippou et al. (2022), and Antoniou et al. (2022) document that ETFs have a positive impact on market efficiency, whereas Israeli et al. (2017) and Bhojraj et al. (2020) find that ETFs have a negative impact on market efficiency. Our findings provide new evidence that stocks owned by AETFs exhibit higher price informativeness.

The remainder of our paper is organized as follows. Section 2 provides an overview of the data we use and discusses the institutional features of AETFs. Section 3 elaborates on the potential benefits of AETFs, whereas Section 4 discusses implications for ETF portfolio choice and underlying assets. In Section 5, we provide additional robustness tests and conclude thereafter.

2 Data and Institutional Details

2.1 Data

We use several data sources: ETF Global, Compustat, CRSP and IHS Markit.

We distinguish actively managed ETFs based on the fund prospectus offered to investors when they are initially listed. ETFs may be declared as actively managed only if they acquire relevant exemptive orders and approval from the SEC before the regulatory reform of Rule 6c-11 in September 2019, or acquire the exemptive relief from the provision of the Rule after 2019. These AETFs, although structurally similar to their passive counterparts, are allowed by the exemptive order/relief to use "custom baskets" that allow the ETF to use redemption and creation baskets that do not reflect the pro-rata representation of the fund's portfolio.[5] An AETF may be created by: (1) establishing a new open-ended fund and acquiring the exemptive relief/orders, (2) being converted from an existing open-ended MF (i.e., either closing the MF or cloning the MF and keeping it open), or (3) creating a new class of an existing active MF. Converted funds do not exhibit deviation in management and style from their predecessor (at the initial stage after conversion), and the only aspect that changes is the legal structure and structure-related characteristics, such as fund fees. We include all three types of AETFs in our analysis and manually collect data on AETFs based on the prospectus and news search, to identify the type of AETFs for subsample tests.

[5] An AETF does not have to mirror (i.e., scale up or scale down) the underlying portfolio, but instead can introduce discretionary choice of the portfolio selection through the redemption and creation process with the authorized participants (APs) on a daily basis, creating the "activeness" of funds under the ETF structure. These "custom baskets" are also typical for bond ETFs (Todorov 2021).

ETF Global offers comprehensive data on ETFs, encompassing details on ETF secondary market trading, ETF counterparties, fund flows, and fund returns on a daily basis. To reduce noise in the daily observations, we aggregated these variables to a weekly level. Other ETF and MF characteristics, including fund size, family size, expense ratio, turnover ratio, and investment style are readily available from the CRSP survivor-bias-free mutual funds database. We prioritize the CRSP dataset for analysis that involves both MFs and ETFs and ETF Global for analysis that involves only ETFs, and analyze only active MFs (no index funds) for most of the analysis. A common problem with the ETF Global and CRSP datasets is the lack of portfolio manager-level information. Thus, we source the complete management history and tenure from the MorningStar dataset.

The main focus of our study is the short-selling activities of AETF shares. We procure equity borrowing market data from IHS Markit, a provider of global securities financing data for securities lending and borrowing. This dataset derives information directly from key industry players in the equity lending market, including prime brokers, custodians, asset managers, and hedge funds, collectively covering over 90% of transactions in the equity lending and borrowing market. Using this dataset, we construct our primary measure of covered shorts, which includes physical share borrowing and lending while excluding those related to dividend trading or financing, as reported by borrowers. We also measure uncovered shorts by subtracting the covered shorts level from the total short interests available from ETF Global and Compustat datasets.[6]

To summarize, our sample covers the period from 2016 until 2023, and contains 627 AETFs, of which 63 are cloned from MFs and 22 are converted from MFs. Table 1 provides summary statistics of our sample and shows that compared to MFs, AETFs are on average smaller, younger, and have lower expense ratios. AETFs engage in more active stock-picking as their turnover ratio is twice as high as that of active MFs. AETFs have positive flow in contrast to active MFs, which lose money on average. This fact is consistent with the recent trend in the asset management industry of money flowing

[6]Compustat offers biweekly total short interest on exchange traded stocks and funds. It fills some of the missing observations for short interest in ETF Global.

out of MFs into AETFs, as shown in Figure 2. The Figure shows that flows into AETFs accelerated after the SEC Rule 6c-11 in 2019 and reached $200 billion at the beginning of 2024, in contrast to MFs, which faced consistent outflows over the same period.

2.2 Institutional background on active ETFs

The popularity of AETFs increased exponentially over the past years, especially since the SEC passed Rule 6c-11 in September 2019.[7] This rule made the formation and operation of AETFs easier as it waived the exemptive orders previously required to set up an AETF wrapper. As a result, assets of equity AETFs increased exponentially and reached almost US$300 billion in 2024 as shown in Figure 1.

AETFs are similar to MFs in that they also employ an active strategy but they differ from MFs because of several ETF-specific features. Just like MFs, AETFs engage in active asset picking and try to generate alpha instead of simply following a benchmark index. Unlike MFs, however, AETFs have in-kind creation and redemption, which allows them to save on taxes as we explain below. In addition, AETFs typically report holdings not just once per month or quarter like MFs, but more frequently.

Crucially, unlike MFs, AETFs can be shorted, even intra-daily, which allows outside investors to hold AETF managers more accountable for their performance. In the MF structure, only existing investors can create negative flow to the fund by divesting, and this is limited by their holdings. In contrast, with AETFs, existing investors can divest their holdings, and both existing and outside investors can short-sell shares, limited only by the number of outstanding shares. This feature enables even outside investors to take action against the AETF if they believe the manager is underperforming. It is precisely this channel that we investigate later in the paper.

AETFs are similar to classic index-tracking PETFs in many dimensions, but the crucial difference lies in their trading strategies: AETFs utilize an active trading strategy

[7] The rule allows ETFs that satisfy certain conditions to operate within the scope of the Investment Company Act of 1940 (the "Act") directly in the financial market without the cost and delay of obtaining hundreds of exemptive orders.

through “custom baskets”, while PETFs simply track a benchmark index using “standard baskets.” Similar to classic ETFs, AETFs are traded like stocks several times a day and can be shorted. They have a NAV and a market price, and APs ensure that the two are aligned through the ETF arbitrage channel (see e.g., Shim and Todorov 2021).

Unlike PETFs, AETFs do not have a benchmark index that they need to follow and to minimize tracking error. In some sense, AETFs combine the benefits of ETFs (e.g., cost-efficiency, transparency, tax benefits) with the benefits of MFs (e.g., more active stock-picking, freedom of portfolio choice relative to ETFs). Unsurprisingly, the new issuance of ETFs is dominated by AETFs instead of classic PETFs as shown in Figure 3. This trend accelerated after the SEC passed Rule 6c-11, which also made AETFs more beneficial by giving ETFs more flexibility in the choice of baskets that are used for creations and redemptions. In 2022, AETFs accounted for 70% of all ETF issuance and about 85% of total assets for newly issued ETFs, overtaking PETFs.

3 AETFs as a disciplining device

In this section, we first describe the clear benefits of AETFs related to tax savings. We then document the higher flow-performance sensitivity of AETFs and show that AETFs can be used as a disciplinary device to bet against poorly performing managers. Specifically, we show that the structure of AETFs allows investors to short-sell a fund and punish bad-performing managers, which eventually increases the probability of them leaving the fund management industry. In this context, AETFs function as a disciplining mechanism by enabling investors to short-sell a fund, ultimately increasing the likelihood of manager’s departure from the fund management industry. We also show that there is a separation of managers based on their quality with the worst managers managing only MFs and the best ones managing only AETFs or a combination of both AETFs and MFs.

3.1 Evident benefits of AETFs: Tax savings

The most evident benefit of AETFs relative to MFs is their lower expense ratio due to ETF features. In-kind creations and redemptions of AETFs allow investors to save on taxes because the underlying securities are not bought or sold in times of creation and redemptions, but exchanged in-kind via AP transfers. These transactions are not considered taxable events. In addition, most of the trading in AETF shares occurs on the secondary market, without the need to trade the securities underlying the ETF on the primary market. This means that most of the trading volume in ETFs does not trigger the sale or purchase of underlying assets, unlike with MFs. Transactions in MF shares mean that the manager most likely needs to buy or sell the underlying securities (unless the manager has sufficient cash), which triggers a taxable event.

The structural efficiency of AETFs allows ETF investors to save on operating and trading costs. This is why AETFs have lower expense ratios compared to MFs (even for identical and cloned AETFs). AETFs charge about a quarter less than MFs: the average expense ratio of an AETF is 0.71% compared with 0.92% for MFs. In addition, AETFs have no tax expenses compared to the 0.33% fee of MFs as seen from Table 2 (i.e., 0.18 + 0.15 in columns 3 and 4).[8] The total cost savings of AETFs relative to MFs amount to 0.37% p.a. as seen from the table.[9] This generates significant potential for reducing investor costs. Given the total size of the MF industry of around \$11 trillion (as of the end 2023), the total benefit of converting all MFs to AETFs amounts to *\$40.7 billion p.a.*, which is a significant number. This benefit of AETFs compared to MFs could be one of the reasons behind the outflows from MFs and the inflows into AETFs documented in Figure 2.

[8] We follow Sialm and Zhang (2019) to calculate taxes for MFs and ETFs. We assume ETFs conduct all trades through the primary market with APs in which ETFs exchange the basket of securities and ETF shares. These exchanges do not constitute sales or purchases of underlying securities and thus the capital gain taxes are not paid by the ETFs or borne by the ETFs investors but by the APs when they realize the gain.

[9] Total tax cost savings are calculated as follows: $(ExpRatio_{AMF} + Tax^{Div}_{AMF} + Tax^{STCGT}_{AMF} + Tax^{LTCGT}_{AMF}) - (ExpRatio_{AETF} + Tax^{Div}_{AETF} + Tax^{STCGT}_{AETF} + Tax^{LTCGT}_{AETF}) = (0.92 + 0.078 + 0.18 + 0.15) - (0.71 + 0.25 + 0 + 0) = 0.37\%$

3.2 AETFs have higher performance-flow sensitivity than MFs

An important fact we establish in this paper is that ETFs have a steeper flow-return sensitivity than MFs. This means that ETFs are punished more severely for underperformance relative to similar MFs as shown in Panel A of Figure 4. This result is robust to using the 4-factor Fama-French-Carhart (Carhart 1997) alphas instead of raw returns (Panel B). The higher sensitivity of AETFs creates stronger incentives for AETF managers to perform better as they are punished more severely for underperforming.

We next study the facts illustrated in Figure 4 in a regression framework by examining the relationship between the fund's alpha (i.e., returns in excess of the Carhart (1997) 4-factors) and fund flows following Goldstein et al. (2017). Table 3 provides the results. The first row of the table illustrates the positive relationship between flows and alphas, and shows that ETFs have approximately three times greater sensitivity to flows (i.e., 0.20 versus 0.57 in columns 2 and 3). The second row shows the convexity in that relationship because positive alphas have disproportionately larger impact on flows than negative alphas. Again, the convexity is approximately three times stronger for AETF than MF flows (i.e., -0.17 versus -0.52). The last column shows that this convexity is absent for heavily shorted ETFs, which means that the performance-flow sensitivity of funds in the bottom quintile is also large for these ETFs, unlike MFs or ETFs that are not shorted. As we discuss in the next section, if investors heavily short-sell an ETF, the fund is likely to perform worse, which increases the likelihood that the manager leaves the fund due to pressure from short-sellers. In other words, short-selling the ETF acts as a disciplinary tool to the manager and helps improve the overall efficiency of the ETF management industry, as shown more formally in the next section.

One concern is that the stark difference in flow-performance sensitivity between AETFs and MFs could be attributed to fundamental differences rather than the disciplinary effect of short-selling. To address this concern, we focus on a subset of AETFs that have undergone conversion from MFs and are thus very similar along several dimensions. These AETFs are often created through the transformation of existing active MFs, where the

AETF replaces the MF. Typically, these converted AETFs maintain the same investment style, portfolio composition, and management team as their predecessor MFs. The first and second columns in Table A1 provide summary statistics for these converted funds before and after the conversion. It is noteworthy that conversions are not strictly one-to-one because asset managers may consolidate multiple MFs with similar styles and teams into one AETF.

Analyzing the sample of converted MFs is beneficial because we can observe the change in the flow-performance relationship of AETF converted from an otherwise equivalent MF. Specifically, for each of the converted AETFs, we use propensity score matching (PSM) based on prior-conversion characteristics including fund size, fund return, fund flow, expense ratio and turnover ratio to match 100 actively managed equity MFs. Then, we compare the post-conversion flow-performance relationship between the converted MF and the non-converted MFs. Table 4 shows that AETFs which were converted from MFs have higher performance-flow sensitivity because the interaction term between the fund's alpha and short interest is positive and significant in all specifications. Since covered shorts are zero for MFs as they cannot be shorted, the estimates show that AETFs (which have a non-zero short interest) have higher flow-performance sensitivity. Short interest acts as an amplifier for the flow-performance relationship since it increases the flow-performance sensitivity of AETFs. The magnitude is large: A one standard deviation increase in the level of covered shorts interest increases the performance flow-sensitivity by more than 50% (i.e., 0.27/0.51) based on the estimates in Column 1 of Table 4. That is, when investors have the ability to short-sell a fund, its flows become more sensitive to performance because investors could create short-driven outflow from the fund.

We conduct a similar test on another subset of AETFs that are cloned from existing MFs where both the MF and AETF co-exist after the cloning. We follow Du, Starks, and Xiaolan (2023) to identify cloned AETFs based on the portfolio overlap between AETFs and MFs managed by the same portfolio managers. However, as documented by Du, Starks, and Xiaolan (2023) and shown in Table A1, this subset of AETFs is cloned from more reputable and successful set of MFs. This means that these funds might be less prone to short-selling. Indeed, the performance of cloned MFs is above the average compared to the rest of the MF sample. Moreover, Table A2 shows that although the level of covered shorts increases the flow-performance sensitivity, the effect is largely statistically insignificant. This implies that the disciplinary effect is less pronounced for better-performing funds, which are cloned.

3.3 AETFs can be used to remove poor-performing managers

In this section, we show that investors are correct in their short-sale strategies against AETFs as more heavily shorted AETFs underperform. This raises the likelihood that such AETFs end up in the bottom quintile of fund performance and ultimately increases the probability of poorly performing managers quitting the industry, thereby enhancing the overall quality of the fund industry as more high-performing managers remain.

We first examine whether investors discipline poor-performing AETFs by running the following regression:

$$Alpha_{i,t+n} = \beta_1 Covered\ Short_{i,t} + \beta_2 Alpha_{i,t+n-1} + \beta_3 ExpRatio_{i,t+n-1} + \beta_4 ln(TNA_{i,t+n-1}) +$$
$$\beta_5 ln(FAMTNA_{i,t+n-1}) + \beta_6 ln(Discount\ Premium_{i,t+n-1}) + \sum_{s=t+n-4}^{t} \beta_s Flow_{i,s} + \gamma_i + \epsilon_{i,t+n},$$

where γ_i are fund fixed effects. If investors are correct in their short bets, AETFs with higher levels of covered shorts should perform worse in the future and $\beta_1 < 0$. Table 5 shows that this is indeed the case. The second column in Table 5 illustrates that higher level of covered shorts predicts negative alpha with the effect being statistically significant starting from the 3rd week from day t. A one standard deviation increase in covered shorts predicts about 10 to 20 bps lower fund alphas per week for the next quarter (12 weeks), which is both economically and statistically significant.

As highly shorted AETFs perform worse, they are more likely to end in the bottom quintile of funds and face outflows as we illustrated in Figure 4. We also verify directly that short sales of AETF shares predict future fund outflows by running the following regression:

$$Flow_{i,t+n} = \beta_1 Covered\ Short_{i,t} + \beta_2 Alpha_{i,t+n-1} + \beta_3 ExpRatio_{i,t+n-1} + \beta_4 ln(TNA_{i,t+n-1}) + \beta_5 ln(FAMTNA_{i,t+n-1}) + \beta_6 ln(Discount\ Premium_{i,t+n-1}) + \sum_{s=t+n-4}^{t} \beta_s Flow_{i,s} + \gamma_i + \epsilon_{i,t+n}.$$

The results from Table 6 show that a one standard deviation increase in covered shorts predicts 1.78% outflow from the fund after two months, and the effect is persistently negative for the next six months. The effect for the first few weeks (Panel A) is negative, but not significant. This could be because it takes some time for investors to react.

