# THREE ESSAYS ON ACTIVE ETFs

# Three Essays on Active ETFs

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# Abstract

This thesis studies actively managed exchange-traded funds (AETFs).

In the first chapter, I investigate the impact of daily holdings disclosure requirement on AETFs' activeness level. Using data on equity AETFs traded in the US market, I find that ETFs are generally more active than their comparable mutual funds (CMFs). The results are robust across various activeness measures and are generally consistent across different investment styles. The greater activeness can be due to the fact that AETFs are a new product and so their managers need to differentiate their funds from mutual funds and try to generate excess returns.

In the second chapter, I extend the investigation into the impact of daily disclosure requirement on the performance of AETFs, using both returns-based and holdings-based approaches. I find that, firstly, AETFs, on average, underperform their CMFs and have more negative market-timing skills. Secondly, an examination of characteristic holdings-based metrics indicates that the average stock-selection ability of AETFs is inferior to that of CMFs. Lastly, an evaluation of portfolio trades suggests that AETFs struggle to generate positive returns from their trades, while the CMFs seem able to generate significant returns from the stocks that they buy.

In the third chapter, I study the factors that affect the likelihood of AETFs termination and compare them to those of actively managed mutual funds (AMFs). I find that age and expenses appear to hold limited significance for AETFs, in contrast to their potential importance for AMFs. Further, contrary to the case

of AMFs, fund excess returns have no discernible impact on the likelihood of liquidation of AETFs. Lastly, the performance of other funds within the same objectives holds more substantial influence over the likelihood of AETFs liquidation than individual fund attributes do.

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# Declaration of Authorship

I, Lulu Zhang, declare that this thesis, entitled, "Three Essays on Active ETFs", and the work presented in it, are my own. I confirm that the thesis comprises the following chapters:

- Active ETFs: The Effect of Daily Holdings Disclosure Requirements on Their Activeness
- Active ETFs: The Effect of Daily Holdings Disclosure Requirements on Their Performance and Trading Strategies
- The Hype of ETFs Closures? Not the case for Active ETFs

This thesis is entirely my own original work unless otherwise indicated. Any use of the work of other authors is acknowledged at their point of use.

# Introduction

Assets poured into actively managed exchange-traded funds (active ETFs, or AETFs) have significantly increased in recent years, and more fund companies have joined the queue to launch more AETFs. Compared to actively managed mutual funds, AETFs have frequent (daily) disclosure requirements, lower expenses, higher tax efficiency, and so on. However, the daily disclosure requirement could bring free-riding risk and front-running risk and limit the ability of active ETF managers to release their investment insights/skill; it reduces their incentives to collect and process information (Agarwal et al. 2015). As a result, managers of active ETFs may be less active than comparable active mutual funds, which face less frequent disclosure demand.

In the first chapter, I investigate the effects of the daily portfolio disclosure requirement on the activeness level of US active ETFs. I find that active ETFs are indeed more active than their comparable mutual funds (CMFs). This finding indicates that issuers need to differentiate their offerings from the existing products (i.e., mutual funds) and may choose to also compete on non-price dimensions such as making their ETFs more active. The second reason could be that ETFs are sold directly to investors, as opposed to (retail) mutual funds that are commonly sold through brokers, bundled with financial advice and portfolio-management service. Guercio and Reuter (2014) show that direct-sold funds do more active management. Lastly, active ETF managers, despite the risk from frequent disclosure, try to be more active in the hope that they will achieve better performance in order to attract fund flows. Consistent with this, Easley et al. (2021) show that highly active ETFs are gaining more market share over less-active ETFs.

In the second chapter, I examine the performance of AETFs and compare it to that of traditional mutual funds in order to determine whether it is affected by the daily portfolio disclosure requirement. This is done through the channel of returns- and holdings-based performance measures. In addition, I analyze the trades that AETFs conduct (i.e., buys and sells) to see how fund managers' actual trades impact fund performance. First, I find that AETFs, despite their higher activeness level, exhibit underperformance against CMFs in terms of returns-based performance measures, both unconditionally and conditionally. Furthermore, AETFs are shown to possess a counterintuitive (negative) timing ability within returns-based timing models, in contrast to CMFs, which typically lack timing proficiency. Secondly, the examination of characteristic holdings-based metrics also indicates the average stock selection ability of AETFs is inferior to that of CMFs. Lastly, an evaluation of portfolio trades suggests that AETFs struggle to generate positive returns from their buy-and-sell transactions, while CMFs seem able to generate significantly positive buy returns from their selected stocks.

High passive ETF closures have been observed in recent years, while the closure risk of active ETFs has not been well documented. The last chapter studies the impact of underlying factors on AETFs liquidations and compares them to those of actively managed mutual funds (AMFs). I find that AETFs and AMFs exhibit commonalities in certain fund-level influencing factors, particularly size and fund inflow, which negatively correlate with the probability of liquidation. However, expense ratios appear to hold limited significance for AETFs, in contrast to their positive influence on AMFs terminations.

Intriguingly, I do not find fund excess return relevant to the liquidation likelihood of AETFs, unlike the significant and negative role it plays for AMFs. In other words, the underperformance does not seem to punish AETFs in the same way as AMFs, and as a result, fund families might be inclined to continue launching AETFs to attract assets, potentially without being concerned about achieving exceptional performance. In a broader context, the performance of the entire objective category holds more substantial influence over the likelihood of AETFs liquidation than that of AMFs.

# Chapter 1

# Active ETFs: The Effect of Daily Holdings Disclosure Requirements on Their Activeness

## 1.1 Introduction

Actively managed exchange-traded funds (henceforth, Active ETFs, or AETFs) are a recent innovation in the ETF market. In contrast to traditional ETFs, which attempt to track equity or bond indices passively, active ETFs are actively managed by their managers, who devise investment strategies and decide on what securities to buy, sell, or hold at their discretion. The first-ever active ETF was introduced in the US market in 2008. Since then, this segment of the market has gradually grown. As of October 2023, there are over 1,200 active ETFs listed on US exchanges with combined assets under management of around $444 billion (Source: Morgan Stanley, see https://www.morganstanley.com/ideas/

actively-managed-etfs-investor-demand, all figures in US dollar).[1] These ETFs invest in various assets such as stocks, bonds, and currencies. Some of them use investment strategies that are typically associated with hedge funds, such as long-short and market-neutral strategies. Outside North America, there are active ETFs traded in major European markets such as the UK and Germany. The products have also been introduced in Asia-Pacific markets such as Australia and South Korea.

The rate of growth of active ETFs varies across markets. In the US, active ETFs have been growing consistently but slowly, and currently account for a small fraction (around 7%) of the whole ETF market (in terms of assets under management).[2] The major reason for the slow growth is that, as with traditional (i.e., passive) ETFs, active ETFs traded in the US market are required to disclose their entire holdings to the public on a daily basis. This is because the Securities and Exchange Commission (SEC) is concerned about pricing efficiency, and so it wants to make sure that the arbitrage linkage between ETF prices and net asset values (NAVs) is in place, which requires knowledge of the details of the portfolios that active ETFs are holding. As a result, several fund providers have indicated that they are reluctant to offer active ETFs for fear that other market participants can free-ride on their research, strategies, and security-picking ability. These fund providers are also concerned about the possibility that the knowledge of their funds' portfolio holdings can be used against them (e.g., other traders can

[1] The number of active ETFs listed in the US market can vary slightly from one source to another because some fund issuers are not very clear in stating the objectives of their funds, and so their classification is open to interpretation.

[2] As a comparison, in the Canadian market, active ETFs have grown rapidly and now (October 2023) represent about 31% of the Canadian ETF market (highest among the G7 countries).

front-run them when they are trying to accumulate a position in a stock.).[3]

In this paper, I investigate the effects of the daily portfolio disclosure requirement on the activeness level of US active ETFs. On the one hand, because the daily disclosure requirement limits the ability of active ETF managers to receive full benefits from their information, it reduces their incentives to collect and process information (Agarwal et al. 2015). As a result, managers of active ETFs may refrain from searching for stocks that have high information asymmetry (e.g., small-cap stocks or stocks with low analyst coverage). That is, the daily disclosure requirement can cause active ETFs to be less active (and thus more resemble index funds) than comparable active mutual funds, which face less frequent disclosure demand.

On the other hand, there are reasons why active ETFs can be more active than comparable active mutual funds. First, active ETFs are a relatively new product. Without a long track record, the issuers need to differentiate their offerings from the existing products (i.e., mutual funds). While ETFs already offer a cost advantage over mutual funds, the providers may choose to also compete on non-price dimensions such as making their ETFs more active. This argument is consistent with a prediction in Mamaysky and Spiegel (2002) that newly created funds should provide trading strategies that are significantly different from

[3] Fund providers recognize that investors are now more conscious about funds' management fees, and the ease of trading in an increasingly volatile market. Since ETFs can be traded during trading hours and have lower management fees than those of comparable mutual funds, fund providers want to offer their products in the form of active ETFs if the daily disclosure requirement can somehow be relaxed. During the past few years, several of them (e.g., Fidelity and T. Rowe Price) have received permission from the SEC to offer their versions of active ETFs that are not fully transparent (often called "non-transparent" or "semi-transparent"). These funds are allowed to disclose their holdings monthly or quarterly (which is similar to what mutual funds do). These new, semi-transparent active ETFs are not the subject of this study.

those of existing funds. Khorana and Servaes (2012) show that both price and non-price (i.e., product differentiation) competition is effective for new funds to gain market share. While these two studies examine competition among mutual funds, it is reasonable to expect that their results also apply to ETFs, which are a closely-related product.

The second reason for the ETFs being more active is that, by design, ETFs are sold directly to investors, as opposed to (retail) mutual funds that are commonly sold through brokers, bundled with financial advice and portfolio-management service. Guercio and Reuter (2014) show that mutual funds marketed directly to retail investors have more incentive to generate alpha or abnormal risk-adjusted returns than funds sold through brokers do. As a result, direct-sold funds do more active management.

Finally, Clifford et al. (2014) show that investors pursue returns of active ETFs in the same way as they chase mutual funds' returns (Berk and Green 2004). Accordingly, active ETF managers, despite the risk from frequent disclosure, try to be more active in the hope that they will achieve better performance in order to attract fund flows. Consistent with this, Easley et al. (2021) show that highly active ETFs are gaining more market share over less-active ETFs.

To measure the ETFs' activeness levels, I use four different approaches that are common in the mutual funds literature. They are tracking error volatility, Active Share, Active Weight, and selectivity (i.e., $1 - R^2$). These approaches use either funds' returns or their holdings as input, and emphasize different aspects of activeness (e.g., stock selection vs. factor timing). Since these approaches have their strengths and weaknesses, they are typically used together in order to provide a complete picture of activeness (see Section 1.3 for a detailed discussion).

I divide the sample of active ETFs traded in the US market into two groups. The first group consists of those whose specified objectives are to outperform broad-based (i.e., diversified) equity benchmarks, while the second group consists of those that concentrate on certain sectors of the market. The two groups are analyzed separately because of their different nature and risk-return profiles. In addition, a few prior studies find that investment ability is more evident among managers who hold portfolios concentrated in one or a few industries than those who hold diversified portfolios (e.g., Kacperczyk et al. 2005).

This paper's findings are as follows. First, diversified active ETFs are generally more active than their control mutual funds. This is true, on average, for all four activeness measures (i.e., all activeness aspects). Secondly, when I divide diversified active ETFs into subgroups according to their investment styles (e.g., multi-cap, large-cap, and small-cap), I find that the differences in the activeness measures between the ETFs and their control funds are generally significant across all subgroups, with a possible exception for the small-cap subgroup, where the results are inconclusive across the four activeness measures. Thirdly, for sector active ETFs, they are also generally significantly more active than their control mutual funds based on all four activeness measures. Finally, there is evidence that sector ETFs are more active (relative to their control mutual funds) than diversified ETFs are (relative to their control funds).

This paper is organized as follows. In the next section, I reviewed the relevant literature. Section 1.3 and Section 1.4 discuss the methodologies and the data that I use, respectively. Section 1.5 shows the results, and Section 1.6 concludes.

## 1.2 Relevant Literature

As active ETFs are a relatively new product, the literature on them is still limited. The existing studies mainly examine the performance of active equity ETFs. They report that these ETFs, in general, do not outperform index (or passive) ETFs (e.g., Dolvin 2014; Garyn-Tal 2013; Rompotis 2009; Rompotis 2011a; Rompotis 2011b; Schizas 2014). Although some of these studies allude to the potential problems of active ETFs' daily disclosure requirement, none of them investigates how the transparent nature of active ETFs affects the funds' activeness or performance.[4]

In comparison, the literature on actively managed mutual funds is vast and extensive. Numerous studies examine the activeness of mutual funds, using well-established measures such as trading error volatility (e.g., Grinold and Kahn 1995), Active Share (e.g., Cremers and Petajisto 2009), and selectivity (e.g., Amihud and Goyenko 2013). Cremers and Petajisto (2009) classify mutual funds with Active Share values greater than 60% as "active", and find that funds with high Active Share values tend to outperform their benchmarks. Amihud and Goyenko (2013) show that higher selectivity predicts better performance. Besides, the concentration of portfolios can also be an indicator of funds' activeness level. Kacperczyk

[4] See Meziani and Meziani (2016) for a detailed description of the concerns of the daily disclosure requirement on active ETFs.

et al. (2005) show that funds with more concentrated holdings within certain industries (i.e., more active by reason of deviating from the market benchmarks) are more likely to achieve better performance.

With respect to the effects of portfolio disclosure requirements on funds' activeness or performance, Wermers (2001) argues that more frequent portfolio disclosure will hurt the returns of mutual funds. The reason is that when funds are required to reveal their holdings frequently, other investors can front-run on their trades and free-ride on their information and trading strategies. Frank et al. (2004) show that copycat funds can earn statistically indistinguishable or possibly higher after-expense returns. Following the regulatory changes by the SEC in 2004 requiring mutual funds to disclose their holdings more frequently (from semi-annually to quarterly), several studies investigate the effects of this change (e.g., Ge and Zheng 2006; Agarwal et al. 2015; Parida and Teo 2018). These studies find that the increased frequency leads to higher costs for funds with informational advantage and causes funds to suffer more front-running activities.

One implication of the above findings on active ETFs is that, because active ETFs are required to reveal their portfolio holdings daily, active ETFs may choose to become less active in order to reduce the possibilities that the public can free-ride on their private information and research.[5] This is what I intend to investigate in this paper.

[5] This may be especially true for fund managers who have an informational advantage and trade frequently to exploit investment opportunities in the short term.

## 1.3 Measures of Funds' Activeness

In this section, I discuss several methodologies commonly used in the literature to measure the activeness of investment funds.

Active managers attempt to add value to their funds by deviating from benchmark indices using one or both of two strategies – stock selection and factor timing. With stock selection, fund managers hold individual securities that they believe have the potential to outperform others. On the other hand, factor timing refers to the time-varying allocation of funds' assets across systematic risk factors according to the managers' outlook of future returns. The risk factors can be, for example, certain industries, certain sectors of the economy, or any systematic risk not fully reflected in the benchmark.

In the mutual funds literature, there are several approaches to measure the activeness of a fund. These approaches use either funds' returns or their holdings to identify the stock selection and/or the factor-timing aspects of activeness. All approaches have their strengths and weaknesses, and are therefore typically used together in order to provide a complete picture of activeness.

### 1.3.1 Tracking Error Volatility

Tracking error volatility is defined as the standard deviation of the time series of differences between a fund's returns and its benchmark's returns (Grinold and Kahn 1995). Formally, denote the fund's return at time $t$ by $R_{fund,t}$ and its benchmark's return by $R_{benchmark,t}$. The tracking error volatility (TEV) is then:

$$TEV = St.dev[R_{fund,t} - R_{benchmark,t}] \tag{1.1}$$

That is, TEV measures the volatility of the fund's returns that is not explained by the benchmark returns. Intuitively, because the performance of a fund manager is typically compared to that of a benchmark, TEV represents the risk that the fund is actively taking in order to outperform the benchmark. The higher the TEV, the more active a fund is.

Petajisto (2013) argues that TEV is more adept at measuring the extent of a fund's factor-timing than the extent of its stock selection. He compares two portfolios – one deviating from the benchmark by overweighting one of the sectors, and the other deviating by investing in only one stock from each sector while keeping the same sector weights as that of the benchmark. The first portfolio will have a higher TEV because it exposes the manager to sector (or factor) risk while most of the risk in the second portfolio's active positions will be diversified away (and thus resulting in a low TEV). In other words, TEV gives more weight to funds that bet on systematic factors (i.e., becoming less diversified than their benchmarks) than funds that select stocks while still being well-diversified.

Cremers and Petajisto (2009) propose a modified version of TEV that nullifies the effects of persistent bets on systematic factors relative to the benchmarks. Their modified TEV is the standard error of the residuals from the regression of the fund's excess return (over the risk-free rate) on the benchmark's excess returns;

i.e.,

$$\begin{aligned} R_{fund,t} - R_{f,t} &= \alpha_{fund} + \beta_{fund}(R_{benchmark,t} - R_{f,t}) + \epsilon_{fund,t} \\ TEV &= St.dev[\epsilon_{fund,t}] \end{aligned} \tag{1.2}$$

Based on this definition of TEV, any persistent bet on systematic factors (e.g., allocation to cash or to high- or low-beta stocks), will be taken into account by the $\beta_{fund}$ coefficient, and thus will not contribute to the TEV value. As a result, this definition better captures fund managers' stock-selecting ability.

Henceforth, I will denote the standard version of tracking error volatility (i.e., Equation (1.1)) by $TEV_{std}$, and the modified version (i.e., Equation (1.2)) by $TEV_{reg}$.

### 1.3.2 Active Share

Cremers and Petajisto (2009) introduce a measure called "Active Share" (AS), which has since become widely used by both academics and practitioners. AS is based on the idea that active management requires deviation from a benchmark. It calculates how the holdings of a fund differ (positively or negatively) from the fund's benchmark weights, i.e.,

$$AS = \frac{1}{2}\sum_{i=1}^{N} |w_{fund,i} - w_{benchmark,i}| \tag{1.3}$$

where $N$ includes all the individual stocks both in the fund and its benchmark, and $w_{fund,i}$ and $w_{benchmark,i}$ are the weights of asset $i$ in the fund and the benchmark, respectively. For funds that do not use leverage or take short positions, AS will always be between 0% (which means that the funds have exactly the same holdings as their benchmarks') and 100% (which means the funds have no holdings in common with their benchmarks'). The higher the AS, the more active a fund is.

One major problem with using AS to measure fund activeness is that it requires the knowledge of the actual (rather than stated) benchmark of the fund. Fund managers may intentionally specify a wrong benchmark in order to make themselves appear more active than they actually are. Cremers and Petajisto (2009) remedy this problem by computing the AS of a fund against various market indices, and assigning the index that yields the lowest AS as the fund's benchmark. Because that index gives the lowest AS, it has the greatest amount of overlap with the fund among all the market indices that they use. (see the discussion in Section 1.5 below)

While AS captures the extent to which the fund manager selects stocks, it cannot indicate the level of risk that the manager takes relative to the benchmark. Cremers and Petajisto (2009) propose that both AS and $TEV_{reg}$ should be used in order to be able to distinguish between stock selection and factor timing (i.e., risk-taking), thus getting a complete picture of active management.[6]

### 1.3.3 Active Weight

To avoid the problem of specifying a benchmark, Doshi et al. (2015) propose a new activeness measure called "Active Weight" (AW). To calculate AW, only

[6] Cremers and Petajisto (2009) also examine whether AS and TEV can predict fund performance. They find that AS has predicting power while TEV does not. Funds with high AS outperform their benchmarks, even after adjusting for risk (using the four-factor Carhart (1997) model), fees, and transaction costs. Funds with low AS do poorly, and even worse after expenses. On the other hand, TEV has a zero or negative (but statistically insignificant) relationship with fund performance.

the information on the fund's holdings and their market capitalizations is needed. Formally, AW is defined as:

$$AW = \frac{1}{2}\sum_{i=1}^{N}|w_{fund,i} - w_{m,i}| \tag{1.4}$$

where $N$ includes all the individual stocks held by the fund, $w_{fund,i}$ is the actual weight of stock $i$ in the fund, and $w_{m,i}$ is the weight of that stock based on its market capitalization relative to the total market capitalization of all the stocks in the fund. In other words, AW is the sum (across the holdings) of the absolute differences between (i) the actual weights and (ii) the value weights (i.e., the weights that the stocks would have if they were weighted in proportion to their market capitalizations).

The rationale behind AW is the belief that managers need to deviate from value-weighted strategies in order to be truly active. For example, a manager who claims to be active but is indeed a closet indexer would hold a portfolio that imitates an index. Since almost all market indices are value-weighted, the manager's portfolio will most likely be a value-weighted one. The AW measure will correctly identify this portfolio as a passive one. On the other hand, if the manager chooses instead to overweight or underweight the stocks in the portfolio, AW will capture such deviation. However, it should be noted that AW can understate the degree of fund activeness. This is because it only analyzes the weights that the fund manager assigns to the stocks in the portfolio, but ignores the manager's ability to pick those stocks from the investment universe. Nevertheless, Stark (2019) shows that choosing the right weights for stocks in a portfolio is more important to performance than selecting which stocks to include.

Doshi et al. (2015) show that AW can predict fund performance, even after controlling for other activeness measures such as Active Share.

### 1.3.4 Selectivity: $(1 - R^2)$

Amihud and Goyenko (2013) propose that fund performance can be predicted by its "selectivity", which they measure by $1 - R^2$, where $R^2$ is obtained from a regression of the fund's returns on a factor model (e.g., CAPM by Sharpe (1964) and Lintner (1965)), or Fama and French three-factor model (Fama and French 1992; Fama and French 1993). By definition,

$$1 - R^2 = \frac{RMSE^2}{Systematic\ Risk^2 + RMSE^2} \tag{1.5}$$

where $Systematic\ Risk^2$ is the return variance due to the benchmark's risk, and $RMSE^2$ is the variance of the residual term. As a result, $1 - R^2$ is the proportion of the fund's return variance that cannot be explained by the factors in the benchmark, and this is why it can be considered to be a measure of selectivity. Higher selectivity (i.e., a higher value of $1-R^2$) means that the fund deviates more from the benchmark. Stated differently, a lower $R^2$ means that the fund tracks the benchmark less closely.

Amihud and Goyenko show that $R^2$ can predict mutual fund performance. In particular, they find that $R^2$ is negatively related to the fund's alpha (i.e., excess return), even after controlling for factors that have been shown in the literature to affect fund performance such as fund characteristics, style, and past performance. In other words, funds' selectivity (i.e., $1-R^2$) is positively related to performance.

The results are robust to the choice of factor models that are used as benchmark (with the main model being the Carhart (1997) four-factor model).

## 1.4 Sample Selection

I measure funds' activeness on two sets of samples. The first set consists of US diversified active ETFs whose specified objectives are to outperform broad-based equity benchmarks, while the second set consists of US active ETFs that concentrate on certain sectors of the market. The two sets are analyzed separately because of their different nature and risk-return profiles. For example, managers of sector funds face self-imposed limits on the sets of securities that they can hold, while managers of broad-based funds retain the choice of sector rotation. In addition, some studies have shown that investment ability is more evident among managers of sector (or concentrated) funds than in broad-based funds (Kacperczyk et al. 2005). Accordingly, each set of active ETFs should be examined and compared within itself.

For each active ETF in the sample, I select a control mutual fund (CMF), using the criteria described in detail below. Both the active ETFs and the control mutual funds are from the survivorship-bias-free US Mutual Fund Database provided by the Center for Research in Security Prices (CRSP). The database contains information on open-end mutual funds and ETFs traded in the US markets. The information provided includes the fund's name, investment style, fee structure, holdings (daily in the case of active ETFs, and quarterly in the case of mutual funds), asset allocation (i.e., percentages of holdings in different asset classes), and other characteristics. The database also includes monthly total returns, monthly total net assets, monthly/daily net asset values, and dividends that funds paid. The market capitalization of funds' constituents (mostly common stocks) is from the CRSP/Compustat Merged Database.

