Active ETFs from Mutual Funds: Competing for Investor Flows

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Abstract

We examine active ETFs, focusing on the recent innovation of less transparent active ETFs, to understand competition in the delegated asset market, particularly between ETFs and mutual funds. We find no cannibalization of mutual fund investor flows from newly cloned ETFs, rather the better reputation of the cloned mutual funds gives the new ETF advantages in attracting flows over their peers, even without better performance. We provide further evidence that investment companies introduce cloned ETFs for flow diversification – some of the cloned ETF flows are driven by a clientele difference from their mutual fund counterparts.

Keywords: Active ETFs, non-transparent ETFs, Fund Flows, Competition, Clientele

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1 Introduction

The consistently high competition for investor flows in the delegated investment management market has led to a number of product innovations such as the introduction of exchange-traded funds (ETFs) in the early 1990s. Moreover, in selecting products for their clients, financial advisers have increasingly preferred ETFs over mutual funds (e.g., Andrus and Cummings (2022). So much so that the ETF market has gained considerable strength on the mutual fund market. According to the 2023 Investment Company Institute Factbook, between 2010 and 2022 ETF assets under management (AUM) grew 653% as compared to the growth in mutual fund AUM of 187%. Further there exist striking differences between the introductions and exits of ETFs and mutual funds. For example, in the U.S. in 2022, 414 new ETFs were introduced while 120 exited. In contrast, 278 new mutual funds were introduced, but 335 mutual funds exited (through mergers or liquidations). Not surprisingly, investment management companies have been offering more ETF products instead of, or alongside, their mutual fund products.

The dominant major competition for mutual funds from the ETF market has been through index funds. However, more recent innovations in the regulatory environment has resulted in the introduction of additional actively managed ETFs.[1] This regulatory innovation from the SEC (as of September 2019) permits new models of actively managed ETFs to hide some of their trading by exempting the managers from having to fully disclose their portfolios daily. Instead, the ETF sponsors can either disclose holdings for a proxy portfolio or disclose their full portfolio holdings only to Authorized Participants (APs). With this accommodation, these new types of ETFs are designed to both hide trading and, at the same time, allow the arbitrage system that is so necessary to the functioning of the ETF market to operate in a way that ensures the ETF market price does not deviate far from its NAV. These new types of actively managed ETFs have been

[1]Easley, Michayluk, O'Hara, and Putniņš (2021) have provided evidence that many of the "passively" managed ETFs are actually actively managed. The difference is that the group of actively-managed ETFs we focus on are actively managing within a portfolio of individual stocks.

commonly referred to as active semi-transparent ETFs or active non-transparent ETFs. Although small differences exist between these two active ETF models, for simplicity, we refer to them collectively as active non-transparent ETFs (ANT ETFs) for the remainder of this paper.

If a mutual fund introduces an active ETF, they have several choices. First, they can simply convert an existing mutual fund into an ETF. Alternatively, they can offer a new ETF in which they clone one of their existing mutual funds, keeping the mutual fund open as well. In addition, they can offer a new ETF with an investment strategy that is different from their current mutual fund strategies. Finally, they can establish the ETF as an additional share class for their mutual fund. [2] These approaches to the launch of new ETFs have varied across mutual fund management companies. For example, Dimensional Fund Advisors have converted some of their mutual funds into active transparent ETFs. Doing so ensures no direct competition between their ETF and a similar mutual fund. In contrast, other mutual fund management companies have chosen to offer ETFs cloned from their mutual funds, which would seem to directly compete with their existing funds. For example, in March 2020, American Century launched the initial ANT ETFs to the market. Their Focused Dynamic Growth ETF and Focused Large Cap Value ETF are both clones of their counterpart mutual funds under the same names. Following these ANT ETF launches, several large fund management companies (Fidelity, T. Rowe Price, and Natixis) introduced their own ANT ETFs, many of which were clones of an active mutual fund they already offered in the marketplace.

Presumably, by not simply converting a mutual fund, the investment management companies are issuing the cloned ETFs in order to offer those strategies in the ETF market while still serving their mutual fund customers. The question then arises as to the impact of the similar or cloned active ETF on the investment management company's existing mutual fund. We hypothesize three possibilities. First, the mutual fund manage-

[2] For many years Vanguard held a patent on this share class approach. With the expiration of their patent mid-2023, multiple fund families have filed with the SEC for permission to launch ETFs as a share class of their existing mutual funds, however, as of December 2024, none have been approved.

ment company may forecast that the mutual fund demand will eventually wind down, in which case we expect the new ETF to cannibalize the existing mutual fund's inflows. If so, we should observe investor outflows from the mutual fund after the introduction of the ETF. Alternatively, the new ETF could attract investment from a different clientele, which could result in two possibilities: either no relation in flows with the existing mutual fund or a positive correlation in flows.

We employ a sample of cloned ETFs (both ANT ETFs and transparent active ETFs) to test these hypotheses. We identify cloned ETFs as funds managed by the same portfolio manager with a high portfolio overlap and similar or identical fund names. This identification results in 48 cloned active ETFs for which we have a total of 40 cloned active ETFs in our sample with the requisite data. Our hypothesis tests show no significant decrease in monthly fund flows to the cloned mutual fund after the introduction of the cloned active ETF. Thus, there is no cannibalization. In fact, we find the opposite. Compared to other similar actively-managed mutual funds, the introduction of a cloned active ETF increases monthly net flows for the counterpart active mutual fund by about 6%.

This evidence of no overall cannibalization by the cloned ETFs is consistent with the hypothesis that the investment company achieves flow diversification through the addition of a new distribution channel. As pointed out by (Wahal and Wang, 2022), flow diversification from different clienteles can benefit investment management companies even if the flows are not for the same fund but are for other portfolios with the same holdings. If the investment management company chooses to offer a cloned ETF due to a flow diversification motivation, we would expect additional empirical observations. First, in order for the mutual fund to attact additional flows, the mutual fund should have a reputation (most likely because of better performance, the size of the mutual fund, and the size of the fund family). Second, the mutual fund managers should be trading in a deep market where the flow diversification would pay off which suggests larger mutual funds;and third, some clientele differences should exist between the cloned ETF and its mutual fund. We test these empirical implications to better understand the motivations behind and outcomes of cloned ETFs.

To start, we characterize which type of mutual funds are selected by a fund family to be cloned. Since the decision occurs at the fund family level, we compare fund characteristics for the cloned mutual funds to other funds in the same family. We find that older and larger funds are significantly more likely to be cloned. We also find that the funds selected to be cloned have higher expense ratios, which may be indicative of more unique or active strategies being chosen to be cloned. Using CAPM, the Fama-French 3 Factor Model, and excess returns over the risk-free rate as alternative measures of performance, we also find that funds that had better performance in the recent 5 years compared to other funds in the same fund family were significantly more likely to be selected for cloning. These results suggest that fund families choose their better performing, older, and larger funds to clone, consistent with our hypothesis that reputation is an important factor in the choice of which mutual fund to clone.

Next, we test whether being cloned from these more reputable mutual funds gives these new active ETFs an advantage in attracting flows over their peers. To do this, we compare the fund flows of cloned active ETFs to non-cloned active ETFs, controlling for fund characteristics such as size, age, past performance, year and investment style fixed effects. We find that cloned active ETFs have about 3% more monthly fund flows than similar active ETFs that do not have a mutual fund counterpart. This increased flow effect is even stronger for the subset of cloned ANT ETFs, resulting in about a 10% increase in monthly fund flows. These findings support our hypothesis that the prior reputation of the cloned mutual fund gives their counterpart ETFs advantages over other new active ETFs in capturing investor flows in the active ETF market. We also find that the increased flow effect is strongest in the months following the ETF launch, but then decreases over time. This result is consistent with the fact that information on past reputation is likely most important when an active ETF is just launched and lacks historical data and becomes less important to investors over time as they learn about the ETF and its managers. Additionally, we find similar results when we examine ETFs that were converted from mutual funds, consistent with the hypothesis that historical reputation and data helps give these ETFs an advantage over similar peer active ETFs.

To better understand what factors drive the advantages that cloned active ETFs have in attracting flows, we analyze the sources of the flows. First, we characterize the clientele in the ANT and transparent active ETF markets. We have shown that the introduction of a cloned ANT ETF results in larger monthly flows than does the introduction of a transparent active ETF. (Most ANT ETFs are clones while the majority of transparent active ETFs are not). If we expect that the advantage that cloned ETFs have is based on the reputation of their counterpart mutual fund, we may also expect a difference in the clientele that they attract. Retail investors are likely to be more sensitive to a new active ETF having a previous reputation. In contrast, institutional investors may be less sensitive to a lack of information on past performance as they have access to other sources of information such as connections to the portfolio manager. Thus, we expect higher retail investor participation in the ANT ETF market compared to the transparent active ETF market. We use institutional holdings data to characterize these two different markets and construct a measure of the market share owned by institutions by aggregating the market value of shares in the ETF held by institutions and dividing it by the total market value of available shares. Consistent with our hypothesis, we find that the transparent active ETF market has significantly more institutional ownership than the ANT ETF market, suggesting that the ANT ETF market clientele is more heavily composed of retail investors.

A further hypothesis regarding the introduction of a cloned ETF is whether the lack of cannibalization we observe is due in part to differences in clientele attracted to the ETF versus the original mutual fund. Since most existing defined contribution platforms are based on the mutual fund model, there exist some limitations to offering ETFs on retirement platforms. Thus, we hypothesize that mutual funds with more retirement accounts would be more likely to be cloned rather than converted. We test this hypothesis through use of BrightScope data and find that funds with a higher percentage of retirement flows are more likely to be cloned than converted. We also confirm that only funds with no retirement flows are ever converted to ETFs. Overall the evidence suggests that some of the additional flows to newly cloned ETFs are driven by differences in clienteles.

Finally, we examine the alternative, but not mutually exclusive mechanism to flow diversification, the "smart money" effect (Gruber, 1996; Zheng, 1999). The question is whether the advantage we document for cloned active ETFs in attracting flows is due to the fact that ETF investors have the ability to select better-performing active ETFs, which would suggest that the cloned active ETFs are superior and managed by more skilled portfolio managers. Specifically, we test whether the cloned active ETFs have better performance by constructing three measures of performance using CAPM, the Fama-French 3 Factor Model, and excess returns over the risk-free rate. Overall, we do not find that the cloned active ETFs have consistently and significantly better performance than similar active ETFs. Thus, we find no evidence that these flows are simply performance-driven. [3]

Our paper contributes to several areas. First, we contribute to the research on mutual fund competition, much of which focuses on the effects of competition on management fees. The evidence suggests that fees are negatively correlated with fund size and market share and that price and product differentiation drive funds' market shares (Coates and Hubbard (2007), Khorana and Servaes (1999)and Khorana and Servaes (2012)). Several papers examine the effects of low-cost index funds on the active mutual fund market and conclude that the increasing presence of index funds decreases fees and increases active shares for actively-managed mutual funds (Cremers, Ferreira, Matos, and Starks (2016)), decreases performance and management team size (Densmore (2022)), and has a selection effect resulting in higher (lower) prices for funds sold through brokers (directly) (Sun (2014)). Dannhauser and Spilker (2023) analyzes the positive impact of passive mutual funds on active mutual funds within the fund family, although the effect of ETFs is insignificant. Our approach differs by identifying competition among active funds, both within the active ETF market as well as the effects of competition from new active ETFs on

[3] We acknowledge a caveat to these results: We do not have a long sample period, and consequently, we may lack sufficient historical data to capture significant performance differences.

their active mutual fund counterparts. Kostovetsky and Warner (2020) argue and present evidence that true innovation in the mutual fund industry develops from the smaller fund families rather than the larger fund families. We add to this finding by showing that innovation in terms of new wrappers for an existing product appears to come from the larger funds of larger fund families. Wahal and Wang (2011) use a measure of portfolio overlap and entry of new funds to demonstrate that competition in the active mutual fund market invokes a price and quantity competition causing a reduction in management fees, flows, alphas, and increase in attrition rates. We employ a unique setting in which fund families introduce seemingly identical strategies under different wrappers that compete with their own existing active mutual funds. This unique strategy provides new perspectives on the competition for flows in the active asset management market.

