Active ETFs Cloned from Mutual Funds: Competing for Investor Flows

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December 4, 2023

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

Competition for investor flows in the delegated investment management market has been high for many years, which has led to product innovations such as the introduction of exchange-traded funds (ETFs) in the early 1990s. Moreover, financial advisers have been increasingly preferring the ETF product over the mutual fund product for their clients (e.g., Andrus and Cummings (2022). In fact, the ETF market has been gaining strength on the mutual fund market. According to the 2023 Investment Company Institute Factbook, since 2010 growth in ETF assets under management has been 653%, while growth in mutual fund assets has been 187%. Evidence on the introduction and exit of ETFs versus mutual funds also shows striking differences. For example, in the U.S. in 2022, there were 414 new ETFs with 120 ETFs exiting. In contrast, the number of new mutual funds introduced to the market was 278 with 335 mutual funds exiting through mergers or liquidations. Not surprisingly, investment management companies have been offering more ETF products instead of, or alongside, their mutual fund products. Until recently, the dominant major competition for mutual funds from the ETF market has been through index funds, but more recent innovations in the ETF market regulatory environment has encouraged the introduction of additional actively managed ETFs.[1]

The innovation that has encouraged more investment managers to introduce actively managed ETFs to the market arises from the ability to hide some of their trading. That is, semi-transparent and non-transparent ETFs have been recently allowed by the SEC (as of September 2019). These new ETF models are designed to be more accommodating towards active management by exempting the managers from having to fully disclose their portfolios daily. Instead, the 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

[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.

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

When an investment management company wants to introduce 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 investment strategy that is differentiated from their current mutual fund strategies either by a small or large amount. Finally, they can establish the ETF as an additional share class for their mutual fund. [2] Mutual fund management companies have chosen each of these approaches. For example, Dimensional Fund Advisors have converted some of their mutual funds into active transparent ETFs. Doing so ensures no direct competition between the 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 this, several large fund management companies (Fidelity, T. Rowe Price, and Natixis) launched 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, 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

[2] Vanguard has held a patent on this approach, but their patent expiration year is 2023.

fund. There exist three possibilities. First, the mutual fund management 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 possible outcomes. (The sample necessarily only covers the period from 2020 to 2022 due to the recent regulatory changes to allow ANT ETFs.) We identify these clones as funds that are managed by the same portfolio manager, have a high portfolio overlap, and have similar or identical fund names. We have a total of 40 cloned active ETFs in our sample.[3] The tests of the three possible outcomes show no cannibalization as there is no significant decrease in monthly fund flows to the cloned mutual fund after the introduction of the cloned active ETF. In fact, we find that 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%.

Little evidence of cannibalization by the cloned ETFs is consistent with flow diversification to the investment company by adding a new distribution channel. Flow diversification (Wahal and Wang, 2022) from different clientele 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 is choosing to offer a cloned ETF because of flow diversification, we would expect the additional empirical observations as follows: (1) 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. (2) the mutual fund should be trading in a deep market where the flow diversification would pay off for the investment manager suggesting larger funds;and (3) more importantly, there should

[3]We identify 48 cloned active ETFs but end up with 40 pairs after merging with our other data sets.

be some clientele differences between the ETFs and mutual funds, even if from the same fund family. 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. 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. 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.

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 being a cloned ANT ETF has a stronger positive effect on monthly flows than a cloned transparent active ETF. In addition, 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. Thus, the evidence suggests that some of these additional flows 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 active ETFs. 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 these 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. [4]

Our paper contributes to several literatures. First, we contribute to the research on competition among mutual funds. Much of the related literature focuses on how competition results in decreasing management fees. The evidence suggests that fees are negatively correlated with fund size and market share (Coates and Hubbard (2007) and Khorana and Servaes (1999)). Khorana and Servaes (2012) conclude that price and product differentiation drive funds' market shares. 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 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 funds rather than the larger funds. We show that innovation in terms of new wrappers for an existing product appears to come from the larger funds. Wahal and Wang (2011) use a measure of portfolio overlap and entry of new funds to show 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 use a unique setting where 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.

[4] 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.

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.