The ETFs' and mutual funds' holdings are reconciled with the holding information from Bloomberg and Thomson Reuters's CDA/Spectrum Mutual Fund Holdings Database. In some cases, CRSP do not keep full records of certain characteristics of active ETFs, especially their expenses and turnover. I use the information from the ETFs' prospectuses and/or annual reports for the missing values, and also double-check CRSP's information. Finally, I note that funds' returns in the CRSP database are calculated based on their NAVs, and thus are net of expenses, commissions, and sales loads.

### 1.4.1 Diversified Active Equity ETFs and Their CMFs

#### 1.4.1.1 Selection of Diversified Active Equity ETFs

As of December 2020, there are altogether 2,672 ETFs (passive and active) in the CRSP database. This number is narrowed down using the following steps. First, I exclude passive (or index) ETFs, active bond ETFs, and active equity ETFs that do not have holdings information. After this step, there are 335 active equity ETFs remaining. Secondly, based on CRSP holdings information, I calculate each fund's percentage holdings of common stocks and choose only those whose average holdings (throughout their lives) are at least 80% of their assets.[7] In addition, a fund is disregarded if the absolute value of its average cash holding

[7] Most active equity ETFs state in their prospectus (under "Principal Investment Strategies") that they intend to invest at least 80% of their assets in US-listed common stocks. The 80% filter rule is also used by Cremers and Petajisto (2009) to classify funds as all-equity mutual funds.

is over 20%.[8] These two criteria exclude balanced funds, hedged funds, leveraged funds, long-short funds, short-oriented funds, and managed futures funds. Thirdly, international funds and funds of funds are left out, leaving the sample with 121 active US equity ETFs.[9] Finally, I exclude 9 funds that have been in existence for only a few months, and 13 funds that are the new type of active ETFs that were recently approved by the SEC. This new type is referred to as non-transparent (or semi-transparent) active ETFs because they are required to disclose their holdings only on a quarterly basis (similar to mutual funds), rather than on a daily basis. The idea is to prevent other market participants from observing the fund managers' trading strategies and stock selection. After this step, the sample includes 99 active equity ETFs, all of which disclose their holdings on a daily basis.

Out of this total, 76 are diversified active US equity ETFs.[10] The classification is done based on CRSP Objective Codes, which CRSP obtains and reconciles from multiple sources such as Lipper objective codes, Strategic Insight, and Wiesenberger. The sample period is from March 2008 to December 2020.

#### 1.4.1.2 Selection of Control Funds

In order to properly judge the activeness level of the ETFs, I need control funds for them. Control funds are comparable actively-managed mutual funds (CMFs)

[8] Berk and Van Binsbergen (2015) argue that funds that hold, on average, more than 20% of their assets in cash should be classified as money market funds. This filter also excludes funds that use excessive leverage.

[9] This filter removes 35 international funds and 14 fund-of-funds. International funds are typically region-specific (e.g., Pacific, Europe, or China), and this can create a problem in measuring their performance without a proper model. Fund-of-funds are excluded because they have two layers of fund expenses and their holdings are other mutual funds or ETFs, which complicates the estimation of their activeness.

[10] The remaining 23 are sector active US equity ETFs, which will be discussed in Section 1.5 below.

that have similar fund characteristics to those of the active ETFs in the sample. They are found using the following two steps. First, for each active ETF, I form a pool of eligible candidates consisting of actively managed mutual funds that meet the following criteria:

1. The mutual funds must be in existence throughout the whole life of the active ETF (i.e., the "matched period"). This is so that comparison can be done over the entire life of the ETF.

2. Their investment styles and objectives, as determined by the CRSP Style Code, Lipper Objective Code, and Lipper Class Code, are the same as those of the active ETF.[11] If a fund's code changes during the matched period, the code that exists for the longest duration is selected as the main style.

3. Their net assets are between 25% and 200% of that of the active ETF.

In the second step, I find the closest-matched mutual fund out of the pool created above, using the matching algorithm in Choi et al. (2016). The algorithm chooses the fund with the smallest matching score based on relevant fund characteristics. In the literature, there are two fund characteristics that have been shown to have strong predictive ability on funds' activeness levels. They are expense ratios and total net assets (see Amihud and Goyenko 2013; Cremers and Petajisto 2009; Doshi et al. 2015). These are the characteristics that I use in the matching

[11] This of course assumes that the information from these sources reflects the funds' true investment style. It is well known that a "style drift" could occur, where the fund's actual investment style deviates from its stated objective. This could happen naturally if there is a dramatic move in the prices of certain securities in the fund, altering their relative weights. It could also happen deliberately in order to, for example, improve the fund's performance and attract inflows (e.g., Berk and Green 2004; Chua and Tam 2020).

algorithm. For each candidate mutual fund, its matching score is calculated as:

$$Matching\ Score = abs(\frac{\log(Candidate's\ TNA)}{\log(Active\ ETF's\ TNA)} - 1) + abs(\frac{\log(Candidate's\ expense)}{\log(Active\ ETF's\ expense)} - 1) \tag{1.6}$$

where TNA is the time-series average of the fund's total net assets and expense is the time-series average expense ratio. The mutual fund with the minimum matching score is chosen as the CMF.

#### 1.4.1.3 Summary Statistics of Diversified Active ETFs and Their CMFs

The summary statistics of the 76 diversified active ETFs are shown in Table 1.1. Except for fund ages (which are as of December 31, 2020, or the ETFs' termination dates, as the case may be), all other statistics (except the means) are calculated as the time-series averages over the ETFs' lengths of life. This reporting approach follows the convention in prior studies of mutual funds (Busse et al. 2021; Jiang et al. 2021; Jiang and Zheng 2018). This is so that the numbers will convey a sense of the average values (e.g., average size) during the whole lives of the funds. The means are calculated as the cross-sectional averages of the time-series averages.

From Panel A of Table 1.1, we can see that the average age of the active diversified ETFs is 3.08 years, while the oldest ETF is 7.64 years old. This reflects the fact that active ETFs are a recent innovation, and so many of them are still young. The average size is \$32.26 million, while the largest ETF in the sample has assets of \$209.81 million. It should be noted that diversified active ETFs are generally not as large as sector active ETFs (see Section 1.5 below) or fixed-income active ETFs.

**Table 1.1:** Summary Statistics of Diversified ETFs

| **Panel A: Fund characteristics** | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Mean | St. Dev. | Min | Q25 | Median | Q75 | Max |
| TNA (in $mil) | 32.26 | 44.05 | 2.14 | 6.22 | 16.72 | 44.91 | 209.81 |
| Expense (annually,%) | 0.72 | 0.17 | 0.43 | 0.62 | 0.73 | 0.84 | 1.00 |
| No.holdings(monthly) | 108 | 108.37 | 27 | 45 | 69 | 122 | 493 |
| Turnover (annually,%) | 106.91 | 95.88 | 17.20 | 46.87 | 78.91 | 144.58 | 341.88 |
| Return (monthly,%) | 0.33 | 1.80 | −2.85 | −0.63 | 0.36 | 1.30 | 4.05 |
| Flow (monthly,%) | 9.24 | 32.37 | −25.98 | −1.76 | 0.57 | 8.19 | 120.15 |
| Common stock (%) | 95.38 | 6.33 | 77.93 | 94.36 | 97.50 | 98.88 | 101.10 |
| Cash (%) | 1.14 | 2.60 | −1.39 | −0.02 | 0.16 | 1.08 | 9.02 |
| Fund age (in yrs.) | 3.08 | 2.09 | 0.25 | 1.08 | 2.88 | 4.41 | 7.64 |
| **Panel B: Correlations** | | | | | | | |
| | TNA | Expense | No.hold | Turnover | Return | Flow | Fund age |
| TNA | 1 | | | | | | |
| Expense | −0.012 | 1 | | | | | |
| No.hold | −0.124 | −0.461 | 1 | | | | |
| Turnover | 0.063 | 0.582 | 0.009 | 1 | | | |
| Return | −0.04 | −0.211 | 0.014 | −0.064 | 1 | | |
| Flow | 0.159 | −0.142 | 0.071 | −0.085 | 0.068 | 1 | |
| Fund age | −0.024 | −0.196 | −0.223 | −0.028 | 0.077 | −0.121 | 1 |

This table presents the summary statistics of selected fund characteristics of 76 domestically actively managed diversified ETFs from 03/2008 to 12/2020. All the statistics are summarized each quarter cross-sectionally for all funds and then the time series average over the whole time period. TNA is the total net assets, measured in million dollars. The number of holdings includes all the positions taken by a fund. Turnover is annualized and calculated as the lesser of the aggregate amount of purchases and sells of securities divided by the total net asset value of the fund. However, few funds survived less than 1 year and have missing turnovers. Return is the monthly total return (including the reinvestment of dividends, if any). Flow is the monthly growth rate in a fund's total net assets that is not attributed to its performance. The common stock and cash percentage in holdings are from CRSP, and they represent the time series average through a fund's life. Fund age is the survival years of a fund and is calculated from the fund's inception date to the latter of its termination date or Dec 31, 2020. The correlations are Pearson.

On average, over 95% of the ETFs' assets is in common stocks, while cash represents only about 1%. The number of stocks that these ETFs hold at any one time varies, ranging from a low of 27 to a high of 493, with an average of 108. With respect to turnover, there is a wide range of numbers – from 17.20% to 341.88%, with an average of 106.91%. That is, on average, the active ETFs in the sample replace all of their holdings in a year, but there is a wide variation among them. Their performance also varies substantially, with a minimum monthly return of $-2.85\%$, a maximum of $+4.05\%$, and a mean (median) of 0.33% (0.36%). As for the expenses, the average diversified active ETF in the sample charges a management fee of 0.72% per year, which is approximately 50 basis points higher than what an average passive (index) ETF charges.[12]

Table 1.2 presents the summary statistics for the matched control mutual funds (CMFs). In general, the CMFs are older and have more assets than the active ETFs in the sample, reflecting the fact that mutual funds are now a mature product in a saturated market (and thus not many new funds were recently introduced).[13] On average, the CMFs hold slightly more cash (1.58% vs. 1.14% for active ETFs), which is to be expected because mutual funds need to hold cash in order to facilitate redemptions. However, the average proportion of assets invested in common stocks is similar at around 95%. The numbers of stocks held are also similar, both in terms of the averages (118 vs. 108) and the medians (72 vs. 69). In terms of turnover, the CMFs have a lower average (74.09% vs. 106.91%), and also less variation among them.[14] This suggests that active ETFs generally rebalance their portfolios more frequently than their control mutual funds do. Still, the average monthly return of the CMFs is comparable to that of active ETFs (0.36% vs.

[12] For passive (index) ETFs, the asset-weighted average fee is approximately 0.20% p.a. (Source: Charles Schwab). Several major providers of passive ETFs have lower averages (as of 2019) such as Vanguard (0.09% p.a.) and State Street (0.16% p.a.) (Source: Barrons).

[13] The number of newly introduced mutual funds has been declining over the years. During the period from 2010 to 2015, the average number of new mutual funds per year was 647. In contrast, the average number of new mutual funds per year during the period from 2016 to 2020 was 386. (Source: author's calculations based on the information in the *2021 Investment Company Fact Book*, published by the Investment Company Institute).

[14] As a point of reference, Kacperczyk et al. (2005) report that the average turnover of over 1,700 US diversified actively-managed mutual funds is 88.28%.

0.33%). Finally, the management fees of the CMFs are higher than those of active ETFs (1.10% p.a. vs. 0.72% p.a.), which is to be expected considering that active ETFs are traded on exchanges while mutual fund investors buy and/or redeem the funds' units directly with the providers.[15]

Panel B of Table 1.1 and Table 1.2 displays the correlations among different fund characteristics of the active ETFs and the CMFs respectively. Some correlations are worth noting. First, for CMFs, the correlation between fund total net assets (TNA) and fund expenses is negative ($-0.426$), which is consistent with the economy of scale reported in the mutual funds literature (e.g., Latzko 1999; Khorana et al. 2009). In contrast, for the active ETFs, the relationship between fund size and fees is close to zero ($-0.012$). One possible explanation for these contrasting findings is that the active ETFs in the sample are still small and have not reached the size that can give them the economy of scale. Another possible explanation is that active ETFs (and ETFs in general) benefit less from economies of scale than mutual funds do. This is because mutual funds have certain types of expenses whose per-unit costs significantly decline as their assets grow, while active ETFs do not. For example, one major component of mutual fund expenses is administrative expenses, which include record keeping and interacting with shareholders. These expenses have a considerable fixed-cost portion.[16] Active ETFs do

[15] Investors of active ETFs face bid-ask spreads when they buy or sell their ETF shares. Pham et al. (2021) report that active ETFs have much wider bid-ask spreads than the average spreads of their underlying portfolio. They attribute the lower liquidity to the smaller size and trading volume of active ETFs. It should also be noted that as with any ETFs, active ETFs' market prices can deviate from their net asset values (NAVs). This possibility adds to the potential transaction costs of trading active ETFs.

[16] Gao and Livingston (2008) show that the decrease in expenses of actively managed mutual funds as their assets grow is due mainly to the reduction of administrative costs such as registration and auditing fees.

**Table 1.2:** Summary Statistics of Diversified CMFs

**Panel A: Fund characteristics**

| | Mean | St. Dev. | Min | Q25 | Median | Q75 | Max |
|---|---|---|---|---|---|---|---|
| TNA (in $mil) | 64.46 | 133.55 | 0.24 | 4.38 | 16.09 | 67.06 | 691.43 |
| Expense (annually,%) | 1.10 | 0.32 | 0.43 | 0.89 | 1.09 | 1.23 | 2.33 |
| No.holdings(quarterly) | 118 | 128.48 | 23 | 52 | 72 | 133 | 695 |
| Turnover (annually,%) | 74.09 | 60.86 | 10.31 | 32.48 | 55.38 | 94.36 | 283.13 |
| Return (monthly,%) | 0.36 | 1.34 | −2.04 | −0.42 | 0.45 | 1.15 | 2.54 |
| Flow (monthly,%) | 6.45 | 24.04 | −11.51 | −1.37 | 0.90 | 2.99 | 70.14 |
| Common stock (%) | 95.31 | 6.52 | 76.53 | 93.53 | 96.52 | 98.30 | 113.75 |
| Cash (%) | 1.58 | 4.80 | −15.53 | 0.21 | 0.99 | 2.33 | 15.18 |
| Fund age (in yrs.) | 12.14 | 9.78 | 0.84 | 6.23 | 9.17 | 15.53 | 49.00 |

**Panel B: Correlations**

| | TNA | Expense | No.hold | Turnover | Return | Flow | Fund age |
|---|---|---|---|---|---|---|---|
| TNA | 1 | | | | | | |
| Expense | −0.426 | 1 | | | | | |
| No.hold | −0.102 | −0.108 | 1 | | | | |
| Turnover | −0.011 | 0.252 | 0.389 | 1 | | | |
| Return | 0.026 | −0.045 | 0.064 | −0.11 | 1 | | |
| Flow | −0.064 | 0.083 | 0.065 | 0.032 | 0.147 | 1 | |
| Fund age | 0.296 | −0.112 | −0.105 | −0.026 | 0.072 | −0.133 | 1 |

This table presents the summary statistics of selected fund characteristics of CMFs for 76 domestically actively managed diversified ETFs from 03/2008 to 12/2020. All the statistics are summarized each quarter cross-sectionally for all funds and then the time series average over the whole time period. TNA is the total net assets, measured in million dollars. The number of holdings includes all the positions taken by a fund. Turnover is annualized and calculated as the lesser of the aggregate amount of purchases and sells of securities divided by the total net asset value of the fund. Return is the monthly total return (including the reinvestment of dividends, if any). Flow is the monthly growth rate in a fund's total net assets that is not attributed to its performance. The common stock and cash percentage in holdings are from CRSP, and they represent the time-series average through a fund's life. Fund age is the survival years of a fund and is calculated from the fund's inception date to the latter of its termination date or Dec 31, 2020. The correlations are Pearson.

not incur these expenses because they are traded on exchanges and record-keeping is done mainly by brokerage firms.

For both active ETFs and their CMFs, management fees are negatively correlated with fund age. This is consistent with the learning-curve hypothesis, where funds gain operating efficiency and thus can reduce costs as they age (e.g., Ferris and Chance 1987).[17] Next, for both active ETFs and their CMFs, management fees (which do not include funds' trading expenses) are positively correlated with turnover. One explanation for this positive relationship is that higher fees may reflect the fact that managers with greater skill charge higher fees (Kacperczyk et al. 2014), and that these managers trade more because they are able to identify a greater number of *perceived* profitable opportunities that really exist (Pástor et al. 2017). Note that higher turnover does not necessarily mean that funds are more active because, as defined in Section 1.3.2 above, activeness depends on how much funds' holdings deviate from their benchmark indices.

## 1.4.2 Sector Active ETFs and Their CMFs

### 1.4.2.1 Selection of Sector Active ETFs

The sector ETFs come from the same database as the one mentioned in the previous section. These ETFs are identified by the CRSP's 3-level style code of E-D-S, which stands for Equity-Domestic-Sector. The same filters used for diversified active ETFs are applied (e.g., minimum percentages of stock holdings and maximum cash holdings). The final sample consists of 23 US sector equity ETFs, and the sample period is from June 2012 to December 2020.

[17] The empirical evidence of the relationship between funds' expenses and ages is mixed. For example, a negative relation is reported by Ying Luo (2002) and Iannotta and Navone (2012). In contrast, a 2000 study by the SEC entitled "Report on Mutual Fund Fees and Expenses" finds a weak, but positive relationship (`https://www.sec.gov/news/studies/feestudy.htm`). A positive relationship can be explained by, for example, the possibility that investors have accumulated capital gains in their funds over time, and so they do not want to redeem the funds in order to avoid paying taxes on the gains. This causes them to become captive clientele of their funds, and fund managers can charge higher fees.

#### 1.4.2.2 Selection of Control Funds

Similar to the case of diversified active ETFs, I obtain control funds for the 23 sector ETFs from the pool of comparable sector mutual funds. The same selection criteria and procedure as described in Section 1.4.1.1. above are followed.

#### 1.4.2.3 Summary Statistics of Sector Active ETFs and Their CMFs

The summary statistics for sector active ETFs are presented in Table 1.3. In general, sector active ETFs are larger than diversified active ETFs. The mean size of sector ETFs is $187.45 million, which is approximately six times larger than that of diversified active ETFs. However, the mean is skewed by a few very large funds, and so a comparison of medians is more appropriate, in which case sector ETFs are approximately 30% larger ($21.81 million vs. $16.72 million).[18] The average age of the sector active ETFs in the sample is 3.25 years, with the oldest fund being 7.78 years old (as of December 2020). These numbers are comparable to those of diversified active ETFs.

On average, sector active ETFs invest approximately 92% of their assets in common stocks, and hold less than 1% of their assets in cash. The average number of stocks that they hold (66) is much lower than the number for diversified active ETFs (108), which is to be expected considering the funds' sector mandate. With respect to turnover, the numbers range from a low of 25% to a (very) high of 1,197%, with a median of 57%. This median number is lower than the median number for diversified active ETFs (79%). During the sample period, the majority

[18] As mentioned earlier, these two numbers are the time-series averages over the ETFs' lengths of life, rather than the amounts of assets as of a certain date. This calculation approach is common in the mutual funds literature.

**Table 1.3:** Summary Statistics of Sector ETFs

**Panel A: Fund characteristics**

| | Mean | St. Dev. | Min | Q25 | Median | Q75 | Max |
|---|---|---|---|---|---|---|---|
| TNA (in $mil) | 187.45 | 445.89 | 3.82 | 9.51 | 21.81 | 90.89 | 1819.86 |
| Expense (annually,%) | 0.69 | 0.18 | 0.48 | 0.52 | 0.75 | 0.82 | 0.93 |
| No.holdings(monthly) | 66 | 42.15 | 26 | 38 | 47 | 91 | 150 |
| Turnover (annually,%) | 209.74 | 378.95 | 25.12 | 37.88 | 56.69 | 125.92 | 1196.50 |
| Return (monthly,%) | 0.09 | 2.85 | −4.61 | −1.50 | −0.15 | 1.47 | 5.22 |
| Flow (monthly,%) | 6.22 | 20.78 | −12.91 | −1.40 | 1.41 | 7.09 | 60.23 |
| Common stock (%) | 91.53 | 6.71 | 78.38 | 87.61 | 92.96 | 96.29 | 98.94 |
| Cash (%) | 0.75 | 1.97 | −0.15 | 0.04 | 0.12 | 0.35 | 7.60 |
| Fund age (in yrs.) | 3.25 | 2.05 | 0.64 | 2.13 | 2.78 | 4.62 | 7.78 |

**Panel B: Correlations**

| | TNA | Expense | No.hold | Turnover | Return | Flow | Fund age |
|---|---|---|---|---|---|---|---|
| TNA | 1 | | | | | | |
| Expense | −0.265 | 1 | | | | | |
| No.hold | 0.177 | −0.524 | 1 | | | | |
| Turnover | 0.513 | 0.179 | 0.085 | 1 | | | |
| Return | −0.048 | −0.028 | −0.029 | −0.22 | 1 | | |
| Flow | 0.216 | −0.253 | 0.019 | −0.234 | 0.253 | 1 | |
| Fund age | 0.101 | 0.607 | 0.099 | 0.145 | 0.099 | −0.111 | 1 |

This table presents the summary statistics of selected fund characteristics of 23 domestically actively managed active sector ETFs from 06/2012-12/2020. All the statistics are summarized each quarter cross-sectionally for all funds and then the time-series average over the whole time period. TNA is the total net assets, measured in million dollars. The number of holdings includes all the positions taken by a fund. Turnover is annualized and calculated as the lesser of the aggregate amount of purchases and sells of securities divided by the total net asset value of the fund. However, few funds survived less than 1 year and have missing turnovers. Return is the monthly total return (including the reinvestment of dividends, if any). Flow is the monthly growth rate in a fund's total net assets that is not attributed to its performance. The common stock and cash percentage in holdings are from CRSP, and they represent the time-series average through a fund's life. Fund age is the survival years of a fund and is calculated from the fund's inception date to the latter of its termination date or Dec 31, 2020. The correlations are Pearson.

of sector active ETFs did not perform well. Their mean and median monthly returns are 0.09% and −0.15% respectively. Finally, the average management fees are 0.69% p.a., which is comparable to the fees of diversified active ETFs (0.72% p.a.). It is also comparable to the average fees of passive sector ETFs (0.61% p.a.).[19]

[19] Source: `https://www.etf.com/`

Table 1.4 displays the summary statistics for the control mutual funds for sector active ETFs. Although the CMFs are much older, their sizes match up well with those of the sector ETFs in terms of medians, means, and ranges of values. On average, the CMFs hold more cash (1.26% vs. 0.75% for sector active ETFs) and have a higher proportion of assets invested in common stocks (95.10% vs. 91.53%) even though the numbers of stocks held are similar. Regarding turnover, the CMFs have a slightly lower average, but a much higher median (112.54% vs. 56.69%). This suggests that the sector active ETFs generally rebalance their portfolios less frequently than their control funds do. As for returns, the CMFs produce negative average monthly returns during the sample period ($-0.21\%$), which is lower than that of the sector ETFs (0.09%). The median monthly return of the CMFs is also lower. Finally, the management fees of the CMFs are higher than those of the sector active ETFs (1.27% p.a. vs. 0.69% p.a.).

The correlations among different fund characteristics of the sector active ETFs and their CMFs are displayed in Panel B of Table 1.3 and Table 1.4 respectively. There are a few things worth noting. First, for both the sector active ETFs and their CMFs, the correlation between fund total net assets (TNA) and fund expenses is negative ($-0.265$ and $-0.515$ respectively). This is consistent with the economy of scale argument, and supports my conjecture in the previous section that a minimum level of assets is needed in order to start benefitting from an economy scale.[20] The diversified active ETFs in the previous section are generally smaller than the sector ETFs in this section, and this can be the reason why the correlation between their size and fees is close to zero.