Our paper also contributes to the growing literature explaining the rise of the ETF market share. Similar to mutual funds, ETF flows are sensitive to past returns (Clifford, Fulkerson, and Jordan (2014) and Dannhauser and Pontiff (2019)). Kostovetsky and Warner (2021) find that flows are sensitive to choice of benchmark index when a significant brand-name effect exists. Related, Ben-David, Franzoni, Kim, and Moussawi (2022) show that some passive fund managers compete for investors' attention by catering to investors' extrapolative beliefs with trending themes. Moussawi, Shen, and Velthuis (2022) attribute tax efficiency to be a primary driver of the outflows from active mutual funds to ETFs in recent years. The previous work has primarily focused on studying the passive ETF market. In contrast, we study the development of the active ETF market and analyze how mutual fund families acquire increased market share in this newly growing market. Luo and Schumacher (2022) show that active fund managers that manage both mutual funds and ETFs have institutional outflows from their active mutual funds and contemporaneous inflows in their ETFs, suggesting that fund managers may be able to exploit manager-client loyalty to retain outflows from mutual funds to their active ETFs. In contrast, our study suggests a channel in which fund families are able to attract new flows without even creating a new strategy.

2 Hypotheses

2.1 Background - Exchange-Traded Funds

According to the 2023 Investment Company Institute Factbook, at the end of 2022, across the world there were 137,892 regulated open-end funds (mutual funds, ETFs, institutional funds) with $60.1 trillion in assets under management. The U.S. market accounted for almost half of these assets with $28.6 trillion, divided between $22.1 trillion in mutual fund assets and $6.5 trillion in ETF assets. Although exchange-traded funds (ETFs) operate similarly to mutual funds, a major difference is that the ETFs, being traded on an exchange, are traded throughout the day. Since the introduction of the first index ETF in 1993, the SEC has required index ETFs to disclose their portfolio holdings daily. The purpose of this requirement is to enable efficient arbitrage so that the ETF shares trade close to their net asset value (NAV). This disclosure requirement has been a deterrent against investment management companies introducing their active strategies into ETFs due to concerns about revealing their strategies and potentially allowing other market participants to front-run their trades. This deterrent has apparently had strong effects. Although the first index ETF began trading in 1993, actively managed strategies were not allowed at that time. The first transparent actively managed ETF started trading in 2008, and the actively managed ETFs still represent only a small proportion of ETFs. The SEC changed their rules on transparency to allow for some non-transparency in September 2019, and the first ETFs of this type began to trade in early 2020.

A proportion of the active ETFs apparently follow the same strategy as a pre-existing mutual fund under the same fund family. These cloned ETFs not only have very similar portfolios to the mutual fund, but they also have the same or a large overlap in portfolio managers. Some of the ETFs are marketed to stress that they follow the same strategy and are essentially clones of a pre-existing well-known fund of the fund family. This phenomenon is even more prevalent for recently launched ANT ETFs, as 20 out of the 32 ANT ETFs in our sample share the same name as their counterpart mutual fund. Unlike the situation in which a fund family converts a mutual fund to an ETF, the original mutual fund is still active when the fund families clone them for the new ETF.

2.2 Cannibalization of Cloned Mutual Fund Flows

We first address the question of whether and how a cloned ETF affects its mutual fund counterpart. Since under a cloned strategy the original mutual fund still operates, the new cloned ETF becomes a competitor to the original mutual fund, which suggests potential cannibalization of flows from the original mutual fund. Because ETFs can be more accessible to investors and have lower expense ratios, the investors may choose to shift their money from the original mutual fund to the cloned ETF that follows the same strategy. Similarly, the cloned active ETF may absorb new flows that would have otherwise gone to the original mutual fund if the cloned active ETF did not exist. This hypothesis implies a significant decrease in flows to the original mutual fund after the introduction of the cloned ETF.

2.3 Cloned Active ETFs vs. non-Cloned Active ETFs

We next address the question of why fund families choose to clone a pre-existing mutual fund rather than converting the fund to an ETF structure or creating a differentiated strategy (given that the family has decided to launch an ETF). As we have discussed earlier, we hypothesize that the launching of the cloned ETF may be designed to reach a new distribution channel and thus provide the investment manager with new flows as well as flow diversification. Moreover, given the cost of marketing mutual funds as found by Roussanov, Ruan, and Wei (2021), having a cloned ETF would share these marketing costs across multiple products. The goal of reaching a new distribution channel would predict a lack of cannibalization of the mutual fund flows and greater flows to the cloned ETF.

If diversification of flows across distribution channels is the goal, then we hypothesize that the mutual funds selected to be cloned should have certain characteristics. In particular, we expect to observe that these mutual funds invest primarily in highly liquid markets and have above average reputations, that is, they should be larger, older and better performing funds, offered by larger fund families.

A related hypothesis is that the cloned active ETFs should attract more flows than similar non-cloned active ETFs using the reputation or past performance of the original mutual fund that they are cloning. The past reputation of a fund should play a more significant role for actively managed ETFs as these funds provide full information on their historical performance (Chevalier and Ellison, 1997; Sirri and Tufano, 1998). This would be consistent with Ben-David, Franzoni, Kim, and Moussawi (2022), who find evidence that specialized passive ETFs that are more complex than plain-vanilla, index ETFs have flows more sensitive to their past performance rather than their expense ratios. Thus, we expect that cloned active ETFs receive higher net flows than similar non-cloned active ETFs.

2.4 Corollary Hypothesis: Source of Flows

If the introduction of cloned active ETFs results in attracting more flows than those to non-cloned active ETFs as we predict, then to support our hypothesis, we examine the source of these flows. We propose two possible explanations: clientele differences and a "smart money effect" as described by Gruber (1996) and Zheng (1999) for mutual funds.

2.4.1 Clientele

The first hypothesis posits that cloned ETFs attract a clientele distinct from that of mutual funds. This distinction arises from the segmented nature of the market as well as the recent popularity of retail trading platforms such as Robinhood, e-Trade, and Vanguard. These platforms have made ETFs accessible to a broader range of investors. In addition, although defined contribution retirement accounts account for a large percentage of mutual fund assets (e.g., Sialm, Starks, and Zhang (2015), they contain relatively little in ETFs. There exist several reasons for the lack of ETFs in defined contribution accounts.

Notably, their tax efficiency does not provide an advantage for tax-deferred retirement accounts. Moreover, existing retirement account platforms have two aspects that are built upon the mutual fund model rather than the ETF model. First, the platforms often assess retirement plan fees through particular mutual fund share classes and ETFs do not offer this capability. Second, most defined contribution platforms do not allow for intraday trading which eliminates another potential benefit of ETFs over mutual funds.[4]. Given these aspects of the ETF model versus the mutual fund model, we hypothesize that active ETFs tend to appeal to a different investor base than active mutual funds, and as a result, cloned active ETFs generate new inflows for the investment manager.

2.4.2 Performance of Cloned Active ETFs

An alternate, but not mutually exclusive, explanation for higher flows can be due to the “smart money" effect (Gruber, 1996; Zheng, 1999), deriving from the ETFs’ return performance. It is possible that the cloned active ETFs perform better on average than similar non-cloned active ETFs after being launched, and investors have abilities to select better ETFs. Perhaps cloned active ETFs tend to have more skilled managers and/or better strategies than non-cloned active ETFs. In other words, the higher flows could simply be driven by better performance.

3 Data

3.1 Data Sources

We focus on U.S. domestic equity mutual funds and ETFs because the regulatory innovation applies only to domestic equity funds, i.e., the SEC ruling restricts the active semi-transparent ETFs or active non-transparent ETFs to those holding domestic equities.

[4]In addition, many plan sponsors do not want their participants to engage in intraday trading. See, for example, https://www.plansponsor.com/in-depth/plan-sponsors-still-arent-embracing-etfs/ or https://www.cnbc.com/2024/10/17/why-401k-plans-are-the-final-frontier-for-exchange-traded-funds.html

We obtain the data for mutual funds and ETFs from the Center for Research in Security Prices (CRSP) Survivor-Bias-Free Mutual Fund Database for the sample period between 2000 and 2021. Daily trading data for ETFs, including returns, are obtained from the CRSP Securities Database. We also gather data on mutual funds and ETFs from Morningstar Direct, including portfolio manager names. For ETF shares outstanding, we construct our data set using both daily data from ETF Global as well as monthly data from CRSP. We use the end-of-month data in ETF Global when available and use data from CRSP for any ETFs not available in ETF Global.[5] Our aggregate sample contains 12,745 U.S. active equity mutual funds and 472 U.S. active equity ETFs.

We measure institutional ownership in the ETFs (and some mutual funds) through quarterly 13-F filing data from SEC Analytics Suite by WRDS. These filings provide us with holdings of institutional managers that exercise investment discretion over $100 million or more. Using this data, we calculate institutional ownership of ETFs by aggregating over all of the institutional managers' holding reports. The 13-F data also provides information on some mutual fund ownership. Although institutions are not required to report holdings of mutual funds in their 13-F filings, we find that many institutional managers do so. In our analysis, we will assume that if the institutional manager reports at least one mutual fund (active or passive) in their holdings, then they have not filtered out any of the mutual funds in their holdings. We find that around 25% of institutional managers that report an ETF also report at least one mutual fund holding in our sample from 2013 to 2021.

We obtain data on 401(k) investments from Brightscope for the 2016 to 2021 sample period, which provides the annual aggregate dollar investment in each fund for each of the plans. Using this data we construct an annual measure of the extent to which each fund's flows derive from retirement accounts. That is, we measure the percentage of a fund's AUM attributable to the 401(k) accounts. We find that 28% of the active mutual funds in our sample appear in at least one 401(k) plan with an average of 7% of their

[5]We primarily use ETF Global for this data because at times CRSP does not update the shares outstanding immediately when new shares are created/redeemed for the ETFs.

AUM derived from 401(k) plans.

3.2 Identification of Cloned Funds

We identify the sample of mutual funds and their cloned ETF pairs in two ways. First, we construct a list of ANT ETFs using *ETF Database* (*ETFdb*). To check the accuracy of *ETFdb*, we further manually check through the ETF prospectus. Most of these ETFs share the same name and managers as a pre-existing active mutual fund. Thus, we manually match them to the corresponding mutual fund strategy that it states it is following using fund name and portfolio manager name. We identify 20 matched ANT ETFs and end up with 17 pairs after merging it with the other data sets. We refer to this matched sample as cloned ANT ETFs.

We also identify a sample of active transparent ETF clones. We do this by matching active transparent ETFs to active mutual funds offered by the same fund family. We filter these matches using several criteria: portfolio manager, strategy classification, and portfolio overlap. For portfolio managers, we require that the mutual fund and ETF must share at least 2 or more of the same portfolio managers. Many of these cloned ETFs consist of the same managers with the addition of a manager that specializes in ETFs. We also require that the funds share the same classification according to their Lipper objective and Lipper class as labeled in the CRSP database. Finally, we compare the first monthly portfolio of the ETF to that of the mutual fund portfolio for the same month and construct several measures of portfolio overlap. We first check whether the top 10 holdings of the ETF overlap with that of the mutual fund. We then measure the number of portfolio positions in the ETF that are not in the mutual fund and consider the portfolio weights of these missing assets as well as the percentage by number of assets. We filter the matching candidates by requiring that more than 65% of assets and 75% of the portfolio weights match. We then ensure that the names of the funds are very similar or identical and that the matches make sense. We identify 28 matched active transparent ETFs. After merging these with our other data sets, we are left with 23 unique matches. We refer to this matched sample as the cloned transparent ETFs.

Table I provides evidence on the matching process as it reports the summary statistics for the matching quality of the pairs of transparent clones we find. The measures reported are constructed by comparing the quarterly portfolio holdings of the active mutual fund and with its matched active ETF for the same quarter. We construct several measures to capture how much the portfolios overlap. *ETF Num Not Matched* is the number of assets in the holdings of the ETF that were not found in the mutual fund. *ETF Weight Not Matched* is the weight of the portfolio that the assets accounted for in the ETF that were not found in the mutual fund. *ETF Percent Not Matched* is the percentage of assets in the ETF's portfolio holdings that were not found in the mutual fund.

In total, we have a sample of 40 cloned active ETFs. We perform most of our analyses on both our total sample of cloned active ETFs as well as our sub-sample of cloned ANT ETFs.

3.3 Identifying Converted Funds

Instead of cloning a mutual fund, some fund families have chosen to convert their mutual fund into an ETF. When this occurs, the new ETF retains all the assets under management of the old mutual fund and is given a new ticker. We identify these ETFs by first identifying funds that have the same CRSP identifier but different names, CUSIP, and/or ticker[6]. We then manually check which funds in this subset of filtered funds are converted by confirming the names, strategy, and managers. We identify 70 converted funds from 2019 to March 2024, 37 of which are active ETFs. Since the CRSP fund information is updated quarterly, we look up each converted fund to get their exact conversion date.