Given that more highly shorted AETFs lose money, the managers of these funds could be more likely to be changed. To see if this effect is true, we study the dynamics of short interest around manager turnovers, encompassing both arrivals and departures. We split managers who join or leave funds into poorly performing (i.e., "bad") managers and well-performing (i.e., "good") managers based on the past three months' cumulative excess returns. A good (bad) manager is defined as one who performs above (below) the median in the 3-months period before the turnover. We then examine the dynamics of short interest using 8-months window around the turnover event.

Panel A in Figure 5 illustrates that short interest remains low before a "bad" manager joins the fund, but spikes as soon as the manager enters the fund. This pattern is consistent with the idea that investors ramp up short sales in a fund managed by a bad manager, taking action against her skills. This surge in short interest is replaced with a drop in instances where a "good" manager joins the fund as seen from Panel B.[10] Conversely, investors tend to decrease their short-sales following the departure of a "bad" manager, as depicted in Panel C of Figure 5. There is not much change in the dynamics of short interest around the time when "good" manager leaves a fund as seen from Panel

[10]Notably, a majority (i.e., 73%) of the joining managers are new managers who have not managed active funds in the past. Since new managers typically perform above the median in their first 3 months, we group them together with good managers to increase the number of observations. However, the plot in Figure 5 is similar if we exclude all new managers.

D.

We next supplement the evidence from Figure 5 with a more rigorous event study under a staggered difference-in-difference (DID) setting. We study the dynamics of short interest of funds that have turnover (treated) compared to similar funds (along the dimensions of age, TNA, expense ratio and performance) funds without turnover (control), around the turnover events. Table 7 reports the DID coefficients from a two-way fixed effects DID model, which includes fund and time fixed effects. We also control for fund level characteristics, such as fund size, fund age, lagged fund flow and lagged fund returns that may correlate with the level of short-selling. The results corroborate the evidence from Figure 5 that the difference of short interest between funds with and without turnover is significantly positive after a "bad" manager joins a fund (columns 1 and 2) while it drops when a "good" manager joins (columns 3 and 4). Short interest does not seem to change when a good or bad manager leaves the fund as seen from columns 5–8. To further investigate the short-selling mechanism, we also dig deeper into bad manager departures and restrict the sample to only cases when a bad manager is replaced by a good manager.[11] We do so because the sample in columns (5) and (6) of Table 7 also includes cases of a bad manager being replaced by another bad manager. The results from columns (9) and (10) show that once a bad manager is replaced by a good one, short interest jumps downwards, which is consistent with our main short-selling mechanism. We also confirm that the parallel trends assumption of the DID framework holds as seen from Figure A1 and Figure A2.

We also confirm that fund flows respond to events surrounding manager turnovers by plotting the dynamics of fund flows for both good and bad managers around the turnover. Figure 6 shows that after a manager's departure, flows increase when a good manager joins a fund relative to when a bad manager joins. The result is true both for bad manager departures (Panel A) as well as for good manager departures (Panel B). This pattern aligns with our main argument that short interest dynamics ultimately

[11] Cases when a good manager is replaced by a bad manager are extremely rare.

predicts changes in fund flows.

We next test if a higher amount of short-sales in AETFs increases the overall efficiency of the active fund management industry. The benefit of AETFs compared to MFs is that investors can discipline the manager by short-selling ETF shares, unlike MF shares. As we showed above, this short-selling predicts worse fund performance and ultimately predicts bad manager departures. However, if highly-shorted bad managers simply relocate to another fund (with similar size), the overall quality of managers in the fund management industry would not improve. Thus, the channel we uncover would not lead to higher efficiency in the industry. To the contrary, if bad managers leave not only the fund but the whole fund management industry, that would mean an increase in the overall quality of fund management, all else equal.

To study whether that is the case, we test if highly shorted managers are more likely to quit the fund management industry. Specifically, to examine the relationship between the probability of managers quitting the active fund management industry and the extent to which they are shorted, we run the following conditional logit regression with fixed effects:

$$Quit_{m,t} = \beta_1 CoveredShort_{m,t} + \beta_2 Tenure_{m,t} + \beta_2 NumFunds_{m,t} + \lambda_t + \epsilon_{m,t},$$

where γ_i are fund fixed effects and λ_t are week fixed effects. We define a quitting manager ($Quit_{m,t} = 1$) if a manager does not manage any fund in the active fund industry after leaving a given AETF. We compute the manager-level covered-shorts measure by calculating the average level of demeaned covered shorts of all AETFs managed by that manager at a given point in time.

Panel A of Table 8 shows that more highly shorted managers are more likely to leave the fund management industry. A one standard deviation increase in covered short interest predicts a 6.1% to 8.9% higher probability of the manager quitting the AETF industry and 4.7% to 6.1% higher probability of the manager quitting the whole active fund management industry as shown by columns (1) - (2) and (5) - (6), respectively.[12] However, managers could leave the fund industry due to mechanical reasons, such as retirement and fund termination. To account for these effects, we include the tenure of the fund manager (*Tenure*) and the number of funds she manages (*NumFund*) in Panel B of Table 8. The magnitude of the effect is larger with these controls: A one standard deviation increase in covered shorts interest predicts a 7.2% to 10.3% (5% to 8%) higher probability of a manager quitting the AETF (whole active fund management) industry. These estimates suggest that the short-selling mechanism of AETFs may incentivize ETF managers to perform better as they could be forced out of the fund management industry otherwise. Thus, a market dominated by AETFs could be more efficient than one dominated by MFs, as investors may force out poorly performing managers more easily in an ETF structure compared to an MF structure.

Similarly, we examine the effect of performance on the probability of a manager quitting the industry as shown in columns (3) - (4) and (7) - (8) in Panel A and B in Table 8. We calculate the performance of the manager, value-weighted by the size of her funds. We then rank the performance and divide managers into quintile groups every week such that the first quintile is the worst performing group of managers and the fifth quintile is the best performing group of managers. The results suggest that moving to one level lower quintile increases the probability of quitting the AETF industry by around 10% to 13.4% and the whole active fund industry by around 4%. This finding is consistent with our main story that the market is efficient in removing bad-performing managers.

3.4 Better performing managers have an AETF

We further show that there is a separation of managers based on their quality and the funds that they manage as seen from Figure 7 (and Table A6). Among managers who manage active funds, poorly performing managers do not convert their MFs to AETFs and stay within the MF structure as seen from the black line in Figure 7, Panels A and

[12] We obtain similar magnitudes when we use a linear probability model.

D ("AMF only"). This is consistent with our mechanism because these managers would be at risk to be forced out in an AETF structure, where short-sellers can bet against their performance. The best-performing managers ("AETF & AMF", green line in the figure, Panels A and D) manage both types of funds as they know their good quality and are probably less afraid of being forced out if they convert to an AETF. These managers keep both the MF and the AETF structure presumably to attract both clients who prefer MFs, and those who prefer AETFs. This conjecture is consistent with Du, Starks, and Xiaolan (2023). Finally, middle-quality managers convert their MFs into AETFs and only manage the latter ("AETF only") as seen from the red line in both Panels.

One concern is that the sample of managers is changing over time as some managers leave the industry, whereas others join. To address this concern, we repeat Panels A and D with a constant sample of managers fixed in January 2021 in Panels B and E, respectively.[13] Another concern is that managers of larger funds should be given more weight, and to address that, we repeat Panels B and E with value-weighted average in Panels C and F. The result that MF-only managers are the worst-performing group of active managers holds true also in these specifications. The ranking between AETF-only and AETF & AMF managers changes with AETF-only managers performing better in the fixed sample of managers.

One observation from Figure 7 is that, on average, all types of active fund managers underperform both the CAPM and the Fama-French-Carhart 4 factors benchmarks. This may suggest that active funds do not bring value to investors and investors could be better off just investing in a passive fund.[14] However, the underperformance of passive fund managers is even more stark as seen from the dashed lines in Figure 7: passive fund managers are the ones that perform the worst among all types of managers. This fact may seem surprising at first; however, it is important to remember that passive fund managers have different objectives than active managers, as they focus on minimizing tracking error

[13] The results with other cutoffs (January 2022 and January 2023) are similar.

[14] In addition, the plots in Figure 7 are for the average manager, but there is a group of AETF and MF managers in the top quintile of performance that beat both benchmarks.

rather than beating a benchmark. Moreover, many benchmarks underperform the market or the Fama-French-Carhart 4 factors.

4 Implications for AETFs' portfolio choice and underlying assets

Given that AETFs have stronger flow-performance sensitivity with top-performing funds generating disproportionately more inflows, they might be more incentivized to perform better relative to otherwise similar MFs. We next study the implications for AETF portfolio choice relative to similar MFs.

We start by examining the portfolio loadings of AETFs versus MFs on standard asset pricing factors in Table 9. The first column of the table shows that AETFs load less on the market portfolio compared to MFs. They are also more exposed to growth stocks and momentum stocks.

Since some of these results might be driven by systematic differences in the investment styles of AETFs versus MFs (and indeed we showed in Table 1 that they are different along several dimensions), we conduct a more granular analysis by focusing on MFs that are converted into AETFs. The second column of Table 9 shows that only the momentum result stays significant for MFs that were converted to AETFs. This means that after the conversion to AETFs, MF managers change their investment strategy and load more on momentum stocks. This result may be suggestive of managers loading on stocks that had a recent run-up in price and generated investors' attention, benefiting from trend-following. For example, ARK funds, which have an AETF structure, notably often load on stocks that performed well in the past, such as Tesla in 2021.

If AETF managers have stronger incentives to perform well and not end up in the bottom quintile, they may take larger positions in less information-sensitive stocks with a higher idiosyncratic component. Table 10 shows that this is indeed the case: one unit increase in a stock's Roll (1988) price informativeness measure is correlated with 20 bps larger AETF ownership as seen from the first column.[15] The higher the measure the lower the price informativeness of the stock. We supplement this finding with alternative measures of price informativeness as robustness checks, including the price-jump ratio (Weller 2017) and price informativeness measures (Davila and Parlatore 2018). These alternative measures paint a similar picture as seen from columns 2–4. This means that AETF managers take larger positions in stocks with a larger idiosyncratic component and have lower correlation with the market and industry return.

So far, we established that AETFs may increase the overall quality of the fund management industry by removing poor-performing managers. The next question we study is whether higher AETF ownership also improves the price informativeness of underlying assets. As discussed previously, compared to MFs, AETFs can be shorted, which would provide a faster channel to incorporate negative market views on the performance of AETF-held stocks compared to MF-held stocks. In addition, compared to passive ETFs, AETFs do not have mechanical demand for stocks induced by index-tracking, and AETF trades could potentially be more informative. Thus, if AETFs provide a channel to incorporate information about the underlying assets faster, these assets would have larger price informativeness. To test this, we regress Roll's price informativeness measure on the percentage of the stock held by AETFs, after controlling for MF ownership, PETFs ownership, and time fixed effects. We run the following regression:

$$PI^{R2}_{s,t+n} = \beta_1 AETF\ Ownership_{s,t} + \beta_2 MF\ Ownership_{s,t} + \beta_3 PETF Ownership_{s,t} + \gamma_t + \epsilon_{s,t+n},$$

where γ_t are time fixed effects and $n \in$ [1 month, 4 months]. The results in Table 11 show that there is a positive relationship between AETF ownership and price efficiency, and the result is statistically significant for all four horizons. This result is consistent

[15] We use Roll (1988) R^2 as the main measure to proxy for price informativeness. Following Chen et al. (2007), Roll (1988) R^2 is measured by taking 1 - R^2, where R^2 is from the following OLS regression:

$$r_{i,j,t} = \beta_{i,0} + \beta_{i,m} r_{m,t} + \beta_{j,m} r_{j,t} + \epsilon_{i,t}$$

, where $r_{i,j,t}$ is the return of stock i in industry j at time t, $r_{m,t}$ is the stock market return at time t and $r_{j,t}$ is the industry return at time t.

with AETFs providing a faster channel to incorporate information about a given stock.

5 Robustness tests

Short-selling AETFs versus taking positions in AETF portfolios. One question of interest is: given that AETFs report their holdings, why can't investors simply mimic the holding changes of the AETF and take the opposite position? For example, if an AETF manager increases its position in a given stock, investors should decrease their position or sell the stock short. The answer is that short-selling the AETF is more cost-efficient because shorting the AETF is cheaper than shorting each individual portfolio firm. This stems from the cost efficiency of ETFs that provide a cheap exposure to portfolios of stocks and is related to the in-kind creation and redemption of ETFs, which allows AETFs to provide cheaper access to such portfolios. Another reason is that not all AETFs disclose holdings daily, and thus investors do not observe the change in the ETF manager's positions frequently.

Uncovered shorts do not react. Another robustness test that we conduct is to check the reaction of uncovered shorts around manager turnovers. Specifically, we conduct a placebo test under the same setting as in Figure 5 and Table 7 but change the dependent variable from covered shorts to uncovered shorts. An uncovered short position is created by APs for immediate liquidity provision in the secondary ETF market without creating new ETF shares. These short positions are in general mechanical and primarily used for operational purposes by ETF APs and should not reflect any patterns related to betting against the performance of the manager. Thus, uncovered shorts should not react significantly around manager turnovers. This is indeed what we find as shown in Figure A3.[16]

[16] There are some statistically significant estimates in the case of good manager leaving as seen from Panel B but these results are the opposite to the covered shorts dynamics as uncovered shorts are high before and after the leave of a good manager, unlike the dynamics of covered shorts.

Cloned MFs. We also replicate Table 4 using ETFs cloned from MFs rather than the full sample of AETFs. As described before, cloned AETFs are managed by the better performing managers and have larger average excess returns and alphas compared to converted funds (see Table A1). Thus, the short-selling disciplinary mechanism should be less pronounced for cloned AETFs. The results in Table A2 are consistent with this conjecture and show that the disciplinary tool is less pronounced in the cloned ETF subsample. This finding is also consistent with the main results of Du, Starks, and Xiaolan (2023) that cloned ETFs are typically better-performing funds.

Longer-horizon performance. One concern may be that 3 months is a short window to measure manager's performance as some investors pay attention to longer-horizon returns and may attribute short-term underperformance to bad luck. To address this concern, we confirm our main regressions with longer window to measure manager's performance: 6 months and 12 months. Figure A4 and Figure A5 illustrate that the main results of Figure 5 hold also with longer horizon. We confirm these findings also for the DID regressions. Moreover, a shorter horizon of 3 months is likely more appropriate for our analysis. ETF investors are likely to react quicker than MF investors to fund's performance and move money from underperforming funds to outperforming funds. ETF shares are traded many times during the day, and their flows are more than 6 times more volatile than those of MFs as indicated in Table 1. Thus, flow reallocation from underperforming funds to outperforming funds is likely to be faster with ETFs and 3 months might not be such a short window to measure fund performance. In addition, we find that manager's performance is somewhat persistent as bad managers are more likely to stay bad in the next 3-month period (75% probability) and good managers are likely to stay good (74% probability).

6 Conclusion

Why do we need a market mechanism, such as short selling, to discipline fund managers when there are other disciplinary tools available? For instance, Berk et al. (2017) suggests that fund families are informed about managers' abilities. Fund families, therefore, could penalize bad managers by reallocating capital to better managers. However, as documented in prior studies, this off-market disciplinary device could be dysfunctional due to frictions from managers (Brown and Davies 2017) or the board (Khorana et al. 2007).

In this paper, we document a novel market-based disciplinary solution thriving in the fund market: market participants proactively engage in short-selling of underperforming funds within the relatively new AETF structure. Due to the stock-like features of AETFs, short-selling AETFs could be used as a disciplinary tool to discipline underperforming managers, increasing the sensitivity of ETF fund flows to performance. On average, AETFs have more than five times the flow-performance sensitivity of comparable MFs, indicating that ETF managers are more severely penalized for poor performance.

We also document that when an underperforming manager joins (leaves) an AETF, investors increase (decrease) their short-selling of fund shares. This suggests that investors use short-selling to discipline underperforming managers. As a result, underperforming managers of AETFs are more likely to exit the asset management industry, thereby enhancing the industry's overall efficiency. We also show that stocks owned by AETFs exhibit improved price informativeness and that there is a sorting of managers based on their quality with the best-performing managers managing AETFs only or both an AETF and an active MF, whereas the worst-performing ones manage passive ETFs and passive MFs.