[20] Due to increased competition, newer funds (thus tend to be smaller in size) are charging lower fees. As a result, this may confound the negative relationship between fund size and expense.

**Table 1.4:** Summary Statistics of Sector CMFs

**Panel A: Fund characteristics**

| | Mean | St. Dev. | Min | Q25 | Median | Q75 | Max |
|---|---|---|---|---|---|---|---|
| TNA (in $mil) | 160.32 | 377.04 | 1.64 | 7.31 | 21.68 | 111.60 | 1538.59 |
| Expense (annually,%) | 1.27 | 0.37 | 0.80 | 0.91 | 1.30 | 1.59 | 1.80 |
| No.holdings(quarterly) | 67 | 30.61 | 23 | 46 | 64 | 84 | 133 |
| Turnover (annually,%) | 170.63 | 168.03 | 22.82 | 66.82 | 112.54 | 210.85 | 626.75 |
| Return (monthly,%) | −0.21 | 2.39 | −3.96 | −1.49 | −0.21 | 0.98 | 3.91 |
| Flow (monthly,%) | 1.73 | 14.12 | −16.02 | −3.07 | −0.78 | 2.27 | 35.75 |
| Common stock (%) | 95.10 | 4.34 | 83.66 | 93.76 | 95.95 | 97.69 | 100.59 |
| Cash (%) | 1.26 | 2.33 | −2.17 | 0.28 | 0.81 | 1.73 | 7.50 |
| Fund age (in yrs.) | 16.69 | 10.87 | 1.42 | 8.46 | 16.03 | 22.83 | 35.43 |

**Panel B: Correlations**

| | TNA | Expense | No.hold | Turnover | Return | Flow | Fund age |
|---|---|---|---|---|---|---|---|
| TNA | 1 | | | | | | |
| Expense | −0.515 | 1 | | | | | |
| No.hold | 0.089 | 0.12 | 1 | | | | |
| Turnover | −0.346 | 0.619 | 0.086 | 1 | | | |
| Return | −0.023 | 0.02 | 0.108 | 0.024 | 1 | | |
| Flow | 0.093 | 0.012 | 0.162 | 0.071 | 0.127 | 1 | |
| Fund age | 0.142 | −0.683 | −0.068 | −0.486 | −0.028 | −0.126 | 1 |

This table presents the summary statistics of selected fund characteristics of CMFs for 23 domestically actively managed active sector ETFs from 06/2012-12/2020. The statistics are summarized each quarter cross-sectionally for all funds and then the time series average over the whole time period. TNA is the total net assets, measured in million dollars. The number of holdings includes all the positions taken by a fund. Turnover is annualized and calculated as the lesser of the aggregate amount of purchases and sells of securities divided by the total net asset value of the fund. Return is the monthly total return (including the reinvestment of dividends, if any). Flow is the monthly growth rate in a fund's total net assets that is not attributed to its performance. The common stock and cash percentage in holdings are from CRSP, and they represent the time-series average through a fund's life. Fund age is the survival years of a fund and is calculated from the fund's inception date to the latter of its termination date or Dec 31, 2020. The correlations are Pearson.

For the CMFs, the correlation between management fees and fund age is negative, which is consistent with the learning curve hypothesis. However, for the sector ETFs, this correlation is positive (0.607). Normally, a positive relationship between fees and fund age can be explained by the possibility that investors are willing to pay higher fees to invest in older funds with longer histories. Alternatively, as alluded to in footnote 17 above, it can be explained by the possibility that investors have accumulated capital gains in their funds over time, and so they do not want to redeem the funds in order to avoid paying taxes on the gains. This causes them to become captive clientele of their funds, and fund managers can charge higher fees (Gil Bazo and Martınez Sedano 2004). However, this alternative explanation is unlikely to apply to the sector active ETFs in the sample because their average return is very small.

## 1.5 Activeness Results

In this section, I present the results on the activeness of the diversified active ETFs and the sector active ETFs. However, before discussing the results, I address the issue of funds' benchmarks. Two of the activeness measures that I use (i.e., tracking errors volatility and Active Share) require specification of the benchmarks against which the ETFs and their control mutual funds are going to be measured.

### 1.5.1 Funds' Benchmarks

The choice of benchmarks has received considerable attention in the mutual funds literature, not only in the context of performance evaluation, but also in the context of activeness measurement (e.g., Angelidis et al. 2013; Cremers and Petajisto 2009; Sensoy 2009). As alluded to in Section 1.3.2 above, fund managers may intentionally specify a wrong benchmark in order to make themselves appear more successful or more active than they actually are. To ensure that my results are not distorted by the wrong choices of benchmarks, I use two different approaches. Under the first approach, I measure the funds' activeness against their self-declared benchmarks. Under the second approach, I measure each fund's activeness against a set of pre-specified, relevant indices, and assign the one against which the fund has the least activeness to be the benchmark for the fund. This approach follows Cremers and Petajisto (2009), and does not rely on the benchmark that the fund declares. Rather, it produces the benchmark with which the fund is most similar. As a result, it circumvents the possibility that the fund's self-declared benchmark can be misleading.

Self-declared benchmarks are obtained from the prospectuses of the active ETFs and their control mutual funds, through the use of the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database.[21] If a fund's benchmark is not disclosed in its prospectus, I use the one specified by Morningstar Category. Morningstar Category specifies funds' benchmarks by examining the funds' holdings. In case the fund is not covered by Morningstar Category, I assign a benchmark based on its Lipper Class Objective.

Under the second approach, the set of pre-specified, relevant indices against which to measure the activeness of the diversified active ETFs and their control funds consists of 14 diversified market indices. The 14 indices include the 12 benchmarks that over 90% of US diversified, actively managed mutual funds declare as their own benchmarks (Sensoy 2009). They are (in the order from the most to the least commonly used) S&P 500, Russell 2000, Russell 1000 Growth, Russell 1000 Value, Russell 2000 Growth, S&P 400, Russell 2000 Value, Russell Midcap Growth, Russell Midcap Value, Russell Midcap, Russell 1000, and S&P 600. In addition to these 12 indices, I add two market-wide indices – S&P1500 and Russell 3000, which cover roughly 90% and 98% of the whole US stock market. Altogether, the

[21] See https://www.sec.gov/edgar.

14 indices represent portfolios of large-cap, mid-cap, and small-cap stocks. Both growth and value styles are also represented.

The set of relevant indices to measure the activeness of sector active ETFs and their control funds (CMFs) consists of 10 sector indices, covering industries from Technology/Science, Financial Services, Healthcare, Consumer Services, Consumer Goods, Industrials, Utility, Metals, Natural Resources, and Basic Materials. The index with the minimum AS is selected as the benchmark for each fund.[22]

### 1.5.2 Activeness of Diversified Active Equity ETFs

Table 1.5 (Panels A to D) presents the activeness estimates of diversified active equity ETFs and their CMFs, using the four measures discussed in Section 1.3 – Active Share (AS), Active Weight (AW), Tracking Error Volatility (TEV), and $R^2$.

#### 1.5.2.1 Active Share

In Panel A, I report two Active Share estimates, one based on the funds' self-declared benchmarks and the other on the set of pre-specified market indices. The reported AS estimates are calculated as follows. First, for each fund, I calculate its monthly AS by using Equation 1.3 based on all of its holdings at the end of each

[22] For both the diversified active ETFs and the sector active ETFs, I also looked at the benchmark with the second smallest AS and checked the level of differences between the two close benchmark indices and their respective AS statistics. Within the 1% difference of AS, these two benchmarks are often close to each other, mostly occurring in the pair of the S&P 500 index and Russell 1000 index and the pair of the S&P 1500 index and Russell 3000 index. As the difference in AS increases, the two nearby benchmarks become more distinct. The difference between the minimum and second minimum AS is large for sector funds, however.

**Table 1.5:** Activeness Measures of Active Diversified ETFs and CMFs

| | AETFs | | | | | CMFs | | | | | Diff. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Min | Median | Max | Mean | SD | Min | Median | Max | $t$-stat |
| **Panel A: Active Share** | | | | | | | | | | | |
| $AS_{\text{self declared}}$ | 80.23 | 12.16 | 59.18 | 80.04 | 97.54 | 76.40 | 10.12 | 60.95 | 75.94 | 91.05 | 3.83*** |
| | | | | | | | | | | | (5.75) |
| $AS_{\text{pre specified}}$ | 78.88 | 11.79 | 58.15 | 78.98 | 95.44 | 77.29 | 10.45 | 60.18 | 77.15 | 91.62 | 1.59** |
| | | | | | | | | | | | (2.56) |
| **Panel B: Active Weight** | | | | | | | | | | | |
| AW | 53.58 | 14.81 | 30.36 | 53.42 | 80.67 | 49.53 | 9.10 | 33.33 | 49.78 | 63.65 | 4.05*** |
| | | | | | | | | | | | (3.00) |
| **Panel C: Tracking Error Volatility** | | | | | | | | | | | |
| $TEV_{trd}$ | 6.01 | 3.34 | 2.83 | 5.26 | 15.97 | 4.06 | 2.24 | 1.77 | 3.62 | 10.15 | 1.95*** |
| | | | | | | | | | | | (7.18) |
| $TEV_{reg}$ | 5.21 | 2.89 | 2.53 | 4.59 | 14.52 | 3.61 | 1.96 | 1.66 | 3.21 | 9.37 | 1.60*** |
| | | | | | | | | | | | (7.98) |
| **Panel D: $R^2$** | | | | | | | | | | | |
| CAPM | 85.03 | 10.47 | 56.66 | 87.96 | 95.94 | 90.22 | 7.16 | 72.75 | 91.95 | 98.01 | −5.19*** |
| | | | | | | | | | | | (−3.41) |
| FFC | 91.06 | 7.37 | 67.70 | 93.29 | 97.87 | 94.52 | 4.81 | 79.07 | 95.93 | 98.55 | −3.46*** |
| | | | | | | | | | | | (−4.38) |

This table presents the summary statistics of active measures of 76 domestically actively managed diversified ETFs and their CMFs. All the measures are reported as in percentage (%). The AS calculation considers all the holdings including positions such as futures and cash equivalents on top of the common stocks. The traditional method of calculating TE is defined as the standard deviation of the return difference between active ETFs and their pre-specified benchmark. The regression method of TE stands for the standard deviation of residuals from the regression of the fund's excess return (over the risk-free rate) on its benchmark's excess return. All the statistics are firstly calculated cross-sectionally for all the funds at each month and then the time series average along the data period. The $R^2$ is calculated with the FFC model using daily return on a quarterly rolling window. The * indicates the significance level of difference of the mean between the two groups using the Welch two-sample test.
*, ** and *** are at the 10%, 5%, 1% significance level, respectively.

month.[23] Then, I calculate the (time-series) average of those monthly AS values. This average is taken to be the AS of that fund.

When the funds' self-declared benchmarks are used, AS estimates of the diversified active ETFs range in value from 59.18% to 97.54%, with a mean of 80.23% and a median of 80.04%. When the set of pre-specified market indices is used, the AS estimates are slightly lower (by about 1 - 2%), ranging from 58.15% to 95.44%, with a mean of 78.88% and a median of 78.98%. Funds with AS values of 60% or greater are considered to be active, while those with AS values between 20% and 60% are considered to be "closet indexers" (Cremers and Petajisto 2009). Based on this criterion, virtually all of the diversified active ETFs in the sample can be considered to be true to their stated active intention.

Compared to their control mutual funds, the mean of the AS estimates for the ETFs is still significantly higher than those of their CMFs, suggesting that the ETFs are, on average, more active than their control mutual funds are.[24] This is true under both choices of benchmarks, especially when the self-declared benchmarks are used. When the self-declared benchmarks are used, the mean AS value is 80.23% for the diversified active ETFs, compared to 76.40% for the control mutual funds. The difference between the two values is significant at the 1% level. When the pre-specified set of benchmarks are used, the mean AS values are 78.88% for the diversified active ETFs and 77.29% for the control mutual funds, with the difference between them being significant at the 5% level.

[23] I also calculate AS using only the funds' common stock holdings. The mean value changes slightly within 0.5% from the current results, and the conclusions do not change.

[24] The mean of the AS estimates of the control mutual funds (76.40%) is very close to the mean AS value of all US actively managed mutual funds (77%) reported in Cremers and Pareek (2016).

#### 1.5.2.2 Active Weight

The Active Weight (AW) estimates of the diversified active ETFs and their CMFs are reported in Panel B of Table 1.5. The AW estimates are calculated monthly by using Equation 1.4 and the holdings information at the end of each month. Then, I calculate the (time-series) average of those monthly AW values. This average is taken to be the AW of that fund.

The AW estimates of the diversified active ETFs range in value from 30.36% to 80.67%, with a mean of 53.58% and a median of 53.42%. In comparison to their control mutual funds, the mean of the AW estimates for the ETFs is significantly higher than that of their CMFs (by about 4%), suggesting that the ETFs are, on average, more active than their control mutual funds are. In addition, as a point of reference, Doshi et al. (2015) report AW estimates of all US diversified actively managed mutual funds to be below 40% during the period from 2008 to 2013, which overlaps with my sample period. Therefore, it appears that the diversified active ETFs are also more active than the diversified mutual funds as a whole.

Recall that AW captures fund managers' decisions on the weighting of the stocks in their portfolios, rather than on stock selection. Accordingly, the above results show that the diversified active ETFs are more active than mutual funds in the sense that the ETFs deviate more from simple value-weighted strategies than actively managed mutual funds do.

#### 1.5.2.3 Tracking Error Volatility

Panel C of Table 1.5 displays the tracking error volatility of the diversified active ETFs and their CMFs. Both the standard and the modified versions of tracking error volatility (i.e., $TEV_{std}$ and $TEV_{reg}$) are estimated using the time series of the funds' and their benchmarks' monthly returns. For each fund, the benchmark used is the one from the set of pre-specified market indices that yields the lowest Active Share. I also repeat the estimation using the funds' self-declared benchmarks. The results are similar, and thus will not be reported.

For the standard version of tracking error volatility ($TEV_{std}$), the estimates for the diversified active ETFs range in value from 2.83% to 15.97%, with a mean of 6.01% and a median of 5.26%. The mean is significantly higher than that of their CMFs (by about 2%). For the modified version ($TEV_{reg}$), the results are qualitatively the same but the estimates are slightly lower, which is to be expected considering that the modified version does not capture fund managers' bets on systematic risks. $TEV_{reg}$ of diversified active ETFs has a mean of 5.21%, which is significantly higher than that of their CMFs (by 1.60%).

The results of both versions of tracking error volatility suggest that the ETFs are, on average, more active than their control mutual funds are.[25] This is true even after factor timing is taken into account.

[25] The results are based on monthly returns. If weekly returns are employed to calculate TEV, the results become smaller in general (due to smoothing); it still shows that active ETFs have higher TEV.

#### 1.5.2.4 Selectivity: $(1 - R^2)$

I obtain $R^2$'s of the diversified active ETFs and their CMFs from regressions of their returns on various factor models, including the CAPM, Fama and French 3-factor, Carhart 4-factor, and Fama and French 5-factor models. Since the results are qualitatively similar, only the $R^2$'s using the CAPM and the Carhart 4-factor model are shown in Panel D of Table 1.5. When the CAPM is used, the average $R^2$ is 85.03% for the active ETFs and 90.22% for their CMFs. Recall that $R^2$ is the proportion of the fund's returns that can be explained by the factor model (CAPM in this case), and thus a lower $R^2$ value indicates that the fund is more active (i.e., $1 - R^2$ is a measure of selectivity or activeness). Accordingly, the results indicate that the diversified active ETFs are, on average, significantly more active than their control mutual funds.

When the Carhart 4-factor model is used in the regressions, $R^2$'s are, as expected, higher, with an average of 91.06% for the active ETFs and 94.52% for the CMFs, indicating that the Carhart model is able to explain a greater proportion of the funds' returns than the CAPM can. However, the same conclusion regarding activeness can be reached; i.e., the ETFs are, on average, significantly more active than their control funds, but the difference between them is not as large as when the CAPM is used.

#### 1.5.2.5 Further Investigation

All four measures of activeness point to the same conclusion; i.e., the diversified active ETFs are significantly more active than their control mutual funds. Recall that different measures emphasize different aspects of activeness. For example, AS captures fund managers' attempts at stock selection, while tracking error volatility (the standard version) reflects managers' attempts at factor timing. The results in Table 1.5 show that the ETFs are, on average, more active than their CMFs in every activeness aspect.

To further investigate, I divide the diversified active ETFs in the sample into five groups according to the funds' investment styles. The five groups are multi-cap, large-cap, mid-cap, small-cap, and equity income. Table 1.6 reports the differences in the activeness measures between the ETFs and their CMFs for these five groups. For the $R^2$ measure, I only report the estimate using the Carhart 4-factor model.

Overall, the differences in the activeness measures are generally significant across all five groups. There are a few exceptions to note. First, for the large-cap funds, the difference in the Active Weight (AW) measures is not significant, suggesting that the managers of the ETFs and the CMFs deviate from market-cap weighting their portfolios to approximately the same degree. Secondly, for the mid-cap funds and the equity income funds, the Active Share results lead to different activeness conclusions, depending on whether the self-declared benchmarks or the pre-specified market indices are used in the calculations of Active Share. For the mid-cap funds, the results show that the diversified active ETFs are significantly more active than their control mutual funds when the self-declared benchmarks are used, but not so when the pre-specified market indices are used. For the equity income funds, the results show that the diversified active ETFs are significantly less active than their control mutual funds when the self-declared benchmarks are used, but not so when the pre-specified market indices are used.

**Table 1.6:** Differences of Active Measures for Active Diversified ETFs and CMFs

| | No. | $AS_{fb}$ | $AS_{sb}$ | AW | $TE_{reg}$ | $TE_{trd}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| Multi-Cap | 26 | 7.51*** | 12.60*** | 14.76*** | 2.46*** | 3.27*** | −4.41*** |
| | | (73.50 , 66.00) | (73.13 , 60.53) | (48.98 , 34.22) | (5.33 , 2.87) | (6.39 , 3.12) | (91.65 , 96.05) |
| Large-Cap | 19 | 4.69*** | 3.77*** | 0.91 | 1.04*** | 0.98*** | −3.94*** |
| | | (74.91 , 70.22) | (76.50 , 72.72) | (48.84 , 47.93) | (4.25 , 3.21) | (4.68 , 3.70) | (92.08 , 96.03) |
| Mid-Cap | 6 | 1.19 | 6.13*** | 3.02*** | 2.09*** | 3.71*** | −10.51*** |
| | | (94.28 , 93.09) | (99.68 , 93.55 ) | (38.04 , 35.01) | (5.89 , 3.80 ) | (7.71 , 4.00 ) | (80.28 , 90.79) |
| Small-Cap | 11 | −5.87*** | −5.05*** | 8.29*** | 0.04 | 0.20 | 1.37 |
| | | (84.18 , 90.06) | ( 85.70 , 90.75) | (40.67 , 32.38) | (5.61 , 5.58) | (6.12 , 5.92) | (93.29 , 91.92) |
| Equity Income | 9 | −0.46 | −2.70*** | 10.76*** | 0.62*** | 2.18*** | −5.72*** |
| | | (75.20 , 75.66) | (76.16 , 78.86) | (52.27 , 41.52 ) | (4.37 , 3.75 ) | (6.41 , 4.23) | (86.11 , 91.84) |

This table presents the mean and the difference with respect to each active measure based on different Lipper Classes Names for 76 active diversified ETFs and their CMFs. All the measures are reported as in percentage (%). Funds that fall into other categories such as "Speciality" or "Alternative" are classified as "others" and are not listed here because of a very limited number of funds in total. The values inside the bracket are the mean of ETFs and their CMFs with respect to each activeness measure. The * indicates the significance level of difference of the mean between the two groups using the Welch two-sample test.

*, ** and *** are at the 10%, 5%, 1% significance level, respectively.

Thirdly, for the small-cap funds, the results are very inconclusive, as different activeness measures yield different results. Based on the AS measure, they are significantly less active than their CMFs under both choices of benchmarks. One possible explanation is that small-cap stocks typically do not have wide analyst coverage, and thus fund managers need to spend a substantial amount of resources to research them, which they may not be willing to do given the daily disclosure requirement requires them to reveal their holdings (i.e., the results of their research) to the public every day. I note, however, the AW measure leads to the opposite conclusion; i.e., the ETFs are more active. These results suggest that the managers of active small-cap ETFs choose to be active by overweighting and/or underweighting the stocks in their portfolios (relative to market-cap weighting), rather than by selecting stocks or market timing. Yet the tracking error volatility and the selectivity $(1 - R^2)$ measures do not show any significant difference.

In conclusion, there is strong evidence that diversified active ETFs are more active than their control mutual funds. For the majority of the ETFs, the results are consistent across all four activeness measures. The only obvious exception is small-cap ETFs, where the results are inconclusive.

Finally, to ensure that the results are not influenced by the selection of CMFs, I repeat the estimation and comparison of Active Shares, tracking error volatility, and $R^2$, using the second closest control fund from the matching process. The results (not shown) are consistent with those reported above.

### 1.5.3 Activeness of Sector Active Equity ETFs

Table 1.7 (Panels A to D) presents the activeness estimates of the sector active equity ETFs and their CMFs.

#### 1.5.3.1 Active Share

As before, I report two Active Share estimates, one based on the funds' self-declared benchmarks and the other on the set of pre-specified sector indices. There are two things to note from the results. First, the mean and the median AS estimates for the sector ETFs are much higher (by about 8%) when the funds' self-declared benchmarks are used than when the set of pre-specified sector indices is used. The same is true, to an even greater extent, for their control mutual funds. This could be an indication of benchmark misspecification. Secondly, whether or not the sector ETFs are more active than their CMFs depends on the choice of benchmarks. When the funds' self-declared benchmarks are used, the sector ETFs and their CMFs are equally active. However, when the set of pre-specified sector indices is used, the ETFs are significantly more active. The uncertainty in benchmark choices is an issue with using AS as an activeness measure. This is why other activeness measures have to be considered as well.

#### 1.5.3.2 Active Weight

The AW estimates of the sector ETFs and their CMFs are reported in Panel B of Table 1.7. For the sector ETFs, the AW estimates have a mean of 57.84% and a median of 58.78%. The mean is significantly higher than that of their CMFs (by about 15%), suggesting that the sector ETFs are, on average, much more active

**Table 1.7:** Activeness Measures of Active Sector ETFs and CMFs

| | AETFs | | | | | CMFs | | | | | Diff. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Min | Median | Max | Mean | SD | Min | Median | Max | t-stat |
| **Panel A: Active Share** | | | | | | | | | | | |
| $AS_{self\ declared}$ | 88.04 | 12.00 | 60.62 | 92.00 | 99.03 | 88.31 | 15.01 | 57.39 | 95.47 | 100.46 | −0.27 (−0.01) |
| $AS_{pre-specified}$ | 80.50 | 17.06 | 61.32 | 84.58 | 93.33 | 73.15 | 15.71 | 50.94 | 77.91 | 88.92 | 6.35*** (7.68) |
| **Panel B: Active Weight** | | | | | | | | | | | |
| AW | 57.84 | 14.74 | 42.47 | 58.78 | 74.04 | 42.71 | 15.03 | 21.08 | 42.79 | 64.64 | 15.13*** (11.61) |
| **Panel C: Tracking Error Volatility** | | | | | | | | | | | |
| $TE_{trd}$ | 9.40 | 5.39 | 4.26 | 9.27 | 15.99 | 7.54 | 3.92 | 3.65 | 6.71 | 18.07 | 1.86*** (4.01) |
| $TE_{reg}$ | 8.44 | 5.34 | 3.51 | 8.19 | 15.07 | 6.17 | 2.61 | 3.91 | 5.81 | 10.59 | 2.27*** (5.92) |
| **Panel D:** $R^2$ | | | | | | | | | | | |
| $CAPM_{pre-specified}$ | 72.26 | 18.66 | 48.80 | 71.92 | 89.68 | 80.62 | 13.77 | 55.51 | 82.98 | 90.25 | −8.36*** (−3.38) |
| FFC | 80.44 | 13.24 | 61.64 | 81.16 | 92.03 | 84.43 | 11.88 | 61.38 | 85.97 | 92.46 | −3.99** (−2.20) |

This table presents the summary statistics of active measures of 23 domestically actively managed sector ETFs and their CMFs. All the measures are reported as in percentage (%). The AS calculation considers all the holdings including positions such as futures and cash equivalents on top of the common stocks. The traditional method of calculating TE is defined as the standard deviation of the return difference between active ETFs and their pre-specified benchmark. The regression method of TE stands for the standard deviation of residuals from the regression of the fund's excess return (over the risk-free rate) on its benchmark's excess return. All the statistics are firstly calculated cross-sectionally for all the funds at each month and then the time-series average along the data period. The $R^2$ is calculated with the FFC model using daily return on a quarterly rolling window. The * indicates the significance level of difference of the mean between the two groups using the Welch two-sample test.