[6]Mutual funds that are converted to ETFs are marked as ETFs in the CRSP mutual fund dataset and the CRSP identifier is not changed. This means, mutual fund flows and fund information show up as an ETF in the CRSP dataset. We update the data to correct for this error. Similarly, the date of origination for these converted ETFs in the dataset correspond to the date of origination of the mutual fund, unlike when ETFs are cloned.

3.4 Identifying Funds with History

In identifying cloned active ETFs, we first consider the existence of a longer past performance and/or reputation that the twin mutual fund provides. The cloned active ETFs are easily matched towards their twin mutual funds as they typically share the same name and portfolio managers. However, we are only able to identify 40 pairs of funds that have a high portfolio overlap. We note that if past history or reputation is important in the active ETF industry, active ETFs that have an active mutual fund that have significant overlap in portfolio managers and are part of the same fund family may have a similar advantage as the cloned active ETFs. In these cases, the active ETF may not be advertised as twins and they don't necessarily share the same name or even have a significant overlap in portfolio holdings. However, the portfolio managers are significantly overlapping with an existing active mutual fund. We require that the pairs invest in similar strategy categories identified by Lipper class so that the ETF is a plausible competitor with the matched mutual fund. Thus, for robustness tests with a larger sample, we construct an additional sample that includes active ETF-mutual fund pairs that share a majority of portfolio managers and are offered by the same fund family.

3.5 Summary Statistics

Table II presents summary statistics for the active equity mutual funds in our sample and the subsamples of cloned and non-cloned mutual funds. On average, the cloned active mutual funds appear to trend older, having an average age of 22 years in contrast to 13 years for the mutual funds paired with transparent clones. The fund families that offer a cloned ETF have on average more funds and larger total assets under management.

Table III presents summary statistics for all active equity ETFs in our sample and the sub-samples of cloned ETFs and non-cloned ETFs. The first active ETF in our sample was introduced in 2004 (Touchstone Moderate ETF Fund) and the first ANT ETF was launched in 2020 (American Century Focused Large Cap Value ETF). We note that the cloned active

ETFs, despite being overall younger, are larger in size and have on average much larger net flows both in amount and percentages.

Overall, we find 81 unique fund families in the active ETF market for our sample period. By the end of our sample period in 2022, few fund families had launched ANT ETFs, possibly due in part to the upfront costs of obtaining a license to enable them to create these new products. In our sample, 7 unique fund families offer ANT ETFs: Fidelity, T Rowe Price, Natixis, Invesco, Franklin Templeton and Fred Alger and if we include transparent cloned ETFs, there exist 18 unique fund families that offer either type of cloned ETF.

4 Empirical Results

4.1 Cloning and mutual fund flows

In this section we examine whether the cloned active ETF affects the underlying mutual fund's flows due to the competition that arises from the introduction of an active ETF that offers essentially the same strategy as a pre-existing mutual fund. That is, the new cloned ETF could serve as a substitute for the pre-existing mutual fund, particularly as it could have the advantages of a lower expense ratio and the ability to be traded more frequently. If cannibalization occurs from the competition, we expect to see a significant decrease in net flows for the cloned active mutual fund after the introduction of the cloned active ETF.

To test this hypothesis, we construct a dummy variable, $cloned_{i,t}$, which equals 1 if the cloned active ETF for active mutual fund i exists at time t. That is, for active mutual funds that are never cloned, *cloned* is always 0. For active mutual funds selected by the investment management company to be cloned, *cloned* is equal to 1 on the introduction of the cloned ETF.

For a first test, we conduct a time-series event study, measuring how the monthly net flows to the cloned mutual fund change before and after the introduction of the cloned

ETF. We employ our sample of cloned mutual funds, which we term "All-Clones." We also conduct this analysis for a sub-sample of the cloned mutual funds, the ANT ETFs, which we term "ANT-Clones." As any effect is likely to be relatively short term, we limit the monthly observations for the mutual funds to 6 months before and after the introduction of the cloned ETF. We then regress *cloned* on a mutual fund's monthly net flows, where the monthly flow is normalized by the previous month's total net assets. We control for lagged fund characteristics including past performance, volatility of the past performance, size measured by log of total net assets, age measured by log of 1 + age of fund in years from initiation, and the fund cost measured by the expense ratio. We also control for fund family level characteristics including fund family size measured by the log of the family's total net assets.

We use month-year fixed effects across all specifications to control for any unobserved effects that vary across time but not across funds. We also include fund fixed effects to control for fund characteristics that are constant over time. Thus, we are comparing net flows within a mutual fund before and after the introduction of its cloned ETF. Standard errors are double clustered at the fund and month-date level.

The results are reported in Panel A of Table IV. The evidence suggests that cannibalization does not occur as the coefficient for *cloned* is not significantly negative. This finding suggests that these cloned mutual funds did not lose a significant amount of monthly net flows after the cloned ETF was introduced, contradicting the hypothesis that the cloned ETFs could serve as substitutes for the matching mutual fund. We do acknowledge though that our sample of cloned active mutual funds is small and even smaller when we take the sub-sample of ANT ETFs. Thus, the sample that we work with in this regression is limiting. However, we believe it is still surprising that we fail to find a negative effect on the net flows to these active mutual funds after a cloned ETF is introduced.

Next, we compare how the monthly net flows of the cloned mutual funds change compare to other similar active mutual funds. The structure of this analysis is similar to a stacked generalized difference-in-difference analysis in which the event is the introduction of a cloned ETF. We regress *cloned* on a mutual fund's monthly net flows with fund and month-date fixed effects. We also control for the same lagged fund and fund-family control variables as before. Standard errors are still double clustered at the fund and month-date level.

Table IV Panel B reports the results of these regressions. The coefficients for *cloned* are positive and statistically significant across all specifications. These results suggest that the cloned mutual funds experience more positive monthly net flows than similar active mutual funds after the introduction of the cloned ETF. In fact, the introduction of a cloned ETF appears to increase relative monthly net flows for the counterpart mutual fund by about 6 percent when compared to the net flows of similar active mutual funds at that time.

As discussed, one potential explanation for these results is that the mutual fund management company is seeking diversification in clienteles and thus, diversification in flows. We examine these hypotheses in the following sections.

4.2 Determinants of cloned mutual funds

Our initial hypotheses predict that the choice of which mutual fund to clone into an active ETF depends on certain fund characteristics. Thus, we first examine the characteristics of active mutual funds offered in a fund family before they introduce a cloned active ETF.

We employ data on these characteristics for up to 5 years just prior to the fund being cloned, that is, just before the launch of the cloned active ETF. In addition, we compare the characteristics of the selected mutual fund to other active mutual fund options the fund family offers at that time. In other words, we compare the active mutual fund characteristics while controlling for fund-family $\times$ month-year fixed effects. This approach allows us to examine how the cloned mutual fund compares to other active mutual funds the fund-family could have chosen to be cloned at the approximate time they were making their decision. Our final sample consists of active domestic equity mutual fund observations from the same fund-family up to 5 years before the launch of a clone ETF.

To determine which types of mutual funds are more likely to be cloned, we perform a logit regression with the dependent variable, *cloned*, which is 1 if the the mutual fund is cloned into an active ETF and zero, otherwise. To estimate mutual fund performance, we construct two relative ranking measures, where the ranks are conducted within the fund-family. Using within family ranks should be more relevant than using how the fund performs overall, as fund-families would presumably select their relative best performing fund to clone. Specifically, $PerformancePercentRank$ is calculated by 1 minus the rank of the fund within the fund family divided by the total number of funds in the fund family. We also construct indicator variables for fund performance percentiles within the fund family: $performance\_25$, $performance\_50$, $performance\_75$. We do not allow overlaps so that means $performance\_50$ is equal to 1 if the fund is in the top 50th-75th percentile. We calculate these performance statistics using three alternative measures: CAPM alpha, Fama-French 3 Factor alpha and excess return over the riskfree rate. (We use the latter because of the short time series for the ANT ETFs.)

Results for the logit regressions are reported in Tables V and VI. Table V reports the results for our sample of all cloned mutual funds while Table VI uses the sub-sample of mutual funds cloned into an ANT ETF. Column headers indicate what model/measure we use to construct the performance measure (CAPM, Fama-French 3 Factor, or Excess Returns). The coefficients reported in the table are odds ratios. Thus, a coefficient greater than 1 means that the factor increases the probability the active mutual fund is chosen to be cloned, while a coefficient less than 1 implies that the factor decreases the probability the fund is chosen to be cloned. The results suggest that active mutual funds that are better ranked or in a higher performance percentile are significantly more likely to be chosen to be cloned into an ETF. In addition, active mutual funds with higher past net flows, larger in size, older, and withhigher expense ratios are more likely to be cloned. The higher expense ratio may be explained if active mutual funds that have a more unique strategy charge a higher expense ratio. Thus, it may be capturing that fund families are choosing their more unique strategies that have recently had the highest performance. Table VI shows that mutual funds chosen to be cloned for the ANT ETFs also tend to have higher past net flows and be older funds.[7]

4.3 Comparison of investor flows between cloned active ETFs and non-cloned active ETFs

A possible explanation for why fund families may choose to clone one of their pre-existing mutual funds rather than creating a new strategy derives from a potential advantage that a cloned ETF may have over a non-cloned ETF, higher net flows due to the reputation of the pre-existing mutual fund, thereby generating higher revenue from the expense ratios they charge. If having a pre-existing mutual fund counterpart offers advantages—such as leveraging past reputation—over introducing an entirely new strategy, we expect cloned active ETFs to attract more flows than similar non-cloned active ETFs.

To test this hypothesis, we construct a dummy variable, *cloned*, that indicates whether an active ETF has a matching pre-existing mutual fund. We regress *cloned* on the net flows of the ETF while controlling for lagged fund characteristics, including past performance, volatility of the past performance, size measured by the log of total net assets, age measured by the log of 1 plus the age of the fund (measured as years from initiation), and the fund cost measured by the expense ratio. We also control for fund family level characteristics including fund family size measured by the log of the total net assets of the fund family. We run the regression for two samples of our data: a sample that includes all of the cloned active ETFs and the non-cloned active ETFs (All-Clones) and a sample that includes only the cloned ANT ETFs and non-cloned active ETFs (ANT-Clones). We measure performance for the All-Clones sample using CAPM alpha. For the sample of cloned ANT ETFs, we measure performance using Excess Return as the ANT ETFs were launched very recently and thus do not have enough historical return observations to

[7] The lack of significance in some of the other characteristics may result from the smaller sample of cloned mutual funds in the ANT ETF sub-sample.

estimate a reasonable alpha.

We use month-year fixed effects across all specifications to control for any unobserved effects that vary across time but not across funds. For example, this would address a concern that there are more flows going into ETFs in general during the sample period. We also control for strategy type by using Lipper class and Lipper objective fixed effects. Standard errors are double clustered at the fund and month-date level.

The results, presented in Table VII, show that the coefficient for *cloned* is positive and statistically significant across all specifications, suggesting that cloned active ETFs attract significantly more flows than non-cloned active ETFs, consistent with our hypothesis. Columns (2) and (3) indicate that being cloned increases an ETF's monthly net flows by about 3 percent. The effect is even stronger for the ANT ETFs as shown in columns 4-6, with a 12 percent or 9 percent increase in monthly net flows from being a cloned ETF.

Table VII also shows in all specifications that expense ratios on their own do not seem to be significant drivers of net flows for active ETFs. In contrast, monthly net flows are sensitive to past performance (which is net of expense ratios). This is consistent with Ben-David et al. (2022), who find that specialized passive ETFs compete more along characteristics (performance) rather than cost (expense ratio) in contrast to passive index ETFs.

It is possible that the advantage to an active ETF's flows of having a counterpart mutual fund may decrease as the ETF ages because more information about the ETF itself arises for investors to employ in evaluating the ETF and its managers. Thus, we expect that being a cloned ETF has less of an impact on monthly flows to ETFs as they age and is most important in the first few months after the launch of the ETF.

As a first step, we plot the average monthly net flows of the cloned active ETFs compared to the non-cloned active ETFs for the first 15 months after launch in Figure I. We find that cloned ETFs attract more flows in the initial months after their introduction, and this effect decreases over time.

To further test this hypothesis, we construct a variable, *age_month*, to capture the number of months after an ETF's launch (i.e. the ETF's age in months). We interact this variable with our dummy variable, *cloned*, and add the interaction term to our base regression to check whether the effect of being a clone changes over the life of an active ETF. We do this for the first 15 months of the active ETFs since the ANT ETFs in our sample are very young. We also only run this regression for our larger combined sample of transparent and ANT clones given the lack of power with the ANT clone sample.