The rest of the paper proceeds as follows. Section 2 presents some institutional background and hypotheses that we will test. Section 3 describes the data. Section 4 presents our results. Section 5 concludes. The Appendices contain additional robustness tables.

2 Hypotheses

2.1 Background - Exchange-Traded Funds

According to the 2022 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

The first main question we address is the effect of the cloned ETF on the mutual fund. Using a cloned strategy means that the original mutual fund is still active, which implies that the new cloned ETF could be a competitor to the original mutual fund, consequently cannibalizing flows from the original mutual fund. Since ETFs are often more accessible to investors and generally 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 be absorbing new flows that would have 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 active mutual fund after the introduction of the cloned active ETF.

2.3 Cloned Active ETFs vs. non-Cloned Active ETFs

The next major question we address is why fund families choose to clone one of their pre-existing mutual funds instead of converting the fund or creating a differentiated strategy (given that they have decided to launch an ETF). As we have hypothesized, 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. In addition, given the cost of advertising mutual funds as found by Roussanov, Ruan, and Wei (2021), having a cloned ETF would share these 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. Past reputation should be more important for actively managed ETFs given that they do have data on past performance. This is 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 cloned active ETFs are attracting more flows than non-cloned active ETFs as we predict, it is important to understand the source of these flows. We propose two possible explanations.

2.4.1 Clientele

The first hypothesis is that the cloned ETF attracts clientele that do not completely overlap with the clientele of the mutual funds. Given the somewhat segmented market between mutual funds, which are often offered through retirement accounts, and ETFs, which are accessible to all investors particularly through popular retail investor trading platforms such as Robinhood, e-Trade, and Vanguard. Thus, we consider that active ETFs attract a different clientele than active mutual funds and, therefore, the cloned active ETFs attract new flows to 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 SEC ruling restricts the ANT ETFs to domestic equity funds. 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 report at least one mutual fund holding in our sample from 2013 to 2021.

[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.

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 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 do require that the pairs invest in similar strategy categories identified by Lipper class so that it makes sense 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.

3.4 Summary Statistics

Table II presents summary statistics for all of 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. There are few fund families that have launched ANT ETFs as of 2022, possibly due in part to the upfront costs of obtaining a license to enable them to create these new products. In our sample, there are 7 unique fund families that offer ANT ETFs: Fidelity, T Rowe Price, Natixis, Invesco, Franklin Templeton and Fred Alger. In our larger sample of matched clones including transparent ETFs, there are 18 unique fund families that offer a cloned ETF.

4 Empirical Results

4.1 The effect of being cloned on the underlying mutual fund

In this section we examine whether the cloned active ETF affects the underlying mutual fund flows. That is, a natural concern when introducing an active ETF that is offering essentially the same strategy as a pre-existing mutual fund is how the cloned ETF could compete for investor demand. The new cloned ETF could serve as a substitute for the pre-existing mutual fund, as these active ETFs follow the same strategy while typically offering the advantage of a lower expense ratio and the ability to be traded more frequently. If cannibalization occurs, 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, we construct a dummy variable, $cloned_{i,t}$, which equals 1 if the cloned active ETF for active mutual fund i exists in time t. In other words, for active mutual funds that are never cloned, *cloned* is always 0. On the other hand, for active mutual funds that are selected by the investment management company to be cloned, *cloned* is equal to 1 once the cloned active ETF is launched.

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 only cloned active mutual funds, which we term "All-Clones." We also run this regression for a sub-sample of the cloned active mutual funds that were cloned into ANT ETFs (i.e. active mutual funds matched with ANT ETFs). We call this sub-sample of cloned active mutual funds "ANT-Clones." As any effect should be relatively short term, we limit the monthly observations for the mutual funds to 6 months before and after the introduction of the cloned active 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 any fund characteristics constant over time. This means the regression is comparing net flows within a fund before and after the introduction of its cloned active

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 did 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 compared to other similar active mutual funds at that same time. The structure of this analysis is similar to a stacked generalized difference in difference, where 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 experienced more monthly net flows than similar active mutual funds after the introduction of the cloned ETF. The introduction of a cloned ETF seems 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 their being cloned, that is, just before the launch of the cloned active ETF. In addition, we compare the characteristics of the chosen active mutual fund to other active mutual fund options the fund family offered at that time. In other words, we want to compare the active mutual fund characteristics while controlling for fund-family $\times$ month-year fixed effects. This approach allows us to examine how the chosen active mutual fund compared 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 mutual fund observations from the same fund-family up to 5 years before the launch of a clone active ETF.