*, ** and *** are at the 10%, 5%, 1% significance level, respectively.

than their control mutual funds are (in the sense that the ETFs deviate more from simple value-weighted strategies than actively managed sector mutual funds do). In addition, I note that the mean and median AW estimates for sector ETFs are higher than the corresponding numbers for the diversified ETFs in Section 1.5.2.2 above.

#### 1.5.3.3 Tracking Error Volatility

Panel C of Table 1.7 displays both the standard and the modified versions of tracking error volatility of the sector active ETFs and their CMFs. For each ETF, the estimates are based on the benchmark from the set of pre-specified sector indices that yields the lowest Active Share in Section 1.5.2.3.

For both versions of tracking error volatility, the means of the ETFs are significantly higher than those of their CMFs (by about 2%). Recall that the standard version of tracking error volatility captures fund managers' bets on systematic factors, while the modified version better captures stock-selecting ability. The results suggest that the sector ETFs are, on average, more active than their control mutual funds are, in both stock selection and factor timing dimensions.

#### 1.5.3.4 Selectivity: $(1 - R^2)$

I obtain $R^2$'s of the sector active ETFs and their CMFs from regressions of their returns on their benchmarks, using various factor models. In these models, I follow the practice that is common in studies of sector mutual fund performance, and replace the market factor with the sector index.[26] For each sector ETF,

[26] Studies of sector funds typically examine "benchmark-adjusted" returns (i.e., fund returns after accounting for the returns on their sector benchmarks), rather than "market-adjusted"

the sector index used is the one from the set of pre-specified sector indices that minimizes its Active Share estimates in Section Section 1.5.2.4. As before, only the $R^2$'s using the one-factor and the 4-factor model are reported. The results from other models are qualitatively similar.

Panel D of Table 1.7 reports the results. The results from the one-factor and the 4-factor model are consistent with each other. For both models, the average $R^2$ is lower (and thus $1 - R^2$ is higher) for the active ETFs than for their CMFs. When the one-factor model is used, the average $R^2$ is 72.26% for the active ETFs and 80.62% for their CMFs. The counterpart numbers for the Carhart 4-factor model are 80.44% for the active ETFs and 84.43% for the CMFs. These results indicate that the sector active ETFs are, on average, more active than their control mutual funds.[27]

### 1.5.4 Discussions

All four activeness measures suggest that both the diversified and the sector active ETFs are generally significantly more active than their control mutual funds. Recall that different measures emphasize different aspects of activeness. For example, AS captures fund managers' attempts at stock selection, while tracking error volatility (the standard version) reflects managers' attempts at factor timing. The

returns. Mateus et al. (2019) report that the use of market-adjusted alphas (where the S&P 500 index is used as the market proxy) overstate the performance of over 60% of the funds that they examine. See also Pástor et al. (2017).

[27] I also run the tests using the S&P500 index as the market factor, instead of using the sector indices. In this case, the differences in activeness between the sector active ETFs and their CMFs are no longer significant. This suggests that the S&P500 index may not be an appropriate benchmark for sector funds.

results in Table 1.5 and Table 1.7 show that the ETFs are, on average, more active than their CMFs in every activeness aspect.

As to why the ETFs are more active, I conjecture that there are three possible reasons. First, active ETFs are a new product. Without a track record, the issuers need to differentiate their offerings from the existing products (i.e., mutual funds). While the ETFs already offer a cost advantage over mutual funds, the providers may also choose to compete on non-price dimensions such as making their ETFs more active. This argument is consistent with a prediction by Mamaysky and Spiegel (2002) that newly created funds should provide trading strategies that are significantly different from those of existing funds. Khorana and Servaes (2012) show that both price and non-price (i.e., product differentiation) competition is effective for new funds to gain market share. While these two studies examine competition among mutual funds, I believe that their results also apply to ETFs, which are closely-related products.

The second reason for the ETFs being more active is that, by design, ETFs are sold directly to investors, as opposed to (retail) mutual funds that are commonly sold through brokers, bundled with financial advice and portfolio-management service. Guercio and Reuter (2014) show that mutual funds marketed directly to retail investors have more incentive to generate alpha or abnormal risk-adjusted returns than funds sold through brokers do. As a result, direct-sale funds do more active management.

Finally, Clifford et al. (2014) show that investors pursue returns of active ETFs in the same way as they chase mutual funds' returns (Berk and Green 2004).

Accordingly, fund managers, despite the risk from frequent disclosure, try to be more active in the hope that they will achieve better performance in order to attract fund flows. Consistent with this, Easley et al. (2021) show that more active ETFs are gaining more market share over less active ETFs.

## 1.6 Conclusions

In this paper, I investigate the effects of the daily portfolio disclosure requirement on the activeness level of U.S. active ETFs. I use four different activeness measures. They are tracking error volatility, Active Share, Active Weight, and selectivity (i.e., $1-R^2$). The sample is divided into two groups - diversified active ETFs and sector active ETFs.

These findings are as follows. First, diversified active ETFs are generally more active than their control mutual funds. Secondly, when I divide diversified active ETFs into subgroups according to their investment styles (e.g., multi-cap, large-cap, and small-cap), the differences in the activeness measures between the ETFs and their control funds are generally significant across all subgroups, with a possible exception for the small-cap subgroup, where the results are inconclusive. Thirdly, sector active ETFs are also generally significantly more active than their control mutual funds based on all four activeness measures. Finally, there is evidence that sector ETFs are more active (relative to their control mutual funds) than diversified ETFs are (relative to their control funds).

There are three possible explanations for why the ETFs are more active than their control funds. First, active ETFs are a new product, and so the issuers need to differentiate their offerings from the existing products (i.e., mutual funds). While the ETFs already offer a cost advantage over mutual funds, the providers may also choose to compete on non-price dimensions such as making their ETFs more active. Secondly, ETFs, by design, are sold directly to investors, as opposed to (retail) mutual funds that are commonly sold through brokers. Guercio and Reuter (2014) show that mutual funds marketed directly to retail investors have more incentive to generate alpha or abnormal risk-adjusted returns than funds sold through brokers do. As a result, direct-sold funds do more active management. Finally, active ETF managers, despite the risk from frequent disclosure, try to be more active in the hope that they will achieve better performance in order to attract fund flows.

# Chapter 2

# Active ETFs: The Effect of Daily Holdings Disclosure Requirements on Their Performance and Trading Strategies

## 2.1 Introduction

Actively managed Exchange-Traded Funds (Active ETFs, or AETFs) have undergone rapid growth since their inception in 2008. As of October 2023, there are over 1,200 active ETFs listed on US exchanges with combined assets under management of around $444 billion (Source: Morgan Stanley, all figures in US dollar).[1] In comparison to actively managed mutual funds, AETFs offer several

[1] https://www.morganstanley.com/ideas/actively-managed-etfs-investor-demand.

advantages, including lower expense ratios, improved tax efficiency due to their creation and redemption process, and the ability to trade throughout the day.

As with passive ETFs, AETFs are required by the U.S. Securities and Exchange Commission (SEC) to disclose their portfolio holdings on a daily basis. This requirement creates potential risks to AETFs because other market participants can infer their trading strategies, leading to problems such as front-running and free-riding.[2] Front-running occurs when other traders, such as market makers or professional investors, anticipate the fund manager's trading moves based on the disclosed portfolio information and trade in advance, thereby influencing prices to their advantage. Free-riding enables other traders to benefit, at no cost, from the fund's research and trading strategies.[3]

In this chapter, I examine the performance of AETFs and compare it to that of traditional mutual funds in order to determine whether it is affected by the daily portfolio disclosure requirement. This is done using both the returns-based and the holdings-based approaches. In addition, I analyze the trades that AETFs conduct (i.e., buys and sells) to see how fund managers' actual trades impact fund performance.

The paper's structure is organized as follows: Section 2.2 covers related literature and motivations; Section 2.3 discusses the methodologies employed, including

[2] To address these concerns, fund companies have introduced nontransparent ETFs that disclose holdings quarterly, aligning with the frequency of disclosure seen in actively managed mutual funds. The SEC approved the first actively managed nontransparent ETFs in late 2019, prompting other major players like BlackRock and Vanguard to follow suit. This less frequent disclosure aims to shield fund managers' strategies and trades, safeguarding their research and investment tactics.

[3] Frank et al. (2004) compares the performance of actively managed mutual funds to that of their copycats. They find that copycat mutual funds could earn indistinguishable gross returns and even higher net returns because of the lower expenses (i.e., free-riding benefit).

performance measurement methods; Section 2.4 presents the data; Section 2.5 and Section 2.6 shows the results for diversified and sector AETFs, respectively; and, finally, Section 2.7 provides the concluding remarks.

## 2.2 Literature

Extensive literature has examined the performance of actively managed mutual funds from both returns-based and holdings-based perspectives.[4] While some limited studies (e.g., Rompotis 2009; Rompotis 2011a; Rompotis 2011b; Garyn-Tal 2013) have explored the performance of AETFs with a small sample size and relatively short history, their findings suggest that, on average, AETFs struggle to outperform their benchmark indices. Additionally, Sherrill and Upton (2018) compare AETFs and actively managed mutual funds and find that they can act as substitutes, though not perfectly.

However, a significant gap remains in understanding the impact of daily holdings disclosure on AETFs' performance and fund managers' skills. The concern arises from the potential for high-frequency disclosure to leak managers' investment insights, particularly short-term predictions, and subsequently discourage managers from sharing proprietary information with the public.[5] Moreover, the increased transparency might lead to reduced levels of fund activity, which, in turn, could affect performance.

[4] See Wermers (2011) for a detailed summarization of the varying performance measures that have been applied to mutual funds in the past few decades.

[5] Please look into Meziani and Meziani (2016) and Wermers (2001) for a detailed description of the risks associated with a more frequent disclosure of fund holdings.

Research in the realm of mutual funds has indicated that increased transparency and disclosure frequency can influence fund performance. Studies, such as Agarwal et al. (2015) and Parida and Teo (2018), following the 2004 SEC regulation change requiring more frequent mutual fund holdings disclosure (from semi-annually to quarterly), observed that high-performance funds suffered a decline in performance. Recent research has also highlighted that more active funds tend to outperform their less active counterparts (e.g., Amihud and Goyenko 2013; Cremers and Petajisto 2009; Guercio and Reuter 2014). Given this context, investigating how AETFs performance is influenced by daily holdings disclosure and subsequent changes in activeness becomes crucial.

This study provides insights into the performance implications of AETFs' daily disclosure and introduces a more precise assessment of managers' skills. Traditional literature on fund manager skills often relies on low-frequency (quarterly) data, which might miss a significant number of trades and lead to erroneous conclusions. For instance, studies have shown that low-frequency data fails to capture the management ability of managers adept at anticipating short-term movements and engaging in frequent trading. Additionally, Elton et al. (2010) and Elton et al. (2012a) show that the use of quarterly data misses a substantial portion of trades estimated using higher-frequency-monthly data. Consequently, utilizing finer data can alter or reverse previous findings regarding fund managers' skills in market timing and stock selection. For example, Nicolosi (2009) also shows that if trading occurs earlier than the assumed holdings disclosure interval, the evidence of sustained stock selection skill disappears.

In summary, this study aims to bridge gaps in the literature by examining how daily holdings disclosure impacts AETF's performance and managers' skill assessment. It also recognizes the importance of high-frequency data in offering more accurate insights into managers' trading behaviors and skill levels.

## 2.3 Methodology

To investigate whether the daily portfolio disclosure requirement affects the performance of AETFs, I measure AETFs' performance and then compare it to that of control mutual funds, which are required to disclose their holdings only on a quarterly basis. Below, I discuss the measurement approaches that I use. The criteria for selecting the control mutual funds are as described in Section 1.4.1.2 in Chapter 1.

There are two primary approaches to measuring fund performance that have been widely employed in the mutual funds literature. They are the returns-based approach and the holdings-based approach. I discuss them in detail in the following two subsections.

### 2.3.1 Returns-based Measures

The returns-based approach measures a fund's performance by estimating the fund's abnormal returns using a regression of the fund's (excess) returns on selected pricing factors (e.g., Carhart (1997) four-factor model). This approach is easy to implement because fund returns data are readily available. However, there are two cautions to keep in mind. First, as has been well documented, this approach can be sensitive to the choice of benchmark factors (e.g., Roll 1978).[6] Secondly, while

[6] In addition, the usual assumptions regarding OLS regressions apply.

this approach can determine whether a fund can generate abnormal returns, it cannot *directly* identify the specific kinds of skills possessed by the fund manager (e.g., stock picking, market timing, etc.).

In this study, I use three returns-based models to measure AETFs' performance. They are (i) the unconditional model; (ii) the conditional model; and (iii) the market-timing model. The three models differ in how they model the regressors, as discussed below.

#### 2.3.1.1 Unconditional Models

The literature on mutual funds extensively employs standard factor models to assess funds' performance based on both the funds' gross and net returns. This entails regressing a fund's excess returns (over the risk-free rate) on a specified standard factor model. For this study, I employ four different factor models in the regressions. They are (i) the Capital Asset Pricing Model (CAPM)(Sharpe 1964; Jensen 1968); (ii) the Fama-French-Carhart four-factor model (FFC) (Carhart 1997); (iii) a single-factor model where the factor is the fund's self-declared benchmark (Single-Factor$_{\text{sb}}$); and (iv) a single-factor model where the factor is the benchmark index against which the fund has the lowest Active Share value and thus has the greatest amount of overlap with (Single-Factor$_{\text{fb}}$).[7]

As an example, the regression equation, assuming that the FFC model is used, is as follows:

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \gamma_i r_{SMB,t} + \delta_i r_{HML,t} + \lambda_i r_{MOM,t} + \epsilon_{i,t} \tag{2.1}$$

[7] Active Share measures the deviation of the fund's holdings from its benchmark. Please see Chapter 1 for details.

where $r_{i,t}$ is the excess return of fund $i$ over the risk-free rate on day $t$; $r_{m,t}$ is the excess return of the CRSP value-weighted market proxy portfolio, and $r_{SMB,t}$, $r_{HML,t}$, $r_{MOM,t}$ are factor mimicking portfolios for size, value (book-to-market), and momentum on day $t$ respectively. The intercept $\alpha_i$ measures fund $i's$ average performance after taking into account the fund's loadings on the four risk factors, and thus represents the unconditional abnormal return that cannot be explained by the FFC factors.

For each AETF, I use two versions of the dependent variable, $r_{i,t}$. One is based on its gross returns, and the other on its net returns. Net returns are calculated using the fund's net asset values (NAVs), while gross returns incorporate the fund's expenses on top of the net returns. The use of both gross and net returns helps to ascertain whether fund managers can generate abnormal returns both before and after the fees that they charge. This is especially important considering that prior research has shown that funds displaying greater expertise tend to charge higher management fees (Berk and Green 2004).

Each AETF is matched with a control mutual fund (CMF), using the same matching procedure as outlined in Chapter 1. I perform the regressions on the whole sample as well as within subgroups of AETFs based on their Lipper Investment Objectives. The subgroup analysis sheds light on how the AETFs perform relative to their control mutual funds across different investment categories.

#### 2.3.1.2 Conditional Models

While the unconditional regression models have been widely used in the mutual funds literature, one of its drawbacks is that it assumes that the loadings on the factors are constant over the measurement period, which ignores the possibility that fund managers may adjust their risk levels through time in response to changing economic conditions. For instance, during periods of low interest rates, fund managers may shift their investment into higher-yield assets such as equity. To address this limitation, Ferson and Schadt (1996) introduced a conditional version of the regressions by incorporating publicly available information variables. Their framework allows fund managers to adapt their portfolio's risk exposure through time in response to varying market conditions, thus enhancing the models' flexibility and capturing the dynamic nature of investment decisions.

The conditional model adds interaction terms between lagged public information variables and market excess returns to the standard factor model. For example, the conditional version of the FFC model is as follows:

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \gamma_i r_{SMB,t} + \delta_i r_{HML,t} + \lambda_i r_{MOM,t} + \sum_{j=1}^{4} \theta_{i,j}(z_{j,t-1} r_{m,t}) + \epsilon_{i,t} \quad (2.2)$$

where $z_{j,t-1}$ is the predetermined demeaned macro-economic variable $j$, and $\theta_{i,j}$ is the sensitivity of fund $i$ to the macro-economic variable $j$.[8] The four macro variables are taken from Crane and Crotty (2018).[9] Specifically, they are (i) one-month Treasury-bill yield, (ii) dividend yield on the value-weighted CRSP Index, (iii) Treasury yield term spread (10-year Treasury yield minus 3-month Treasury

[8] Each demeaned macro-economic variable is calculated as the deviation from its time-series mean.

[9] As Ferson and Schadt (1996) point out, these predetermined information variables are selected because they have been shown to be able to predict security returns and risks over time.

yield), and (iv) credit spread in the corporate bond market (Baa minus Aaa corporate bond yields). The intercept, $\alpha_i$, represents the conditional abnormal performance within the conditional FFC framework, indicating whether the fund is able to generate returns beyond what can be predicted by the FFC factors and the macroeconomic variables.

The adoption of a conditional model aims to lessen biases in estimating fund performance. For instance, suppose that a fund manager takes more risk during market upswings and less risk during downturns. This strategic risk-taking creates a positive correlation between the fund's beta and market return. In an unconditional regression, this will show up as a positive abnormal performance. In contrast, in a conditional regression, the positive correlation is likely to be partly captured by the interaction term, thus moderating the level of positive abnormal returns.

The process of estimating conditional alphas for each fund and the entire sample aligns with that described in the unconditional models. The daily returns of the four lagged public information variables are synchronized with the daily returns of AETFs and their respective CMFs.

#### 2.3.1.3 Market Timing Models

While a standard regression can determine whether the funds can generate abnormal returns, it does not identify their sources. In the mutual fund literature, there are two returns-based models that are commonly used to examine the market-timing ability of fund managers. The two approaches were originally proposed by Treynor and Mazuy (1966) and Henriksson and Merton (1981), respectively, and have since been used in various mutual funds studies (e.g., Bollen and Busse 2001; Chen et al. 2010; Kaushik et al. 2010).

The Treynor and Mazuy (1966, TM) model augments the standard CAPM regression equation with a quadratic term, represented as follows:

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \gamma_i r_{m,t}^2 + \epsilon_{i,t} \tag{2.3}$$

where $r_{i,t}$ is the fund's excess return over the risk-free rate, and $r_{m,t}$ and $r_{m,t}^2$ are the excess returns on the market and its square respectively, and $\epsilon_{i,t}$ is the residual term. The coefficient $\gamma_i$ measures the fund manager's market-timing ability, with a positive $\gamma_i$ suggesting that the fund manager exhibits market-timing skills. This arises from the notion that a skilled manager can dynamically adjust the fund's beta (i.e., exposure to market risk) by increasing it when the market goes up and decreasing it in a market downturn, resulting in a convex, nonlinear relationship between the fund's returns and the market returns. In addition, the intercept term $\alpha_i$ indicates the fund's ability to generate abnormal returns through stock selection.

The Henriksson and Merton (1981, HM) model introduces an option-like element to the standard CAPM regression:

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \gamma_i Max(-r_{m,t}, 0) + \epsilon_{i,t} \tag{2.4}$$

where all the variables are defined as before. The $Max(-r_{m,t}, 0)$ can be thought of as the payoff of a put option on the market portfolio where the exercise price is the risk-free rate. Here, $\gamma_i$ captures fund managers' market-timing ability. The rationale is that a skilled market timer will be able to protect his/her portfolio with an implicit put option. When the market excess return is positive (i.e., $-r_{m,t} < 0$), there is no need for protection from the implicit put option, and the fund benefits from the excess return. On the other hand, when the market excess return is negative (i.e., $-r_{m,t} > 0$), the manager is able to minimize its impact (i.e., the implicit put's payoff offsets the market's decline).

Thus, if a fund manager demonstrates an ability to positively adjust portfolio beta during market upturns and reduce portfolio beta during market downturns, effective market timing is exhibited, and the coefficient $\gamma$ will likely be significantly positive. As Goetzmann et al. (2000) argue, an ideal market timer would have a $\beta$ equal to one and a timing coefficient $\gamma$ equal to one. This argument assumes that a market timer would either be fully invested or completely out of the market (i.e., shifting from the market portfolio to risk-free returns), implying that the pure timer's portfolio beta oscillates between zero and one.

### 2.3.2 Holdings-based Measures

The holdings-based approach analyzes a fund's holdings to determine whether the manager exhibits a superior trading ability. This approach allows detailed performance attribution to different aspects of a fund manager's skills, including, but not limited to, stock selection and market timing.[10] Stock selection ability refers to a fund manager's capacity to identify profitable securities within the investment universe based on his/her research and insight. Market timing ability

[10] In addition, the holdings-based approach can help to uncover whether (and, if so, by how much) the funds have a "style drift," defined as the tendency for the fund managers to deviate from the funds' stated benchmark in search of better performance (Wermers 2012). However, the "style drift" is not the focus of this paper. Thus, this aspect is not further explored.

involves a fund manager's skill in making timely adjustments to portfolio weights of various asset classes and/or weights of different sectors within the same asset class.

Early holdings-based studies typically use holdings information to determine whether the portfolio choices of fund managers could subsequently earn significantly positive risk-adjusted returns (e.g., Grinblatt and Titman 1989; Grinblatt and Titman 1993). Later holdings-based studies extend the approach by attributing fund performance to different aspects of fund managers' skills (e.g., Daniel et al. 1997). This approach (henceforth the "DGTW approach") has gained widespread application in the literature.

The premise of the DGTW approach is that there are three different skills that fund managers may possess that can contribute to fund performance – stock selection, timing, and choice of investment style. The key to their approach is to decompose funds' *hypothetical* returns into these three components and then determine whether the managers outperform the benchmark in any of the three components. That is, using DGTW's notations,

$$Fund's\ gross\ return = CS + CT + AS_{style}, \tag{2.5}$$

where $CS$ is Characteristic Selection (i.e., the portion of the returns that is attributed to the manager's ability to choose outperforming stocks); $CT$ is Characteristic Timing (i.e., the portion of the returns that is attributed to the manager's timing decisions), and $AS_{\text{style}}$ is Average Style (i.e., the portion of the returns that is attributed to the manager's investment style such as holding stocks with certain characteristics).[11]

The returns used in the analysis are hypothetical because they are constructed to approximate the funds' gross returns (i.e., before subtracting fees, expenses, and trading costs) over specific measurement periods. Specifically, they are generated by buying the number of shares of each stock held by the fund on the first day of the measurement period and holding the portfolio until the first day of the following measurement period. Although the hypothetical returns overestimate the actual returns that investors receive from holding the fund (which are net of fees, expenses, and trading costs), DGTW argue that the hypothetical returns are appropriate to use in the analysis because they will be compared to benchmark returns that also ignore the expenses.