Our study demonstrates that while AETFs offer benefits to investors compared to MFs, such as lower costs and greater transparency, these new securities may also facilitate the removal of underperforming fund managers, thereby improving the industry's performance and efficiency. Our novel approach shows that AETFs provide a market-based solution to discipline underperforming managers. This “unique” benefit may contribute to the rapid expansion of AETFs in recent years, in contrast to the declining popularity of MFs.

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Figure 1: Growth of total assets in AETFs

The graph illustrates the growth of total net asset value of actively managed equity exchange-traded funds (AETFs) in the United States from 2016 to 2024. The dashed vertical line marks the enactment of Rule 6c-11 by the U.S. Securities and Exchange Commission (SEC). This analysis specifically targets ETFs structured as open-end funds, while excluding those organized as unit investment trusts (UITs), leveraged or inverse ETFs, share class ETFs of multi-class funds, and non-transparent ETFs, as these are not governed by the Rule. Rule 6c-11 provides exemptions from certain exemptive orders required for ETFs to operate under the Securities Exchange Act of 1934, including the order permitting the use of “custom baskets” that do not need to reflect a pro-rata representation of the AETF’s portfolio during redemption and creation activities.

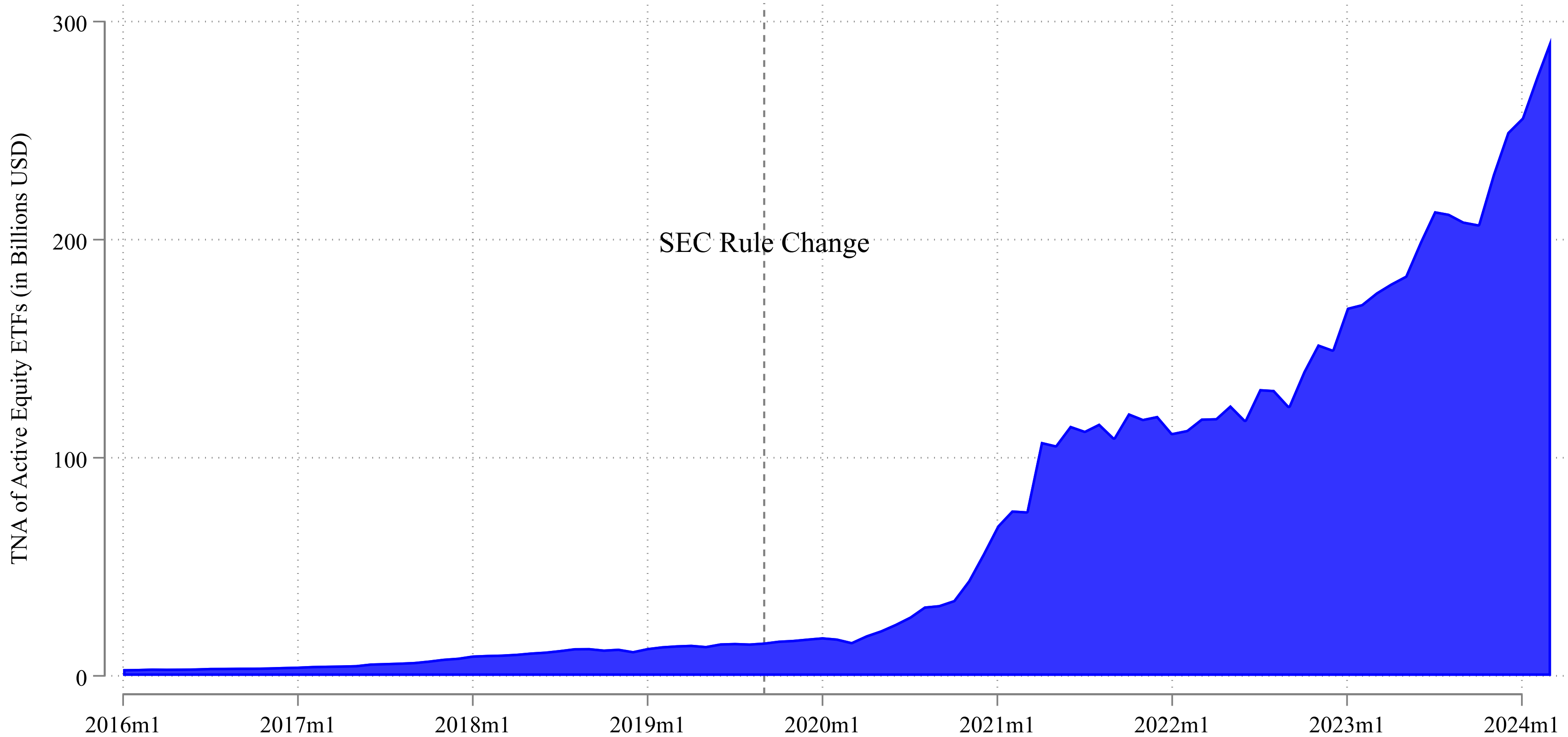


Figure 2: Cumulative flows of actively managed equity mutual funds and ETFs Post-Rule 6c-11

This graph depicts the cumulative inflows and outflows of actively managed equity mutual funds and exchange-traded funds (ETFs) since the implementation of Rule 6c-11 on September 26, 2019, marked by the red vertical line. An ETF is classified as actively managed if it complies with Rule 6c-11 and explicitly identifies as such in its fund prospectus. For mutual funds, we use Lipper's investment style criteria, categorizing a fund as actively managed if it has one of the following Lipper objective codes: 'EI', 'G', 'GI', 'I', 'MC', 'MR', 'SG', 'LSE', or 'EMN'. To exclude index funds, we filter out those with names containing terms such as 'Index', 'Ind', 'Ix', 'Indx', 'S&P', '500', 'Dow', 'DJ', 'Nasdaq', 'Mkt', 'Barra', 'Wilshire', and 'Russell'.

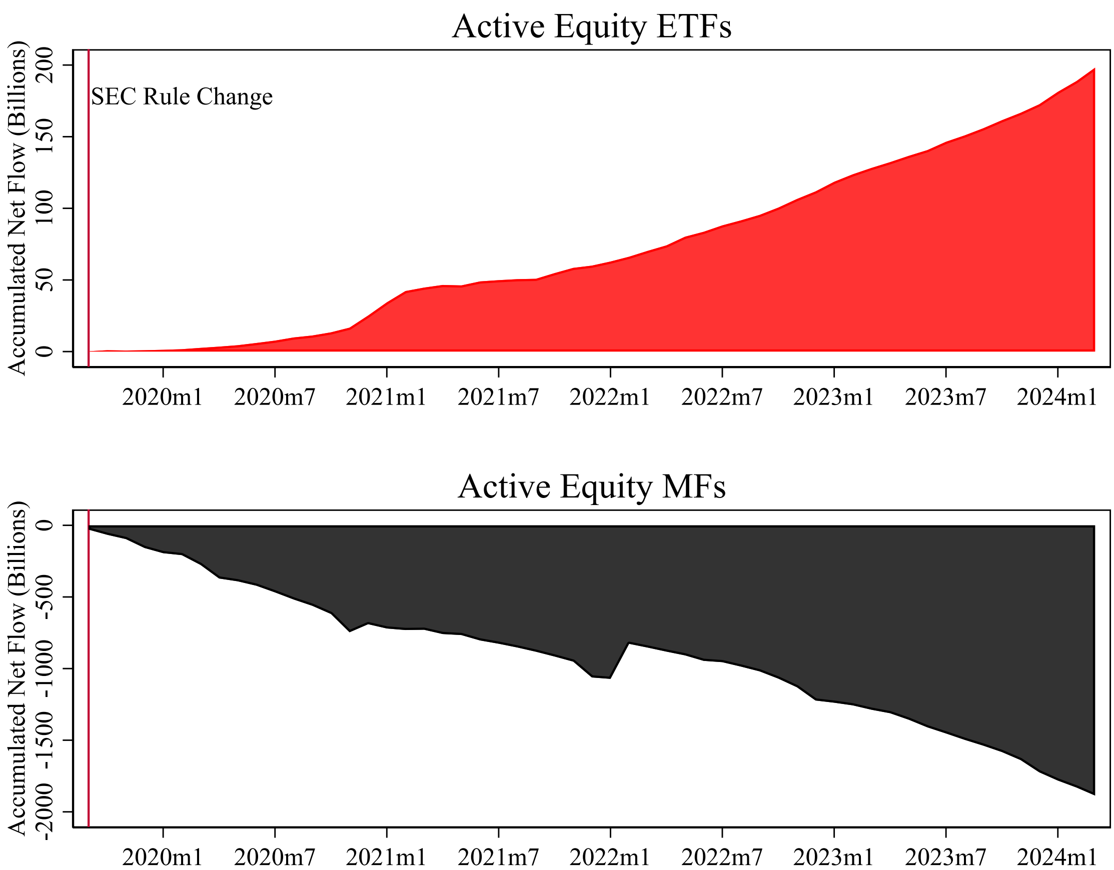
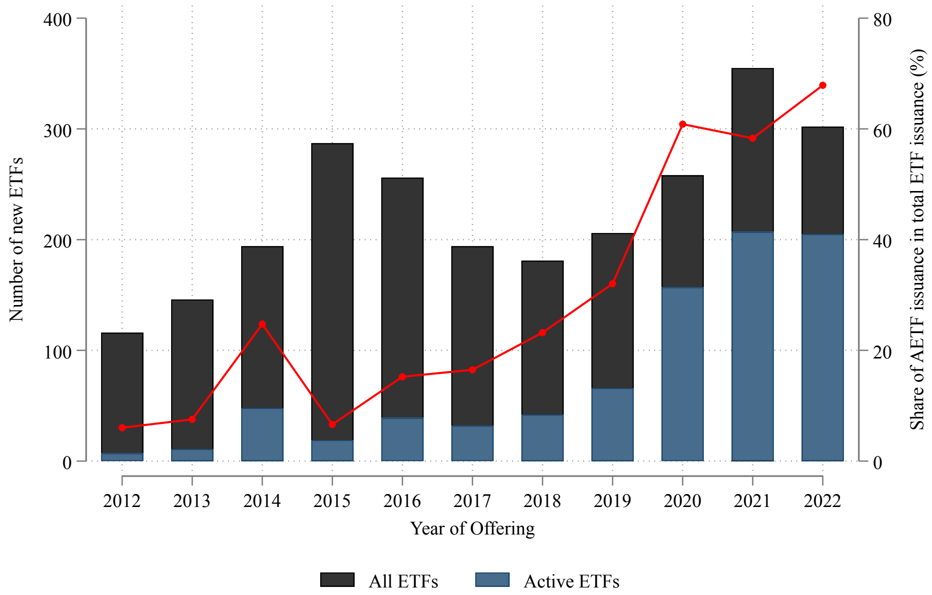
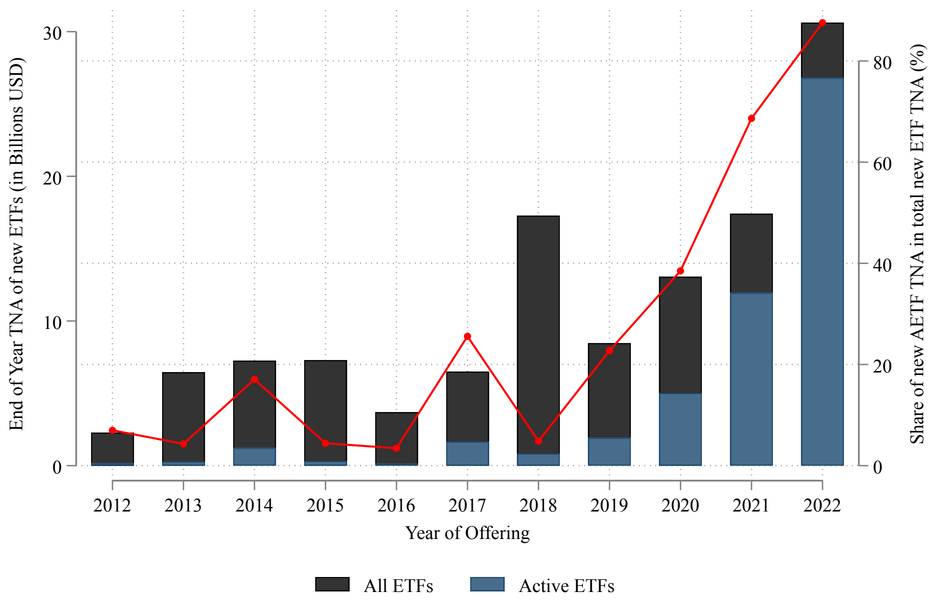


Figure 3: AETFs dominate new ETF issuance

This graph presents an analysis of the number and total net asset value (TNA) of newly launched active and passive exchange-traded funds (ETFs). In Panel A, the bar charts on the left y-axis illustrate the quantity of newly established passive and active equity ETFs. The red line on the right y-axis signifies the proportion of active equity ETFs relative to the total issuance of equity ETFs. In Panel B, the bar charts on the left y-axis depict the end-of-year TNA, expressed in billions of USD, for both newly established passive and active equity ETFs. The red line on the right y-axis indicates the ratio of the TNA of newly issued active equity ETFs to the TNA of all newly issued equity ETFs.



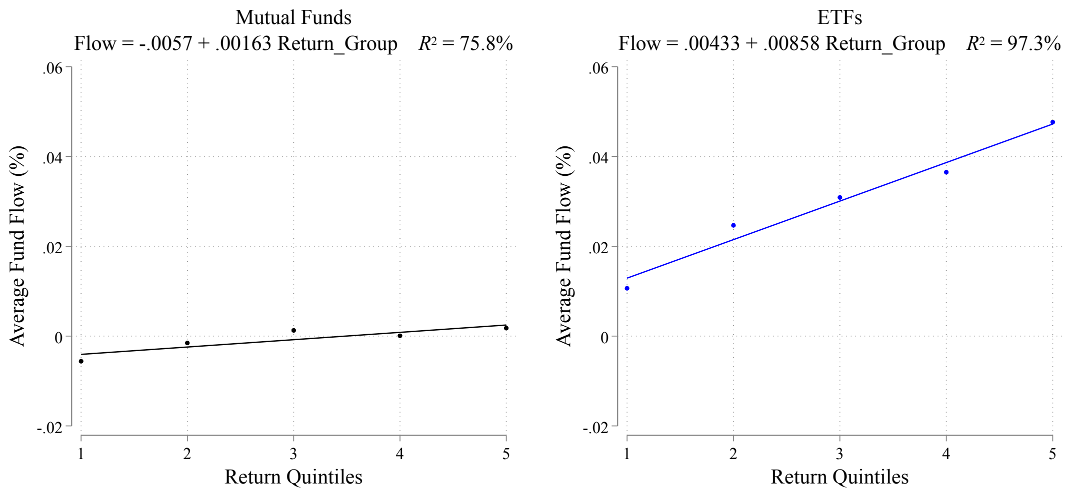
(a) Panel A: Number of ETFs issuance



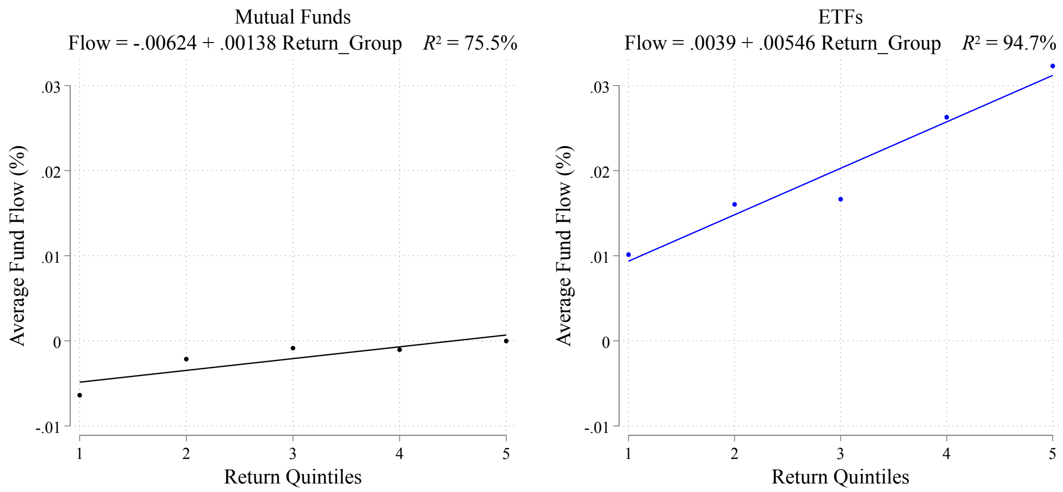
(b) Panel B: TNA of newly issued ETFs

Figure 4: Flow-performance sensitivity of active MFs and AETFs

This graph examines the relationship between average monthly fund flows and portfolio return quantiles for actively managed equity exchange-traded funds (ETFs) and actively managed equity mutual funds. In Panel A, funds are categorized into return quintiles based on lagged 3-month accumulated raw excess returns, whereas Panel B classifies funds according to Fama-French-Carhart 4-factor alphas. Each panel features fitted regression lines, accompanied by their respective slope coefficients and intercepts, thereby elucidating the dynamics of fund flows in relation to various performance metrics.