The results for this regression are reported in Table VIII. Consistent with our hypothesis, we find that the advantage of being a clone in attracting monthly fund flows for these active ETFs decreases by about 2% a month after the initial launch.

Additionally, we examine active mutual funds that were converted to active ETFs. If cloning a mutual fund proves effective in attracting new flows within the active ETF market due to an historical information advantage, we would expect active ETFs converted from mutual funds to exhibit a similar benefit. Thus, similar to our analysis of cloned active ETFs, we compare a converted active ETF's monthly net flows to other active ETFs with no history. Consistent with our hypothesis, Table IX shows that these converted ETFs attract about 5% more monthly flows than comparable active ETFs that had no historical information when launched. We also check whether the effect is more substantial right after the converted ETF is launched, as we find for the cloned ETFs. Table X shows that the effect slightly declines over time after the launch of the ETF. However, the magnitude of the decline is much smaller than the decline we see in cloned ETFs.

In the previous two specifications, we have compared converted ETFs to other similar active ETFs. To further examine the effects of conversion, we also compare converted ETFs to comparable mutual funds to assess whether transitioning to the ETF market enhances the flows a fund can attract. Since converted ETFs are identical to the original mutual fund as they generally keep their original clientele, performance history, and managers, they provide an ideal setting to test the advantage of being an ETF versus a mutual fund. We conduct a difference-in-difference regression in which the treated group is the converted mutual funds and the control group consists of similar mutual funds. Table XI shows that the converted mutual funds increase their monthly flows by about 2% upon becoming an ETF.

Overall, these results suggest that in the months right after their launch, active ETFs that are cloned or converted from a pre-existing mutual fund are able to attract more monthly net flows than active ETFs that have no matching pre-existing mutual fund. These results are consistent with the advantage of having historical information and as our earlier results on selection suggest, having a reputation.

4.4 Clientele of active ETFs

To better understand the source of the flows into the active ETFs, we conduct two analyses. In the first analysis, we examine the proportion of retail investors in the active ETFs and mutual funds. In the second analysis, we consider the role of retirement accounts in the delegated asset market.

We first use institutional holdings data to characterize the clientele of the ETFs and mutual funds by constructing a measure of the market share owned by institutions. To do so we aggregate the market value of shares held by institutions and divide it by the total market value of available shares.

In Figure II, we plot the percentage market share for active ETFs and passive ETFs represented by institutional ownership over time. The figure shows that over our sample period the passive ETF market has a higher percentage of institutional investors compared to the active ETF market. This is unsurprising since institutional investors often employ passive ETFs to manage their investment flows.

Next, we examine whether a difference exists in the clientele of the active ETF market for transparent active ETFs versus ANT ETFs. Since many of the active ETFs are launched during our sample period, some of them are initially held by their sponsor (an institutional investor). That is, an investment management sponsor may choose to hold a large proportion of the shares of their ETF when they first launch it and then gradually sell it over time. Because we also want to capture the institutional ownership that is separate from that of sponsors holding onto their ETF shares during new launches, we construct a second measure of institutional ownership that filters out any holdings of the sponsor (where we match the sponsors by the name of the management firm). Figure III plots the institutional ownership of the transparent ETF market and the ANT ETF market over time. The measures plotted in Panel (a) include all institutional ownership and demonstrates a steep decline in institutional ownership for the ANT ETF market that is largely driven by sponsors owning a major portion of the shares for some ANT ETFs when they were initially launched and then gradually selling them. The measures plotted in Panel (b) includes the ownership of the two types of ETFs after removing sponsor ownership. As the figure shows, once we remove sponsor ownership, the institutional ownership remains relatively flat for both types of ETFs. Interestingly, it does not seem that the shares of the sponsors are necessarily going to other institutions, as we don't see an increase in non-sponsor institutional ownership. There is up to about 70% of the ANT ETF market shares that can't be explained by institutional owners, which suggests that these shares are owned by retail investors. Comparing the ANT ETF market to the transparent ETF market in Panel (b) shows that the transparent active ETF market has more institutional ownership. Thus, it appears that the ANT ETF market attracts relatively more retail investors than the transparent active ETF market.

Plotting institutional ownership over time may be misleading as the results may be driven by the fact that many of the ANT ETFs are much younger than some of the transparent active ETFs. Thus, in Figure IV we plot the institutional ownership of the two markets by the ETF's age to compare similar age ETFs. We calculate the age in quarters since our data is at the quarterly level. The figure shows that even when controlling for age, the ANT ETFs have much less institutional ownership than the transparent active ETFs, at least during the early periods of their launch. This result suggests that the ANT ETF market clientele is more heavily composed of retail investors compared to other active ETFs.

To further examine the clientele of the active ETFs, we consider the retirement account clientele of the mutual funds and the cloned versus converted active ETFs. Specifically, we construct an annual measure of the percentage of a fund's flows that derive from 401(k) plans. As discussed earlier, we hypothesize that mutual funds with more flows from defined contribution retirement accounts, indicating a higher proportion of retirement investor clientele, would be more likely to be cloned due to the differences between the mutual fund and ETF models for the defined contribution retirement accounts. Consistent with this hypothesis, Table XII columns (1) and (3) show that compared to similar funds that have the same Lipper class, funds with more retirement flows are significantly more likely to be cloned. Interestingly, this effect goes away when we use fund family fixed effects instead of comparing funds within a fund family. This suggests that fund families that have funds with more retirement flows are more likely to clone their mutual funds, which makes sense as fund families with little or no retirement flows can easily convert their mutual funds into ETFs instead of cloning them. In fact, we confirm that all of the mutual funds that were found to be converted had no retirement flows as measured using the Brightscope data.

4.5 Performance of cloned active ETFs

We next consider whether performance is a primary driver of flows to the cloned active ETFs. If cloned active ETFs tend to have better risk-adjusted returns than non-cloned active ETFs, then it is highly possible that the excess flows we document to the cloned ETFs are simply driven by performance. The cloned active ETFs could have better performance if the cloned active mutual fund managers have better skills than the non-cloned active fund managers.

To test this hypothesis, we regress *clone* on the performance of the active ETF while controlling for lagged fund characteristics including past performance, volatility of the past performance, size measured by log of total net assets, age measured by log of 1 + age of fund in years from initiation, and the cost measured by the expense ratio. We also control for fund family level characteristics including fund family size measured by log of the total net assets of the fund family.

Our regressions include month-year fixed effects across all specifications to control for any unobserved effects that vary across time but not across funds. For example, this would address a concern that the performance of the equity market in general in the last couple of years, when most of the cloned active ETFs were launched, was better than in other periods. We also control for strategy type by using Lipper class and Lipper objective fixed effects. Standard errors are double clustered at the fund and month-date level.

We conduct the regression for two samples of our data: a sample that includes all of the cloned and non-cloned active ETFs (All-Clones sample) and a sample that includes only the cloned ANT ETFs and non-cloned active ETFs (ANT-Clones sample). We measure performance for the All-Clones sample using CAPM alpha and for the ANT-Clones sample using Excess Returns.

Table XIII reports the results for the regressions. Although the coefficient for *cloned* is positive for all specifications of the sample of All-Clones, it is not statistically significant in the specifications that include Lipper objective fixed effects or no style fixed effects. Thus, the results are not consistently significant. In fact, for the ANT-Clones sample, we find the coefficient to be negative for these two specifications (columns (4) and (6)). Thus, it does not appear that cloned active ETFs exhibit significantly better performance than non-cloned active ETFs.[8]

Overall, not only do the cloned active ETFs seem to be attracting new flows not driven by performance, the active mutual funds that were chosen to be cloned end up attracting significantly more net flows compared to similar active mutual funds. These results oppose the hypothesis that introducing a cloned active ETF may have negative impact on the flows of the cloned mutual fund. Instead, the results seem more consistent with a theory in which the cloned active ETF and its mutual fund counterpart are complementary. This may be possible if different clientele invest in ETFs versus mutual funds and the cloned active ETF may provide some advertising or positive signal about the original mutual fund's quality. In such a case, we may not observe a significant decrease in net

[8]Given that a number of the cloned active ETFs were launched relatively recently, we may lack enough historical data to capture significant positive or negative performance.

flows or even an increase in net flows after the introduction of the clone active ETF.

5 Conclusions

Innovations in the ETF market have contributed to growing competition for investors' flows in the delegated asset market. Beyond the rise of passive investing through that market, we show that the introduction of active ETFs, although still a relatively small segment of the market, has itself had effects on the competitive environment. In particular, the change in SEC rules to allow semi-transparent and non-transparent ETFs (in our terms, the ANT ETFs) provides the opportunity for additional active investment strategies to be offered through the ETF product because this model allows the managers to hide some of their trading strategies. We examine the introduction of active ETFs that cloned their mutual fund counterpart's trading strategies to study how investment companies compete for market share. We find surprisingly, the mutual fund's flows are not cannibalized by the active cloned ETF's flows. We develop hypotheses to explain these results based on the concept that investment management companies seek flow diversification (e.g., Wahal and Wang (2022)). In support of these hypotheses we find that the investment companies tend to select mutual funds with better reputations, i.e., better performing, larger and older funds, to clone. Being cloned from these more reputable mutual funds gives the new active ETFs an advantage in attracting flows over their peers, although the cloned active ETFs do not necessarily perform better than their peers. We also show differences between the transparent active ETFs and the ANT ETFs — in particular, the ANT ETF market is more heavily composed of retail investors. We find evidence suggesting that some of the additional flows to the cloned active ETFs are driven by a difference in clientele from their mutual fund counterpart.

Our results suggest that competition in the delegated asset market is affected by innovation in products. Khorana and Servaes (2012) present evidence for mutual fund families that by innovating through the introduction of new products, such families can attain higher market share and that this is particularly the case if the new funds' portfolio characteristics differ from existing funds. Our evidence indicates that fund management companies can also compete by offering their same fund strategies to additional clienteles.

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Table I. Summary Statistics: Matching Quality

This table presents summary statistics for the portfolio overlap in the pairs of matched active mutual funds and active ETFs that we identify to be clones. *ETF Num Not Matched* is the number of assets in the holdings of the ETF that were not found in the mutual fund. *ETF Weight Not Matched* is the weight of the portfolio that the assets accounted for in the ETF that were not found in the mutual fund. *ETF Percent Not Matched* is the percentage of assets in the ETF's portfolio holdings that were not found in the mutual fund.

	Total							
	sd	min	p10	p25	mean	p75	p90	max
ETF Total Holdings	1122.77	11.04	27.35	30.86	719.33	1005.38	2703.86	3501.86
MF Total Holdings	962.00	12.17	28.65	36.00	656.36	1142.38	2447.00	2811.00
ETF Num Not Matched	238.48	1.75	1.86	2.00	129.45	168.75	483.86	835.57
ETF Weight Not Matched	11.28	0.21	0.46	1.88	9.54	11.05	30.23	37.28
ETF Percent Not Matched	0.16	0.01	0.04	0.06	0.18	0.24	0.45	0.53

Table II. Summary Statistics: Active Mutual Funds

Panel A of this table presents summary statistics for the active equity mutual funds in our sample and the different sub-samples we construct. Panel B presents summary statistics of the fund-families of these active mutual funds in our sample. Columns (1) include all active mutual funds, (2) include all mutual funds that were not chosen to be cloned, (3) include all mutual funds that were cloned into a transparent ETF, and (4) include all mutual funds that were cloned into an ANT ETF. Mutual fund age is measured in years. Mutual fund size is the total net assets in $millions. Alphas are calculated using the past 35 months of returns while volatility of alphas and returns are calculated using the past 12-month observations. Alphas are reported in the table as percentages. Net flow is reported in millions of dollars while percentage net flow is net flow normalized by the fund's total net assets the previous month.