To determine which types of active mutual funds are more likely to be cloned, we perform a logit regression with the dependent variable, *cloned*, which is 1 if the the active mutual fund was 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 all cloned active mutual funds while Table VI uses the sub-sample of active mutual funds that were cloned into an ANT ETF. Column headers indicate what model/measure was used 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 active mutual 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 that had higher past net flows, are larger in size, older, and have a higher expense ratio 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. With the exception of expense ratio and fund size, we find the results to be consistent for the ANT results reported in Table VI. [6]

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 instead of creating a new strategy derives from a potential advantage that a cloned active ETF has over a non-cloned active ETF. Since a fund family's goal is to increase net flows to earn more return on the expense ratios they charge, a natural test is to study the effect that being a clone has on an active ETF's net flows. If having a pre-existing mutual fund counterpart has an advantage, such as past reputation or perfor-

[6] The lack of significance in some of the effects may also be a result of the smaller sample of cloned mutual funds in the sub-sample.

mance, over introducing a completely new strategy, we expect that being a clone would have a positive effect on the net flow for active ETFs. In other words, 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 an 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 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 and most of the cloned active ETFs were launched during that time 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 are presented in Table VII. 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 flow 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 includes 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 ETF's flows of having a counterpart mutual fund may change over time. In particular, we expect that the importance of having a pre-existing mutual fund may decrease over time as the active ETF ages as there is then more historical information about the ETF itself for investors to employ in evaluating the active ETF and its managers. Thus, we may 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 its launch in Figure I. We find that cloned ETFs attract more flows in the initial months right after their launch 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.

These results suggest that active ETFs that are cloned from a pre-existing mutual fund are indeed able to attract more monthly net flows than active ETFs that have no matching pre-existing mutual fund, especially in the months right after their launch. Our next natural questions are then what is driving these flows and what is the source of these flows. We shed light on these questions in the rest of the paper.

4.4 Clientele of active ETFs

To better understand the source of the flows into the active ETFs, we use institutional holdings data to characterize the clientele of the different products that we are studying. We construct a measure of the market share that is owned by institutions by aggregating the market value of shares held by institutions and dividing it by the total market value of available shares.

In Figure II, the percentage market share for active ETFs and passive ETFs with regard to institutional ownership are plotted over time. Over the sample period, the figure shows that the passive ETF market has a higher percentage of institutional investors compared to the active ETF market. This is not surprising since institutional investors often employ 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. Many of the active ETFs are launched during our sample period. As a result, the data shows that some of them are initially held by their sponsor. 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 two measures. The first shows the institutional ownership of the transparent ETF market and the ANT ETF market over time using our measure including all ownership and second shows the ownership of the two types of ETFS after we exclude sponsor ownership. As the first figure shows, there exists 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. Once we remove sponsor ownership, the institutional ownership remains relatively flat. 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 the second figure 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 compared to some transparent active ETFs. Thus, we also plot the institutional ownership of the two markets by age of the ETF to compare similar age ETFs in Figure IV. 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 ETF market has a lot less institutional ownership than the transparent active ETF, at least during the early periods. This result suggests that the ANT ETF market clientele is more heavily composed of retail investors compared to active ETFs.

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 was good and most of the cloned active ETFs were launched during that time 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.

We run the regression for two samples of our data: a sample that includes all of the cloned active ETFs 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 IX 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 when there are 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 (column (4) and (6)). Thus, it does not appear that cloned active ETFs significantly exhibit better performance than non-cloned active ETFs.[7]

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

[7]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.

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 this case, we may not see a significant decrease in net 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 an additional clientele.

References

Andrus, D., and B. Cummings. 2022. 2022 trends in investing. *Journal of Financial Planning* 35:44–9.