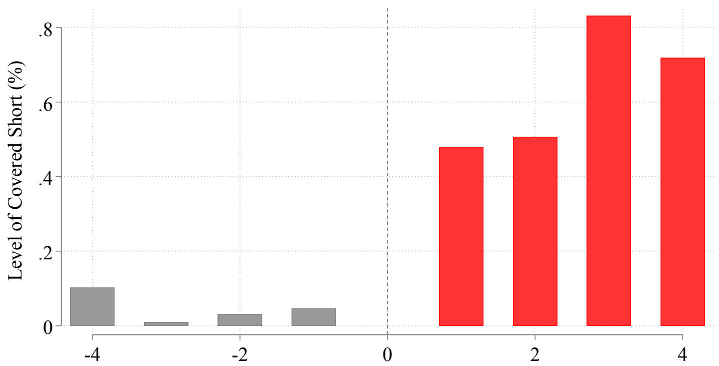
(a) Panel A: Performance measured by raw excess returns



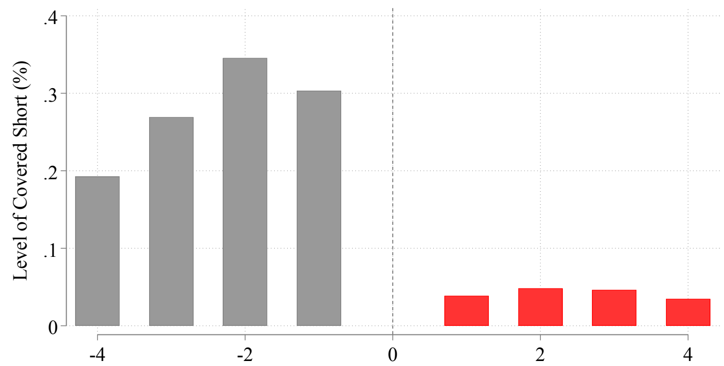
(b) Panel B: Performance measured by risk-adjusted returns

Figure 5: Dynamics of covered short interest around manager turnovers

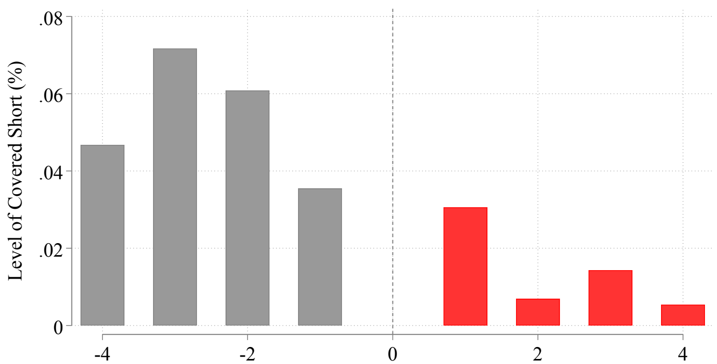
This graph plots the average levels of covered shorts in the context of portfolio manager turnovers. Portfolio managers are classified as good or bad based on the median of the three-month accumulated raw fund return, weighted by the total net assets (TNA) of the funds they managed prior to the turnover event. Notably, a majority (73%) of the joining managers are new managers who have not managed active funds in the past, and investors generally have a non-negative prior about these new managers. Consequently, we group good and new managers together to compare the trend of covered shorts between good/new managers and bad managers. The figure presents covered shorts within a ± 4 month window surrounding the turnover of managers, with distinct panels for bad (Panel A) and good/new (Panel B) managers who are joining, as well as for bad (Panel C) and good (Panel D) managers who are departing. Cases of manager turnover due to fund terminations or fund inceptions are excluded from this analysis.



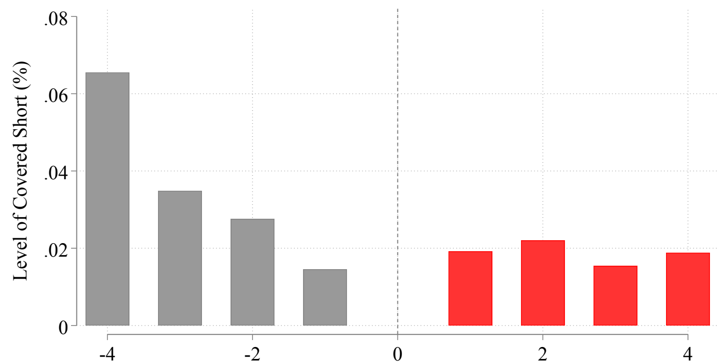
(a) Panel A: Covered shorts of funds joined by bad manager



(b) Panel B: Covered shorts of funds joined by good/new manager



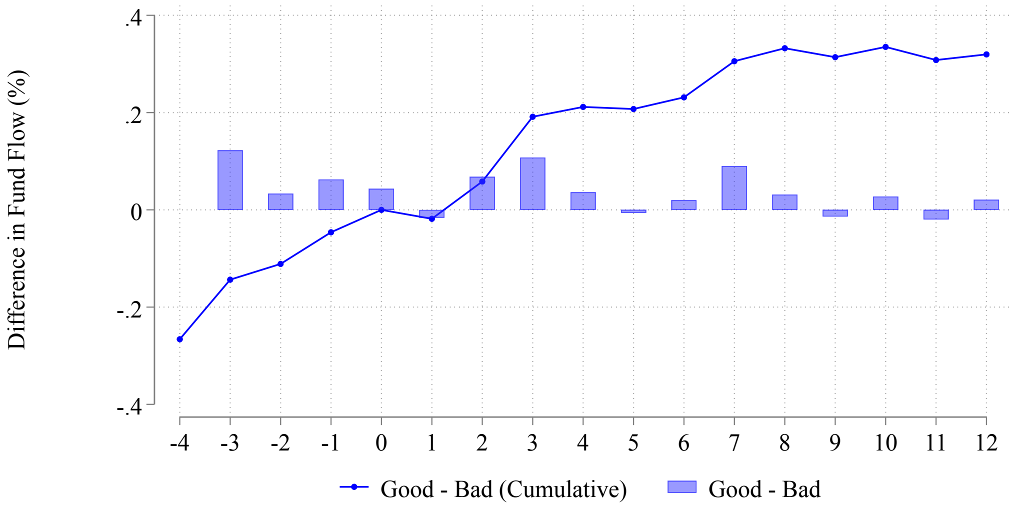
(c) Panel C: Covered shorts of funds left by bad manager



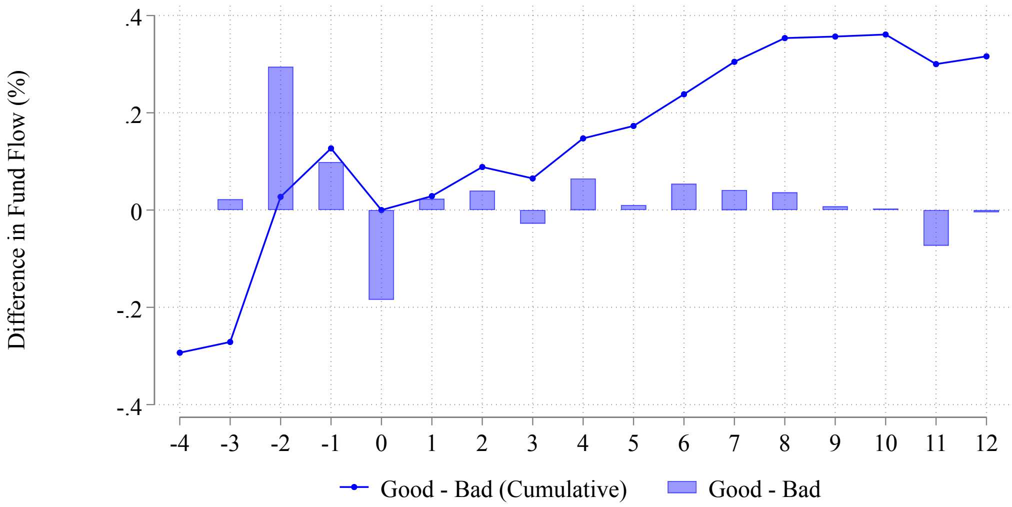
(d) Panel D: Covered shorts of funds left by good manager

Figure 6: Cumulative fund flows around portfolio manager turnovers

This graph plots the difference in cumulative fund flow between good and bad managers joining the fund. Portfolio managers are classified as good or bad based on the median of the three-month accumulated raw fund return, weighted by the total net assets (TNA) of the funds they managed prior to the turnover event. Fund flow percentage is defined as the net fund flow scaled by the TNA of the funds. Panel A (B) displays the difference in cumulative fund flow percentage between good and bad managers since the turnover event when they replace a bad (good) manager.



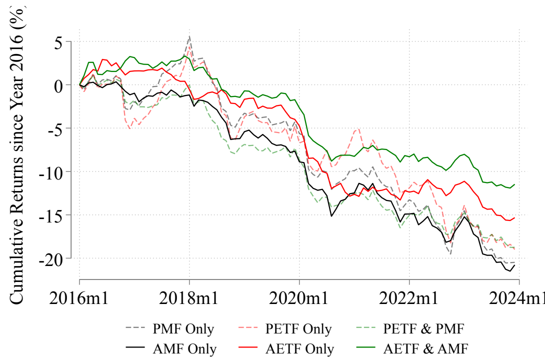
(a) Panel A: Average difference in fund flow % when bad manager leaves



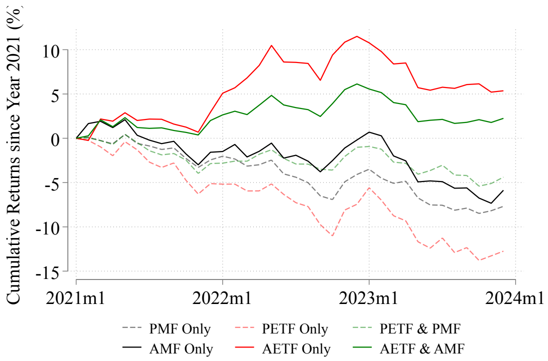
(b) Panel B: Average difference in fund flow % when good manager leaves

Figure 7: Performance of portfolio managers over time

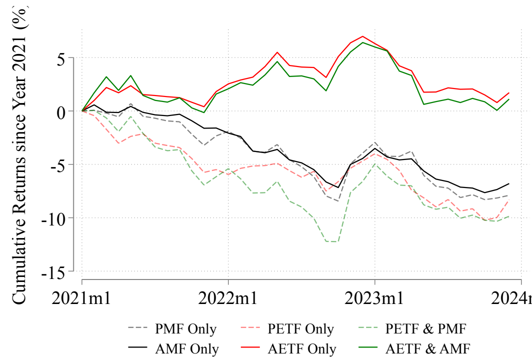
This graph plots the cumulative performance of funds managed by portfolio managers who: 1) managed only passive or only active mutual funds (*PMF only* or *AMF only*), 2) managed only passive of only active ETFs (*PETF only* or *AETF only*), and 3) managed both MFs and ETFs (*PETF & PMF* or *AETF & AMF*). Manager performance is defined as the value-weighted performance of the managed fund(s) based on the total net assets (TNA) managed by the manager. In cases where a fund has multiple managers, we assume each manager manages an equal TNA of the fund. To create the figures, we average the manager performance for each group (simple average in Panels A, B, D, E and TNA-weighted average in Panels C and F each month and compute the cumulative performance of each fund group. Panel A (D) shows the cumulative performance measured by CAPM alpha (Fama-French-Carhart 4-factors alpha) since 2016. Panel B (E) fixes the manager universe and classification as of January 2021 and displays cumulative performance measured by CAPM alpha (Fama-French-Carhart 4-factors alpha) since 2021, when more ETF managers are present in the sample. Panel C (F) follows Panels B (E) but weights the average performance by the total TNA managed by the manager. The straight (dotted) line represents active (passive) funds.



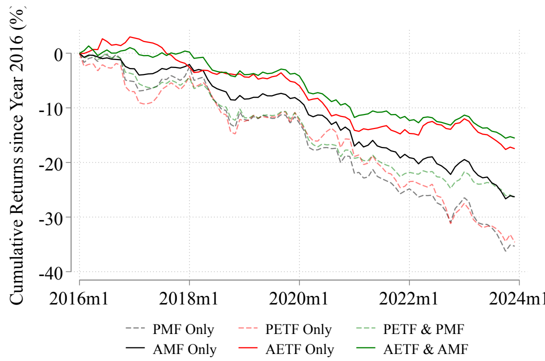
(a) Panel A: CAPM Alpha



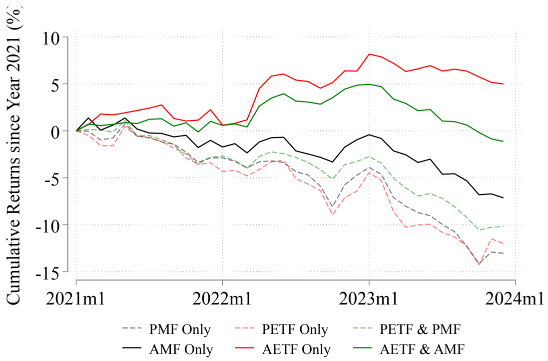
(b) Panel B: CAPM Alpha (Fixed 2021m1)



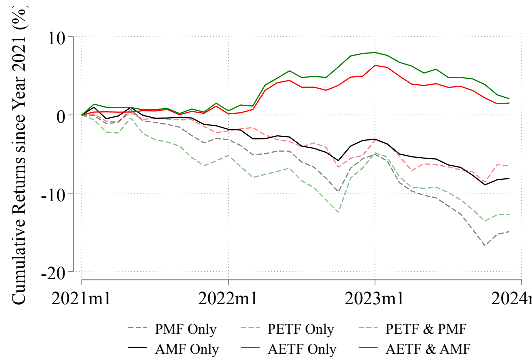
(c) Panel C: CAPM Alpha (Fixed 2021m1, value-weighted)



(d) Panel D: FF4 Alpha



(e) Panel E: FF4 Alpha (Fixed 2021m1)



(f) Panel F: FF4 Alpha (Fixed 2021m1, value-weighted)

Table 1: Descriptive statistics on AETFs and active MFs, 2016–2023

This table presents descriptive statistics for AETFs and active MFs that are included in the analysis. The observations are at the fund × month level and the unit of reported variables is in parentheses. *Total Net Asset Value* (TNA) is measured in million USD. *ExpRatio* is the annual percentage expense ratio charged by the fund. *TurnRatio* is the reported annual turnover ratio. *Age* is number of years since the inception of the fund. *Flow* is the monthly net flow into the fund as percentage of TNA in the last month. *ExcessReturn* is the monthly return after fees, in excess of the risk-free rate and in %. *CAPM Alpha*, *FF3 Alpha*, *FF4 Alpha* and *FF5 Alpha* are the % risk-adjusted abnormal returns relative to the market (MRKRF), the Fama-French 3-factors (MRKRF, SMB, HML), the Fama-French-Carhart 4-factors (MRKRF, SMB, HML, UMD) and the Fama-French 5-factors (MRKRF, SMB, HML, RMA and CMA), respectively. *InstOwn* is the percentage of total institutional ownership by all 13-F institutions. *Discount/Premium* is the percentage deviation of ETF share price from the net asset value (NAV). *CoveredShort* is the level of covered short interest as percentage of shares outstanding.