Panel A: Fund-level Variables

	(1)		(2)		(3)		(4)	
	All		No Clones		Transparent Clones		ANT Clones	
	mean	sd	mean	sd	mean	sd	mean	sd
MF Year of Initiation	1999	12	1999	12	1999	8	1989	15
MF Age (years)	12.34	11.74	12.31	11.72	12.72	7.78	21.91	16.29
ln(1+MF Age)	2.24	0.88	2.24	0.88	2.39	0.75	2.86	0.80
MF Expense Ratio (bps)	9.29	6.46	9.28	6.47	10.16	5.59	9.62	3.59
MF Size (TNA)	1031.24	2647.31	1018.19	2615.79	1398.89	2296.06	5044.10	6882.91
MF ln(TNA)	5.07	2.23	5.06	2.23	6.10	1.76	7.09	2.16
MF CAPM Alpha	-0.12	0.13	-0.12	0.13	-0.12	0.13	-0.13	0.13
σ(MF CAPM Alpha) (12 month)	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01
MF FF 3 Factor Alpha	-0.12	0.13	-0.12	0.13	-0.12	0.13	-0.13	0.13
σ(MF FF 3 Factor Alpha) (12 month)	0.01	0.01	0.01	0.01	0.02	0.01	0.02	0.01
MF Excess Return	-0.10	0.18	-0.10	0.18	-0.09	0.15	-0.10	0.15
σ(MF Excess Return) (12 month)	0.05	0.04	0.05	0.04	0.06	0.03	0.06	0.03
MF Net Flow	-1.27	178.41	-1.23	177.67	-1.48	81.01	-16.00	376.56
MF Net Flow (%)	0.01	0.07	0.01	0.07	0.01	0.06	0.00	0.05
MF Turnover Ratio	0.62	0.91	0.62	0.91	0.43	0.44	0.66	0.61
MF-ETF Expense Ratio (bps)	1.91	4.23	.	.	2.04	4.65	1.39	1.39
Observations	1322413		1314981		3473		3959	

Panel B: Fund-Family Level Variables

Fund Family Size (TNA)	12098.21	34420.03	9512.63	28322.66	65421.61	78067.00	91604.99	89585.30
ln(Fund Family Size)	6.96	2.50	6.81	2.42	10.11	2.08	10.97	1.60
Num of Funds in Fund Family	12.19	22.01	10.36	15.64	49.84	62.76	72.21	83.88
Observations	102300		97569		4731		1956	

Table III. Summary Statistics: Active ETFs

This table presents summary statistics for the active equity ETFs in our sample and the different sub-samples we construct. Column (1) includes all active equity ETFs, Column (2) includes all ETFs that have no counterpart mutual fund, Column (3) includes all cloned transparent ETFs, and Column (4) includes all cloned ANT ETFs. ETF age is measured in years. ETF size is the total net assets in $millions. Alphas are calculated using the past 35 months of returns and volatility of returns are calculated using the past 12-month observations. Alphas are reported in the table as proportions. Net flow is reported in millions of dollars while percentage net flow is net flow normalized by the fund's total net assets the previous month.

	(1) All		(2) No Clones		(3) Transparent Clones		(4) ANT Clones	
	mean	sd	mean	sd	mean	sd	mean	sd
ETF Year of Initiation	2014.16	5.20	2014.03	5.25	2014.43	4.41	2020.03	0.18
ETF Age (years)	3.38	3.53	3.47	3.61	2.98	2.62	0.77	0.43
ln(1 + ETF Age)	1.20	0.72	1.22	0.73	1.20	0.60	0.54	0.25
ETF Expense Ratio (bps)	7.21	3.50	7.39	3.59	5.93	2.71	6.19	1.57
ETF Size (TNA)	130.66	319.73	124.13	310.47	218.40	424.75	72.21	101.93
ETF ln(TNA)	3.35	1.73	3.32	1.71	3.70	1.98	3.34	1.50
ETF Excess Return	-0.04	0.10	-0.04	0.10	-0.04	0.10	0.02	0.05
σ(ETF Excess Return) (12 month)	0.05	0.04	0.05	0.04	0.06	0.04	0.05	0.02
ETF CAPM Alpha	-0.06	0.07	-0.06	0.07	-0.07	0.06	-0.01	0.01
σ(ETF CAPM Alpha) (12 month)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
ETF Net Flow	5.99	79.87	4.06	63.53	28.32	184.15	5.03	10.46
ETF Net Flow (%)	0.04	0.13	0.04	0.13	0.05	0.12	0.08	0.15
Observations	12993		11753		1019		221	

Table IV. Effect of Cloned ETF Introduction on Cloned Mutual Fund's Net Flows

This table presents results for the following regression:

$$MF\_NetFlow_{i,t} = \beta_1 cloned_{i,t} + \Gamma X_{i,t-1} + \alpha \lambda_{f,t-1} + \gamma_i + \eta_t + \epsilon_{i,t}$$

where $cloned_{i,t}$ is a dummy variable equal to 1 if the cloned ETF corresponding to the mutual fund i has been introduced at time t, $MF\_NetFlow$ is a mutual fund's monthly net flow normalized by the previous month's total net assets, X are fund level lagged control variables including log fund size, log fund age, net flow, lagged CAPM alpha, volatility of CAPM alpha, and expense ratio, and λ is a fund-family level control: log of fund family size. The All-Clones sample includes mutual fund flows of all mutual funds that were cloned into an active equity ETF. The ANT-Clones sample consists of mutual fund flows of the mutual funds that were cloned into a semi-transparent or non-transparent ETF. The time period consists of observations 6 months before and after the event. The bottom row "Sample" indicates whether the full sample of active equity mutual funds were included ("Full") or just the sample of cloned (cloned) active equity mutual funds are used ("Cloned"). Standard errors are double clustered at fund and month-date level. Standard errors in parentheses. * (p<.1) ** (p<.05) and *** (p<.01).

	Panel A		Panel B			
	(1) All-Clones	(2) ANT-Clones	(3) All-Clones	(4) All-Clones	(5) ANT-Clones	(6) ANT-Clones
cloned	0.003	0.023	0.042***	0.060***	0.056***	0.070***
	(0.011)	(0.028)	(0.010)	(0.012)	(0.010)	(0.012)
lagged ln(MF Size)	-0.098**	-0.055		-0.071***		-0.071***
	(0.042)	(0.050)		(0.009)		(0.009)
ln(MF Age)	0.301	0.065		-0.015		-0.014
	(0.277)	(0.348)		(0.022)		(0.022)
MF CAPM Alpha	1.302	3.668		0.002		0.002
	(2.713)	(2.543)		(0.034)		(0.034)
σ(MF CAPM Alpha) (12 month)	-5.823**	-11.794**		-0.142		-0.133
	(2.457)	(5.416)		(0.241)		(0.243)
lagged ETF Expense Ratio	26.846	46.804		1.514		1.530
	(32.078)	(29.878)		(1.855)		(1.857)
lagged ln(Fund Family Size)	-0.109	-0.072		0.001		0.001
	(0.121)	(0.082)		(0.002)		(0.002)
Constant	1.075	1.290	-0.009***	0.296***	-0.009***	0.294***
	(1.515)	(2.320)	(0.000)	(0.060)	(0.000)	(0.060)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund Cluster	Yes	Yes	Yes	Yes	Yes	Yes
MonthDateCluster	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Treated	Treated	Full	Full	Full	Full
N	433	186	80063	78887	79776	78621
R2	0.407	0.455	0.203	0.231	0.202	0.231

Table V. Determinants of Mutual Funds Cloned for Active ETFs

This table presents results (***odds ratios***) for the following logit regression of mutual fund characteristics on being cloned:

$$cloned_i = \beta_1 Performance\_Measure_{i,t} + \beta_2 \sigma(MFPastPerformance)_{i,t} + \Gamma X_{i,t} + \lambda_{f,t} + \epsilon_{i,t}$$

where *cloned* represents an indicator variable equal to one if the mutual fund is cloned into an ETF. $Performance\_Measure$ includes $PerformancePercentRank$ calculated by rank of fund within the fund family divided by total number of funds in the fund family and $performance\_25$, $performance\_50$, $performance\_75$ are dummy variables for whether the mutual fund is in the 25th, 50th, or 75th percentile (based on CAPM alpha, Fama-French 3 Factor alpha or excess returns). $\sigma(MFPastPerformance)$ is the standard deviation of the past 12-month performance of the mutual fund based on the the performance measure used. X includes fund level controls including log of the mutual fund size, log of the mutual fund age, expense ratio in percentages, and turnover ratio. $\lambda_{f,t}$ are fund-family times month-year fixed effects. The regression sample includes all cloned active equity mutual funds and active equity mutual funds that are a part of the same fund family as those cloned. The sample excludes the observations of mutual funds after they have been cloned and includes the characteristics for the chosen mutual funds up to 5 years before they were cloned. Standard errors are clustered at the fund-family level. Standard errors in parentheses. * (p<.1) ** (p<.05) and *** (p<.01).

	(1) CAPM	(2) CAPM	(3) FF3	(4) FF3	(5) Excess Ret	(6) Excess Ret
Performance Percent Rank	2.336**		1.950**		1.583***	
	(0.937)		(0.650)		(0.164)	
performance_25		1.240		1.412		0.880
		(0.270)		(0.394)		(0.106)
performance_50		1.000		1.540		1.093
		(0.274)		(0.445)		(0.146)
performance_75		2.139***		1.975**		1.386***
		(0.606)		(0.597)		(0.106)
σ(MF Past Performance)	0.811	0.790	0.827	0.820	1.074	1.064
	(0.229)	(0.225)	(0.271)	(0.273)	(0.069)	(0.068)
MF Net Flow (%)	24.878***	22.618***	30.846***	30.560***	29.892***	29.866***
	(19.444)	(17.287)	(23.342)	(22.781)	(19.323)	(19.269)
MF ln(TNA)	1.220**	1.225**	1.228**	1.225**	1.246**	1.249**
	(0.122)	(0.124)	(0.124)	(0.123)	(0.127)	(0.128)
ln(MF Age)	1.496**	1.497**	1.487**	1.477**	1.483**	1.480**
	(0.276)	(0.272)	(0.276)	(0.274)	(0.275)	(0.274)
MF Expense Ratio (%)	1.714*	1.676*	1.717*	1.751*	1.553	1.515
	(0.517)	(0.505)	(0.517)	(0.533)	(0.507)	(0.493)
MF Turnover Ratio	0.829	0.859	0.837	0.849	0.892	0.895
	(0.181)	(0.161)	(0.175)	(0.166)	(0.167)	(0.159)
FundFamilyxMonthYear FE	Yes	Yes	Yes	Yes	Yes	Yes
N	88687	88687	87705	87705	89749	89749

Table VI. Determinants of Mutual Funds Cloned for ANT ETFs

This table presents results (***odds ratios***) for the following logit regression of mutual fund characteristics on being cloned:

$$cloned_i = \beta_1 Performance\_Measure_{i,t} + \beta_2 \sigma(MFPastPerformance)_{i,t} + \Gamma X_{i,t} + \lambda_{f,t} + \epsilon_{i,t}$$

where $cloned$ is an indicator variable equal to one if the mutual fund is cloned into an ETF. $Performance\_Measure$ includes $PerformancePercentRank$ calculated by rank of fund within the fund family divided by total number of funds in the fund family and $performance\_25$, $performance\_50$, $performance\_75$ are dummy variables for whether the mutual fund is in 25th, 50th, or 75th percentile (based on CAPM alpha, Fama-French 3 Factor alpha or Excess Returns). $\sigma(MFPastPerformance)$ is the standard deviation of the past 12-month performance of the mutual fund based on the the performance measure used. X includes fund level controls including log of the mutual fund size, log of the mutual fund age, expense ratio in percentages, and turnover ratio. $\lambda_{f,t}$ are fund-family times month-year fixed effects. The regression sample includes all semi-transparent or non-transparent ETFs and active mutual funds that are a part of the fund families that have an ANT ETF. The sample excludes the observations of mutual funds after they have been cloned and includes the characteristics for the chosen mutual funds up to 5 years before they were cloned. Standard errors are clustered at the fund-family level. Standard errors in parentheses. * (p<.1) ** (p<.05) and *** (p<.01).