Ben-David, I., F. Franzoni, B. Kim, and R. Moussawi. 2022. Competition for attention in the ETF space. *Forthcoming Review of Financial Studies* .

Clifford, C. P., J. A. Fulkerson, and B. D. Jordan. 2014. What drives ETF flows? *Financial Review* 49:619–42.

Coates, J. C., and R. G. Hubbard. 2007. Competition in the mutual fund industry: Evidence and implications for policy. *Journal of Corporation Law* 33:151–222.

Cremers, M., M. A. Ferreira, P. Matos, and L. Starks. 2016. Indexing and active fund management: International evidence. *Journal of Financial Economics* 120:539–60.

Dannhauser, C. D., and J. Pontiff. 2019. Flow. *Available at SSRN 3428702* .

Dannhauser, C. D., and H. D. Spilker. 2023. The modern mutual fund family. *Journal of Financial Economics* 148:1–20. ISSN 0304-405X. doi:https://doi.org/10.1016/j.jfineco.2023.02.001.

Densmore, M. 2022. The growth of passive indexing and smart-beta: Competitive effects on actively managed funds. *Available at SSRN 3823328* .

Easley, D., D. Michayluk, M. O'Hara, and T. J. Putniņš. 2021. The active world of passive investing. *Review of Finance* 25:1433–71.

Gruber, M. J. 1996. Another puzzle: The growth in actively managed mutual funds. *The Journal of Finance* 51:783–810. doi:https://doi.org/10.1111/j.1540-6261.1996.tb02707.x.

Khorana, A., and H. Servaes. 1999. The determinants of mutual fund starts. *The Review of Financial Studies* 12:1043–74.

———. 2012. What drives market share in the mutual fund industry? *The Review of Finance* 16:81–113.

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

———. 2021. The market for fund benchmarks: Evidence from ETFs. *Available at SSRN 3804002* .

Luo, M., and D. Schumacher. 2022. Why is there so much side-by-side management in the ETF industry? *Available at SSRN 3890147* .

Moussawi, R., K. Shen, and R. Velthuis. 2022. ETF heartbeat trades, tax efficiencies, and clienteles: The role of taxes in the flow migration from active mutual funds to ETFs. *Available at SSRN 3744519* .

Roussanov, N., H. Ruan, and Y. Wei. 2021. Marketing mutual funds. *Review of Financial Studies* 34:3045–94.

Sun, Y. 2014. The effect of index fund competition on money management fees. *Available at SSRN 2432361* .

Wahal, S., and A. Y. Wang. 2011. Competition among mutual funds. *Journal of Financial Economics* 99:40–59.

———. 2022. Flow diversification. *Available at SSRN 4013988* .

Zheng, L. 1999. Is money smart? a study of mutual fund investors' fund selection ability. *The Journal of Finance* 54:901–33. doi:https://doi.org/10.1111/0022-1082.00131.

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) All		(2) No Clones		(3) Transparent Clones		(4) 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	5369.000
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 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) All-Clones
treated	0.194***	0.202***	0.188***	0.202***
	(0.073)	(0.075)	(0.063)	(0.064)
treated × 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	1721.000	1722.000	1723.000	1721.000
R2	0.124	0.098	0.157	0.176

Table IX. 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.