In the three subsections below, I discuss how the fund's hypothetical returns are decomposed into the three components and then compared with their benchmark returns.

#### 2.3.2.1 Characteristic Selection ($CS$) Measure

The Characteristic Selection ($CS$) measure determines the fund manager's stock-selection ability. This is done through the following steps:

1. For each measurement period and for each stock that the fund holds (say, stock $j$), find a passive portfolio (of stocks in the investment universe) that matches the characteristics of stock $j$ along three dimensions – size, book-to-market ratio, and momentum. These three characteristics are chosen because they have been shown in prior studies to explain cross-sectional stock

[11] This notation is to differentiate it from AS (Active Share) in Chapter 1.

returns.[12] The matched passive portfolio will be used as the benchmark for stock $j$ (henceforth referred to as $\text{MPP}_j$). (See Appendix A1 for how MPPs are constructed and matched with the stocks in the fund.)

2. For measurement period $t$, the $CS$ measure for the fund is calculated as:

$$\begin{aligned} CS_t &= \sum_{j=1}^{N} w_{j,t-1}(R_{j,t} - R_t^{b_{j,t-1}}) \\ &= \sum_{j=1}^{N} w_{j,t-1}R_{j,t} - \sum_{j=1}^{N} w_{j,t-1}R_t^{b_{j,t-1}} \end{aligned} \tag{2.6}$$

where $w_{j,t-1}$ is the weight of stock $j$ in the fund at the end of measurement period $t-1$, $R_{j,t}$ is the return of stock $j$ over measurement period $t$, and $R_t^{b_{j,t-1}}$ is the return of $\text{MPP}_j$ over the measurement period $t$, where the matching of $\text{MPP}_j$ to stock $j$ is done based on the information as of measurement period $t-1$.[13] That is, the $CS$ measure for measurement period $t$ is the difference between the fund's return in that period and the return on the portfolio of MPPs that are matched to the stocks in the fund (where the weight of $\text{MPP}_j$ is the same as the weight of stock $j$ in the fund). As constructed, if the value of $CS$ is zero, it indicates that the performance of the fund could, on average, be replicated by simply holding portfolios of stocks with the same size, book-to-market, and momentum characteristics as the stocks that the fund holds.

[12] See, e.g., Fama and French (1993), Carhart (1997), Grinblatt and Titman (1989), and Jegadeesh and Titman (1993).

[13] It is important to note that I am working with two distinct sample groups: AETFs and CMFs. Due to their varying holding frequencies, I calculate these performance measures at different time intervals. Specifically, for each AETF, the time "$t$" refers to each month, while for each CMF, the time "$t$" is set every quarter. Thus, I gather monthly time-series measures for each AETF and quarterly measures for each CMF. When comparing these measures between AETFs and CMFs, an exact matching of the measurement periods is necessary. Consequently, only quarterly measures are retained for the AETFs.

In contrast, a positive and significant $CS$ suggests that the manager has the additional ability to select securities.

3. Finally, the time-series average of $CS_t$ over all measurement periods is the $CS$ measure for that fund during the sample period.

#### 2.3.2.2 Characteristic Timing ($CT$) Measure

The Characteristic Timing ($CT$) measure assesses the fund manager's ability to time the market by adjusting portfolio weights in accordance with their predictions of changes in expected returns on the size, book-to-market, and/or momentum characteristics (or investment styles). The $CT$ measure for measurement period $t$ is defined as:

$$\begin{aligned} CT_t &= \sum_{j=1}^{N}(w_{j,t-1}R_t^{b_{j,t-1}} - w_{j,t-k}R_t^{b_{j,t-k}}) \\ &= \sum_{j=1}^{N} w_{j,t-1}R_t^{b_{j,t-1}} - \sum_{j=1}^{N} w_{j,t-k}R_t^{b_{j,t-k}} \end{aligned} \tag{2.7}$$

where $w_{j,t-k}$ is the weight of stock $j$ at the end of measurement period $t-k$, and $R_{j,t-k}$ is the return of MPP$_j$ over measurement period $t$, where the matching of MPP$_j$ to stock $j$ is done based on the information as of measurement period $t-k$, where $k$ is a constant that can be chosen to be any number depending on what time period over which the market-timing ability is assessed. That is, the $CT$ measure for measurement period $t$ is the difference between (i) the return over measurement period $t$ on the portfolio of MPPs that is matched to the fund's holdings in the most recent measurement period; and (ii) the return over measurement $t$ period on the portfolio of MPPs that is matched to the fund's holdings $k$ periods ago. As such, the $CT$ measure captures the returns that the manager can generate from altering the weights of the stocks in the fund through time. For example, if the manager anticipates that small stocks will outperform large stocks, he/she can increase the weights of small stocks in the fund. If his/her prediction comes true, This leads to higher fund's returns, resulting in a positive value for $CT$.

Similar to the case of the $CS$ measure above, the fund's overall $CT$ measure is the average of the time-series of $CT$ values.

#### 2.3.2.3 Average Style ($AS_{\text{style}}$) Measure

The Average Style ($AS_{\text{style}}$) measure captures the return over measurement period $t$ on the MPPs that are matched to the fund's holdings $k$ periods ago; i.e.,

$$AS_{\text{style}_t} = \sum_{j=1}^{N} w_{j,t-k} R_t^{b_{j,t-k}} \tag{2.8}$$

where the variables are as defined above, and $k$ is the same constant (i.e., has the same value) as in the case of $CT$ in the above equation. As defined, $AS_{\text{style}}$ is the benchmark return that reflects the fund's tendency to invest in stocks with certain characteristics (i.e., fund's style). Since it is based on the fund's style $k$ periods ago, it does not include the returns from the manager's market-timing decisions that were recently made (which would be captured by $CT$). For example, suppose that the length of one measurement period is a month, and $k$ is chosen to be 13. If the fund's style has always been to hold momentum stocks, $AS_{\text{style}}$ will capture the returns from choosing that style. However, if the fund has only decided to invest in momentum stock within the past 12 months, the returns from doing so will be captured by $CT$. A positive and significant $AS_{\text{style}}$ suggests that fund managers possess an average skill across size, value, or momentum strategies.

Again, similar to the case of the $CS$ and $CT$ measures above, the fund's overall $AS_{\text{style}}$ measure is the average of the time-series of $AS_{\text{style}}$ values.

In the calculations of $CS$, $CT$, and $AS_{\text{style}}$ values, it is important to note that holdings information of AETFs are available at a much finer frequency (daily) than holdings information of CMFs (quarterly).

### 2.3.3 Portfolio Trades Analysis

While the DGTW approach provides a breakdown of fund performance based on three aspects of skills, it does not directly examine how fund managers' actual trades (buying and selling securities) impact fund performance. For instance, one may want to find out whether fund managers can consistently buy stocks with higher returns and sell those with lower returns. Portfolio holdings information can be used to analyze the managers' trading activities.

I follow the method proposed by Kacperczyk et al. (2005, KSZ) to analyze portfolio trades, which builds upon the measure introduced by Chen et al. (2000). The idea is to compare the returns on the stocks that a fund manager buys vs. sells over a period of time. This is done through the following steps:

1. Determine the duration of time over which to examine the manager's trading activities; say, from $k$ periods ago (i.e., time $t-k$) to now.

2. For each stock in the fund, compare $(a)$ its current weight, defined as the weight at the start of the current period (i.e., at the end of the previous period), $w_{j,t-1}$ to $(b)$ its "lagged" weight, $\tilde{w}_{j,t-k}$, defined as the weight that it currently would have if the manager had not bought or sold any more shares of any security in the portfolio since period $t-k$. Formally, $\tilde{w}_{j,t-k}$ is calculated as:

$$\tilde{w}_{j,t-k} = \frac{w_{j,t-k}\prod_{n=1}^{k-1}(1+R_{j,t-n})}{\sum_j w_{j,t-k}\prod_{n=1}^{k-1}(1+R_{j,t-n})} \tag{2.9}$$

3. If $w_{j,t-1} > \tilde{w}_{j,t-k}$, it implies that over the past $k$ periods, the manager has increased the weight of stock $j$ in the portfolio. All stocks that meet this condition are classified as belonging to the "buys" group. Similarly, if $w_{j,t-1} < \tilde{w}_{j,t-k}$, it implies that over the past $k$ periods, the manager has decreased the weight of stock $j$ in the portfolio. All stocks that meet this condition are classified as belonging to the "sells" group.

4. Calculate and compare the average returns of the "buys" and "sells" groups for the current period (i.e., period $t$) as follows:

$$\begin{aligned} R_t^{buys} &= \frac{\sum_{w_{j,t-1}>\tilde{w}_{j,t-k}}(w_{j,t-1}-\tilde{w}_{j,t-k})R_{j,t}}{\sum_{w_{j,t-1}>\tilde{w}_{j,t-k}}(w_{j,t-1}-\tilde{w}_{j,t-k})} \\ R_t^{sells} &= \frac{\sum_{w_{j,t-1}<\tilde{w}_{j,t-k}}(w_{j,t-1}-\tilde{w}_{j,t-k})R_{j,t}}{\sum_{w_{j,t-1}<\tilde{w}_{j,t-k}}(w_{j,t-1}-\tilde{w}_{j,t-k})} \\ R_t^{buys-sells} &= R_t^{buys} - R_t^{sells} \end{aligned} \tag{2.10}$$

## 2.4 Data

The sample consists of 76 diversified equity AETFs during the period from March 2008 to December 2020, and 23 sector equity AETFs during the period from June 2012 to December 2020. Each AETF is matched with at least one control mutual fund (CMF), using the same procedure as described in Chapter 1.[14]

Data for AETFs and CMFs come from various sources. The fund statistics of AETFs and CMFs, including total net assets (TNA), expense ratios, turnover rates, and daily returns, are obtained from the Center for Research in Security Prices (CRSP) Survivorship-Bias-Free Mutual Fund Database (MFDB). Daily holdings information for AETFs is from ETF Global, while CMFs' holdings are from the Thomson Reuters Mutual Fund Holdings database, with the datasets being linked using the MFLINKS tool from the WRDS platform.

For the returns-based methods, the excess returns on the market portfolio are the value-weighted market excess returns obtained from CRSP. Returns on the other risk factors (i.e., SMB, HML, and MOM) are obtained from Professor Kenneth French's website.[15] Lagged public information variables in the conditional model are collected from the Federal Reserve Economic Data (FRED), except for dividend yields, which are sourced from CRSP.

[14] For all the tests in this chapter, I also perform them using an alternative set of CMFs characterized by the second best matching score. In general, this usage yields conclusions that are qualitatively similar to those observed using the primary set of CMFs.

[15] Please refer to https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

The selection of benchmarks for AETFs and their CMFs follows the same procedure as outlined in Chapter 1. That is, each fund has two benchmarks. One is self-declared based on its prospectus and/or Morningstar, while the other is picked from the set of pre-specified, relevant indices (i.e., the one against which the fund has the lowest Active Share value and thus has the greatest amount of overlap with).

For the holdings-based methods, the formation of DGTW characteristic-benchmark portfolios involves all stocks listed on the NYSE, AMEX, and Nasdaq. Style categorizations such as value, book-to-market, and momentum are derived from CRSP stock files and merged with COMPUSTAT data.

The diversified AETFs and the sector AETFs will be analyzed separately because of their different nature and risk-return profiles. Sector funds are restricted by the sets of securities that they can hold, while diversified funds have no such restriction. In addition, it has been documented that investment ability is more evident among managers of sector (or concentrated) funds than in diversified funds (Kacperczyk et al. 2005).

## 2.5 Results for Diversified AETFs

### 2.5.1 Returns-Based Tests

#### 2.5.1.1 Unconditional Models

To estimate the unconditional performance of the diversified AETFs and their CMFs, I run the regressions described in Section 2.3.1.1 above. I follow the standard approach outlined in prior studies (e.g., Fama and French 1992; Fama and French 1993; Carhart 1997; Angelidis et al. 2013) to obtain individual funds' alphas and the average alpha for the whole sample. First, time-series regressions are performed to estimate each fund's alpha within each quarter. Then, for each quarter, I cross-sectionally average the individual alphas to obtain the cross-sectional average alpha for that quarter. Finally, I calculate the average of the time series of the quarterly alphas. This average represents the entire sample's average abnormal performance. The *t*-statistics for the time series are adjusted using Newey and West (1987) robust standard errors.

Table 2.1 provides the unconditional gross and net abnormal returns (alpha's) for diversified AETFs and their CMFs during the sample period. As mentioned earlier, for each fund, the abnormal returns are estimated using four different models – CAPM, FFC, single factor where the factor is the fund's self-declared benchmark (Single-Factor$_{sb}$), and single factor where the factor is the benchmark index against which the fund has the lowest Active Share value (Single-Factor$_{\mathrm{fb}}$).[16,17]

**Table 2.1:** Unconditional Performance of Diversified AETFs and CMFs

| | Single-Factor$_{fb}$ | | Single-Factor$_{sb}$ | | CAPM | | FFC | |
|---|---|---|---|---|---|---|---|---|
| | GR | NR | GR | NR | GR | NR | GR | NR |
| AETFs | $-0.38^{*}$ | $-0.57^{***}$ | $-0.22$ | $-0.41$ | $-0.50$ | $-0.68^{***}$ | $-0.49^{***}$ | $-0.67^{***}$ |
| | $(-1.98)$ | $(-2.92)$ | $(-0.71)$ | $(-1.29)$ | $(-1.59)$ | $(-2.17)$ | $(-2.70)$ | $(-3.70)$ |
| CMFs | $0.11$ | $-0.14$ | $0.19^{*}$ | $-0.05$ | $-0.10$ | $-0.34^{**}$ | $0.05$ | $-0.19^{*}$ |
| | $(0.97)$ | $(-1.21)$ | $(1.72)$ | $(-0.44)$ | $(-0.59)$ | $(-2.01)$ | $(0.51)$ | $(-1.92)$ |
| Diff. | $-0.49^{***}$ | $-0.43^{**}$ | $-0.42$ | $-0.36$ | $-0.40^{*}$ | $-0.34$ | $-0.54^{***}$ | $-0.48^{**}$ |
| | $(-2.83)$ | $(-2.47)$ | $(-1.35)$ | $(1.15)$ | $(-1.77)$ | $(-1.51)$ | $(-2.79)$ | $(-2.48)$ |

This table shows the unconditional alphas for 76 diversified AETFs and CMFs from 03/2008 to 12/2020. Average alphas and other statistics are computed for each quarter using daily returns cross-sectionally for all funds available and then time-series average over the sample period. The alphas are presented quarterly in percentage, and parentheses are $t$-statistics adjusted for autocorrelation and heteroscedasticity with Newey and West (1987). The Net Return (NR) is a NAV-based return that is net of transaction costs, management fees, and other expenses, but not sales charges; Gross Return (GR) adds back the fund expense ratios. The Single-Factor$_{fb}$ and Single-Factor$_{sb}$ follows $R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{benchmark,t} - R_{f,t}) + \varepsilon_{i,t}$ where $R_{benchmark,t}$ is return of fund $i$ fixed set of benchmark and self-claimed benchmark, respectively.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

There are a few things to note from Table 2.1. First, under all four models, the average abnormal returns of diversified AETFs are negative on both the gross and net bases, with the majority of them being statistically significantly different from zero. In comparison, the average abnormal returns for the CMFs are generally

[16] In the sample, the self-declared benchmark generally remains the same for each fund throughout its life span. For the few cases where funds change their declared benchmarks, the regression results are qualitatively similar with or without incorporating the shifts of benchmarks. For the lowest-Active-Share benchmark, it could change when the fund's holdings change, and thus may not remain the same throughout a fund's life. For some funds, the lowest-Active-Share benchmark is the same as the self-declared benchmark.

[17] For robustness, I have also run the regressions using the Fama-French three-factor and five-factor models (Fama and French 1992; Fama and French 1993; Fama and French 2016). The results are not qualitatively different from those under the FFC model.

positive but not significantly different from zero on the gross basis, and negative (significantly so under two of the four models) on the net basis. Across all four models, diversified AETFs underperform their CMFs on both the gross and net bases, with the underperformance being significant under the Single-Factor$_{\text{fb}}$ and the FFC models. The magnitude of the underperformance ranges from 0.40% to 0.54% (gross) and 0.34% to 0.48% (net). Note that these numbers are per quarter, so the magnitude of the underperformance is approximately between 1.50% and 2% per year, which is substantial. This is despite the fact that, on average, diversified AETFs typically charge lower management fees than their control mutual funds do (0.72% vs. 1.10% per year, see Table 1.1 of Chapter 1).[18]

Furthermore, I note that among the four models used, the abnormal returns (on both gross and net bases) of diversified AETFs and CMFs are highest when their self-declared benchmarks are used as the regressor (i.e., Single-Factor$_{\text{sb}}$ model). This finding is consistent with the results in a mutual funds study by Cremers et al. (2022) that mutual funds that have a benchmark discrepancy (i.e., their self-declared benchmarks are different from the benchmarks that best match their investment strategies), on average, outperform their self-declared benchmarks but underperform the best-matched benchmarks.

In summary, the results on the funds' unconditional performance suggest that diversified AETFs, on average, tend to underperform their CMFs. This is especially true when the FFC and the Single-Factor$_{\text{fb}}$ models are used to measure the

[18] In unreported summary statistics, both the gross and net abnormal returns of diversified AETFs are more volatile than their CMFs counterparts. This is likely due, at least in part, to the fact that diversified AETFs change their portfolios more often (i.e., have higher portfolio turnovers) than their CMFs do, causing diversified AETFs' raw returns to be more volatile (See Table 1.1 and Table 1.2 of Chapter 1).

performance. To ensure the robustness of these results, I repeated the above procedure, with alphas being estimated monthly rather than quarterly. This change does not qualitatively alter the results. Next, I used the Fama-French 3-factor and 5-factor models in the regressions. Again, the results are qualitatively similar. Finally, I use a different definition of the dependent variable. Instead of fund's excess returns over the risk-free rate, I use funds' excess returns over the returns of their self-declared benchmarks and excess returns over the returns of their lowest-Active -Share benchmark.[19] The results are similar to those under the standard FFC model reported in Table 2.1; i.e., AETFs significantly (at the 5% level) underperform their CMFs.

#### 2.5.1.2 Conditional Models

To examine the possibility that fund managers may adjust the risk levels of their portfolios through time in response to changing economic conditions, I run regressions based on Equation (2.2), using both gross and net excess returns as the dependent variable. These findings are presented in Table 2.2.

In general, the abnormal returns for both diversified AETFs and their CMFs are more negative (or less positive) than under the unconditional model. This is true for three of the four models used (with CAPM being the exception). In addition, the abnormal returns have greater statistical significance than under the unconditional model. This is consistent with prior research (Kacperczyk et al. 2005; Ferson and Schadt 1996), which shows that conditional performance tends

[19] Kacperczyk et al. (2005) and Cremers and Petajisto (2009) argue that the use of excess returns over the risk-free rate as the dependent variable may not be appropriate for measuring funds' abnormal performance. This is because most funds are benchmarked against certain equity indices rather than the risk-free asset.

to display enhanced statistical robustness. When comparing diversified AETFs to their CMFs, the same trend as in the unconditional case is observed – diversified AETFs underperform their CMFs on both the gross and net bases, with the underperformance being significant under the Single-Factor$_{\text{fb}}$ and the FFC models.

**Table 2.2:** Conditional Performance of Diversified AETFs and CMFs

| | Single-Factor$_{fb}$ | | Single-Factor$_{sb}$ | | CAPM | | FFC | |
|---|---|---|---|---|---|---|---|---|
| | GR | NR | GR | NR | GR | NR | GR | NR |
| AETFs | $-0.51^{**}$ | $-0.69^{***}$ | $-0.33$ | $-0.51$ | $-0.45$ | $-0.63^{*}$ | $-0.56^{**}$ | $-0.74^{***}$ |
| | $(-3.23)$ | $(-4.38)$ | $(-1.13)$ | $(-1.76)$ | $(-1.48)$ | $(-2.08)$ | $(-2.89)$ | $(-3.83)$ |
| CMFs | $-0.01$ | $-0.26^{*}$ | $0.01$ | $-0.23^{*}$ | $-0.04$ | $-0.29$ | $0.04$ | $-0.20$ |
| | $(-0.11)$ | $(-2.38)$ | $(0.13)$ | $(-2.09)$ | $(-0.24)$ | $(-1.66)$ | $(0.40)$ | $(-1.87)$ |
| Diff. | $-0.50^{**}$ | $-0.43^{*}$ | $-0.34$ | $-0.28$ | $-0.41$ | $-0.34$ | $-0.60^{**}$ | $-0.54^{*}$ |
| | $(-2.99)$ | $(-2.62)$ | $(-1.15)$ | $(-0.94)$ | $(-1.81)$ | $(-1.53)$ | $(-2.89)$ | $(-2.59)$ |

This table shows the conditional alphas for 76 diversified AETFs and CMFs from 03/2008 to 12/2020. Average alphas and other statistics are computed for each quarter using daily returns cross-sectionally for all funds available and then time-series average over the sample period. The alphas are presented quarterly in percentage and parentheses are $t$-statistics adjusted for autocorrelation and heteroscedasticity with Newey and West (1987). The Net Return (NR) is a NAV-based return net of transaction costs, management fees, and other expenses, but not sales charges; the Gross Return (GR) adds back the fund's expense ratios. The Single-Factor$_{fb}$ and Single-Factor$_{sb}$ follows $R_{i,t}-R_{f,t} = \alpha_i+\beta_i(R_{benchmark,t}-R_{f,t})+\varepsilon_{i,t}$ where $R_{benchmark,t}$ is return of fund $i$ fixed set of benchmark and self-claimed benchmark, respectively. The conditional models include the interaction of four predetermined information variables with the market return; the four demeaned variables are the Treasury bill yield, the dividend yield of the value-weighted CRSP Index, the Treasury yield term spread (10-year minus 3-month Treasury yield), and the credit spread in the corporate bond market (Baa minus Aaa corporate yields).
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

#### 2.5.1.3 Performance by Investment Objectives

Table 2.3 looks further into the quarterly abnormal returns (net return alphas) based on diverse investment objectives for both diversified AETFs and their corresponding CMFs, focusing on unconditional performance measures.[20] The funds are classified into five groups in accordance with their Lipper Investment Objectives: Value, Growth, Core, Income, and Others.[21] Each factor model consists of three columns, displaying net-of-fee abnormal returns for AETFs, CMFs, and the difference between the two.

An interesting pattern emerges from the data. On average, Growth AETFs significantly underperform with net alphas of $-0.78\%$ for the Single-Factor$_{fb}$ model and $-0.92\%$ for the Fama-French-Carhart (FFC) model. In contrast, CMFs in the same category produce net alphas that are statistically indistinguishable from zero. This results in a consistently negative difference in abnormal performance for the Growth investment objective, with the discrepancy becoming particularly significant for the FFC model, reaching $-0.85\%$ per quarter.

This finding appears contrary to conventional wisdom. Traditionally, Growth funds are believed to exhibit superior risk-adjusted performance compared to Value or Income-focused funds, as suggested by prior research like Chen and Knez (1996)

[20] I also look at the gross alphas differences in the unconditional models and the net and gross alphas in the conditional models. In general, these findings with respect to different investment objectives do not qualitatively change the conclusion. Thus, only net return alphas differences are reported here.

[21] The investment categories of "Value," Growth," and "Income" funds are relatively straightforward to understand. According to the mutual funds' guidelines of Lipper Class investment objectives, "Core" funds have more latitude in the companies in which they invest, and these included companies usually have average price-to-earnings ratio, price-to-book ratio, and three-year sales-per-share growth value, compared to common market-cap indices. "Others" has the smallest number of funds (5) and tends to have objectives such as 'long-short equity,' so this category is dropped in the reported results.