	(1) CAPM	(2) CAPM	(3) FF3	(4) FF3	(5) Excess Ret	(6) Excess Ret
Performance Percent Rank	5.030***		4.709***		1.648***	
	(1.889)		(1.124)		(0.198)	
performance_25		1.730*		2.168**		0.958
		(0.506)		(0.679)		(0.167)
performance_50		1.460		3.568***		1.368
		(0.570)		(1.107)		(0.308)
performance_75		3.538***		4.392***		1.390***
		(0.709)		(0.966)		(0.123)
σ(MF Past Performance)	2.163	2.084	3.288**	3.681**	1.094	1.094
	(1.444)	(1.496)	(1.910)	(1.994)	(0.067)	(0.074)
MF Net Flow (%)	51.289***	54.785***	62.595***	70.079***	116.870***	119.432***
	(59.201)	(63.633)	(72.649)	(77.655)	(129.765)	(130.818)
MF ln(TNA)	1.243	1.251	1.251	1.251	1.312	1.311
	(0.249)	(0.250)	(0.255)	(0.251)	(0.268)	(0.267)
ln(MF Age)	2.297***	2.296***	2.281**	2.268**	2.372***	2.378***
	(0.701)	(0.700)	(0.731)	(0.723)	(0.778)	(0.773)
MF Expense Ratio (%)	1.452	1.420	1.437	1.529*	1.298	1.294
	(0.394)	(0.386)	(0.401)	(0.386)	(0.362)	(0.346)
MF Turnover Ratio	1.117	1.102	1.115	1.119	1.248	1.248
	(0.140)	(0.144)	(0.142)	(0.152)	(0.179)	(0.181)
FundFamilyxMonthYear FE	Yes	Yes	Yes	Yes	Yes	Yes
N	45765	45765	45391	45391	46124	46124

Table VII. ETF Net Flows

This table presents results for the following regression:

$$ETF\_NetFlow_{i,t} = \beta_1 cloned_i + \Gamma X_{i,t-1} + \alpha\lambda_{f,t-1} + \gamma_i + \eta_t + \epsilon_{i,t},$$

where $cloned_i$ is a dummy variable equal to 1 if the ETF was cloned from a pre-existing mutual fund, $ETF\_NetFlow$ is a ETF's monthly net flow normalized by the previous month's total net assets, X are fund level lagged control variables including log fund size, log fund age, net flow, CAPM alpha, volatility of CAPM alpha, and expense ratio, and λ is a fund-family level control: log of fund family size. The ANT sample consists of cloned non-transparent ETFs and all non-cloned active equity ETFs. The Equity sample includes all active equity ETFs. Standard errors are double clustered at fund and month-date level. Standard errors in parentheses. * (p<.1) ** (p<.05) and *** (p<.01).

	(1) All-Clones	(2) All-Clones	(3) All-Clones	(4) ANT-Clones	(5) ANT-Clones	(6) ANT-Clones
treated	0.018**	0.031***	0.029***	0.087***	0.120***	0.094**
	(0.009)	(0.009)	(0.007)	(0.032)	(0.041)	(0.041)
ETF CAPM Alpha	0.079	0.252**	0.172*			
	(0.107)	(0.106)	(0.093)			
σ(ETF CAPM Alpha) (12 month)	0.545	-0.028	0.189			
	(0.472)	(0.432)	(0.438)			
ETF Excess Return				0.225**	0.221**	0.220**
				(0.092)	(0.102)	(0.102)
σ(ETF Excess Return) (12 month)				0.540***	0.474***	0.435***
				(0.150)	(0.123)	(0.115)
ETF ln(TNA)	0.000	-0.006***	-0.003	-0.001	-0.007***	-0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln(1 + ETF Age)	-0.029***	-0.029***	-0.029***	-0.028***	-0.021**	-0.024***
	(0.005)	(0.007)	(0.007)	(0.005)	(0.008)	(0.007)
ETF Expense Ratio	-1.536	-0.734	-1.178	-1.439	-0.803	-1.229
	(1.015)	(1.190)	(1.198)	(0.920)	(1.074)	(1.129)
ln(Fund Family Size)	0.001	0.006**	0.003	0.001	0.007**	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Constant	0.067***	0.112***	0.091***	0.059***	0.086***	0.082***
	(0.025)	(0.024)	(0.022)	(0.022)	(0.026)	(0.026)
Lipper Class FE	No	Yes	No	No	Yes	No
Lipper Obj FE	No	No	Yes	No	No	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund Cluster	Yes	Yes	Yes	Yes	Yes	Yes
MonthDateCluster	No	Yes	Yes	No	Yes	Yes
N	5862	5862	5861	5369	5369	5369
R2	0.050	0.094	0.089	0.065	0.102	0.095

Table VIII. ETF Net Flows - Months after Launch

This table presents results for the following regression:

$$ETF\_NetFlow_{i,t} = \beta_1 cloned_i + \beta_2 cloned_i \times age\_month_i + \Gamma X_{i,t-1} + \alpha\lambda_{f,t-1} + \gamma_i + \eta_t + \epsilon_{i,t},$$

where $cloned_i$ is a dummy variable equal to 1 if the ETF was cloned from a pre-existing mutual fund, age_month_i is an number of months after the ETF i has been launched, $ETF\_NetFlow$ is a ETF's monthly net flow normalized by the previous month's total net assets, X are fund level lagged control variables including log fund size, log fund age, net flow, CAPM alpha, volatility of CAPM alpha, and expense ratio, and λ is a fund-family level control: log of fund family size. The sample includes all active equity ETFs. Standard errors are double clustered at fund and month-date level. Standard errors in parentheses. * (p<.1) ** (p<.05) and *** (p<.01).

	(1) All-Clones	(2) All-Clones	(3) All-Clones	(4) All-Clones
cloned	0.194***	0.202***	0.188***	0.202***
	(0.073)	(0.075)	(0.063)	(0.064)
cloned × age_month	-0.018***	-0.019***	-0.021***	-0.020***
	(0.007)	(0.007)	(0.007)	(0.006)
ETF CAPM Alpha	0.516*	0.408	0.530*	0.499*
	(0.272)	(0.267)	(0.270)	(0.295)
σ(ETF CAPM Alpha) (12 month)	-0.232	-0.290	-0.417	-0.700
	(0.638)	(0.718)	(0.713)	(0.802)
ETF ln(TNA)	-0.011**	-0.007	-0.017***	-0.024***
	(0.005)	(0.005)	(0.005)	(0.006)
ln(1 + ETF Age)	0.192***	0.201***	0.261***	0.287***
	(0.067)	(0.063)	(0.065)	(0.072)
ETF Expense Ratio	-4.892**	-3.684	-4.753	-2.671
	(2.382)	(2.278)	(3.044)	(3.609)
ln(Fund Family Size)	0.008	0.006	-0.020**	-0.026**
	(0.005)	(0.005)	(0.008)	(0.011)
Constant	0.091*	0.039	0.269***	0.342***
	(0.051)	(0.049)	(0.082)	(0.094)
Lipper Class FE	Yes	No	No	Yes
Lipper Obj FE	No	Yes	No	No
Fund-Family FE	No	No	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes
Fund Cluster	Yes	Yes	Yes	Yes
MonthDateCluster	Yes	Yes	Yes	Yes
N	1721	1722	1723	1721
R2	0.124	0.098	0.157	0.176

Table IX. ETF Net Flows - Converted ETFs

This table presents results for the following regression:

$$ETF\_NetFlow_{i,t} = \beta_1 converted_i + \Gamma X_{i,t-1} + \alpha \lambda_{f,t-1} + \gamma_i + \eta_t + \epsilon_{i,t},$$

where $converted_i$ is a dummy variable equal to 1 if the ETF was converted from a pre-existing mutual fund, $ETF\_NetFlow$ is a ETF's monthly net flow normalized by the previous month's total net assets, X are fund level lagged control variables including log fund size, log fund age, net flow, CAPM alpha, volatility of CAPM alpha, and expense ratio, and λ is a fund-family level control: log of fund family size. The sample consists of all converted active equity ETFs and other active equity ETFs excluding cloned ETFs. Standard errors in parentheses. * (p<.1) ** (p<.05) and *** (p<.01).

	(1) Converted	(2) Converted	(3) Converted
treated	0.048***	0.052***	0.053***
	(0.008)	(0.009)	(0.009)
etf_excess_return	0.187***	0.173***	0.175***
	(0.045)	(0.046)	(0.046)
sd of etf_excess_return	0.226***	0.087	0.089
	(0.058)	(0.069)	(0.069)
ETF ln(TNA)	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)
ln(1 + ETF Age)	-0.042***	-0.040***	-0.039***
	(0.003)	(0.004)	(0.004)
ETF Expense Ratio	-1.448**	-2.100***	-2.540***
	(0.637)	(0.793)	(0.772)
ln(Fund Family Size)	0.006***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)
Constant	0.090***	0.107***	0.110***
	(0.014)	(0.016)	(0.015)
Lipper Class FE	No	Yes	No
Lipper Obj FE	No	No	Yes
Month-Year FE	Yes	Yes	Yes
Fund Cluster	Yes	Yes	Yes
MonthDateCluster	Yes	Yes	Yes
N	19520	19519	19519
R2	0.047	0.060	0.057

Table X. ETF Net Flows - Months after Launch - Converted ETFs

This table presents results for the following regression:

$$ETF\_NetFlow_{i,t} = \beta_1 converted_i + \beta_2 converted_i \times age\_month_i + \Gamma X_{i,t-1} + \alpha\lambda_{f,t-1} + \gamma_i + \eta_t + \epsilon_{i,t},$$

where $converted_i$ is a dummy variable equal to 1 if the ETF was converted from a pre-existing mutual fund, age_month_i is an number of months after the ETF i has been launched, $ETF\_NetFlow$ is a ETF's monthly net flow normalized by the previous month's total net assets, X are fund level lagged control variables including log fund size, log fund age, net flow, CAPM alpha, volatility of CAPM alpha, and expense ratio, and λ is a fund-family level control: log of fund family size. The sample consists of all converted active equity ETFs and other active equity ETFs excluding cloned ETFs.Standard errors are double clustered at fund and month-date level. Standard errors in parentheses. * (p<.1) ** (p<.05) and *** (p<.01).

	(1) Converted	(2) Converted	(3) Converted	(4) Converted
converted	0.045***	0.047***	0.039***	0.034**
	(0.010)	(0.010)	(0.013)	(0.014)
converted × age_month	-0.000	-0.001	-0.001*	-0.001*
	(0.000)	(0.000)	(0.001)	(0.001)
ETF CAPM Alpha	-0.022	-0.014	-0.032	-0.007
	(0.030)	(0.030)	(0.034)	(0.032)
σ(ETF CAPM Alpha) (12 month)	-0.119	-0.116	-0.107	-0.086
	(0.128)	(0.130)	(0.130)	(0.128)
ETF ln(TNA)	-0.002	-0.002	-0.003**	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
ln(1 + ETF Age)	-0.034***	-0.034***	-0.032***	-0.029***
	(0.004)	(0.004)	(0.005)	(0.005)
ETF Expense Ratio	-1.913**	-2.406***	0.384	-1.202
	(0.776)	(0.749)	(1.067)	(1.112)
ln(Fund Family Size)	0.005***	0.004***	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)
Constant	0.071***	0.075***	0.110***	0.143***
	(0.015)	(0.014)	(0.021)	(0.020)
Lipper Class FE	Yes	No	No	Yes
Lipper Obj FE	No	Yes	No	No
Fund-Family FE	No	No	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes
Fund Cluster	Yes	Yes	Yes	Yes
MonthDateCluster	Yes	Yes	Yes	Yes
N	18686	18686	18688	18686
R2	0.049	0.047	0.059	0.069

Table XI. Event Study Net Flows - Converted ETFs

This table presents results for the following regression:

$$Fund\_NetFlow_{i,t} = \beta_1 aftertreatment_{i,t} + \Gamma X_{i,t-1} + \alpha\lambda_{f,t-1} + \gamma_i + \eta_t + \epsilon_{i,t},$$

where $aftertreatment_i$ is a dummy variable equal to 1 if the month t is after fund i was converted from a pre-existing mutual fund, $Fund\_NetFlow$ is the fund's monthly net flow normalized by the previous month's total net assets, X are fund level lagged control variables including log fund size, log fund age, net flow, CAPM alpha, volatility of CAPM alpha, and expense ratio, and λ is a fund-family level control: log of fund family size. The sample contains all converted funds. Standard errors are double clustered at fund and month-date level. Standard errors in parentheses. * (p<.1) ** (p<.05) and *** (p<.01).

	(1) Converted	(2) Converted	(3) Converted
aftertreatment	0.020*	0.014	0.019
	(0.011)	(0.015)	(0.013)
etf_excess_return	0.175***	0.133**	0.125**
	(0.036)	(0.053)	(0.050)
sd of etf_excess_return	-0.021	-0.036	-0.043
	(0.081)	(0.130)	(0.121)
ETF ln(TNA)	-0.042***	-0.062***	-0.056***
	(0.003)	(0.005)	(0.005)
ln(1 + ETF Age)	-0.032***	-0.036**	-0.037**
	(0.010)	(0.015)	(0.015)
ETF Expense Ratio	-1.223	-2.890	-4.854*
	(1.864)	(2.779)	(2.814)
ln(Fund Family Size)	0.020***	0.013***	0.016***
	(0.003)	(0.005)	(0.005)
Constant	0.428***	0.695***	0.623***
	(0.032)	(0.065)	(0.058)
Fund FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
Lipper Class - Date FE	No	Yes	No
Lipper - Date Obj FE	No	No	Yes
Fund Cluster	Yes	Yes	Yes
MonthDateCluster	Yes	Yes	Yes
N	21503	18727	19491
R2	0.129	0.134	0.141

Table XII. Determinants of Mutual Funds Cloned - Retirement Flows

This table presents results (***odds ratios***) for the following logit regression of mutual fund characteristics on being cloned:

$$cloned_i = \beta_1 perc\_retirement + \Gamma X_{i,t} + \epsilon_{i,t}$$

where *cloned* is an indicator variable equal to one if the mutual fund is cloned into an ETF, X are fund level control variables including log fund size, log fund age, net flow, CAPM alpha, volatility of CAPM alpha, and expense ratio. The regression sample includes all semi-transparent or non-transparent ETFs and active mutual funds that are a part of the fund families that have an ANT ETF. The sample excludes the observations of mutual funds after they have been cloned and includes the characteristics for the chosen mutual funds up to 5 years before they were cloned. Standard errors are clustered at the fund-family level. Standard errors in parentheses. * (p<.1) ** (p<.05) and *** (p<.01).