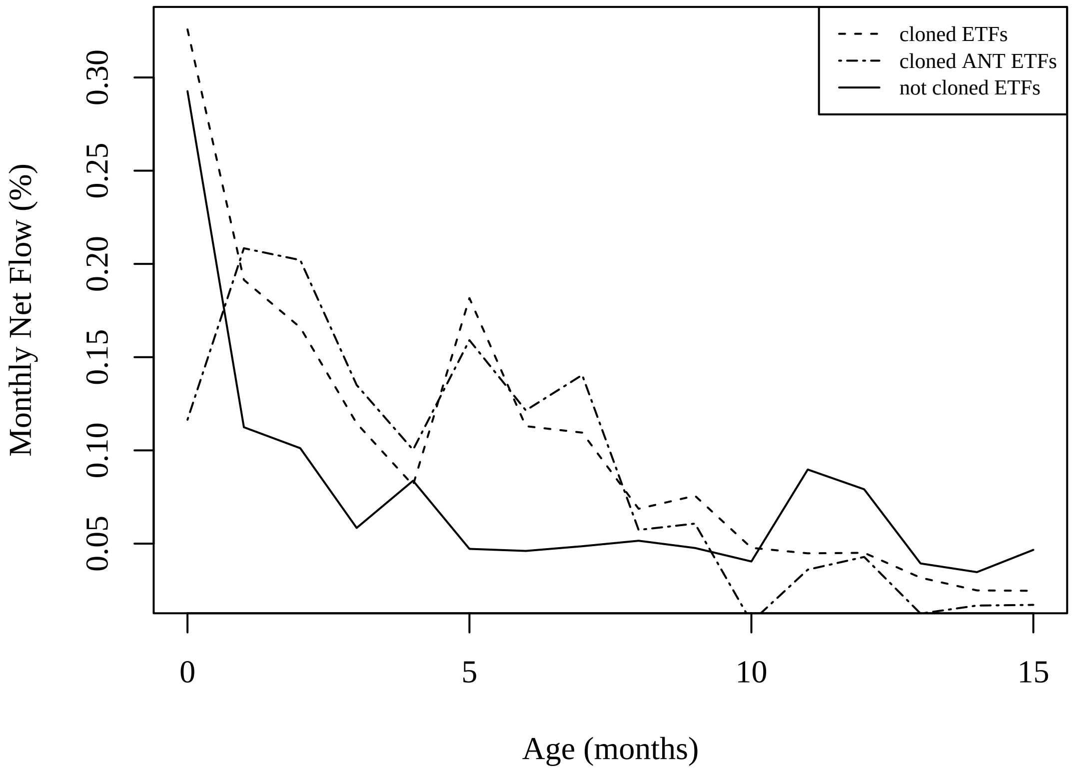


Figure II. Passive vs Active Institutional Ownership

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.