	(1) MFs			(2) AETFs			
	Mean	SD	Median	Mean	SD	Median	Mean (1) - Mean (2)
TNA ($mn)	1979	8148	287	275	1323	42	1703.23***
ExpRatio (%)	0.92	0.49	0.94	0.71	0.28	0.75	0.20***
TurnRatio	0.71	1.7	0.44	1.5	4.5	0.41	-0.81***
Age (Year)	16	12	14	2.7	3.1	1.8	13.17***
Flow (% of TNA)	-0.021	4.5	-0.5	6.1	28	0.1	-6.10***
Excess Return(%)	0.71	4.5	0.93	0.38	5.4	0.62	0.33***
CAPM Alpha (%)	-0.23	2.1	-0.14	-0.24	2.9	-0.11	0.01
FF3 Alpha (%)	-0.26	1.8	-0.19	-0.22	2.6	-0.13	-0.04*
FF4 Alpha (%)	-0.29	2	-0.2	-0.26	2.8	-0.15	-0.03*
FF5 Alpha (%)	-0.17	2	-0.15	-0.1	2.9	-0.067	-0.07***
InstOwn (%)	0.15	2.8	0	45	31	45	-44.70***
Discount/Premium (%)	0	0	0	0.12	2.9	0.0095	-0.12***
CoveredShort (%)	0	0	0	0.42	1.27	0.067	-0.42***
Number of funds		5468			627		

Table 2: Tax-efficiency of actively managed ETFs versus actively managed mutual funds

This table reports summary statistics of hypothetical annual costs paid by a top marginal taxpayer who invests in the U.S. fund market. Panel A (B) presents the expense ratio *ExpRatio* and tax implications for actively managed equity ETFs (mutual funds, MFs) from 2016 to 2023. The relevant tax rate for the top marginal taxpayer is obtained from the U.S. Department of the Treasury for the same period. *ExpRatio* is the reported annual expense ratio charged by the fund, measured in %. Tax^{DIV} represents the annual tax implication of distributed dividends, calculated by multiplying the annual fund dividend yield by the top marginal tax rate for dividend income. Tax^{STCGT} and Tax^{LTCGT} are the tax implications for short-term and long-term capital gains, respectively, based on a one-year investment horizon cut-off, following Sialm and Zhang (2019). Given that our sample starts in 2016, we assume that portfolio holdings established before 2016 are acquired at the market value at the beginning of 2016. Throughout our sample period, the top marginal short-term capital gains tax rate decreased from 40% to 37% in 2018, while the top marginal long-term capital gains tax rate and dividend tax rate remained stable at 20%. We also add a 4% surtax to the tax calculations, applicable to taxable income over US$1,000,000.

Panel A: Tax Implication of Active Equity ETFs

	ExpRatio (%)	Tax^{DIV} (%)	Tax^{STCGT} (%)	Tax^{LTCGT} (%)
Mean	0.71	0.25	0	0
Std.	0.28	0.50	0	0
Bottom 1%	0.12	0.00	0	0
Median	0.75	0.08	0	0
Top 1%	1.70	3.10	0	0
Observations	2008	911	1199	1082

Panel B: Tax Implication of Actively Managed Equity MFs

	ExpRatio (%)	Tax^{DIV} (%)	Tax^{STCGT} (%)	Tax^{LTCGT} (%)
Mean	0.92	0.078	0.18	0.15
Std.	0.49	0.30	0.81	1.10
Bottom 1%	0.00	0.00	0.00	0.00
Median	0.94	0.01	0.01	0.00
Top 1%	2.20	1.40	2.10	1.60
Observations	24662	14498	22992	24816

Table 3: Fund performance and flow convexity

This table presents the results from a monthly OLS regression of fund flows on fund performance from 2016 to 2023. The variable of interest is the interaction term of *Alpha*, which is the Fama-French-Carhart 4-factors alpha, and $\mathbb{1}$(Alpha $<$ 0), a binary variable that takes the value of one when alpha is negative, and zero otherwise. Control variables include the annual expense ratio of the fund (*ExpRatio*), the log of the fund's total net assets (*ln(TNA)*), the log of fund age (*ln(Age)*), and fund flow as a percentage of TNA (*Flow*). We include year-month fixed effects and compute heteroskedasticity-robust t-statistics clustered by fund, following Goldstein et al. (2017). Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively.

	(1) All Funds	(2) Mutual Funds	(3) AETFs	(4) AETFs; Not Shorted	(5) AETFs; Shorted
$Alpha_{t-1}$	0.21***	0.20***	0.57***	0.57***	0.39**
	(0.01)	(0.01)	(0.13)	(0.16)	(0.17)
$Alpha_{t-1} \times \mathbb{1}(Alpha_{t-1} < 0)$	-0.18***	-0.17***	-0.52***	-0.59***	-0.22
	(0.02)	(0.02)	(0.14)	(0.19)	(0.22)
$\mathbb{1}(Alpha_{t-1} < 0)$	-0.00***	-0.00***	-0.00	0.00	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
$ExpRatio_{t-1}$	-0.62***	-0.62***	-0.71	-1.14*	0.53
	(0.05)	(0.05)	(0.56)	(0.62)	(0.97)
$ln(TNA_{t-1})$	-0.00***	-0.00***	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$ln(Age_{t-1})$	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Flow_{t-1}$	0.12***	0.12***	0.09***	0.08***	0.20***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)
Constant	0.03***	0.03***	0.04***	0.04***	0.03**
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Observations	600,542	585,148	15,394	11,626	3,768
R-squared	0.04	0.04	0.02	0.02	0.11
Year-Month FE	Yes	Yes	Yes	Yes	Yes

Table 4: Relationship between covered shorts and flow-performance

This table presents the result from a monthly OLS regression that examines the impact of covered shorts on the monthly performance-flow relationship of an AETF converted from a mutual fund. The dependent variable is monthly fund flow as percentage of TNA. The variable of interest is the interaction term of *AccAlpha*, which is the lagged 3-months accumulated alpha, and the variable *Covered Short*, which is the covered short interest. *Alpha* is measured using CAPM, Fama-French 3 factors, Fama-French-Carhart 4 factors and Fama-French 5 factors models. The control variables include 1) *ExpRatio*, which is the annual expense ratio of the fund, 2) *ln(TNA)*, which is the log of fund's total net assets, 3) *ln(Age)*, which is the log of fund age, 4) *Flow*, which is the fund flow percentage, 5) *DiscountPremium*, which is the average discount or premium of the ETF's price to its NAV and 6) *InstOwn*, the percentage of total institutional ownership by all 13-F institutions. We compute heteroskedasticity-robust t-statistics clustered by group, fund and month. Statistical significance at the 1%, 5%, and 10% level is denoted as ***, **, and *, respectively.

	(1) CAPM	(2) Alpha FF3	(3) Alpha FF4	(4) Alpha FF5
$AccAlpha_{t-1} \times CoveredShort_{t-1}$	0.027**	0.031***	0.026**	0.029**
	(0.012)	(0.008)	(0.012)	(0.014)
$AccAlpha_{t-1}$	0.051**	0.041*	0.027	0.035*
	(0.022)	(0.021)	(0.019)	(0.019)
$CoveredShort_{t-1}$	-0.001**	-0.000	-0.001**	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)
$ExpRatio_{t-1}$	0.758	0.757	0.804	0.831
	(1.480)	(1.463)	(1.480)	(1.428)
$ln(TNA_{t-1})$	-0.032***	-0.032***	-0.032***	-0.032***
	(0.006)	(0.006)	(0.006)	(0.006)
$ln(Age_{t-1})$	0.088***	0.091***	0.095***	0.093***
	(0.030)	(0.030)	(0.029)	(0.030)
$Flow_{t-1}$	-0.069***	-0.065***	-0.056**	-0.055**
	(0.024)	(0.024)	(0.022)	(0.022)
$DiscountPremium_{t-1}$	0.284	1.011	1.441	0.102
	(4.038)	(2.880)	(2.964)	(3.163)
$InstOwn_{t-1}$	0.031*	0.032*	0.032*	0.034*
	(0.016)	(0.016)	(0.016)	(0.017)
Constant	-0.066	-0.078	-0.088	-0.084
	(0.070)	(0.069)	(0.067)	(0.069)
Observations	34,135	34,088	34,098	34,074
R-squared	0.234	0.232	0.228	0.230
Group FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes

Table 5: Do covered shorts predict returns?

This table displays the predictive power of covered shorts on future abnormal returns, defined by future $n \in [1, 12]$ weekly CAPM alpha, Fama-French 3-factor alpha, Fama-French-Carhart 4-factor alpha, and Fama-French 5-factor alpha. The coefficients on covered shorts (β_1) are presented below and estimated from the following regression:

$$Alpha_{i,t+n} = \beta_1 Covered\ Short_{i,t} + \beta_2 Alpha_{i,t+n-1} + \beta_3 ExpRatio_{i,t+n-1} + \beta_4 ln(TNA_{i,t+n-1}) + \beta_5 ln(FAMTNA_{i,t+n-1}) + \beta_6 ln(DiscountPremium_{i,t+n-1}) + \sum_{s=t+n-4}^{t} \beta_s Flow_{i,s} + \gamma_i + \epsilon_{i,t+n}.$$

The control variables include the lagged $s \in [0, 4]$ *Flow %*, the weekly fund flow as a percentage of the fund's TNA; *Alpha*, the weekly excess returns on the fund; *ExpRatio*, the annual expense ratio of the fund; *ln(TNA)*, the log of fund's total net assets; *ln(FAMTNA)*, the log of the total net assets of the fund's family; and *DiscountPremium*, the average discount or premium of the ETF's price relative to its NAV. We compute heteroskedasticity-robust standard errors by clustering at the weekly level. Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively.

	(1) Alpha CAPM		(2) Alpha FF3		(3) Alpha FF4		(4) Alpha FF5	
t + 1 week	-0.122	(0.077)	-0.068	(0.064)	-0.048	(0.056)	-0.107*	(0.060)
t + 2 week	-0.143**	(0.073)	-0.079	(0.062)	-0.069	(0.053)	-0.099	(0.060)
t + 3 week	-0.169**	(0.073)	-0.101*	(0.061)	-0.096*	(0.051)	-0.122**	(0.059)
t + 4 week	-0.166**	(0.072)	-0.110*	(0.059)	-0.106**	(0.048)	-0.134**	(0.058)
t + 5 week	-0.170**	(0.072)	-0.121**	(0.056)	-0.107**	(0.046)	-0.130**	(0.054)
t + 6 week	-0.188***	(0.071)	-0.118**	(0.053)	-0.103**	(0.044)	-0.124**	(0.050)
t + 7 week	-0.201***	(0.067)	-0.135***	(0.051)	-0.148***	(0.053)	-0.154***	(0.046)
t + 8 week	-0.185***	(0.069)	-0.127***	(0.049)	-0.119***	(0.045)	-0.135***	(0.043)
t + 9 week	-0.148**	(0.075)	-0.114**	(0.049)	-0.105**	(0.045)	-0.127***	(0.042)
t + 10 week	-0.125	(0.079)	-0.133***	(0.048)	-0.128***	(0.044)	-0.147***	(0.043)
t + 11 week	-0.116	(0.076)	-0.125***	(0.048)	-0.112***	(0.042)	-0.133***	(0.041)
t + 12 week	-0.115	(0.076)	-0.143***	(0.051)	-0.111**	(0.047)	-0.145***	(0.041)
Controls	Yes		Yes		Yes		Yes	
Fund FE	Yes		Yes		Yes		Yes	
Year-Week FE	Yes		Yes		Yes		Yes	

Table 6: Do covered shorts predict fund flows?

This graph displays the relationship between the level of covered shorts and the future fund flow of AETFs. We regress the percentage of fund flow on the standardized level of covered shorts over a future window of $n \in [1, 12]$ weeks (column 1) or months (column 2) using the following specification:

$$Flow_{i,t+n} = \beta_1 Covered\ Short_{i,t} + \beta_2 Alpha_{i,t+n-1} + \beta_3 ExpRatio_{i,t+n-1} + \beta_4 ln(TNA_{i,t+n-1}) +$$
$$\beta_5 ln(FAMTNA_{i,t+n-1}) + \beta_6 ln(DiscountPremium_{i,t+n-1}) + \sum_{s=t+n-4}^{t} \beta_s Flow_{i,s} + \gamma_i + \epsilon_{i,t+n}.$$

The coefficients on covered shorts (β_1) are presented in columns 1 and 2. The control variables include the lagged $s \in [0, 4]$ *FundFlow %*, which represents the weekly (monthly) fund flow as a percentage of the fund's TNA; *Alpha*, the weekly (monthly) Fama-French-Carhart 4 factors alpha on the fund; *ExpRatio*, the annual expense ratio of the fund; *ln(TNA)*, the log of the total net assets reported by the fund; *ln(FAMTNA)*, the log of the total net assets of the fund's family; and *DiscountPremium*, the average discount or premium of the ETF's price relative to its NAV. We compute heteroskedasticity-robust standard errors by clustering at the weekly (monthly) level. Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively.

	(1) Weekly Flow (%)		(2) Monthly Flow (%)	
t + 1	0.092	(0.072)	-0.099	(1.115)
t + 2	-0.015	(0.055)	-1.777***	(0.559)
t + 3	-0.052	(0.053)	-1.131***	(0.418)
t + 4	-0.093*	(0.051)	-1.019**	(0.440)
t + 5	-0.099**	(0.041)	-0.266	(0.406)
t + 6	-0.091**	(0.041)	-0.680*	(0.346)
t + 7	-0.048	(0.091)	-1.476**	(0.562)
t + 8	-0.088	(0.108)	0.042	(0.460)
t + 9	-0.115***	(0.038)	-0.694*	(0.368)
t + 10	-0.108***	(0.040)	-0.070	(0.364)
t + 11	-0.127***	(0.041)	-0.045	(0.404)
t + 12	-0.130***	(0.037)	-0.554*	(0.296)
Controls	Yes		Yes	
Fund FE	Yes		Yes	
Year-Week FE	Yes		No	
Year-Month FE	No		Yes	

Table 7: Difference-in-differences regressions of covered shorts around portfolio manager turnovers

This table presents the results from a difference-in-differences regression of covered shorts around portfolio manager turnovers:

$$\begin{aligned} CoveredShort_{i,t} =& \beta_{DID} \mathbb{1}(Post_t) \times \mathbb{1}(Turnover_i) + \beta_2 ln(TNA_{i,t-1}) + \beta_3 ln(Age_{i,t-1}) \\ &+ \beta_4 ExcessRet_{i,t-1} + \beta_5 Flow_{i,t-1} + \lambda_t + \gamma_i + \epsilon_{i,t+n} \end{aligned}$$

The control group is the sample of matched AETFs which have never experienced any manager turnover (*never treated*). The variable of interest is the level of covered shorts (*CoveredShort*). The control variables include the log of the fund's total net assets (*ln(TNA)*), the log of fund age (*ln(Age)*), fund returns in excess of the risk-free rate (*ExcessRet*), and fund flow as a percentage of TNA (*Flow*). We include fund and month fixed effects and compute heteroskedasticity-robust t-statistics clustered by fund and month. $Post_t = 1$ after the turnover event for a given fund. The regression compares funds with manager turnover ($Turnover_i = 1$) to similar funds (based on fund's age, TNA, expense ratio and performance) that have never experienced manager turnover. Portfolio managers are classified into good and bad managers based on the median of the three-month accumulated raw fund return, weighted by the fund's TNA managed by the manager prior to the turnover event. Each column reports the difference-in-differences coefficient, β_{DID}: Columns 1–2 (5–6) show the results for bad managers joining (leaving) the fund; columns 3–4 (7–8) for good managers joining (leaving) the fund. Columns 9–10 show the results when a bad manager leaves and is replaced by a good manager. Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Bad Join		Good Join		Bad Leave		Good Leave		Bad Leave Good Join	
β_{DID}	0.906***	0.848***	-0.102*	-0.112*	0.001	0.004	0.028	0.054	-0.116	-0.200**
	(0.242)	(0.205)	(0.055)	(0.060)	(0.041)	(0.036)	(0.039)	(0.047)	(0.097)	(0.100)
Observations	576	483	18,288	15,454	8,640	7,482	15,264	12,845	1,152	1,005
R-squared	0.664	0.720	0.478	0.494	0.587	0.624	0.427	0.450	0.581	0.657
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: The probability of a manager quitting the fund industry

This table presents the results from a logit regression that examines the relationship between the probability of a manager quitting the active fund management industry and the extent to which the manager's funds are shorted:

$$\mathbb{1}(Quit_{m,t}) = \beta_1 CoveredShort_{m,t} + \beta_2 NumFunds_{m,t} + \beta_3 Tenure_{m,t} + \lambda_t + \epsilon_{m,t}.$$

The unit of observation is at the manager × week level. $\mathbb{1}$(Quit) is a dummy variable that takes the value of one for a manager who has not managed any active fund after leaving the last AETF, and zero otherwise. We examine whether the manager quits either the AETF industry only (columns 1–4) or the entire open-end fund industry (columns 5–8). *CoveredShort* is the manager-level covered short measure calculated by averaging the level of demeaned covered shorts of all AETFs managed by that manager. In columns (3), (4), (7), and (8), we replace *CoveredShort* with *PerfQuintile*, which is the quintile of manager's performance (higher is better performance) based on the lagged 3-month accumulated returns of the manager, to examine the relationship between the probability of a manager quitting the active fund industry and their performance. Panel A reports the results from logit regressions without fund manager controls, while Panel B reports results with controls: *NumFund*, the number of funds managed, and *Tenure*, the number of years the manager has spent in the fund management industry. We include year-week fixed effects in columns (2), (4), (6), and (8) and report bootstrapped t-statistics. Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively.