	(1) Equity	(2) Equity	(3) ANT	(4) ANT
perc_retirement	2.186***	-1.260	2.707***	-0.845
	(0.161)	(1.778)	(0.185)	(2.442)
MF Net Flow (%)	4.718***	4.544***	4.572***	5.056**
	(0.414)	(1.389)	(0.577)	(1.970)
MF ln(TNA)	0.170***	0.228*	0.290***	0.295
	(0.0136)	(0.138)	(0.0225)	(0.216)
ln(1+MF Age)	0.136***	0.545*	0.329***	0.974***
	(0.0380)	(0.302)	(0.0487)	(0.373)
MF CAPM Alpha (%)	0.268***	0.152***	0.376***	0.151***
	(0.0523)	(0.0279)	(0.0318)	(0.0309)
σ(MF CAPM Alpha) (%)	0.0713	0.665***	0.477***	0.835***
	(0.241)	(0.160)	(0.0700)	(0.160)
MF Expense Ratio (%)	0.0767	0.201	0.726***	-0.0688
	(0.0776)	(0.319)	(0.0955)	(0.446)
MF Turnover Ratio	-0.0937**	0.164	0.125**	0.131
	(0.0467)	(0.131)	(0.0575)	(0.192)
LipperClass-Time FE	Yes	No	Yes	No
FundFamily FE	No	Yes	No	Yes
N				
N	67929	63970	55591	50236

Table XIII. Performance of Cloned vs. non-Cloned ETFs

This table presents results for the following regression:

$$CAPM\_Alpha_{i,t} = \beta_1 cloned_i + \Gamma X_{i,t-1} + \alpha \lambda_{f,t-1} + \eta_t + \epsilon_{i,t}$$

where *cloned* is a dummy variables indicating whether the ETF was cloned from a pre-existing mutual fund, X are fund level lagged control variables including log fund size, log fund age, net flow, lagged CAPM alpha, volatility of CAPM alpha, and expense ratio, and λ is a fund-family level control: log of fund family size. Standard errors are double clustered at fund and month-date level. Standard errors in parentheses. * (p<.1) ** (p<.05) and *** (p<.01).

	(1) All-Clones	(2) All-Clones	(3) All-Clones	(4) ANT-Clones	(5) ANT-Clones	(6) ANT-Clones
cloned	0.031	0.074*	0.058	-0.020	0.125	-0.042
	(0.027)	(0.044)	(0.044)	(0.189)	(0.211)	(0.224)
lagged ln(ETF Size)	0.009	0.005	0.007	0.006	0.005	0.005
	(0.006)	(0.007)	(0.007)	(0.006)	(0.005)	(0.006)
ln(1 + ETF Age)	-0.134***	-0.129**	-0.146**	-0.152***	-0.163**	-0.189**
	(0.026)	(0.058)	(0.058)	(0.034)	(0.076)	(0.076)
lagged ETF Net Flow (%)	0.083	0.117*	0.097	0.049	0.087	0.062
	(0.052)	(0.066)	(0.068)	(0.055)	(0.061)	(0.063)
lagged ETF CAPM Alpha (%)	0.973***	0.961***	0.967***	0.975***	0.961***	0.969***
	(0.005)	(0.005)	(0.007)	(0.005)	(0.006)	(0.008)
σ(ETF CAPM Alpha) (%)	0.041**	0.031	0.030	0.007	-0.001	-0.009
	(0.019)	(0.026)	(0.029)	(0.018)	(0.029)	(0.032)
lagged ETF Expense Ratio	1.404	2.341	3.833	3.929	8.655**	9.860**
	(2.835)	(3.497)	(3.869)	(2.945)	(4.240)	(4.472)
lagged ln(Fund Family Size)	-0.004	-0.004	-0.002	-0.006	-0.007	-0.003
	(0.007)	(0.006)	(0.007)	(0.008)	(0.007)	(0.009)
Constant	-0.146*	-0.235**	-0.191	-0.076	-0.198	-0.123
	(0.083)	(0.112)	(0.128)	(0.092)	(0.135)	(0.150)
Lipper Class FE	No	Yes	No	No	Yes	No
Lipper Obj FE	No	No	Yes	No	No	Yes
Fund-Family FE	No	No	No	No	No	No
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund Cluster	Yes	Yes	Yes	Yes	Yes	Yes
MonthDateCluster	No	Yes	Yes	No	Yes	Yes
N	5449	5449	5449	4765	4765	4765
R2	0.997	0.997	0.997	0.997	0.997	0.997

Figure I. ETF Fund Flows after Launch

This figure plots the monthly fund flows for the subsamples of cloned and non-cloned active ETFs over the first 15 months after their launch. The subsample cloned ETFs includes both transparent and ANT ETFs while cloned ANT ETFs only includes the relevant ANT ETFs.

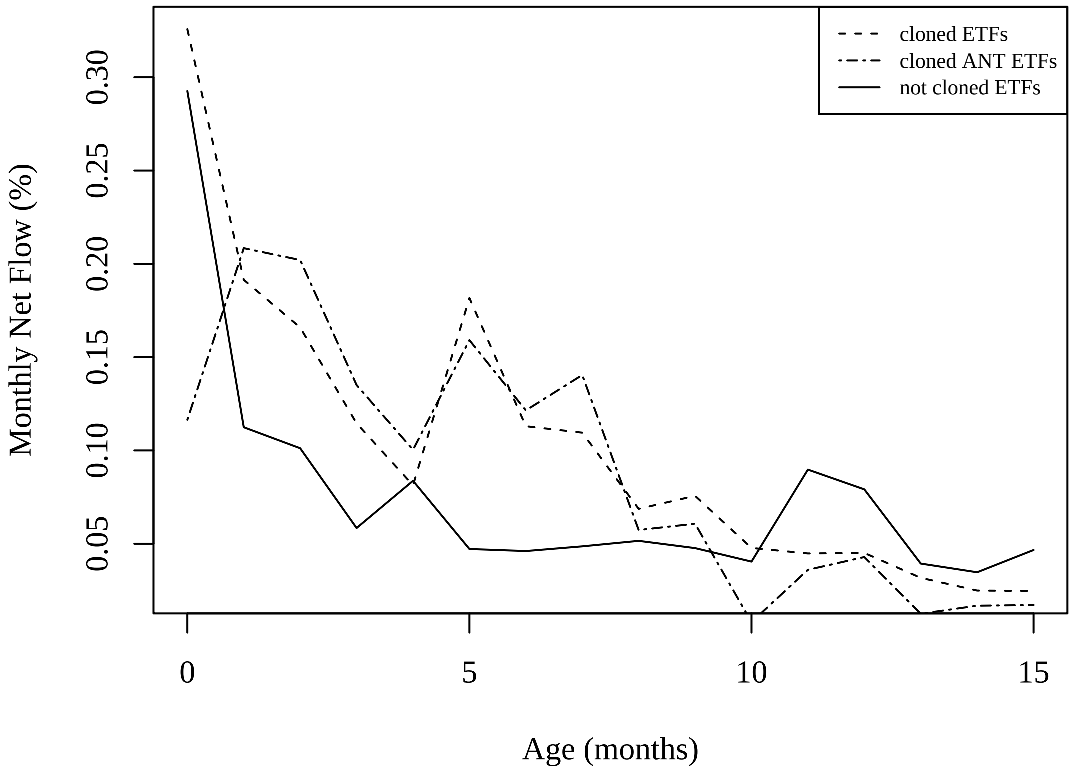


Figure II. Passive vs Active Institutional Ownership

This figure presents the time series of institutional ownership of active ETFs and passive ETFs over the 2018 - 2021 sample period. The data is plotted at the quarterly level and is sourced from 13-F filings. Market share is calculated as the market share value owned by institutions that report a 13-F filing divided by the total market shares of the ETFs. End of the month price and shares outstanding are used to calculate the market value.

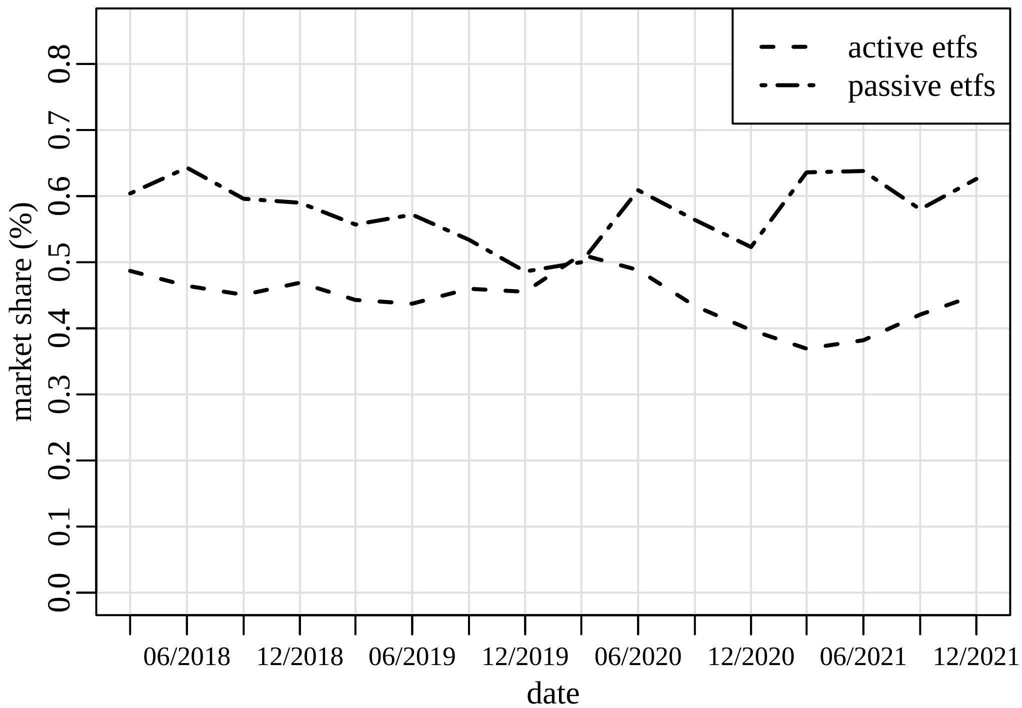
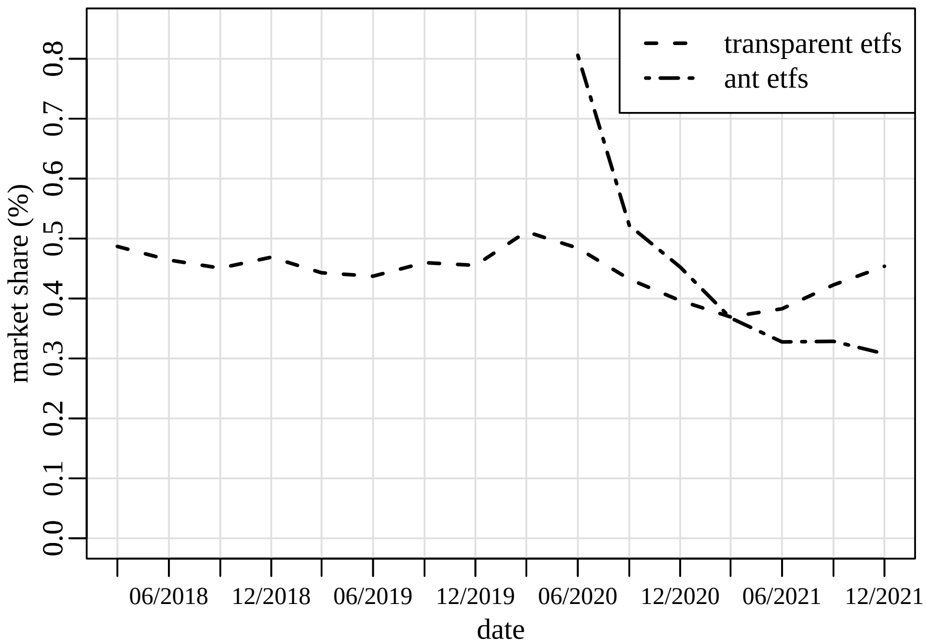
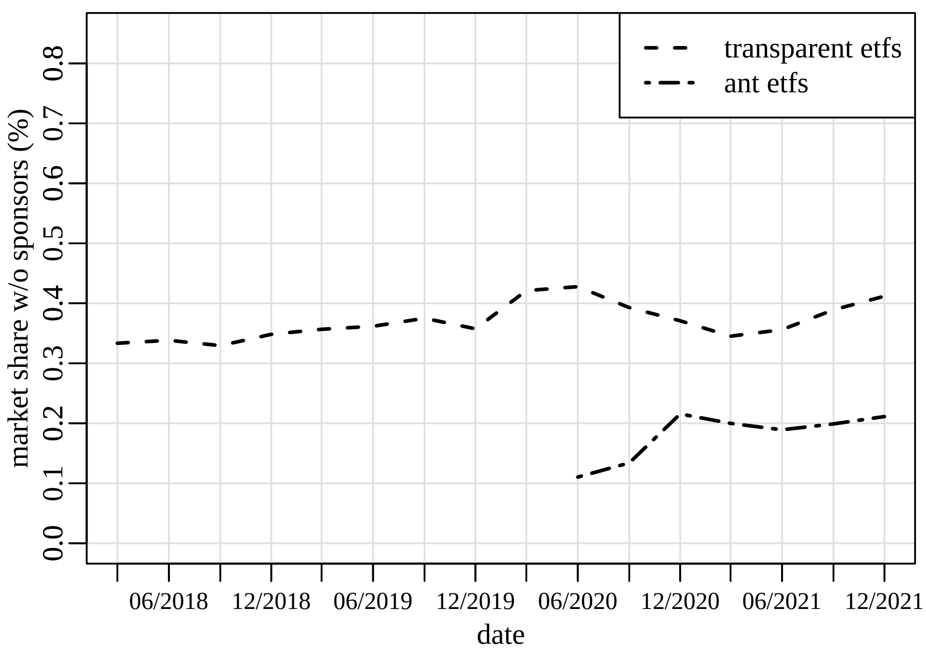