**Table 2.3:** Performance of Diversified AETFs and CMFs in Subgroups

| | Single-Factor$_{fb}$ | | | Single-Factor$_{sb}$ | | | CAPM | | | FFC | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AETFs | CMFs | Diff. | AETFs | CMFs | Diff. | AETFs | CMFs | Diff. | AETFs | CMFs | Diff. |
| Value | 0.01 | −0.17 | 0.18 | 0.01 | −0.07 | 0.07 | −1.03* | −1.25** | 0.22 | −0.11 | −0.44*** | 0.33 |
| | (0.02) | (−0.89) | (0.58) | (0.01) | (−0.35) | (0.25) | (−1.82) | (−2.45) | (0.85) | (−0.45) | (−2.44) | (1.27) |
| Growth | −0.78** | −0.23 | −0.55 | −0.59 | −0.31 | −0.28 | −0.42 | 0.02 | −0.44 | −0.92** | −0.07 | −0.85** |
| | (−2.02) | (−1.38) | (−1.38) | (−1.13) | (−1.57) | (−0.56) | (−0.80) | (0.09) | (−1.01) | (−2.14) | (−0.42) | (−2.21) |
| Core | −0.33 | −0.01 | −0.32 | −0.18 | 0.09 | −0.27 | −0.65* | −0.43** | −0.23 | −0.28 | −0.12 | −0.17 |
| | (−1.15) | (−0.04) | (−1.07) | (−0.67) | (0.56) | (−0.91) | (−1.98) | (−2.16) | (−0.77) | (−1.26) | (−0.69) | (−0.64) |
| Income | −0.20 | −0.21 | 0.01 | −0.12 | −0.14 | 0.02 | −0.35 | −0.74** | 0.39 | −0.14 | −0.48*** | 0.33 |
| | (−0.72) | (−1.11) | (0.01) | (−0.38) | (−0.76) | (0.05) | (−1.17) | (−2.25) | (1.28) | (−0.67) | (−2.31) | (1.49) |

This table shows the differences of unconditional net alphas in various subgroups (by Lipper Investment Objective) for 76 diversified AETFs and CMFs from 03/2008 to 12/2020. Average alphas and the statistics are computed for each quarter using daily net returns cross-sectionally and then time-series average over the sample period. The alphas are presented quarterly in percentage and parentness are $t$-statistics adjusted for Newey and West (1987) robust standard errors. The Single-factor$_{fb}$ and Single-factor$_{sb}$ follows $R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{benchmark,t} - R_{f,t}) + \varepsilon_{i,t}$ where $R_{benchmark,t}$ is return of fund $i$ fixed set of benchmark and self-claimed benchmark, respectively.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

and Daniel et al. (1997). However, this study unveils that AETFs in the Growth category may not conform to this pattern. Instead, their fund managers seem to be performing relatively poorly in this investment category. Interestingly, CMFs exhibit underperformance in the Value, Core, and Income categories, although the differences in risk-adjusted returns remain statistically insignificant.

In unreported results, when funds are grouped by different market capitalizations, it emerges that Mid-Cap funds stand out as the only category where AETFs consistently underperform, displaying a significant underperformance of over $-2\%$ per quarter across all models. This observation is intriguing, considering that Cremers et al. (2013) found that the Mid-Cap index tends to exhibit better excess returns than large-cap and small-cap indexes on average. In other words, AETFs face their most substantial performance gap compared to CMFs in a category that traditionally performs well.

Overall, the findings indicate that AETFs struggle to compete with their CMF counterparts in the Growth category, with a significant difference of $-0.85\%$. However, in the Value and Income categories, where CMFs have underperformed, the performance differences between AETFs and CMFs remain statistically insignificant.

#### 2.5.1.4 Market Timing Models

The results of return-based market-timing tests for diversified AETFs and their CMFs are presented in Table 2.4. Both the Treynor and Mazuy (1966, TM) model and the Henriksson and Merton (1981, HM) model are used. Within each model, I estimate the abnormal returns (alphas) and the market-timing coefficients

($\gamma$'s) in both unconditional and conditional settings.[22] The final two rows display the differences between diversified AETFs and their CMFs, together with their respective robust $t$-statistics (Newey and West 1987).

**Table 2.4:** Market Timing Coefficients of Diversified AETFs and CMFs

| | Treynor-Mazuy | | | | Henriksson-Merton | | | |
|---|---|---|---|---|---|---|---|---|
| | Unconditional | | Conditional | | Unconditional | | Conditional | |
| | $\alpha_{\%}$ | $\gamma$ | $\alpha_{\%}$ | $\gamma$ | $\alpha_{\%}$ | $\gamma$ | $\alpha_{\%}$ | $\gamma$ |
| AETFs | −0.44 | −0.727* | −0.46 | −0.686 | −0.10 | −0.028** | −0.24 | −0.019 |
| | (−1.34) | (−1.916) | (−1.37) | (−1.254) | (−0.26) | (−2.244) | (−0.61) | (−1.349) |
| CMFs | −0.36 | 0.094 | −0.27 | 0.040 | −0.28 | −0.003 | −0.26 | −0.002 |
| | (−1.54) | (0.445) | (−1.29) | (0.143) | (−0.89) | (−0.376) | (−0.88) | (−0.239) |
| Diff. | −0.08 | −0.821** | −0.19 | −0.726 | 0.18 | −0.025** | 0.02 | −0.017 |
| | (−0.35) | (−2.334) | (−0.73) | (−1.598) | (0.56) | (−2.526) | (0.05) | (−1.516) |

This table shows the market timing coefficients for 76 diversified AETFs and CMFs from 03/2008 to 12/2020 respective to the Treynor and Mazuy (1966) and Henriksson and Merton (1981) model. Average $\alpha$s and $\gamma$s are computed for each quarter using daily returns cross-sectionally and then time-series average over the sample period. $\alpha$ is expressed quarterly in percentage and parentness are $t$-statistics adjusted for Newey and West (1987) robust standard errors. The Treynor-Mazuy model is $r_{i,t} = \alpha_i + \beta_i r_{m,t} + \gamma_i r_{m,t}^2 + \varepsilon_{i,t}$ and the Henriksson-Merton model is $r_{i,t} = \alpha_i + \beta_i r_{m,t} + \gamma_i max(r_{m,t}, 0) + \varepsilon_{i,t}$. The conditional models include the interaction of four predetermined information variables with the market return; the four demeaned variables are the Treasury bill yield, the dividend yield of the value-weighted CRSP Index, the Treasury yield term spread (10-year minus 3-month Treasury yield), and the credit spread (Baa minus Aaa corporate yields).
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In the unconditional version, the market-timing coefficient ($\gamma$) for diversified AETFs is negative and significant (at the 10% level for the TM model and the 5% level for the HM model). This indicates that managers of diversified AETFs exhibit negative timing ability. In contrast, CMFs generally show no timing ability, as their $\gamma$ is statistically insignificant and close to zero under both models. As a

[22] For the conditional regressions, the cross-product terms between the pre-determined (demeaned) macroeconomic variables (as specified in Section 2.3.1.2) and the excess market returns are added to the regression equations Equation (2.3) and Equation (2.4).

result, there is a significant difference in market-timing ability between diversified AETFs and their CMFs under both models.

In the conditional version, while the market-timing coefficients of diversified AETFs are negative, they are not significantly different from zero under both models. For the CMFs, their coefficients remain statistically insignificant and close to zero. As a result, there appears to be no difference in market-timing ability between diversified AETFs and their CMFs when the conditional regressions are used.

For diversified AETFs, the findings of negative market-timing ability when the unconditional version is used and insignificant market-timing ability when the conditional version is used, are consistent with the results in Ferson and Schadt (1996) and Becker et al. (1999). Ferson and Schadt (1996) offer three conjectures for this pattern of results. First, the fund managers may systematically predict market moves in the wrong direction. Secondly, the funds may use hedging strategies such as options. However, such use should create positive alphas, which is not the case here. Finally, the unconditional model may be misspecified, and the conditional version helps to remedy it.

All of the abnormal returns (alphas) are negative but not statistically different from zero, indicating that diversified AETFs and their CMFs fail to generate significant abnormal returns through stock selection. Furthermore, the slightly lower conditional alphas (more negative) suggest that funds perform worse after introducing interaction terms between market excess returns and predetermined information variables.

In summary, there is no evidence that diversified AETFs or their CMFs have positive timing ability. Rather, the results of the unconditional test provide some evidence that diversified AETFs have adverse timing ability. However, this finding could be due to the possibility that the unconditional models, which are widely used in the literature, are misspecified.

### 2.5.2 Holdings-Based Tests

#### 2.5.2.1 Characteristic Returns

Table 2.5 provides a comprehensive overview of the three components of holding-based fund performance – Characteristic Selectivity ($CS$), Characteristic Timing ($CT$), and Average Style ($AS_{\text{style}}$) – for diversified AETFs and their CMFs.[23]

As shown in Table 2.5, Characteristic Selectivity ($CS$), which measures fund managers' stock-selecting ability, is negative but statistically insignificant for both diversified AETFs and their CMFs. For Characteristic Timing, which measures a fund manager's ability to time the market, the results are positive but not statistically significant. These results suggest that the managers of these funds do not exhibit an ability to pick outperforming stocks or to time the market, which is consistent with the findings from the return-based tests in the previous sections.[24] Finally, Average Style ($AS_{\text{style}}$), which measures funds' tendency to invest in stocks with certain characteristics, is positive and significant (at the 10%

[23] The measurement $t$ is for one-quarter, and for the calculation of $CT$ and $AS_{\text{style}}$, I go back to the previous half-year for AETFs and CMFs.

[24] I note, however, that the AETFs and CMFs in my sample are equity funds with insignificant holdings of fixed-income securities. As such, their managers cannot do market timing in terms of asset allocation between equities and fixed income. This is in contrast with the results in a few prior studies of mutual funds in general (which include balanced funds), which report that mutual fund managers have market-timing ability (e.g., Elton et al. 2012a; Jiang et al. 2007)

**Table 2.5:** Holdings-based Returns of Diversified AETFs and CMFs

| $CS$ | | | $CT$ | | | $AS_{\text{style}}$ | | |
|---|---|---|---|---|---|---|---|---|
| AETFs | CMFs | Diff. | AETFs | CMFs | Diff. | AETFs | CMFs | Diff. |
| −1.81 | −0.46 | −1.34 | 0.58 | 0.25 | 0.33 | 2.47* | 1.18 | 1.29 |
| (−0.91) | (−0.21) | (−0.59) | (0.30) | (0.13) | (0.12) | (1.81) | (0.90) | (0.66) |

This table shows the Daniel et al. (1997) characteristic-benchmarked returns for 76 diversified AETFs and CMFs from 03/2008 to 12/2020. The average returns are expressed quarterly and in percentage (%) and parentness are $t$-statistics adjusted for Newey and West (1987) robust standard errors. The $CS$ is calculated as $CS_t = \sum_{j=1}^{N} w_{j,t-1}(R_{j,t} - R_t^{b_{j,t-1}})$, the $CT$ is calculated as $CT_t = \sum_{j=1}^{N}(w_{j,t-1}R_t^{b_{j,t-1}} - w_{j,t-k}R_t^{b_{j,t-k}})$ and the $AS_{\text{style}}$ measure is calculated as $AS_{\text{style}_t} = \sum_{j=1}^{N} w_{j,t-k}R_t^{b_{j,t-k}}$.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

level) for diversified AETFs and positive but insignificant for the CMFs. These results can be interpreted as showing mild evidence that diversified AETFs can generate positive returns by adopting certain investment styles.

In summary, the characteristic returns analysis indicates that managers of AETFs do not exhibit stock-selection or market-timing ability, but may possess an ability to choose investment styles. The CMFs, on the other hand, do not show any significant ability across all three return components. When comparing the AETFs to their CMFs, there are no statistically significant differences across all three skill categories.[25]

#### 2.5.2.2 Trade Returns

Table 2.6 presents trade returns for buys and sells and the respective return differences for diversified AETFs and CMFs.[26] Both fund types exhibit positive returns for their buys, a trend commonly observed in previous literature (e.g., Chen et al. 2000; Nicolosi 2009; Pinnuck 2003). However, a crucial distinction emerges in the difference between buy and sell returns. This difference is negative for both AETFs and CMFs, indicating that the returns from the stocks they have bought are lower than those from the stocks they have sold. This finding diverges from prior research, such as Baker et al. (2010) and Chen et al. (2000), which report that the stocks bought by mutual funds tend to outperform those that they

[25] I divide the whole sample into four subgroups based on the funds' Lipper Investment Objectives –value, growth, core, and income. For all four groups, the conclusions on $CS$ and $CT$ are the same as for the whole sample (i.e., no statistical significance). The results on $AS_{\text{style}}$ are positive and significant for the Growth and Income groups, but not for the Core group.

[26] I follow Kacperczyk et al. (2005) to go back to the previous half year to analyze the buys and sells returns.

sell.[27]

## 2.6 Results for Sector AETFs

### 2.6.1 Return-Based Tests

#### 2.6.1.1 Unconditional Models

Table 2.7 reports the unconditional return-based performance of sector AETFs and their CMFs during the period from June 2012 to December 2020. Under all four regression models, the unconditional alphas for sector AETFs (based on both gross and net returns) are, on average, positive.[28] However, the results are not statistically significant.[29]

The results exhibit two similar patterns to those of diversified AETFs in the previous section. That is, first, across all four regression models, sector AETFs underperform their CMFs on both the gross and net bases. However, the performance differences are not statistically significant.[30] Secondly, among the four models used, the abnormal returns (on both gross and net bases) of sector AETFs

[27] In unreported results where the whole sample is divided into four subgroups based on the funds' Lipper Investment Objectives, no significant buy or sell returns are evident across each investment category. It appears that Growth AETFs might be capable of generating positive buy-and-sell returns, while CMFs tend to exhibit this trend within the Value category. Notably, the most substantial difference in buy-and-sell returns between AETFs and CMFs stands in the Income category

[28] The calculations of gross return and net return follow a similar approach to that of diversified funds.

[29] One possible reason for this is the relatively high variation in their (time-series) values as the sample of sector AETFs is limited to 23 funds.

[30] In unreported summary statistics, both the gross and net abnormal returns of sector AETFs are more volatile than their CMFs counterparts. Again, this is likely due, at least in part, to the fact that sector AETFs change their portfolios more often (i.e., have higher portfolio turnovers) than their CMFs do (see Table 1.3 and Table 1.4 of Chapter 1).

**Table 2.6:** Trades Returns of Diversified AETFs and CMFs

| Buy | | | Sell | | | Buy-Sell | | |
|---|---|---|---|---|---|---|---|---|
| AETFs | CMFs | Diff. | AETFs | CMFs | Diff. | AETFs | CMFs | Diff. |
| 1.72 | 1.15 | 0.57 | 2.74 | 1.66 | 1.08 | −1.02 | −0.50 | −0.52 |
| (0.83) | (0.66) | (0.32) | (1.61) | (0.98) | (0.84) | (−0.93) | (−0.78) | (−0.42) |

This table shows the Kacperczyk et al. (2005) trade returns for 76 diversified AETFs and CMFs from 03/2008 to 12/2020. The statistics are computed for each quarter using daily returns cross-sectionally and then time-series average over the sample period; the average returns are expressed quarterly and in percentage (%) and parentness are $t$-statistics adjusted for Newey and West (1987) robust standard errors.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

are highest when their self-declared benchmarks are used as the regressor (i.e., Single-Factor$_{\mathrm{sb}}$ model).

**Table 2.7:** Unconditional Performance of Sector AETFs and CMFs

| | Single-Factor$_{fb}$ | | Single-Factor$_{sb}$ | | CAPM | | FFC | |
|---|---|---|---|---|---|---|---|---|
| | GR | NR | GR | NR | GR | NR | GR | NR |
| AETFs | 0.47 | 0.28 | 0.36 | 0.17 | 0.26 | 0.07 | 0.28 | 0.09 |
| | (0.64) | (0.38) | (0.53) | (0.25) | (0.41) | (0.10) | (0.49) | (0.16) |
| CMFs | 0.53 | 0.24 | 0.78 | 0.49 | $0.94^{*}$ | 0.65 | $1.27^{***}$ | $0.98^{**}$ |
| | (1.05) | (0.47) | (1.52) | (0.96) | (1.89) | (1.31) | (2.57) | (1.99) |
| Diff. | −0.06 | 0.04 | −0.42 | −0.32 | −0.68 | −0.59 | −0.99 | −0.89 |
| | (−0.12) | (0.07) | (−0.57) | (−0.43) | (−1.15) | (−0.98) | (−1.67) | (−1.50) |

This table shows the unconditional performance for 23 sector AETFs and CMFs from 06/2012 to 12/2020. Average alphas and the statistics are computed for each quarter using daily returns cross-sectionally and then time-series average over the sample period. The alphas are presented quarterly in percentage and parentness are $t$-statistics adjusted for Newey and West (1987) robust standard errors. The Net Return(NR) is a NAV-based return that is net of transaction costs, management fees, and other expenses, but not sales charges; Gross Return(GR) adds back the fund expense ratios. The Single-Factor$_{fb}$ and Single-Factor$_{sb}$ follows $R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{benchmark,t} - R_{f,t}) + \varepsilon_{i,t}$ where $R_{benchmark,t}$ is return of fund $i$ fixed set of benchmark and self-claimed benchmark, separately.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Another point of interest is that the positive alphas of sector AETFs are in distinct contrast with the negative alphas of diversified AETFs in the previous section, suggesting that sector AETFs perform slightly better than their diversified counterparts. This outcome is consistent with the findings in the literature that concentrated funds tend to perform better than broadly diversified funds after controlling for risks (e.g., Huij and Derwall 2011; Kacperczyk et al. 2005).

In summary, the results of the unconditional regressions indicate that, on average, sector AETFs generate positive, but statistically insignificant, abnormal returns.[31]

#### 2.6.1.2 Conditional Performance

Table 2.8 presents the conditional performance analysis of sector AETFs and their CMFs. The abnormal returns of AETFs and their CMFs are all not statistically different from zero. In addition, there is no significant difference in abnormal returns between AETFs and CMFs. This result reinforces the finding in the unconditional setting (in the previous section) that sector AETFs perform better than their diversified counterparts.

Compared to the results under the unconditional models in Table 2.7, the abnormal returns are generally lower. This finding is similar to what is observed in the case of diversified AETFs.

#### 2.6.1.3 Market Timing Models

Similar to the case of diversified AETFs above, I examine the market-timing ability of sector AETFs using the TM and HM models, both in unconditional and conditional versions. The results are reported in Table 2.9.

Under the unconditional setting, the coefficient $\gamma$ for sector AETFs is negative and statistically significant under both timing models, suggesting that sector AETFs exhibit negative timing ability. In contrast, $\gamma$ for their CMFs is positive but statistically insignificant. The difference between the two's $\gamma$ coefficients is

[31] Similar to the robustness tests for diversified funds, I run the regression every month and apply other factor models, such as FF3 and FF5, for sector funds; the results do not quantitatively differ from those of FFC.

**Table 2.8:** Conditional Performance of Sector AETFs and CMFs

| | Single-Factor$_{fb}$ | | Single-Factor$_{sb}$ | | CAPM | | FFC | |
|---|---|---|---|---|---|---|---|---|
| | GR | NR | GR | NR | GR | NR | GR | NR |
| AETFs | −0.34 | −0.54 | −0.17 | −0.40 | 0.23 | −0.01 | 0.51 | 0.31 |
| | (−0.49) | (−0.76) | (−0.26) | (−0.58) | (0.36) | (−0.01) | (1.18) | (0.72) |
| CMFs | 0.04 | −0.20 | 0.73 | 0.50 | 0.49 | 0.24 | 0.04 | −0.21 |
| | (0.09) | (−0.41) | (0.91) | (0.61) | (0.93) | (0.43) | (0.05) | (−0.23) |
| Diff. | −0.38 | −0.34 | −0.90 | −0.90 | −0.26 | −0.24 | 0.47 | 0.52 |
| | (−0.70) | (−0.60) | (−0.89) | (−0.87) | (−0.46) | (−0.41) | (0.48) | (0.53) |

This table shows the conditional performance for 23 sector AETFs and CMFs from 06/2012 to 12/2020. Average alphas and the statistics are computed for each quarter using daily returns cross-sectionally and then time-series average over the sample period. The alphas are presented quarterly in percentage and parentness are $t$-statistics adjusted for Newey and West (1987) robust standard errors. The Net Return(NR) is a NAV-based return that is net of transaction costs, management fees, and other expenses, but not sales charges; Gross Return(GR) adds back the fund expense ratios. The Single-factor$_{fb}$ and Single-factor$_{sb}$ follows $R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{benchmark,t} - R_{f,t}) + \varepsilon_{i,t}$ where $R_{benchmark,t}$ is return of fund $i$ fixed set of benchmark and self-claimed benchmark, separately. The conditional models include the interaction of four predetermined information variables with the market return; the four demeaned variables are the Treasury bill yield, the dividend yield of the Value-Weighted CRSP Index, the Treasury yield term spread (10-year minus 3-month Treasury yield), and the credit spread in the corporate bond market (Baa minus Aaa corporate yields).
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

significantly negative, suggesting that sector AETFs underperform their CMFs in terms of market timing in the unconditional setting.

For the conditional setting, the coefficient  for sector AETFs is still negative but no longer statistically significant, while $\gamma$ for their CMFs is very close to zero. As a result, in this setting, there is no significant difference in market-timing ability between sector AETFs and their CMFs.

With respect to the coefficient $\alpha$, which indicates the fund manager's ability

**Table 2.9:** Market Timing Coefficients of Sector AETFs and CMFs

| | Treynor-Mazuy | | | | Henriksson-Merton | | | |
|---|---|---|---|---|---|---|---|---|
| | Unconditional | | Conditional | | Unconditional | | Conditional | |
| | $\alpha_{\%}$ | $\gamma$ | $\alpha_{\%}$ | $\gamma$ | $\alpha_{\%}$ | $\gamma$ | $\alpha_{\%}$ | $\gamma$ |
| AETFs | 1.38* | −2.721** | 1.19 | −1.581 | 2.47** | −0.094** | 2.08 | −0.060 |
| | (1.79) | (−2.089) | (1.36) | (−0.944) | (2.28) | (−2.174) | (1.72) | (−1.252) |
| CMFs | 0.47 | 0.319 | 0.89 | 0.080 | 0.46 | 0.019 | 1.21 | −0.008 |
| | (0.59) | (0.405) | (1.45) | (0.184) | (0.45) | (0.694) | (1.49) | (−0.251) |
| Diff. | 0.91 | −3.039** | 0.30 | −1.661 | 2.01** | −0.113** | 0.88 | −0.052 |
| | (1.22) | (−2.14) | (0.37) | (−0.822) | (2.03) | (−2.475) | (0.81) | (−0.950) |

This table shows the market timing coefficients for 23 sector AETFs and CMFs from 06/2012 to 12/2020, respective to Treynor and Mazuy (1966) model and Henriksson and Merton (1981) model. Average $\alpha$s and $\gamma$s the statistics are computed for each quarter using daily returns cross-sectionally and then time-series average over the sample period. $\alpha$ is expressed quarterly in percentage and parentness are $t$-statistics adjusted for Newey and West (1987) robust standard errors. The Treynor-Mazuy model is $r_{i,t} = \alpha_i + \beta_i r_{m,t} + \gamma_i r_{m,t}^2 + \varepsilon_{i,t}$ and the Henriksson-Merton model is $r_{i,t} = \alpha_i + \beta_i r_{m,t} + \gamma_i Max(r_{m,t}, 0) + \varepsilon_{i,t}$. The conditional models include the interaction of four predetermined information variables with the market return; the four demeaned variables are the Treasury bill yield, the dividend yield of the value-weighted CRSP Index, the Treasury yield term spread (10-year minus 3-month Treasury yield), and the credit spread (Baa minus Aaa corporate yields).
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

to generate abnormal returns through stock selection, it is positive and significant for sector AETFs (at the 10% level for the TM model and the 5% level for the HM model) in the unconditional setting. In the conditional setting, is positive but no longer significant.