Panel A: Logit regressions without fund manager controls

$\mathbb{1}(Quit)$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fund Universe: AETFs				Fund Universe: AETFs & MFs			
$CoveredShort_t$	0.061***	0.089***			0.061***	0.047***		
	(0.013)	(0.016)			(0.016)	(0.016)		
$PerfQuintile_t$			-0.127***	-0.134***			-0.038***	-0.035***
			(0.009)	(0.017)			(0.006)	(0.008)
Observations	30,521	30,361	63,079	55,964	25,621	25,621	49,048	49,048
Year-Week FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Logit regressions with fund manager controls

$\mathbb{1}(Quit)$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fund Universe: AETFs				Fund Universe: AETFs & MFs			
$CoveredShort_t$	0.103***	0.072***			0.080***	0.050***		
	(0.015)	(0.021)			(0.017)	(0.018)		
$PerfQuintile_t$			-0.098***	-0.108***			-0.038***	-0.035***
			(0.010)	(0.015)			(0.009)	(0.008)
$NumFunds_t$	-0.009***	0.012***	-0.142***	-0.111***	0.080***	0.090***	-0.012***	-0.013***
	(0.002)	(0.003)	(0.009)	(0.006)	(0.010)	(0.009)	(0.004)	(0.003)
$Tenure_t$	-0.101***	-0.076***	-0.051***	-0.044***	-0.022***	-0.012***	-0.027***	-0.024***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Observations	30,113	29,925	54,732	45,464	26,995	26,994	48,956	48,956
Year-Week FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 9: Investment style of AETFs and MFs

This table presents the results from OLS regressions examining the differences in investment style between MFs and AETFs. The baseline regression in column 1 compares investment styles by regressing the fund's excess return on the Fama-French-Carhart four factors (i.e., *MRKRF, SMB, HML, UMD*), including their interaction with a dummy variable, $\mathbb{1}$(ActiveETF), which takes the value of one if the fund is AETF and zero if it is MF. The matched difference-in-differences (DID) regression in column 2 uses the matched sample from Table 4 to conduct a quasi DID comparison of factor loadings before and after the conversion of a subset of AETFs from MFs. Control variables include *ln(TNA)*, the log of fund's total net assets; *ln(Age)*, the log of fund age; and *Flow*, the fund flow as a percentage of TNA. We include fund and year-month fixed effects and compute heteroskedasticity-robust t-statistics clustered by fund and year-month.

VARIABLES	(1) Excess Return (Baseline)	(2) Excess Return (Matched DID)
$\mathbb{1}(ActiveETF)\times \text{MKTRF}_t$	-0.05**	
	(0.02)	
$\mathbb{1}(ActiveETF)\times \text{SMB}_t$	0.02	
	(0.03)	
$\mathbb{1}(ActiveETF)\times \text{HML}_t$	-0.07***	
	(0.02)	
$\mathbb{1}(ActiveETF)\times \text{MOM}_t$	0.05***	
	(0.01)	
$\mathbb{1}(Post_t) \times \mathbb{1}(Conversion)\times \text{MKTRF}_t$		0.02
		(0.03)
$\mathbb{1}(Post_t) \times \mathbb{1}(Conversion)\times \text{SMB}_t$		0.08
		(0.07)
$\mathbb{1}(Post_t) \times \mathbb{1}(Conversion)\times \text{HML}_t$		0.06
		(0.04)
$\mathbb{1}(Post_t) \times \mathbb{1}(Conversion)\times \text{MOM}_t$		0.10**
		(0.05)
$\ln(\text{TNA}_{t-1})$	-0.00***	-0.00
	(0.00)	(0.01)
$\ln(\text{Age}_{t-1})$	0.00***	0.00
	(0.00)	(0.00)
Flow_{t-1}	-0.00	-0.02
	(0.00)	(0.01)
Observations	387,810	63,741
R-squared	0.74	0.66
Fund FE	Yes	Yes
Year-Month FE	Yes	Yes

Table 10: Stock price efficiency and ownership by AETFs

This table presents the results from an OLS regression of stock price informativeness measures on the total ownership by equity AETFs. The unit of the observation is stock × month. The dependent variables are measures of stock's price informativeness. The first measure PI^{R2} is the Roll (1988) measure for price informativeness. The measure is defined as 1 - R^2, where R^2 is computed from the following regression using past 30-months rolling window:

$$r_{i,j,t} = \beta_{i,0} + \beta_{i,m} r_{m,t} + \beta_{j,m} r_{j,t} + \epsilon_{i,t}.$$

$r_{i,j,t}$ is the return of stock i in industry j in the quarter t, $r_{m,t}$ is value-weighted stock market return in quarter t, and $r_{j,t}$ is value-weighted industry j return in quarter t. *The higher the* PI^{R2} *measure, the lower the price-informativeness* of the security. The second measure PI^{PJR} is Weller (2017)'s price-jump ratio. It is the ratio of post-announcement price variation as a fraction of the total variation prior and including the earning announcement:

$$PI_{i,t}^{PJR} = \frac{CAR_{it}^{T-1,T+b}}{CAR_{it}^{T-a,T+b}}$$

We follow Weller (2017) to set $a = 21$ and $b = 2$. The third (PI^{DP}) and forth measures (PI^{DPR}) are the absolute and relative price informativeness measures from Davila and Parlatore (2018), respectively. PI^{PJR}, $PI^{DP}$and PI^{DPR} are increasing in price informativeness so *the higher the measures, the higher the price-informativeness* of the security. The variable of interest is the percentage of ownership by AETFs in a given stock *AETF Holding (%)*. Control variables include book to market equity *BEME*, operating profitability *OP*, investments *INV*, dividends *DIV*, and 12-months accumulated stock returns. We include month fixed effect and compute heteroskedasticity-robust t-statistics clustered by year-month. Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively.

	(1) PI^{R2}	(2) PI^{PJR}	(3) PI^{DP}	(4) PI^{DPR}
AETFHolding_t(%)	0.20**	0.30	-2.96***	-1.57***
	(0.10)	(0.31)	(0.72)	(0.35)
BEME_t	28.75***	-30.90***	-754.89***	-157.43***
	(4.62)	(8.85)	(13.64)	(12.36)
OP_t	-0.08***	0.04***	-0.04***	0.22***
	(0.00)	(0.01)	(0.01)	(0.02)
INV_t	-0.08***	0.06***	-0.89***	-0.59***
	(0.01)	(0.02)	(0.02)	(0.03)
DIV_t	-0.30***	-0.22***	-1.20***	-0.08
	(0.01)	(0.06)	(0.07)	(0.07)
Acc12Ret_t	0.01	-0.02*	0.03	0.16***
	(0.01)	(0.01)	(0.03)	(0.02)
Observations	88,847	29,926	83,037	83,395
R-squared	0.14	0.03	0.09	0.03
Month FE	Yes	Yes	Yes	Yes

Table 11: Change of price efficiency of the underlying stocks

This table presents the results from an OLS regression that examines the relationship between a stock's future price informativeness and the percentage of shares held by AETFs. The dependent variables are the measures of underlying stock's price informativeness in the next 1 to 4 quarters (columns 1 to 4). Specifically, we use Roll (1988) measure for price informativeness. The measure is defined as 1 - R^2, where R^2 is computed from the following regression using past 30-months rolling window:

$$r_{i,j,t} = \beta_{i,0} + \beta_{i,m} r_{m,t} + \beta_{j,m} r_{j,t} + \epsilon_{i,t},$$

where $r_{i,j,t}$ is the return of stock i in industry j in the quarter t, $r_{m,t}$ is value-weighted stock market return in quarter t, and $r_{j,t}$ is value-weighted industry j return in quarter t. We then examine the change in stock's price informativeness under the following specification in columns (1) - (4):

$$PI^{R2}_{s,t+n} = \beta_1 AETFHolding_{s,t} + \beta_2 MFHolding_{s,t} + \beta_3 PETFHolding_{s,t} + \gamma_t + \epsilon_{s,t+n},$$

where $n \in [1, 4]$ quarters, and $AETFHolding_{s,t}$, $MFHolding_{s,t}$ and $PETFHolding_{s,t}$ are the share of a company's stock owned by AETFs, active MFs and PETFs, respectively. The unit of observation is at the stock×quarter level. We include quarter fixed effects and compute heteroskedasticity-robust t-statistics clustered by stock and quarter. In column (5), we analyze the first time a stock is bought by an AETF and compare the price informativeness of the stock around the purchase event. Specifically, for each stock, we match it with five similar stocks (based on market capitalization and price informativeness) prior to the purchase and these five stocks have not been bought by the AETF. We then conduct a difference-in-differences analysis to examine the effect of AETF purchase using the following specification:

$$PI^{R2}_{s,t} = \beta_{DID} \mathbb{1}(Bought_s) \times \mathbb{1}(Post_t) + \beta_1 \mathbb{1}(Bought_s) + \beta_2 MFHolding_{s,t} + \beta_3 PETFHolding_{s,t} + \gamma_t + \epsilon_{s,t},$$

where $\mathbb{1}(Bought_s)$ is a binary variable that takes the value of one if a stock is bought by any AETF for the first time and zero otherwise. $\mathbb{1}(Post_t)$ is a binary variable that indicates period after the purchase. We include year-quarter fixed effects and compute heteroskedasticity-robust t-statistics clustered by stock and year-month. Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively.

	(1) $\text{PI}^{R2}_{s,t+1}$	(2) $\text{PI}^{R2}_{s,t+2}$	(3) $\text{PI}^{R2}_{s,t+3}$	(4) $\text{PI}^{R2}_{s,t+4}$	(5) DID
AETFHolding$_t$(%)	-0.12***	-0.11***	-0.11***	-0.11***	
	(0.04)	(0.04)	(0.04)	(0.03)	
$\mathbb{1}(Bought_s) \times \mathbb{1}(Post_t)$					-0.02***
					(0.01)
$\mathbb{1}(Bought_s)$					0.00
					(0.02)
AMFHolding$_t$(%)	-0.00	-0.00	-0.00	-0.00	0.11*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)
PETFHolding$_t$(%)	0.40***	0.38***	0.33***	0.34***	0.48*
	(0.06)	(0.06)	(0.06)	(0.06)	(0.22)
Observations	171,594	162,092	151,603	142,053	95,263
R-squared	0.07	0.07	0.07	0.07	0.02
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes

Appendix

Table A1: Descriptive statistics on cloned AETFs, converted AETFs and their counterparties

This table presents the descriptive statistics of converted ETFs, cloned ETFs, and the corresponding MFs. The level of observation is fund$\times$month level, and the unit of reporting is in percentages unless otherwise stated. *Total Net Asset Value* (TNA) is measured in million USD. *ExpRatio* is the annual percentage expense ratio charged by the fund. *TurnRatio* is the reported annual turnover ratio. *Age* is number of years since the inception of the fund. *Flow* is the monthly net flow into the fund as percentage of TNA in the last month. *ExcessReturn* is the monthly return after fees, in excess of the risk-free rate and in %. *CAPM Alpha*, *FF3 Alpha*, and *FF4 Alpha* are the % risk-adjusted abnormal returns relative to the market (MRKRF), the Fama-French 3-factors (MRKRF, SMB, HML), and the Fama-French-Carhart 4-factors (MRKRF, SMB, HML, UMD), respectively. *InstOwn* is the percentage of total institutional ownership by all 13-F institutions. *Discount/Premium* is the percentage deviation of ETF share price from the net asset value (NAV). *CoveredShort* is the level of covered short interest as percentage of shares outstanding.

	(1) Converted funds: Before conversion			(2) Converted funds: After conversion			(3) Cloned funds: Mutual funds			(4) Cloned funds: ETFs		
	Mean	SD	P50	Mean	SD	P50	Mean	SD	P50	Mean	SD	P50
TNA ($mn)	1225	1921	215	3011	4952	299	13632	31814	3921	1075	2846	105
ExpRatio	0.83	0.45	0.73	0.66	0.4	0.65	0.71	0.35	0.74	0.48	0.2	0.55
TurnRatio	0.82	1.1	0.54	0.51	0.78	0.13	0.39	0.31	0.31	0.33	0.25	0.24
Age (Year)	12	6.5	12	16	6.5	14	26	21	22	3.5	5.5	1.8
Flow	0.25	6.7	-0.15	0.38	5.4	0.068	-0.033	3.8	-0.43	6.9	24	1.7
Excess Return	0.64	5.1	1	0.73	5.1	0.65	1.1	5.1	1.5	0.91	5.7	1.4
CAPM Alpha	-0.33	2.9	-0.21	-0.19	2.4	0.016	-0.093	2.1	-0.063	-0.00024	2.4	0.037
FF3 Alpha	-0.33	3	-0.14	-0.16	1.9	0.0096	-0.084	1.4	-0.056	-0.035	1.7	-0.017
FF4 Alpha	-0.39	3.2	-0.16	-0.065	2.1	0.05	-0.079	1.6	-0.035	-0.023	1.8	-0.00046
InstOwn	5.5	19	0	41	31	44	0.099	0.73	0	46	33	57
CoveredShort	0	0	0	0.052	0.084	0.025	0	0	0	0.16	0.55	0.057
Number of funds	45			22			63			63		

Table A2: Relationship between covered shorts and performance-flow for cloned AETFs

This table presents the result from an OLS regression that examines the impact of covered shorts on the monthly performance flow relationship of an ETF cloned from a MF. Following Du et al. (2023) to identify the pairs, an AETF has to be managed by the same portfolio manager within the same management company and needs to have at least 65% of an overlap in its portfolio holdings with the total weight of overlap in portfolio exceeding 75%. The dependent variable is monthly fund flow percentage. The variable of interest is the interaction term of *Alpha*, which is the lagged return, and the binary variable, $\mathbb{1}(ActiveETF)$, which takes the value of one for active ETFs, and zero otherwise. *Alpha* is measured using CAPM, Fama-French 3 factors, Fama-French-Carhart 4 factors and Fama-French 5 factors models. The control variables include: 1) *ExpRatio*, which is the annual expense ratio of the fund, 2) *ln(TNA)*, which is the log of fund's total net assets, 3) *ln(Age)*, which is the log of fund age, 4) *Flow*, which is the fund flow as percentage of TNA, 5) *DiscountPremium*, which is the average discount or premium of the ETF's price to its NAV and 6) *InstOwn*, the percentage of total institutional ownership by all 13-F institutions. We compute heteroskedasticity-robust t-statistics clustered by group, fund and month. Statistical significance at the 1%, 5%, and 10% level is denoted as ***, **, and *, respectively.