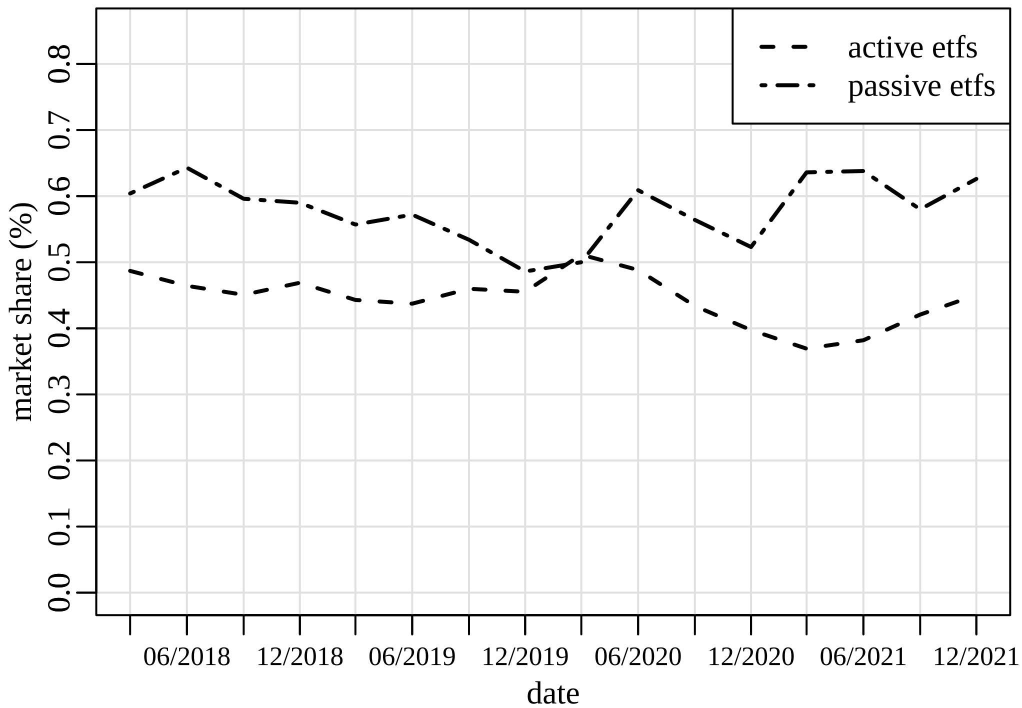
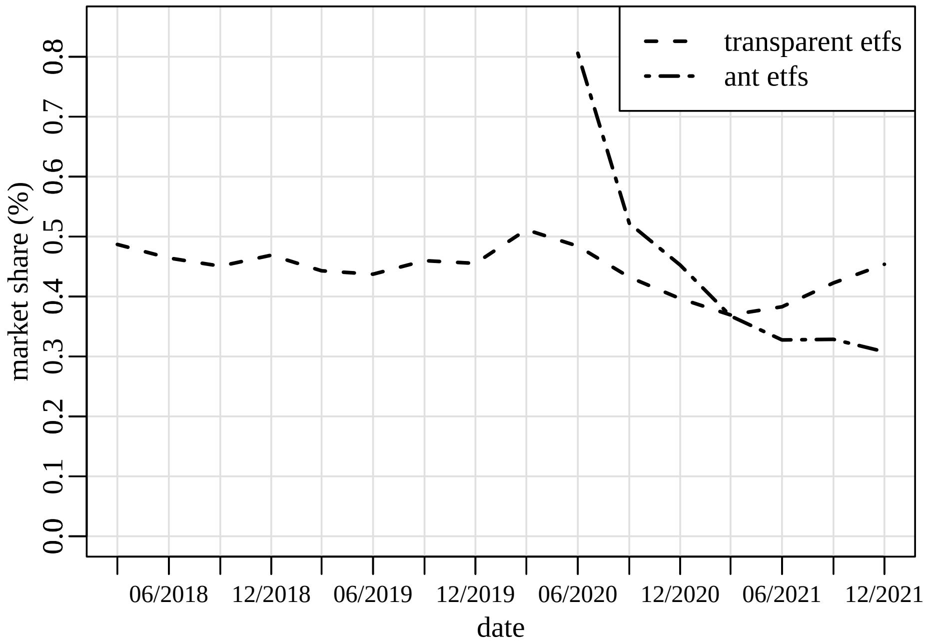
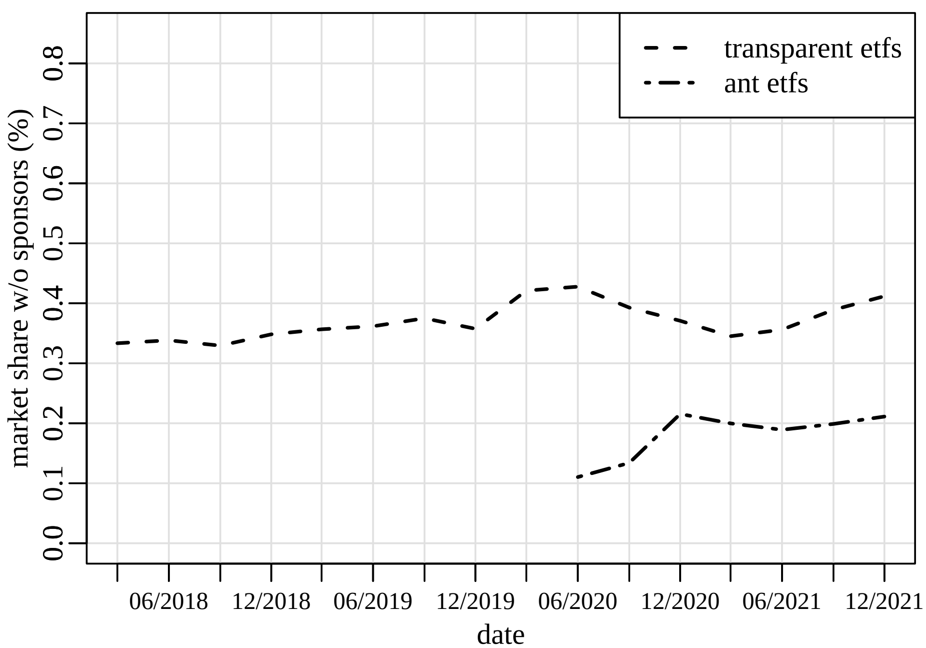


Figure III. Institutional Ownership of Active ETF Market By Date

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.