In summary, there is no evidence that sector AETFs or their CMFs have positive timing ability. Rather, the results of the unconditional test provide some evidence that sector AETFs have adverse timing ability. This finding is similar to the case of diversified AETFs above. In addition, the results show that managers of sector AETFs may have the ability to generate abnormal returns through stock selection. However, the same argument mentioned earlier applies, which is that this finding could be due to the possibility that the unconditional models are misspecified.

### 2.6.2 Holdings-Based Tests

#### 2.6.2.1 Characteristic Returns

Table 2.10 reports the results of the holdings-based characteristic returns analysis for sector AETFs and their CMFs. In general, sector AETFs demonstrate a pattern similar to that of their diversified counterparts. That is, the Characteristic Selectivity ($CS$) return is negative but insignificant, the Characteristic Timing ($CT$) return is positive but small and insignificant, and the Average Style ($AS_{\text{style}}$) return is positive and significant.

When comparing sector AETFs to their CMFs, there is no statistically significant difference in the $CS$ and $CT$ returns. However, there is a significant difference in $AS_{\text{style}}$ returns, implying that sector AETFs exhibit a superior ability to invest in stocks with certain characteristics (i.e., fund's style).

**Table 2.10:** Holdings-based Returns of Sector AETFs and CMFs

| $CS$ | | | $CT$ | | | $AS_{\text{style}}$ | | |
|---|---|---|---|---|---|---|---|---|
| AETFs | CMFs | Diff. | AETFs | CMFs | Diff. | AETFs | CMFs | Diff. |
| $-2.95$ | 0.39 | $-3.34$ | 0.63 | $-0.17$ | 0.79 | 3.82** | 0.24 | 3.59* |
| ($-1.41$) | (0.15) | ($-1.29$) | (0.30) | ($-0.08$) | (0.26) | (2.66) | (0.17) | (1.81) |

This table shows the Daniel et al. (1997) characteristic-benchmarked returns for 23 sector AETFs and CMFs from 06/2012 to 12/2020. All returns are reported as percentages (%). The average returns are expressed quarterly and percentage and parentness are $t$-statistics adjusted for Newey and West (1987) robust standard errors.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

#### 2.6.2.2 Trade Returns

Table 2.11 reports the trade returns of buy and sell actions for sector AETFs and CMFs. On average, sector AETFs demonstrate both positive buy and sell returns, yet their buy minus sell returns is negative. This trend parallels the pattern observed among diversified AETFs. These outcomes imply that, overall, AETFs tend to hold securities with lower returns compared to the stocks they have divested.

In contrast, sector CMFs manage to generate significant, positive buy returns of 4.41%, which exceeds the corresponding sell returns. Consequently, this leads to a positive buy minus sell returns of 2% per quarter. This observation contrasts with the findings for diversified CMFs, which show small negative buy minus sell returns (as seen in Table 2.6). The findings for sector CMFs generally correspond to Kacperczyk et al. (2005), who report that mutual funds' purchased stocks tend to outperform sold stocks and that more concentrated funds, akin to sector funds, tend to have better success in security selection due to higher buy minus sell returns.

**Table 2.11:** Trades Returns of Sector AETFs and CMFs

| Buy | | | Sell | | | Buy-Sell | | |
|---|---|---|---|---|---|---|---|---|
| AETFs | CMFs | Diff. | AETFs | CMFs | Diff. | AETFs | CMFs | Diff. |
| 1.88 | 4.41* | −2.54 | 2.24 | 2.42 | −0.17 | −0.37 | 2.00 | −2.37 |
| (0.80) | (1.94) | (−1.26) | (0.88) | (1.06) | (−0.12) | (−0.33) | (1.50) | (−1.49) |

This table shows the Kacperczyk et al. (2005) trade returns for 23 sector AETFs and CMFs from 06/2012 to 12/2020. The statistics are computed for each quarter using daily returns cross-sectionally and then time-series average over the sample period; the average returns are expressed quarterly and in percentage (%) and parentness are $t$-statistics adjusted for Newey and West (1987) robust standard errors.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

## 2.7 Conclusion

This study has examined the performance and the skills of fund managers managing diversified and sector-focused AETFs, as well as their corresponding CMFs, within the context of mandatory daily disclosure requirements.

First, the analysis shows that AETFs, particularly those concentrated in specific sectors, tend to display a greater dispersion in their performance and the skill levels of their fund managers compared to CMFs. Notably, AETFs, on average, exhibit underperformance against CMFs in terms of returns-based performance measures, both unconditionally and conditionally. Furthermore, AETFs are shown to possess a counterintuitive (negative) timing ability within returns-based TM and HM timing models, in contrast to CMFs, which typically lack timing proficiency.

Secondly, the examination of characteristic holdings-based metrics indicates that while a few AETF fund managers demonstrate significant positive $CS$ and $AS_{\text{style}}$ returns, the average stock selection ability of AETFs is inferior to that of CMFs. Additionally, both AETFs and CMFs generally exhibit negligible market timing ability. Lastly, an evaluation of portfolio trades suggests that AETFs struggle to generate positive returns from their buy-and-sell transactions, while CMFs seem able to create significant buy returns from their selected stocks.

Future research avenues could explore the relationship between investment inflows into AETFs and CMFs based on their performance, thereby shedding light on how AETFs remain popular despite their disappointing overall performance. Furthermore, AETFs and mutual funds may have different types of investors with specific tax preferences, as these two investment vehicles have different tax efficiency. For instance, AETFs, due to their in-kind creation and redemption mechanism, are much more tax efficient and may attract a specific type of tax-sensitive investors. As a result, if further research could incorporate this tax difference, it would link investor inflows and performance to be more sound and less biased.

# Chapter 3

# The Hype of ETFs Closures? Not the case of Active ETFs

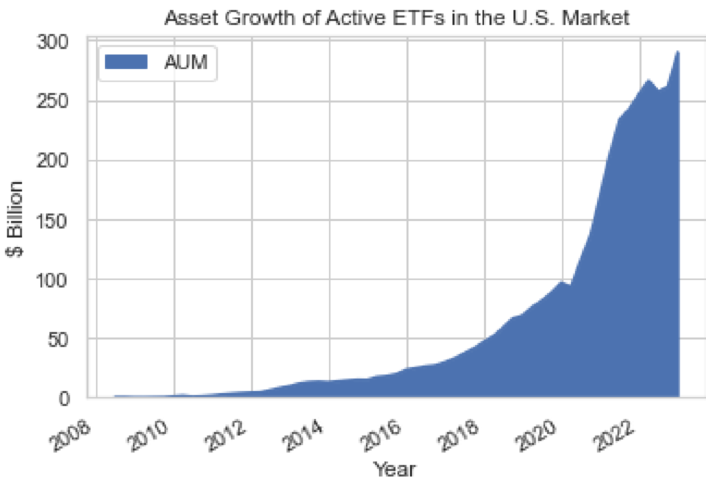
## 3.1 Introduction

Passive investing using ETFs has dominated the investment landscape over the last two decades. However, since the introduction of the first actively managed ETF (hereafter active ETF, or AETF) in March 2008, the number of ETFs within the realm of active management has proliferated to over 1,000 in the U.S. market, accumulating assets under management (AUM) close to $300 billion (as shown in Figure 3.1). Notably, there has been a substantial surge in AUM and the number of AETFs offerings since 2020, surpassing the number of offerings of passive ETFs.[1] On average, AETFs tend to have higher fees due to their specialized investment strategies aimed at outperforming benchmarks. This growth trend

[1] See the trend in Figure 3.2.

in AETFs underscores investors' willingness to pay elevated fees in pursuit of improved risk-adjusted returns (Box et al. 2020).

**Figure 3.1:** Asset Growth of Active ETFs from 2008 to 2022




In the spectrum of active management, actively managed mutual funds (referred to as AMFs) have long been dominant. However, the rise of AETFs has been primarily attributed to their lower costs, lower investment thresholds, enhanced transparency in holdings, and trading convenience when compared to AMFs.[2] Furthermore, the superior tax efficiency of ETFs has attracted tax-sensitive investors (Gastineau 2004).[3]

[2] AETFs, on average, have lower expense ratios, and because of the daily portfolio disclosure requirement, they have higher transparency in their holdings. In addition, AETFs are traded on exchanges, and so investors can trade them anytime, bringing a high level of convenience. In some cases, AETFs can be traded in fractional shares, and there is no initial investment requirement.

[3] AETFs are more tax efficient than traditional AMFs. This is because AETFs have the in-kind creation and redemption mechanism, which allows the Authorized Participants (APs) to exchange the basket of securities with the shares of ETFs. Moreover, these transactions can be made in a way that allows the lowest-cost basis securities to be swapped out in a redemption and the highest-cost basis securities to remain in the ETF. These transactions are not taxable to the investor (Madhavan 2016). The AMFs, however, have to deal with sales of securities to meet investors' withdraws, and this action may trigger the capital gain tax for the investor.

Beyond these factors, AETFs have drawn investors seeking tailored solutions for their specific active investment needs.[4] Consequently, numerous fund companies have entered this rapidly expanding AETFs market, aiming to attract both retail and younger investors, thereby augmenting their AUM and fee revenue (Bhattacharya et al. 2017).

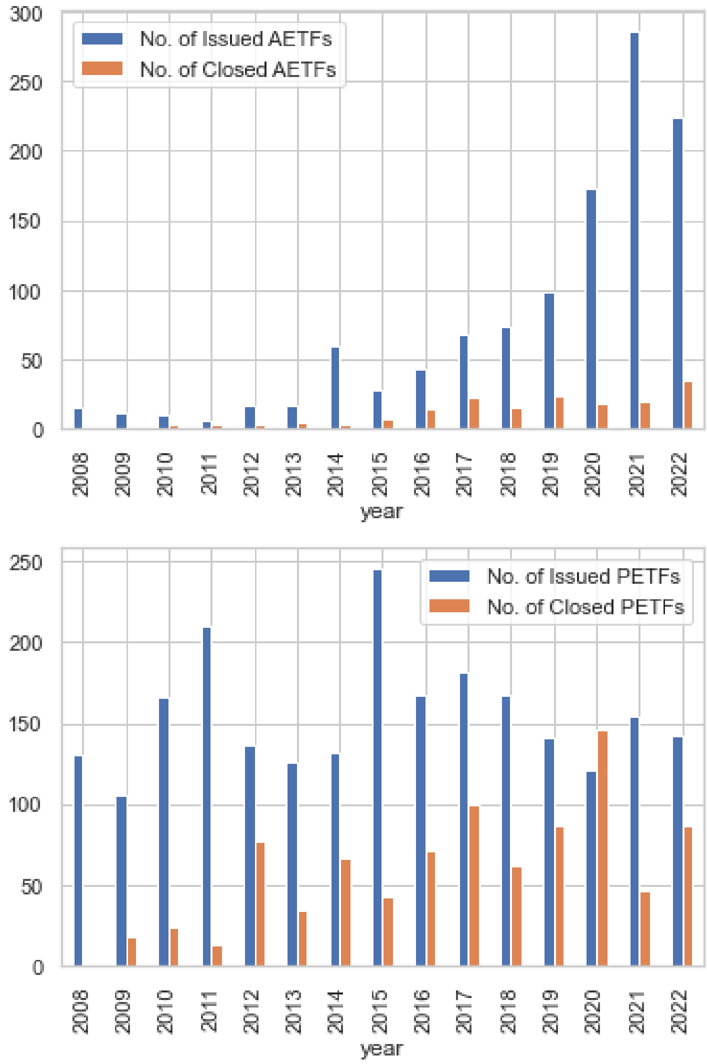
Figure 3.2 illustrates the number of issues and closures for passive ETFs (PETFs) and active ETFs (AETFs). Remarkably, active ETFs, despite an average of fewer offerings, have a lower closure rate (the number of closures divided by total offerings). As a result, it is interesting to investigate what underlying factors contribute to the closure of AETFs. This examination holds significant implications for investors concerned about closure risks, as such events may result in unforeseen losses or unfavorable tax implications due to capital gains upon liquidation.[5]

This paper finds that fund size remains a primary driver of fund closure, a pattern observed in actively managed mutual funds. Moreover, fund flows prove to be highly significant in predicting the termination of AETFs. Nevertheless, the findings indicate that fund performance does not appear to influence closure decisions. This is consistent with the findings in Chevalier and Ellison (1997) that fund companies have an incentive to take actions that increase the inflow

[4] There are many popular AETFs that are theme ETFs, such as Biotech ETFs and Tesla-specific ETFs. These customized designs have certainly attracted a lot of young and specific retail investors who have these targets of preferences.

[5] When a fund is liquidated, it usually goes through the following procedures: the announcement of the closure, trading and creation/redemptions halted, suspension of trading on exchanges, liquidation, and then the distribution of cash. In the last step, investors will have to face unexpected tax consequences. In some cases, funds are closed by merging into other funds, and investors' assets are transferred to the merged funds. Historically, AETFs mergers do not occur as often as mutual funds mergers do. Yet, it is becoming common. For example, big fund companies, such as Blackrock and WisdomTree, have begun to either merge small-size funds within the family or merge (sell) them with other fund companies.

**Figure 3.2:** No. of ETFs Inception and Closures



of investments (such as taking undue risk) so that they can maximize the fees that they receive (which depend on the size of the funds), even if such actions are incompatible with the goal of the investors, which is to maximize the risk-adjusted returns of their investments. Given the increasing popularity of AETFs, fund companies might attempt to attract inflows rather than solely focusing on outperforming benchmarks.

This paper is structured as follows: Section 3.2 encompasses the literature review, Section 3.3 details the methodology, Section 3.4 covers the data and presents summary statistics, Section 3.5 reveals the results under various settings, and Section 3.6 provides the concluding remarks.

## 3.2 Literature

To my knowledge, the subject of actively managed ETFs (AETFs) closures has not been examined before.[6] There have been, however, studies on exit decisions of actively managed mutual funds (AMFs) and *passive* ETFs. Sherrill and Stark (2018) examine liquidation decisions of passive ETFs and find that passive ETFs with small fund size and the ones within a struggling fund family or a struggling investment objective are likely to incur a failure. Akhigbe et al. (2020) use a different model to look into the likelihood of ETF closures and arrive at a similar conclusion that ETFs need to grow fast in the first few years to survive, and fund characters such as expense ratio, tracking error, performance, and investment style all matter to ETFs' survival.

[6] Prior research on AETFs has primarily focused on aspects such as trading behavior, performance evaluation, and comparisons with other investment vehicles (e.g., Pham et al. 2021; Rompotis 2011a; Rompotis 2011b; Schizas 2014).

For AMFs, the literature on their exit decisions starts with Jayaraman et al. (2002), who examine the determinants of mutual fund mergers. Zhao (2005) extends this line of research to various forms of mutual fund exits, including liquidations, mergers within families, and mergers across families. Zhao's study focused on portfolio-level findings (aggregating different share classes under the same portfolio), influenced by prior works by Khorana and Servaes (1999) and Wermers (2000).[7] The study reveals that defunct portfolios tend to be younger, smaller, and experience lower inflows compared to active ones. Families with fewer share classes were more prone to portfolio liquidations, while larger families were more likely to consolidate within the family. Poorly performing families exhibited a greater tendency for cross-family mergers.

This paper differs by looking into the likelihood of closure for active ETFs, which have been mixed together with passive ETFs in the study of liquidations by previous research. Although active and passive ETFs share the same organizational structures, they belong to distinct management styles. Therefore, it is crucial to differentiate the effect of underlying factors on AETFs alone. Furthermore, this paper compares the determinants of fund liquidation between AETFs and AMFs, both belonging to active management but with distinct organizational structures. Research has indicated that AETFs and AMFs are not perfect substitutes, with AETFs gaining market share due to tax advantages (Sherrill and Stark 2018). However, no existing studies have investigated the differences in exit decisions between these two products.

[7] The majority of mutual funds have multiple share classes, and each share class is listed as an independent identity ("fund") in the CRSP database. When a portfolio decides to exit, it is more likely to liquidate all its share classes instead of just shutting down only one share class.

I follow Zhao (2005) and look at mutual funds exit at the aggregated level (or at the portfolio level, as previously stated). As AETFs exist as individual funds and do not have a share class structure, to avoid confusion, hereafter, I use "funds" to describe both AETFs and AMFs.

Thus far, this paper represents the first comprehensive investigation into the liquidation of AETFs despite their position within a niche market. However, as the popularity of AETFs continues to grow, the practical significance of studying the factors driving their liquidation decisions will also increase. Additionally, this study undertakes a comparative analysis of liquidation factors across various investment products, spanning AETFs and AMFs.

## 3.3 Methodology

When assessing the likelihood of fund closure, several attributes of the funds are expected to play a role. I discuss below the potential factors for funds survival/closure, how to measure fund performance, and a structured framework for analyzing the determinants of AETF closure.

### 3.3.1 Possible Factors

Prior studies on the closures of AMFs propose various factors that could contribute to the decisions to terminate funds.(e.g., Zhao 2005) These factors are listed in Table 3.1 together with their hypothesized effects on AMFs. To this, I add my hypothesized effects on AETFs. The factors are classified into three groups

– fund, family, and investment objectives. The expected effects are denoted as positive (+), negative (−), or unclear (?).

At the fund level, there are eight contributing factors. First, the size of a fund is a very important determinant. A larger AUM is expected to correlate with a lower chance of fund closure, as larger funds benefit from economies of scale that small funds struggle to generate (Brown and Goetzmann 1995; Elton et al. 1996; Elton et al. 2012b; Indro et al. 1999; Perold and Salomon Jr 1991). Larger funds also have more resources and, due to their perceived stability, are more likely to attract new investments. In fact, most funds, in their formal closure announcements, attribute their closures to the failure to attract enough assets to maintain operation.

Secondly, because fund (net) inflows directly contribute to fund size, they should be negatively correlated with the likelihood of closure. A stronger trend of fund inflow could indicate investor interest and confidence in the fund's performance, making the fund less likely to be shut down. Thirdly, fund performance, defined as commonly done in the literature, as excess returns on the funds after adjusting for risk using a chosen factor model (see Section 3.3.2 below), is expected to negatively relate to closure risk. This is because high-performing funds typically attract inflows, which increases fund size (e.g., Wermers 2003).

The fourth contributing factor at the fund level is expense ratios. High fund expense ratios can deter investors, especially when the fund performance is not commensurate with the fees. In such a case, high expense ratios will lead to

**Table 3.1:** Hypotheses of Terminating AETFs and AMFs

| Attributes | | Likelihood of termination | |
|---|---|---|---|
| | | AETFs | AMFs |
| **Fund level** | Size | $-$ | $-$ |
| | Inflow | $-$ | $-$ |
| | Performance | $-$ | $-$ |
| | Expense | $+$ | $+$ |
| | Bid/Ask Spread | $+$ | $N/A$ |
| | Premium-to-NAV | $-$ | $N/A$ |
| | Age | $-$ | $-$ |
| | Team Management | $-$ | $-$ |
| **Family level** | No. of Funds | $+$ | $+$ |
| | Performance | ? | $+$ |
| | Inflow | $-$ | $-$ |
| **Objective level** | No. of Funds | ? | ? |
| | Performance | $-$ | $-$ |
| | Inflow | $-$ | $-$ |

This table provides an overview of potential factors and their hypothesized effects on liquidation decisions. The attributes are categorized into three levels: fund, family, and the whole investment objective. A positive sign $(+)$ implies an anticipated increase in the likelihood of liquidation, while a negative sign $(-)$ indicates an expected decrease. Factors with an unclear impact have a sign of (?). If a factor is not relevant for a specific fund type, it is denoted as $N/A$.

diminished inflows, smaller fund size, and an increased likelihood of liquidation.[8] Next, bid-ask spreads and premium-to-NAV (Net Asset Value) are factors that affect ETFs, which are traded on stock exchanges. For example, a wider bid-ask spread increases the trading cost of an ETF, thus making it less attractive. It may also suggest that the ETF has thin trading, possibly raising closure risk.

[8] See Sirri and Tufano (1998) for the finding of a negative relationship between higher expenses and fund flows. English et al. (2011) further document that higher fees can lead to a higher likelihood of fund failure.

A positive premium-to-NAV means that the ETF is trading above its intrinsic value (or NAV), indicating high demand for it and thus reducing the chance of liquidation.[9] Finally, fund age is expected to negatively relate to fund closure risk as older funds have established track records that investors can use as baselines to judge current performance (Brown and Goetzmann 1995).

At the family level, the reputation and strength of the issuing fund family can be another significant factor. Specifically, greater family inflows are projected to decrease the probability of a specific fund's liquidation across both fund types. However, family performance could have either a positive or negative effect on the probability of AETFs liquidation. Higher family performance is associated with increased peer pressure and internal competition, potentially leading to more liquidations (Zhao 2005). On the other hand, a stronger family performance could also have positive spillover effects (i.e., a fund's inflow is affected by other funds in the family), thus decreasing the likelihood of liquidation (Nanda et al. 2004). As a result, the overall effect of fund family on AETFs liquidation is unclear and needs to be examined. Finally, the number of portfolios within a family is expected to positively affect the likelihood of liquidation. This effect stems from industrial literature (e.g., Audretsch 1994), which shows that independent establishments face a lower exit likelihood than those under larger entities. In other words, a solely managed fund has a lower risk of closure than a fund under families managing multiple funds.

[9] Due to ETFs' in-kind creation/redemption process, there is an arbitrage mechanism that keeps prices of ETFs (especially large, domestic ones) close to their NAVs. Still, premiums/discounts can, from time to time, exist, especially in volatile markets and/or for small, illiquid ETFs and international-equity ETFs.

Funds' investment objectives could influence their chances of survival. As Ilmakunnas and Topi (1999) demonstrate, industries with low growth experience higher exit rates, suggesting a negative relationship between an objective's inflow and performance and a fund's liquidation risk. As for the number of funds with the same objective, they can signify competition levels in the industry, but their impact is unclear for actively managed funds. For example, a small number of funds indicates a niche market with higher risk, enhancing liquidation risk, whereas fewer portfolios within an industry may also suggest unique expertise, attracting investment-specific clients and reducing the likelihood of termination.[10]

Finally, management structure plays a role in active funds. Bär et al. (2005) highlight systematically different behaviors between team-managed and individually-managed funds.[11] Team-managed funds often exhibit lower risk and superior performance, as evidenced by Patel and Sarkissian (2017). Furthermore, Bliss et al. (2008) show that even after controlling for performance, risk, and expenses. team-managed funds attract significantly greater flows than individually-managed funds. As such, team management is perceived as a negative factor for liquidating active funds (AETFs and AMFs).

[10] By similar logic, a higher number of actively managed funds shows a more common investment objective, thereby making it easier to manage. However, it also indicates the competition is stronger, and this may lead to a higher likelihood of liquidation.

[11] Bär et al. (2005) find that team management takes less overall risk compared to single-person management and that this difference in behaviors is mostly attributed to a lower level of unsystematic risk.

### 3.3.2 Performance Measures

Active management aims to outperform benchmarks, making performance an important factor in liquidating actively managed funds. I evaluate funds' performance using risk-adjusted returns based on different factor models tailored for equity and fixed-income funds.

For equity funds, I use the Capital Asset Pricing Model (CAPM) and the four-factor Fama-French-Carhart (FFC) model, as shown below:

$$\begin{aligned} r_{i,t} &= \alpha_i + \beta_i r_{m,t} + \epsilon_{i,t} \\ r_{i,t} &= \alpha_i + \beta_i r_{m,t} + \gamma_i r_{SMB,t} + \delta_i r_{HML,t} + \lambda_i r_{MOM,t} + \epsilon_{i,t} \end{aligned} \tag{3.1}$$

where $r_{i,t}$ is the excess return of fund $i$ over the risk-free rate at time $t$; $r_{m,t}$ is the excess return of the CRSP value-weighted market proxy portfolio, and $r_{SMB,t}$, $r_{HML,t}$, $r_{MOM,t}$ are factor mimicking portfolios for size, value (book-to-market), and momentum at time $t$ respectively. The intercept $\alpha_i$ measures fund $i$'s average performance and represents the abnormal return (or *alpha*) that cannot be explained by the equity factors.