	(1) CAPM	(2) Alpha FF3	(3) Alpha FF4	(4) Alpha FF5
$Alpha_{t-1} \times \mathbb{1}(ActiveETF)$	0.059	0.266*	0.178	0.332
	(0.057)	(0.156)	(0.147)	(0.205)
$Alpha_{t-1}$	0.019	0.021	0.020	0.017
	(0.018)	(0.017)	(0.017)	(0.018)
$\mathbb{1}(ActiveETF)$	-0.006	0.035	0.036	0.044
	(0.018)	(0.029)	(0.029)	(0.036)
$CoveredShort_{t-1}$	0.008***	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
$ExpRatio_{t-1}$	1.136	1.209	1.249	1.222
	(2.654)	(2.685)	(2.657)	(2.691)
$ln(TNA_{t-1})$	-0.004	-0.003	-0.003	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
$ln(Age_{t-1})$	-0.003	-0.002	-0.002	-0.002
	(0.005)	(0.006)	(0.006)	(0.006)
$Flow_{t-1}$	-0.001	0.013	0.011	0.003
	(0.041)	(0.046)	(0.046)	(0.044)
$DiscountPremium_{t-1}$	6.916	7.312	6.820	6.401
	(10.165)	(9.688)	(9.686)	(9.286)
$InstOwn_{t-1}$	-0.012	-0.012	-0.011	-0.008
	(0.024)	(0.024)	(0.024)	(0.024)
Constant	0.029	0.026	0.026	0.031
	(0.022)	(0.023)	(0.023)	(0.024)
Observations	2,783	2,802	2,802	2,802
R-squared	0.213	0.213	0.213	0.218
Clonepair FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes

Table A3: Descriptive statistics on lending of AETFs and active mutual funds, 2016-2023

This table presents descriptive statistics of equity lending for common stocks, PETFs, and AETFs. The observations are at the security $\times$ day level, and the unit of reported variables is stated in parentheses. *Lendable %* is the fraction of shares outstanding available to borrow. *Actually Lent %* is the fraction of shares outstanding that is actually lent. *Actually Lent Adj %* is the fraction of shares outstanding that is actually lent for purposes other than dividend and financing trades, as reported by the borrower *Tenure* is the average maturity of the loan in days. *Indicative Fees* represent the annual expected borrowing cost of the security for a hedge fund on a given day, serving as an indication of the standard market cost. *Actual Fees* is the annual average borrowing cost of the security for a hedge fund on a given day. *BorrCencent %* (*LendCencent %*) measures the concentration of borrowers (lenders) distribution, where a very small number indicates a large number of borrowers (lenders), while a value of 100% indicates a single borrower (lender).

	(1) Common Stock			(2) PETFs			(3) AETFs		
	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
Lendable (%)	24	17	24	4.4	53	0.2	2.4	76	0.037
Actually Lent (%)	3.4	5.2	1.4	0.86	5.7	0.096	0.49	2.1	0.067
Actually Lent Adj. (%)	3.1	4.8	1.2	0.67	5	0.073	0.47	1.7	0.056
Tenure (Days)	71	70	55	27	49	12	23	44	8
Indicative Fees (Annual, %)	3.1	12	0.38	6.2	8.4	4.3	7.4	11	4.6
Actual Fees (Annual, %)	2.4	12	0.3	4.5	9.4	2	6.4	11	3.3
BorrConcent (%)	33	22	26	67	29	66	82	24	100
LendConcent (%)	37	21	30	82	25	100	93	17	100
Number	5456			1236			553		

Table A4: Description of Variables

Variable	**Definition**
Excess Return	Fund return, net of fees and risk free return.
Alpha	Risk-adjusted excess return over risk related returns estimated using CAPM model or Carhart(1997) four-factor model over the past 12 months.
Flow	Proportional monthly growth in total net assets under management.
Covered Short	The number of exchange traded share shorted by physically borrowing the shares from other market participants, excluding the number of shares on loan with dividend trading and financing trades.
TNA	Total net assets under management of the fund.
FAMTNA	Total net assets under management of the fund's family.
ExpRatio	Reported annual expense ratio of the fund.
TurnRatio	Reported turnover ratio of the fund.
FundAge	Fund age measure in year.
DiscountPremium	The percentage difference between the price and the net asset value of the exchange traded fund.
MKTRF, SMB, HML, MOM	Risk factors from Carhart (1997). Specifically, MKTRF is the excess return on a value-weighted market portfolio; SMB, HML and MOM are value-weighted, zero-investment, factor mimicking portfolios for size, book-to-market equity, and 12-month momentum in stock returns, respectively. All factors are readily available in Kenneth French's Data Library.
BEME	Firm's book to market ratio measure by the ratio of book equity to market equity.
OP	Firm's profitability measured by the ratio of operating profits to book equity.
INV	Firm's investment measured by the annual growth rate of assets.
DIV	Firm's dividend measured by the ratio of annual dividends to prior year book equity.
Acc12Ret	Accumulated return for the past 12 month excluding the recent 2 months for the stock.
PI^{R2}	Roll (1988) price informativeness measure 1-R2. R2 is estimated by regressing the stock returns on contemporary value-weighted market returns and industry returns over a 30-months rolling window.
TAX^{STCGT}	Annual realized capital gain tax burden on short term assets that are acquired within a year prior to the sale with realized profits. The amount is estimated based on top marginal tax rate on short term capital gains.
TAX^{LTCGT}	Annual realized capital gain tax burden on short term assets that are acquired over a year prior to the sale with realized profits. The amount is estimated based on top marginal tax rate on long term capital gains.
TAX^{DIV}	Annual realized mutual fund dividend tax burden. The amount is estimated based on top marginal tax rate on dividend income.
Quit	A binary variable that indicates the portfolio manager leave the active fund industry.
NumFunds	The number of funds managed by the given portfolio manager.

Table A5: Descriptive statistics on ANETFs and ATETFs

This table presents the descriptive statistics of the actively managed transparent ETFs (i.e., *ATETFs*) and non-transparent ETFs (i.e., *ANETFs*). The level of observation is fund×month and the unit of reporting is in percentages unless otherwise stated. *Total Net Asset Value* (TNA) is measured in million USD. *ExpRatio* is the annual percentage expense ratio charged by the fund. *TurnRatio* is the reported annual turnover ratio. *FundAge* is number of years since the inception of the fund. *FundFlow* is the monthly net flow into the fund as percentage of TNA in the last month. *ExcessReturn* is the monthly return after fees, in excess of the risk-free rate and in %. *CAPM Alpha*, *FF3 Alpha*, *FF4 Alpha* and *FF5 Alpha* are the % risk-adjusted abnormal returns relative to the market (MRKRF), the Fama-French 3-factors (MRKRF, SMB, HML), the Fama-French-Carhart 4-factors (MRKRF, SMB, HML, UMD) and the Fama-French 5-factors (MRKRF, SMB, HML, RMA and CMA), respectively. *InstOwn* is the percentage of total institutional ownership by all 13-F institutions. *Discount/Premium* is the percentage deviation of ETF share price from the net asset value (NAV). *CoveredShort* is the level of covered short interest as percentage of shares outstanding.

	(1) ATETFs			(2) ANETFs		
	Mean	SD	Median	Mean	SD	Median
TNA ($mn)	288	1364	43	74	111	26
ExpRatio	0.72	0.28	0.76	0.57	0.18	0.59
TurnRatio	1.6	4.7	0.4	0.58	0.49	0.45
Fund Age (Year)	2.8	3.1	2	1.5	0.9	1.5
Fund Flow	6.1	29	0.075	5.3	21	1.1
Excess Return	0.37	5.4	0.62	0.61	6.1	0.58
CAPM Alpha	-0.25	2.9	-0.11	0.00073	2.4	-0.031
FF3 Alpha	-0.23	2.7	-0.14	-0.021	2	-0.026
FF4 Alpha	-0.27	2.8	-0.15	-0.047	2.2	-0.072
InstOwn	45	31	45	45	35	42
CoveredShort	0.11	0.68	0	0.044	0.23	0
Number of funds		584			43	

Table A6: Summary statistics on portfolio managers

This table presents the number and characteristics of the portfolio managers' universe. For each fund, we obtain specific information about the portfolio manager(s) from the MorningStar dataset. We classify and group managers into three categories: 1) managed only active mutual funds (*AMF only*), 2) managed only active ETFs (*AETF only*), and 3) managed both AMFs and AETFs (*AETF&AMF*). Panel A summarizes the number of portfolio managers in each group from 2016 to 2023. Panel B reports the characteristics of the portfolio managers, including the first year when the manager started managing either AMF or AETF (*TenureStart*), the last year when the manager managed either AMF or AETF (*TenureEnd*), the average number of funds managed (*NumFund*), a binary variable that takes the value of 1 if the manager is male (*isMale*), a binary variable that takes the value of 1 if the manager has a Master's degree (*isMaster*), a binary variable that takes the value of 1 if the manager has an MBA degree (*isMBA*), a binary variable that takes the value of 1 if the manager has a PhD degree (*isPhD*), and a binary variable that takes the value of 1 if the manager has a degree from an Ivy League university (*isIvy*).

Panel A: Number of portfolio managers, 2016-2023

	(1) Manager of only AMFs	(2) Manager of only AETFs	(3) Manager of both AMFs & AETFs
2016	3625	87	37
2017	3663	100	50
2018	3700	113	60
2019	3753	130	73
2020	3692	175	112
2021	3640	235	205
2022	3739	360	286
2023	3856	321	346

Panel B: Characteristics of portfolio managers

	(1) Manager of only AMFs			(2) Manager of only AETFs			(3) Manager of both AMFs & AETFs		
	Mean	Median	N	Mean	Median	N	Mean	Median	N
TenureStart	2013	2014	6077	2019	2020	506	2014	2016	416
TenureEnd	2022	2023	6077	2022	2023	506	2023	2023	416
NumFund	2.29	1	6077	2.84	1	506	6.76	4.00	416
IsMale	0.91	1	5054	0.91	1	428	0.88	1	373
IsMaster	0.60	1	3010	0.51	1	209	0.56	1	257
IsMBA	0.48	0	3010	0.34	0	209	0.43	0	257
IsPhD	0.05	0	3010	0.02	0	209	0.04	0	257
IsIvy	0.23	0	3211	0.14	0	233	0.21	0	275

Table A7: Performance of AETF and AMF managers, 2016-2023

This table reports summary statistics of the performance of AETFs and AMFs managers. Performance of portfolio manager is measure by averaging the performance of funds managed by the manager. Panel A reports the average manager performance based on simple-weighted fund returns, Panel B based on TNA-weighted average fund returns. The unit of observation is manager-month level.

Panel A: Simple weighted performance of portfolio managers

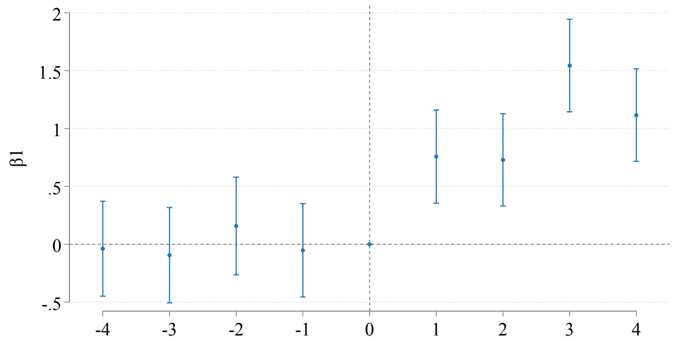
	(1) Manager of only AMFs			(2) Manager of only AETFs			(3) Manager of both AETFs & AMFs		
	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
Excess Return (%)	0.73	4.7	1	0.51	5.2	0.82	0.57	5.2	0.9
CAPM Alpha (%)	-0.25	2.2	-0.18	-0.2	2.3	-0.11	-0.19	1.9	-0.11
FF3 Alpha (%)	-0.28	1.9	-0.21	-0.21	2.1	-0.13	-0.22	1.5	-0.19
FF4 Alpha (%)	-0.32	2.1	-0.2	-0.23	2.3	-0.16	-0.25	1.7	-0.19
FF5 Alpha (%)	-0.18	2.2	-0.16	-0.16	2.3	-0.13	-0.089	1.8	-0.1

Panel B: TNA-weighted performance of portfolio managers

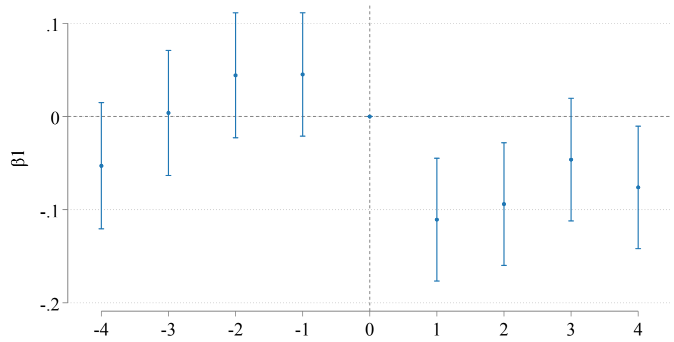
	(1) Manager of only AMFs			(2) Manager of only AETFs			(3) Manager of both AETFs & AMFs		
	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
Excess Return (%)	0.74	4.7	1	0.51	5.2	0.83	0.61	5.2	1
CAPM Alpha (%)	-0.25	2.2	-0.17	-0.19	2.3	-0.11	-0.14	2	-0.078
FF3 Alpha (%)	-0.28	1.9	-0.2	-0.21	2.2	-0.13	-0.19	1.6	-0.16
FF4 Alpha (%)	-0.32	2.1	-0.19	-0.22	2.4	-0.15	-0.2	1.8	-0.12
FF5 Alpha (%)	-0.18	2.2	-0.15	-0.17	2.4	-0.14	-0.081	1.9	-0.093
Number of managers		6077			506			416	

Figure A1: The level of covered shorts around portfolio manager turnovers: DID dummies plots

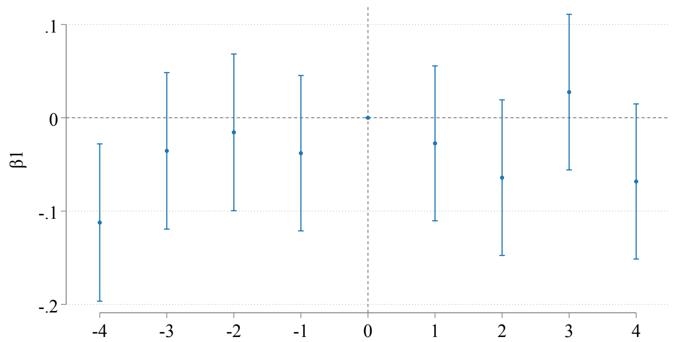
This graph plots the dynamics of the difference-in-difference coefficient, β_{DID}, as shown in Table 7 for different time periods around the turnover event. It compares funds that have experienced manager turnover with those that have not. Portfolio managers are classified as good or bad based on the median of the three-month accumulated raw fund return, weighted by the total net assets (TNA) of the funds they managed prior to the turnover event. The figure illustrates the levels of covered shorts within a ±4 month window surrounding the manager turnover for managers joining (Panels A and B) and managers leaving (Panels C and D). Cases of manager turnover due to fund terminations or inceptions are excluded from this analysis.