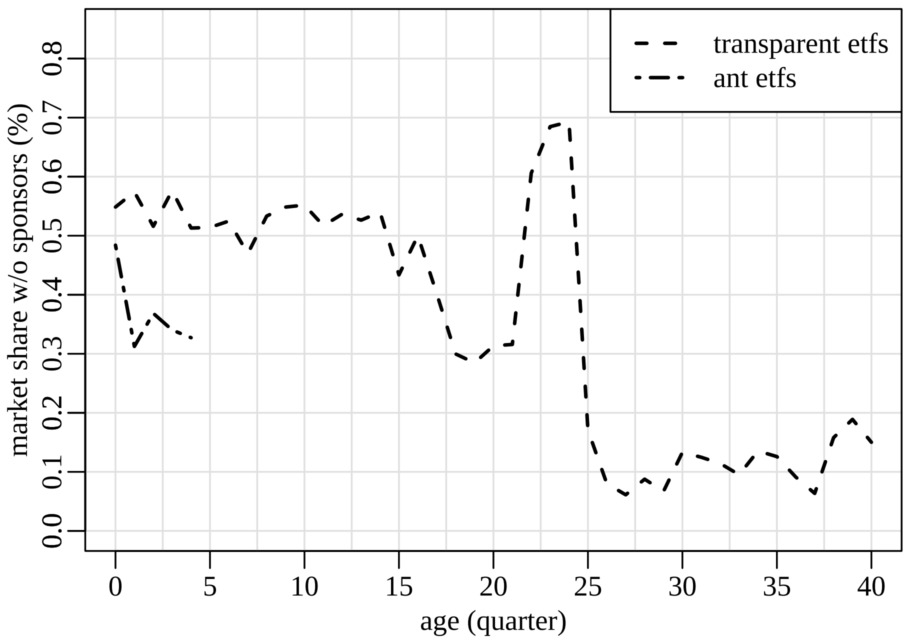
(a) Market Share with Sponsors



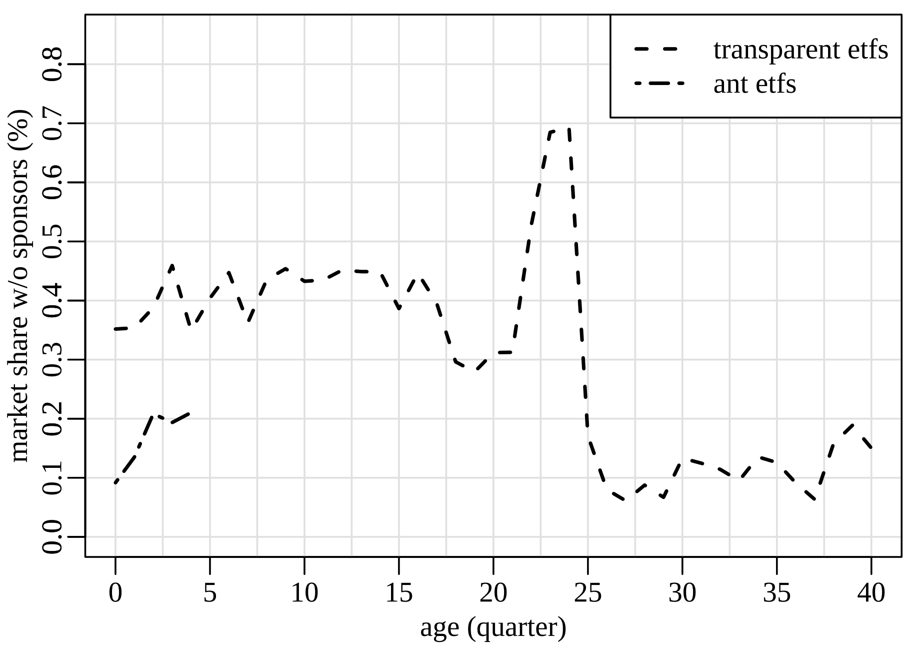
(b) Market Share without Sponsors

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 X. 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 XI. 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