Figure III. Institutional Ownership of Active ETF Market By Date

These figures plot a time series of the institutional ownership of transparent ETFs and ANT ETFs from 2018 to 2022. The data is plotted at the quarterly level and is sourced from 13-F filings. Market shares is calculated as the market share value owned by institutions that report a 13-F filing divided by the total market shares of the ETFs. End of the month price and shares outstanding are used to calculate the market value. Market shares without sponsors represent the market share of the respective markets excluding sponsors of the ETF. For example, if the ETF is released by Vanguard, and holdings of the ETF reported by Vanguard is excluded.



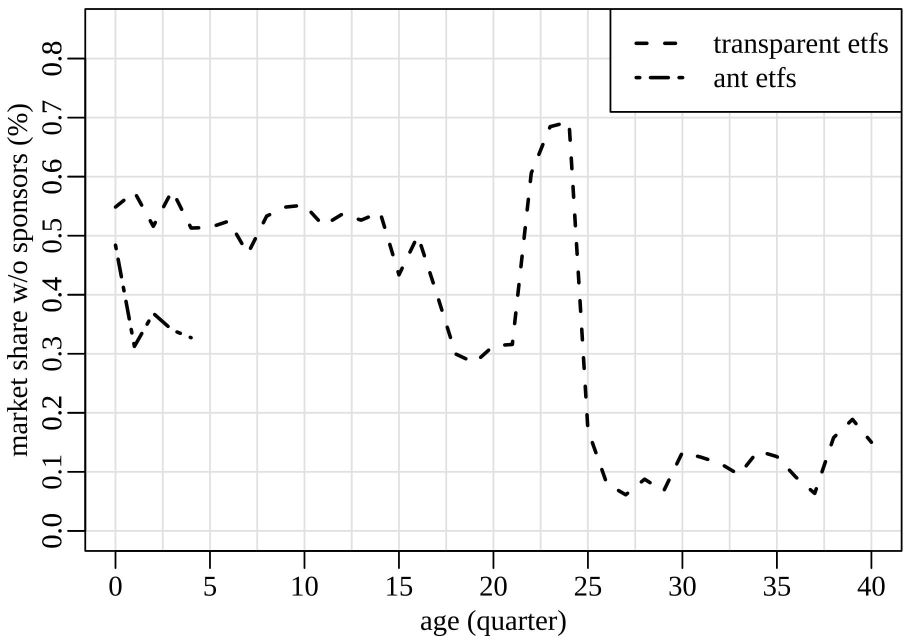
(a) Market Share with Sponsors



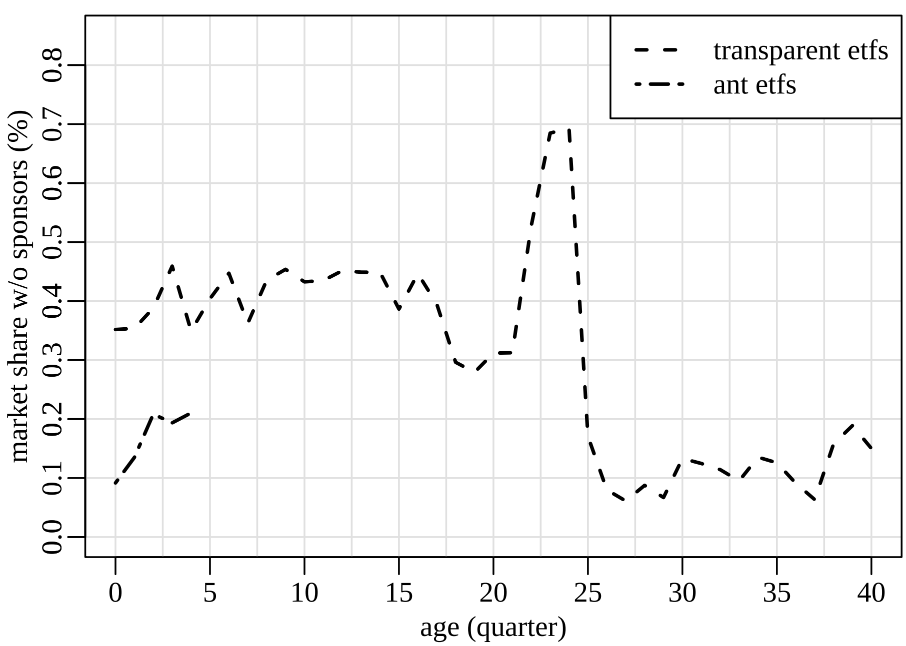
(b) Market Share without Sponsors

Figure IV. Institutional Ownership of Active ETF Market By Age

These figures plot the relationship between institutional ownership of transparent ETFs and ANT ETFs and the age of the ETF. The age of an ETF is calculated in quarters rounded down. This is because the 13-F data is at the quarterly level. Market shares is calculated as the market share value owned by institutions that report a 13-F filing divided by the total market shares of the ETFs. End of the month price and shares outstanding are used to calculate the market value. Market shares without sponsors represent the market share of the respective markets excluding sponsors of the ETF. For example, if the ETF is released by Vanguard, and holdings of the ETF reported by Vanguard is excluded.



(a) Market Share with Sponsors



(b) Market Share without Sponsors

Appendix

Table XIV. ETF Net Flows - Matched

This table presents results for the following regression:

$$ETF\_NetFlow_{i,t} = \beta_1 cloned_i + \Gamma X_{i,t-1} + \alpha\lambda_{f,t-1} + \gamma_i + \eta_t + \epsilon_{i,t},$$

where $cloned_i$ is a dummy variable equal to 1 if the majority of the portfolio managers of the ETF manage an active mutual fund in the same fund family, $ETF\_NetFlow$ is a ETF's monthly net flow normalized by the previous month's total net assets, X are fund level lagged control variables including log fund size, log fund age, net flow, CAPM alpha, volatility of CAPM alpha, and expense ratio, and λ is a fund-family level control: log of fund family size. The ANT sample consists of cloned non-transparent ETFs and all non-cloned active equity ETFs. The Equity sample includes all active equity ETFs. Standard errors are double clustered at fund and month-date level. Standard errors in parentheses. * (p<.1) ** (p<.05) and *** (p<.01).

	(1) ETF F Net Flow (%)	(2) ETF F Net Flow (%)	(3) ETF F Net Flow (%)
cloned	0.013*	0.020**	0.019***
	(0.008)	(0.008)	(0.007)
ETF ln(TNA)	-0.000	-0.006***	-0.003
	(0.002)	(0.002)	(0.002)
ln(1 + ETF Age)	-0.028***	-0.029***	-0.028***
	(0.005)	(0.007)	(0.007)
ETF CAPM Alpha	0.099	0.285***	0.200**
	(0.108)	(0.108)	(0.095)
σ(ETF CAPM Alpha) (12 month)	0.555	0.011	0.236
	(0.480)	(0.444)	(0.454)
ETF Expense Ratio	-1.621	-0.868	-1.470
	(1.026)	(1.215)	(1.205)
ln(Fund Family Size)	0.001	0.006**	0.003
	(0.002)	(0.002)	(0.002)
Constant	0.072***	0.116***	0.097***
	(0.025)	(0.024)	(0.022)
Lipper Class FE	No	Yes	No
Lipper Obj FE	No	No	Yes
Month-Year FE	Yes	Yes	Yes
Fund Cluster	Yes	Yes	Yes
MonthDateCluster	No	Yes	Yes
N	5862	5862	5861
R2	0.049	0.093	0.088

Table XV. Performance of Matched vs. non-Matched ETFs

This table presents results for the following regression:

$$CAPM\_Alpha_{i,t} = \beta_1 cloned_i + \Gamma X_{i,t-1} + \alpha\lambda_{f,t-1} + \eta_t + \epsilon_{i,t}$$

where *cloned* is a dummy variables indicating if the majority of the portfolio managers of the ETF manage an active mutual fund in the same fund family, X are fund level lagged control variables including log fund size, log fund age, net flow, lagged CAPM alpha, volatility of CAPM alpha, and expense ratio, and λ is a fund-family level control: log of fund family size. Standard errors are double clustered at fund and month-date level. Standard errors in parentheses. * (p<.1) ** (p<.05) and *** (p<.01).

	(1) CAPM	(2) CAPM	(3) CAPM	(4) FF3	(5) FF3	(6) FF3
cloned	0.385	0.106	0.142	0.267	-0.148	0.122
	(0.345)	(0.432)	(0.344)	(0.304)	(0.432)	(0.355)
lagged ln(ETF Size)	0.194**	0.296***	0.157*	0.141*	0.246**	0.143*
	(0.084)	(0.103)	(0.086)	(0.073)	(0.097)	(0.084)
ln(1 + ETF Age)	0.416	0.588	0.831	0.784***	0.950	0.906
	(0.299)	(0.766)	(0.671)	(0.245)	(0.765)	(0.702)
lagged ETF Net Flow (%)	0.606	1.035**	0.887**	0.226	0.703**	0.661*
	(0.483)	(0.407)	(0.373)	(0.459)	(0.340)	(0.369)
σ(ETF CAPM Alpha) (%)	0.752***	0.724***				
	(0.263)	(0.234)				
lagged ETF Expense Ratio	115.389***	82.422	67.477	102.123***	67.809	94.810
	(36.537)	(63.305)	(55.619)	(34.942)	(62.922)	(59.887)
lagged ln(Fund Family Size)	0.315***	0.173	0.306***	0.316***	0.210*	0.338***
	(0.096)	(0.126)	(0.108)	(0.086)	(0.121)	(0.113)
σ(ETF FF3 Alpha) (%)			0.796***	0.816***	0.519**	0.851***
			(0.223)	(0.271)	(0.250)	(0.267)
Constant	-12.802***	-12.248***	-12.854***	-13.171***	-12.534***	-13.427***
	(0.625)	(1.064)	(1.004)	(0.647)	(1.006)	(1.045)
Lipper Class FE	No	Yes	No	No	Yes	No
Lipper Obj FE	No	No	Yes	No	No	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund Cluster	Yes	Yes	Yes	Yes	Yes	Yes
MonthDateCluster	No	Yes	Yes	No	Yes	Yes
N	5998	5998	5710	5710	5710	5710
R2	0.860	0.900	0.902	0.876	0.906	0.891