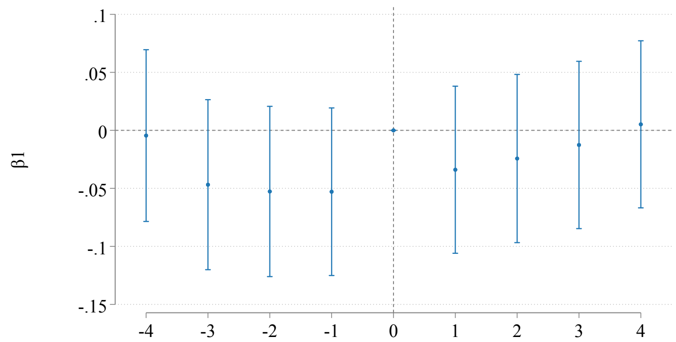
(a) Panel A: Covered shorts of funds joined by bad manager



(b) Panel B: Covered shorts of funds joined by good/new manager



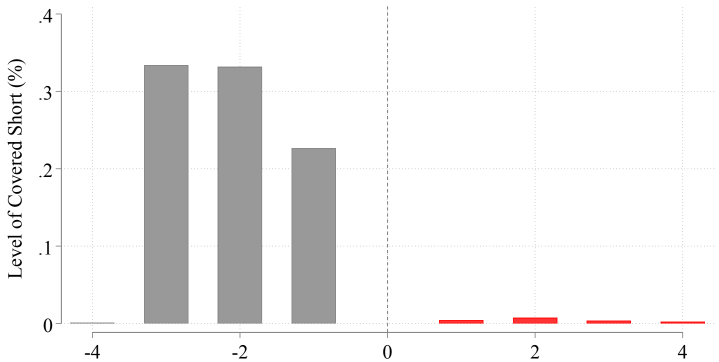
(c) Panel C: Covered shorts of funds left by bad manager



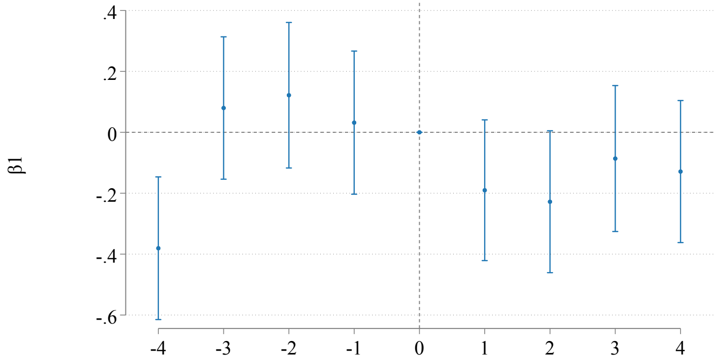
(d) Panel D: Covered shorts of funds left by good manager

Figure A2: The level of covered shorts around portfolio manager turnovers when a good/new manager joins

This graph plots the average levels of covered shorts and the DID estimates around manager turnovers when a good manager replaces a leaving manager. Portfolio managers are categorized as ”good” or ”bad” based on the median of the three-month accumulated average raw fund return, weighted by the total net assets (TNA) managed by the manager prior to the turnover event. Panel A illustrates the average levels of covered shorts surrounding portfolio manager turnover events, conditional on a bad manager replaced by a good or new manager. These panels depict covered shorts within a ±4 month window around the turnover event. Panels B presents the difference-in-difference coefficient, β_{DID}, as shown in Table 7, for different time periods around the turnover event.



(a) Panel A: Covered shorts of funds joined by good/new manager conditional on bad manager leaving



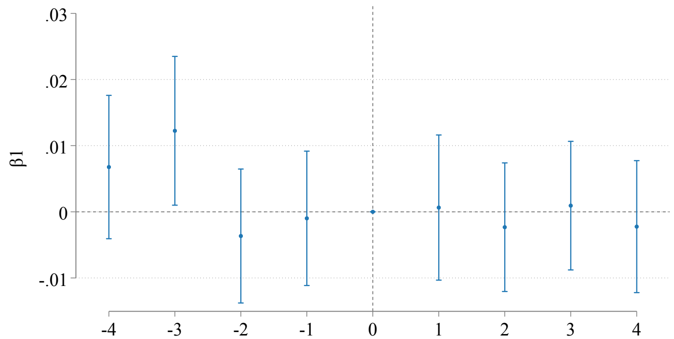
(b) Panel B: Covered shorts of funds joined by good/new manager conditional on bad manager leaving

Figure A3: The level of uncovered shorts around portfolio manager turnovers

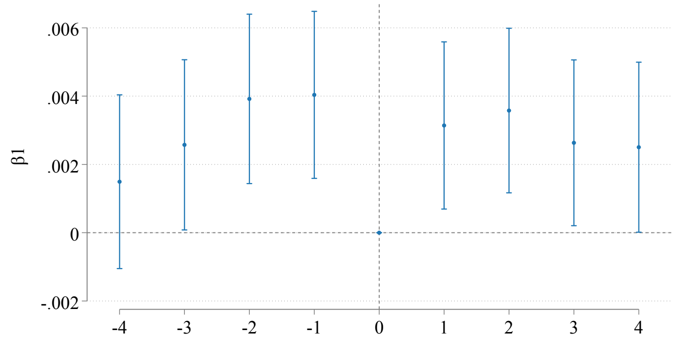
This graph replicates Figure A1 and plots the dynamic of difference-in-difference coefficient β_{DID} of the following equation:

$$
\begin{aligned}
UncoveredShort_{i,t} =& \beta_{DID}\mathbb{1}(Post_t) \times \mathbb{1}(Turnover_i) + \beta_2 ln(TNA_{i,t-1}) + \beta_3 ln(Age_{i,t-1}) \\
&+ \beta_4 ExcessRet_{i,t-1} + \beta_5 Flow_{i,t-1} + \lambda_t + \gamma_i + \epsilon_{i,t+n}
\end{aligned}
$$

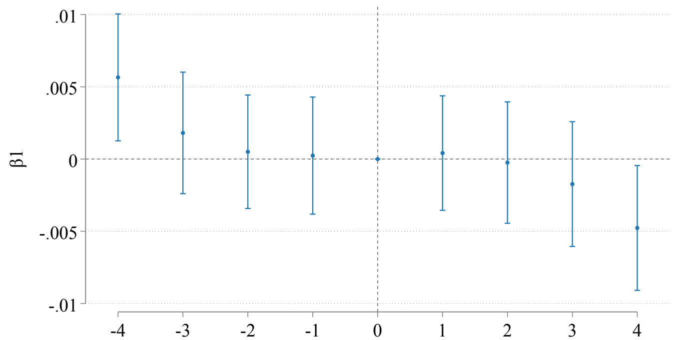
Funds with manager turnover are compared to those that have never experienced such turnovers. The control variables include the log of the fund's total net assets (*ln(TNA)*), the log of fund age (*ln(Age)*), fund returns in escess of the risk-free rate (*ExcessRet*), and fund flow as a percentage of TNA (*Flow*). We include fund and month fixed effects and compute heteroskedasticity-robust t-statistics clustered by fund and month. Portfolio managers are classified as good or bad based on the median of the three-month accumulated raw fund return, weighted by the total net assets (TNA) managed by the manager prior to the turnover event. The figure illustrates the levels of uncovered shorts within a ±4 month window surrounding the manager turnover for managers joining (Panels A and B) and managers leaving (Panels C and D). Cases of manager turnover due to fund terminations or inceptions are excluded from this analysis.



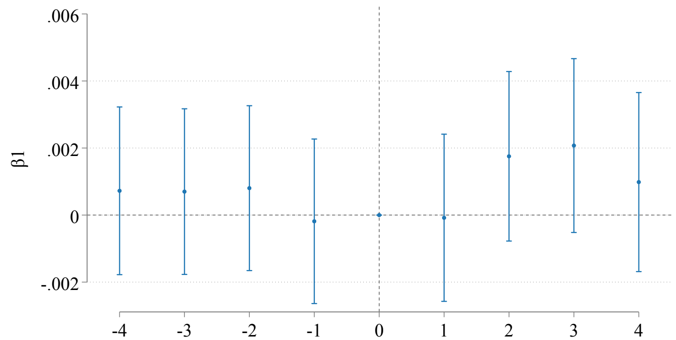
(a) Panel A: Uncovered shorts of funds joined by bad manager



(b) Panel B: Uncovered shorts of funds joined by good/new manager



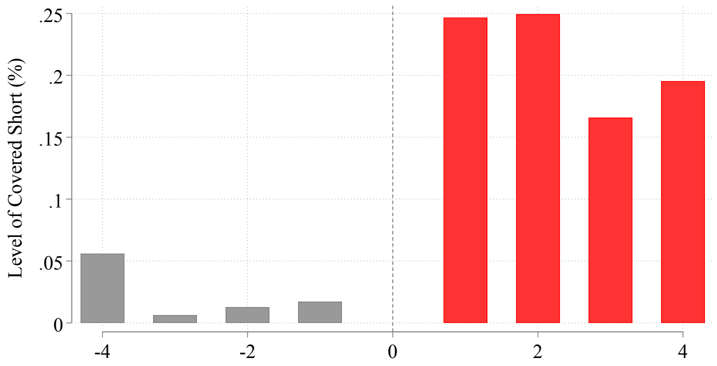
(c) Panel C: Uncovered shorts of funds left by bad manager



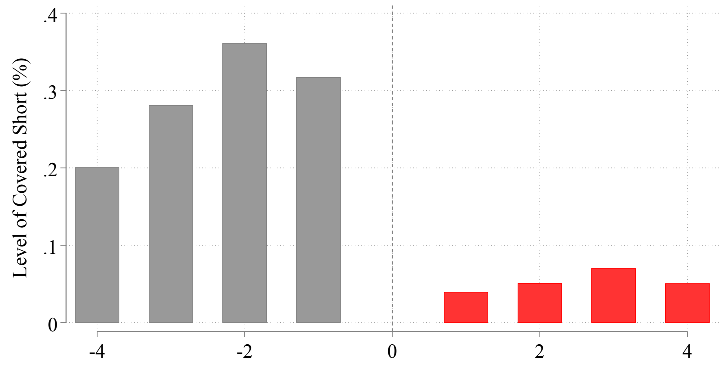
(d) Panel D: Uncovered shorts of funds left by good manager

Figure A4: The level of covered shorts around portfolio manager turnovers using 6-months window to measure manager's performance

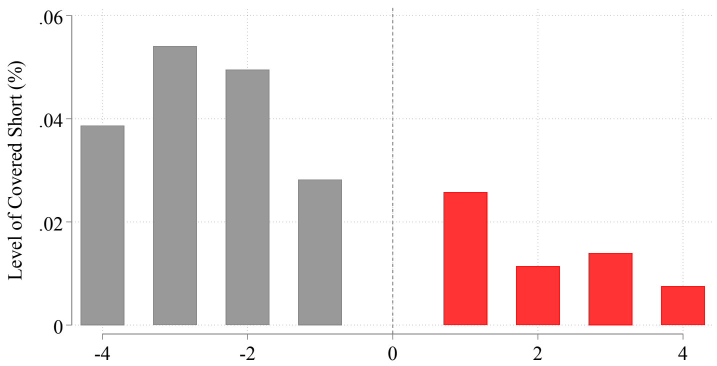
This graph replicates Figure 5 and plots the average level of covered shorts around portfolio manager turnovers. Portfolio managers are classified as good or bad based on the median of the 6-month accumulated raw fund return, weighted by the total net assets (TNA) managed by the manager prior to the turnover event. The figure displays covered shorts within a ±4 month window around the manager turnover for bad (Panel A) and good (Panel B) managers joining, as well as bad (Panel C) and good (Panel D) managers leaving. Cases of manager turnover due to fund terminations or fund inceptions are excluded from this analysis.



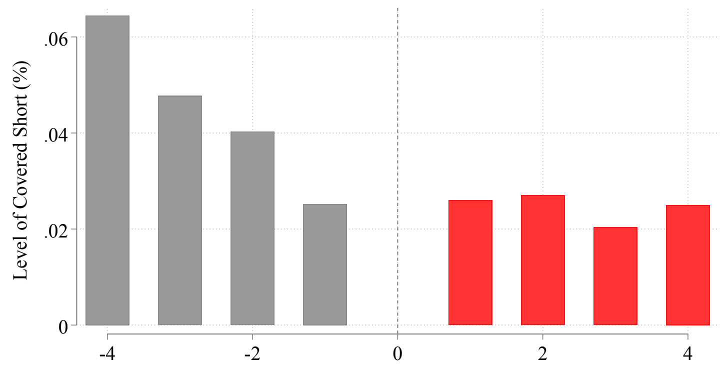
(a) Panel A: Covered shorts of funds joined by the bad manager using 6-month cutoff



(b) Panel B: Covered shorts of funds joined by the good/new manager using 6-month cutoff



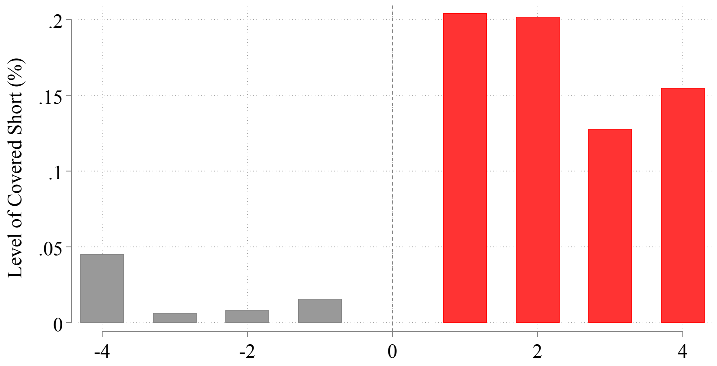
(c) Panel C: Covered shorts of funds left by the bad manager using 6-month cutoff



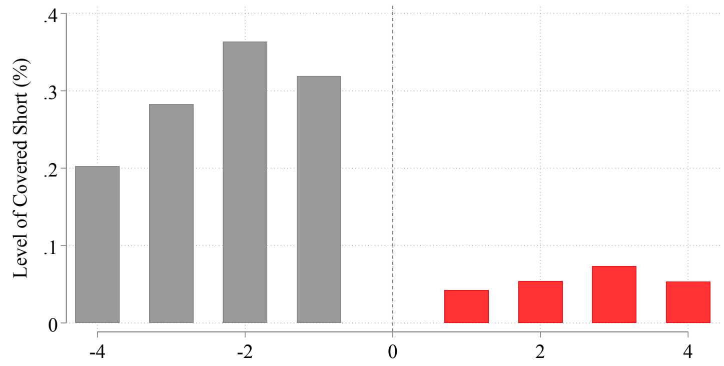
(d) Panel D: Covered shorts of funds left by the good/new manager using 6-month cutoff

Figure A5: The level of covered shorts around portfolio manager turnovers using 12-months window to measure manager's performance

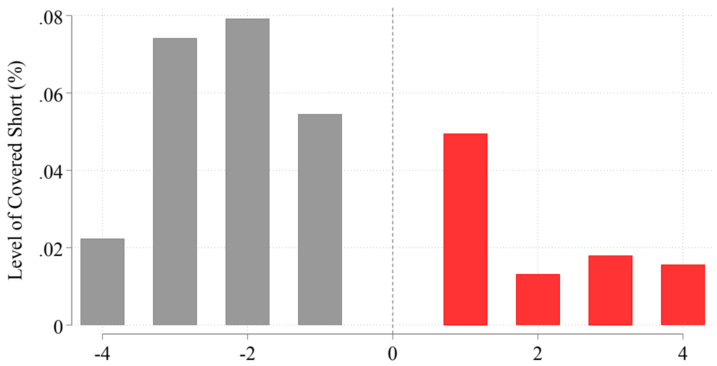
This graph replicates Figure 5 and plots the average level of covered shorts around portfolio manager turnovers. Portfolio managers are classified as good or bad based on the median of the 12-month accumulated raw fund return, weighted by the total net assets (TNA) managed by the manager prior to the turnover event. The figure displays covered shorts within a ±4 month window around the manager turnover for bad (Panel A) and good (Panel B) managers joining, as well as bad (Panel C) and good (Panel D) managers leaving. Cases of manager turnover due to fund terminations or fund inceptions are excluded from this analysis.



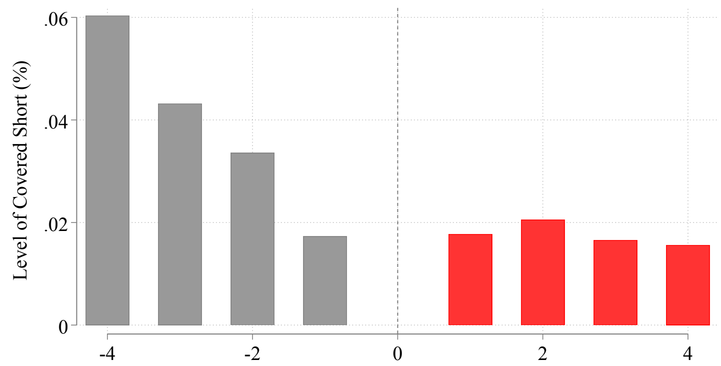
(a) Panel A: Covered shorts of funds joined by the bad manager using 12-month cutoff



(b) Panel B: Covered shorts of funds joined by the good/new manager using 12-month cutoff



(c) Panel C: Covered shorts of funds left by the bad manager using 12-month cutoff



(d) Panel D: Covered shorts of funds left by the good/new manager using 12-month cutoff

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