For fixed-income funds, I adopt a modified CAPM framework using the Bloomberg Barclays US Aggregate Bond Index (the *Agg*) as the market portfolio. Additionally, I employ the four-factor model introduced by Jayaraman et al. (2002) to estimate risk-adjusted excess returns. The modified CAPM and four-factor model for fixed-income funds are shown as follows:

$$
\begin{aligned}
r_{i,t} &= \alpha_i + \beta_i r_{Agg,t} + \epsilon_{i,t} \\
r_{i,t} &= \alpha_i + \beta_i r_{Agg,t} + \gamma_i r_{MBS,t} + \delta_i r_{TLT,t} + \lambda_i r_{IEI,t} + \epsilon_{i,t}
\end{aligned}
\tag{3.2}
$$

where $r_{i,t}$ is the excess return of fund $i$ over the risk-free rate at time$t$; $r_{Agg,t}$ is the excess return of the Bloomberg Barclays US Aggregate Bond portfolio; $r_{MBS,t}$ is the excess return of the Lehman Brothers Mortgage-Backed Securities Index; $r_{TLT,t}$ is the excess return of the Lehman Brothers Long-Term US Aggregate Bond portfolio; and $r_{IEI,t}$ is the excess return of the Lehman Brothers Intermediate-Term US Aggregate Bond portfolio.[12] The intercept $\alpha_i$ measures fund $i$'s average performance and represents the abnormal return (or *alpha*) that cannot be explained by the bond factors.

### 3.3.3 Decisions to liquidate a fund

I employ the multinomial logit model, following Sherrill and Stark (2018) and Zhao (2005), to analyze the distinct exit forms of AETFs and AMFs.[13] Note that AETFs exit in the form of direct liquidation, while AMFs can be either directly liquidated or merged. This model allows for examining the likelihood of fund termination based on characteristics related to the fund, its family, and investment objectives.

[12] See Blake et al. (1993) for detailed coverage of these bond factors specifications.

[13] See Glonek and McCullagh (1995) for detailed description and estimation of multinomial logit model.

In general, this multinomial logit model is expressed as follows:

$$Prob\ (Y = j) = \frac{1}{1 + \sum_{k=1}^{N} \exp -\hat{\beta}_j X_j}\ for\ j = 1, 2...N \tag{3.3}$$

where $j$ represents each exit choice, and $k$ ranges from 1 to $N$, encompassing the various available choices for AETFs and AMFs.[14]

The underlying regression model involves characteristics at the fund, family, and objective levels, considering different time lags ($t-1$ and $t-2$):[15]

$$\begin{aligned}
\hat{\beta}_j X_i = {} & \alpha_0 + \beta_1 (\textit{fund size})_{i,t-1} + \beta_2 (\textit{fund expense})_{i,t-1} + \beta_3 (\textit{fund age}) \\
& + \beta_4 (\textit{fund inflow})_{i,t-1} + \beta_5 (\textit{fund inflow})_{i,t-2} \\
& + \beta_6 (\textit{fund performance})_{i,t-1} + \beta_7 (\textit{fund performance})_{i,t-2} \\
& + \gamma_1 (\textit{family inflow})_{i,t-1} + \gamma_2 (\textit{family inflow})_{i,t-2} \\
& + \gamma_3 (\textit{family performance})_{i,t-1} + \gamma_4 (\textit{family performance})_{i,t-2} \\
& + \gamma_5 (\textit{family no. of funds})_{i,t-1} \\
& + \delta_1 (\textit{objective inflow})_{i,t-1} + \delta_2 (\textit{objective inflow})_{i,t-2} \\
& + \delta_3 (\textit{objective performance})_{i,t-1} + \delta_4 (\textit{objective performance})_{i,t-2} \\
& + \delta_5 (\textit{objective no. of funds})_{i,t-1} \\
& + \lambda_1 (\textit{team mgmt})_{i,t-1} + \varepsilon_{i,t}
\end{aligned}$$

[14] For example, in the case of analyzing the factors to the likelihood of AETFs and AMFs closures, $k$ is 4, representing four choices at each quarter, which are 1) the fund keeping alive; 2) an AETF is liquidated; 3) an AMF is liquidated; 4) an AMF is merged.

[15] *Bid-ask spread* and *premium-to-NAV* are added to this regression model when analyzing AETFs because they are traded on exchanges. The correlation of these variables is below 0.5, and the test shows that the multinomial analysis is free from the multicollinearity issue. In addition, a longer lag for each level of the variable can be added, but I find that they are not significant in predicting the likelihood of closure.

At the fund level, *size* is the natural logarithm of the fund's total net asset (TNA), *age* measures the length (in years) of the fund's survival from inception to its closure date or December 31, 2022, whichever comes earlier. *Inflow* is calculated to capture the growth rate of the fund's TNA not attributed to its return (i.e., the holding period return, *Ret*, as noted below); it is shown in Equation (3.4).

$$Inflow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + Ret_{i,t})}{TNA_{i,t-1}} \tag{3.4}$$

Note that *fund performance* denotes the fund's objective-excess return, obtained by subtracting the asset-weighted return of other funds with the same investment objective from the fund's return.

In a similar logic, when calculating the values of family-level parameters, the specific fund is excluded, and only the rest of the funds in the family are considered. Therefore, *family inflow* is the family's net asset growth not attributed to the return of the rest of the funds in the family; *family no.of funds* is the number of the rest of the existing funds managed by the same family; *family performance* represents the asset-weighted objective-excess returns of all the rest of funds in its family.[16]

At the objective level, *objective inflow* captures the growth of total net assets for all other existing funds with the same objective; *objective performance* denotes the asset-weighted return for the rest of the funds with the same investment objective;

[16] At the family level, the regression could also be expanded to include family size (sum of the assets of all the funds in the family), family expenses, and family age. However, these variables are highly correlated with the variables already included in the model, and, therefore, are excluded.

*objective no.of funds* is the total count of all other existing funds with the same investment objective.

Furthermore, the variable *team mgmt* is a binary indicator. It takes the value of 1 if the fund is managed by a team, and 0 if managed by an individual manager.[17]

Lagged variables ($t-1$ and $t-2$) are included at all three levels – fund, family, and objective – to account for short-term (one-quarter) and longer-term (half-year) effects and ascertain their significance in influencing fund termination decisions. Standard errors in the multinomial logit regression are clustered at the family level, acknowledging that the decision to terminate the fund rests with the fund family. In the multinomial logit model, funds variables are standardized with a mean of 0 and a standard deviation of 1. Quarter dummies are also incorporated to control for time-fixed effects.[18] Additionally, in the panel data setting, $t$-statistics are reported using standard errors that address autocorrelation and heteroscedasticity (Newey and West 1987).

In the following sections, I analyze the likelihood of the termination of AETFs and then compare it to the termination of AMFs.

#### 3.3.3.1 AETFs

The initial case focuses solely on AETFs, resulting in a simplified binary logit model. Each quarter, the fund family managing AETFs faces a binary decision – whether to continue or terminate the fund. In this case, $N$ is equal to 2; that is,

[17] The decision to have a team or individual management is typically made at the family level. In other words, each fund family is likely to have a consistent choice of management for all the funds in the family.

[18] Fund families make decisions every quarter. Therefore, adding quarter dummies is more appropriate than adding year dummies.

the indicator variable assumes a value of 1 if the fund remains operational, and 2 if the fund is liquidated. The underlying regression encompasses all the explanatory variables outlined earlier.

Taking into account the accelerated growth of AETFs and the onset of the global pandemic in 2020, the sample period is divided into two segments: 2008 to 2019 and 2020 to 2022. This division enables us to assess whether the effects of the underlying factors evolve over time. Additionally, the sample is categorized into two primary asset classes – equity and fixed income, allowing for an examination of the distinctions (if any) in liquidation factors across the two primary asset classes.

#### 3.3.3.2 Active Management - AETFs and AMFs

The second case compares AETFs to AMFs, given their shared status within the active management spectrum. This analysis sheds light on the distinct exit decisions of actively managed funds with different organizational structures. I employ a multinomial logit model featuring four choices in every quarter, with the indicator variable $j$ being assigned a value of 1 if either fund remains operational, 2 if an AETF is liquidated, 3 if an AMF is liquidated, 4 if an AMF is merged (within- or across-family). Accordingly, $N$ ranges from 1 to 4, representing the four potential choices.[19]

### 3.3.4 Family Decision Interactions

Within fund families that manage *both* AETFs and AMFs, a dynamic interplay may exist in decision-making regarding the creation or termination of different

[19] This regression removes the variables $spread_{i,t-1}$ and $premium_{i,t-1}$ so that there are the same underlying factors for AETFs and AMFs.

investment products (e.g., AETFs or AMFs), particularly in the context of investment objectives. In light of this, I examine the interactions in the decisions made by fund families that target active management.

I employ a series of probit regression models every quarter to examine the dynamics of fund family behavior, particularly regarding the launch and closure of AETFs and AMFs. Specifically, each probit model includes dummy variables to account for fund families' actions in the previous quarter, which include the creation and termination of AETFs and AMFs. In addition, the regressors also include control variables such as size, expense ratios, fund inflow, fund age, and quarterly returns. These control variables are averaged across the family, and these family-quarter variables are standardized to have a mean of 0 and a standard deviation of 1. This procedure is repeated when the regression is run at a more detailed family objective level. That is, funds are grouped based on their investment objectives, and the family decisions are examined on funds following the same objective.

## 3.4 Data

The data used in this study is sourced from the Center for Research in Security Prices (CRSP) Survivorship-Bias-Free U.S. Mutual Fund Database. This dataset contains the characteristics of AETFs and AMFs. Information such as total net assets (TNA), expense ratios, net asset values (NAV), turnover ratios, investment objectives, and family and management names are recorded quarterly, while fund returns are recorded monthly.[20] Additional trading details, such as bid-ask spreads,

[20] Funds' investment objectives are represented by CRSP obj codes, which cover equity, fixed income, mixed, and others. Fund families are classified by advisor names, and not by the management names. A fund's management name often changes during its life, while the advisor

trading volumes, and outstanding shares, are extracted from the CRSP daily stock file. Monthly equity and bond factors are acquired from Dr. Kenneth French's website and Federal Reserve Economic Data (FRED at St. Louis FED).[21] The average monthly alphas of the funds within each dataset are asset-weighted.[22]

To ensure comparability, the study's sample period spans from March 2008 (i.e., the launch of the first AETF) to December 2022.[23] I exclude funds with missing CRSP fund or portfolio numbers, currency funds, money market funds, and exchange-traded notes (ETNs). The final sample comprises 1,148 AETFs from March 2008 to December 2022. Among these AETFs, there are 175 dead funds, reaching an average closure rate (the ratio of dead funds to the total number of issues) of 15%.

As for AMFs, 9,668 AMFs are recorded over the sample period, and there are 3,689 defunct funds, translating to a closure rate of approximately 38%, which is much higher than that of AETFs. Among these, 2,642 funds experience a liquidation (a direct closure), and 1,047 funds undergo a merger.

Table 3.2 provides a detailed overview of the numbers of closed AETFs and AMFs, respectively. I utilize the first two digits of CRSP's classification for funds'

names are consistent for the whole period of the fund. In order to trace the fund's family from its inception to closure, the advisor's name is used to denote the fund family. The identity of the advisor can also be confirmed by the fund's official website.

[21] For equity factor returns, visit https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html and for bond factor returns, visit https://fred.stlouisfed.org/. In addition, both equity and bond factor returns are double-checked and reconciled with CRSP.

[22] For robustness, I also calculate daily alphas with the daily equity factors and bond factors. The results do not qualitatively change the analysis and the conclusion.

[23] Bear Stearns launched its first AETF, the current yield ETF (ticker YYY, with an expense ratio of 0.35% per annum) that began trading on the American Stock Exchange on March 25, 2008. It was, however, liquidated within half a year and delisted on September 30, 2008.

investment objectives. It is noticeable that both types of funds have the lowest closure rates in the Income category. Furthermore, AETFs show a relatively higher closure rate in the Foreign Income and Domestic Equity categories, while the rates of AMFs closures are similar across these investment categories. On average, AMFs have a higher closure rate, but this could be due partially to the fact that many AETFs were still relatively young as of the recorded date of December 2022.

**Table 3.2:** Number of Liquidated Funds by CRSP Investment Objectives

| CRSP Objectives | AETFs | | | AMFs | | |
|---|---|---|---|---|---|---|
| | No. Dead | No. Issues | % Dead | No. Dead | No. Issues | % Dead |
| Domestic Equity | 85 | 436 | (19.5% ) | 1,696 | 4,213 | (40.3%) |
| Foreign Equity | 21 | 138 | (15.2%) | 759 | 1,829 | (41.4%) |
| Income (general) | 24 | 218 | (11.0%) | 455 | 1,723 | (26.4%) |
| Foreign Income | 5 | 20 | (25.0%) | 120 | 289 | (41.5%) |
| Mixed & Others | 40 | 336 | (11.9%) | 659 | 1,614 | (40.8%) |
| Total | 175 | 1,148 | (15.2%) | 3,689 | 9,668 | (38.2%) |

This table summarizes the count of defunct funds, the count of issued funds, and the proportion of discontinued funds relative to each investment objective. This analysis encompasses two fund categories: AETFs and AMFs. Note that, for AMFs, the statistics include both liquidations and mergers. The investment objectives of "Mixed" and "Others" are combined as a result of similarities in the types of funds in these two objectives. In addition, when counting the total number of AMFs closures, I do not further differentiate the within-family and across-family merges alongside their liquidations.

In order to examine the decision-making on the creation and liquidation of AETFs and AMFs within the same fund family (refer to Section 3.3.4), I target fund families that manage both AETFs and AMFs and present the allocation of funds within various CRSP investment objectives in Table 3.3.[24] The last row in the table shows that the total number of AMFs far surpasses that of AETFs, with 1,906 AMFs compared to 426 AETFs. On average, there are approximately 3 AETFs and 13 AMFs within these families. Both types of active funds are

[24] This table covers a subsample from the previous whole sample.

concentrated in the Domestic Equity category, followed by the Income and Foreign Equity objectives. Furthermore, it appears that fund families are inclined to launch AETFs aligned with their AMFs offerings in the same investment categories. This synergy could result from shared research costs and heightened investor interest in AETFs.

**Table 3.3:** Fund Families and Objectives

| CRSP Objectives | No. | Mean | Median | SD | No. | Mean | Median | SD |
|---|---|---|---|---|---|---|---|---|
| *Total No. of families that manage both AETFs and AMFs: 75* | | | | | | | | |
| | ATFs | | | | AMFs | | | |
| Domestic Equity | 201 | 3.79 | 3.00 | 3.85 | 1,130 | 21.32 | 15.00 | 23.90 |
| Foreign Equity | 73 | 2.92 | 2.00 | 2.96 | 284 | 11.36 | 8.00 | 10.87 |
| Income (general) | 120 | 2.40 | 2.00 | 1.87 | 420 | 8.40 | 5.50 | 7.87 |
| Foreign Income | 5 | 1.00 | 1.00 | 0.00 | 15 | 3.00 | 4.00 | 1.87 |
| Mixed & Others | 27 | 1.53 | 1.00 | 0.95 | 57 | 3.20 | 2.00 | 3.32 |
| Overall | 426 | 2.80 | 2.00 | 2.92 | 1,906 | 12.54 | 5.00 | 16.85 |

This table provides a summary of statistics for fund families operating in active management that contain both AETFs and AMFs. The investment objectives are classified using the initial two-digit CRSP objective code. The investment objectives of "Mixed" and "Others" are combined as a result of similarities in the types of funds in these two objectives.

### 3.4.1 Summary Statistics

Table 3.4 provides the medians of funds characteristics for AETFs and AMFs for the period from March 2008 to December 2022.[25] The data reveal significant differences between living and dead AETFs. Overall, median total net assets (TNA) for deceased AETFs stand at \$11.42 million, significantly smaller than that of their living counterparts (\$83.98 million). Dead AETFs have higher expenses

[25] The median values are reported. This is consistent with the practice in the relevant literature (e.g., Sherrill and Stark 2018; Zhao 2005).

and turn-over their portfolios more frequently than surviving funds. Similarly, the median inflow of dead AETFs (0.24% per quarter) is significantly smaller than that of their living counterparts (11.55% per quarter). In terms of performance, deceased AETFs exhibit a lower raw quarterly return (0.15% vs. 0.45% for living AETFs), and their one-factor alpha (−0.54%), four-factor alpha (−0.68%), and objective-adjusted return (−0.23%) are all negative and significantly lower than those of surviving ones.

Moreover, compared to the living AETFs, liquidated AETFs exhibit distinct characteristics, including wider bid-ask spreads, lower premium-to-NAV, and lower trading volumes. The analysis for one, five, and nine quarters before liquidation reveals a consistent decline in AETFs' liquidated assets and inflows, with all values being significantly smaller than those for surviving AETFs. While expenses remain relatively steady, quarterly returns decline from +1.91% (at nine quarters, or two years, before fund termination) to −0.47% (at one quarter before termination). Both one-factor and four-factor alphas consistently decline and are negative for all quarters preceding liquidation.

In contrast, for AMFs, both liquidated and merged mutual funds are of significantly larger sizes ($17.23 million and $38.42 million respectively) than that of deceased AETFs ($11.42 million). Additionally, their expense ratios (1.07% for liquidated AMFs and 0.95% for merged AMFs), encompassing management fees and 12-1b fees, are significantly higher (0.57% for deceased AETFs). AMFs tend to be older at the time of termination (e.g., 3.2 years for liquidated AMFs). Quarter inflow (−2.57% for liquidated funds and −3.53% for merged funds) is negative and significantly lower than for deceased AETFs. Four-factor alphas for deceased

**Table 3.4:** Funds' Characteristics - Medians

| | AETFs | | | | | AMFs | |
|---|---|---|---|---|---|---|---|
| | Living | Dead | Quarters Near Liquidation | | | Liq. | Merged |
| | | | −1 | −5 | −9 | | |
| TNA (in $mil) | 83.98 | 11.42*** | 15.67*** | 23.13*** | 25.14*** | 17.23*** | 38.42*** |
| Expense (annual, %) | 0.57 | 0.63*** | 0.64 | 0.75** | 0.76** | 1.07*** | 0.95*** |
| Quarter Return (%) | 0.45 | 0.15 | −0.47** | −0.08* | 1.91*** | 0.22 | 0.68* |
| Quarter Flow (%) | 11.55 | 0.24*** | −3.69*** | −0.96*** | 7.97** | −2.57*** | −3.53*** |
| Quarter One-factor Alpha (%) | 0.08 | −0.54*** | −1.13*** | −0.97*** | −0.71** | −0.59 | −0.32** |
| Quarter Four-factor Alpha (%) | −0.06 | −0.68*** | −0.97*** | −0.72*** | −0.61** | −0.56** | −0.34*** |
| Quarter Obj-adjusted Return (%) | −0.007 | −0.23* | −0.70 | −0.90 | 1.20 | −0.32 | −0.12 |
| Turnover (annual, %) | 47.67 | 61.05*** | 225.22 | 269.76** | 215.15** | 65.08 | 50.74*** |
| Fund age (yrs) | 1.53 | 1.80** | 2.44** | 2.39 | 2.56** | 3.20*** | 4.21*** |
| Bid-ask Spread (daily, bp) | 0.08 | 0.18*** | 0.11** | 0.16*** | 0.14*** | | |
| Premium-to-NAV (daily, %) | 0.038 | 0.009*** | −0.031*** | −0.094** | −0.030*** | | |
| Trading Volume (daily, # of shares) | 29,264 | 2923*** | 4973*** | 4661*** | 7006*** | | |
| Shares Outstanding (daily, 1k) | 2028 | 388*** | 659*** | 874*** | 827*** | | |

This table presents the medians of funds' characteristics for the whole sample from 03/2008 to 12/2022. There $TNA$ is the total net assets, measured in millions of dollars. *Quarter return* is the quarterly total return (including the dividend reinvestment, if any). *Quarter flow* is the quarterly growth rate in a fund's total net assets that are not attributed to its performance. The one-factor and four-factor alpha is obtained by running funds' monthly return on bonds factors (for fixed-income funds) and equity factors (for equity funds). The details of factor models are shown in Section 3.3.2. *Turnover* is annualized and calculated as the lesser aggregate amount of purchases and sells of securities divided by the total net asset value of the fund. *Fund age* is the survival years of a fund and is calculated from the fund's inception date to the latter of its termination date or December 31, 2022. The $bid - ask\ spread$ is the difference between the daily close bid price and the ask price, averaged over a quarter and expressed in basis points. The *trading volume* and outstanding shares are directly from the CRSP stock file, all expressed daily. Finally, the *premium to* $NAV$ is calculated as the difference between the daily close price and its NAV divided by NAV, expressed in percentage. All the statistics are summarized each quarter cross-sectionally for all funds, and then the time-series average over the whole period. The Wilcoxon signed rank test is first applied for the significance of the difference between living AETFs and dead AETFs, and between living AETFs and dead ones before different quarters to liquidation. It is further applied to test the difference between dead AETFs, liquidated mutual funds, and merged mutual funds.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

mutual funds (−0.56% for liquidated AMFs and −0.34% for merged AMFs) are significantly higher than for dead AETFs (−0.68%). The objective-adjusted quarterly returns for liquidated mutual funds (−0.32%) and for merged mutual funds (−0.12%) are not significantly different from those of deceased AETFs (−0.23%).

## 3.5 Empirical Results

The empirical results are presented in Table 3.5 and Table 3.6 with respect to the factors influencing the liquidation decisions of AETFs and the comparison between AETFs and AMFs. Later on, I analyze the subsamples based on small size (Table 3.7) and the objective returns (Table 3.8) to further explore how these factors affect the liquidation differently.

### 3.5.1 AETFs

Table 3.5 presents the results of the binary-logit regressions, focusing exclusively on AETFs. The results are presented for three different sample periods – the first includes data from 2008 to 2022 (i.e., the whole sample), the second covers the period before 2020, and the third covers the period after 2020. This division of the sample accounts for the significant growth of AETFs after 2020. I also classify AETFs into equity and fixed income based on the CRSP 2-digit asset class code and compare their characteristics in the last two columns (using data from the whole sample).

The results show that size is a significant determinant of AETF liquidation throughout the whole period. For example, a one standard deviation (SD) increase

**Table 3.5:** AETFs Liquidations Determinants

| | Sample Periods | | | Asset Classes | |
|---|---|---|---|---|---|
| | Whole | Before 2020 | After 2020 | Equity | Fixed Income |
| $Fund\ size_{t-1}$ | −1.224*** | −1.294*** | −0.486 | −0.794*** | −2.234*** |
| | (−5.77) | (−5.76) | (−1.53) | (−3.87) | (−4.91) |
| $Fund\ expense_{t-1}$ | 0.131 | 0.110 | 0.554* | −0.005 | 0.208 |
| | (0.63) | (0.49) | (1.81) | (−0.02) | (1.21) |
| $Fund\ age$ | −0.027 | −0.095 | −0.468 | −0.131 | 0.353 |
| | (−0.16) | (−0.50) | (−1.61) | (−0.72) | (1.46) |
| $Fund\ inflow_{t-1}$ | −0.384*** | −0.232** | −1.257** | −0.436** | −0.466*** |
| | (−2.62) | (−2.20) | (−1.98) | (−2.36) | (−2.60) |
| $Fund\ inflow_{t-2}$ | −0.172 | −0.206 | 0.086 | −0.066 | −0.157 |
| | (−1.15) | (−1.32) | (1.29) | (−1.02) | (−1.30) |
| $Fund\ performance_{t-1}$ | −0.015 | −0.012 | −0.175 | −0.012 | −0.250*** |
| | (−0.31) | (−0.23) | (−1.19) | (−0.25) | (−2.81) |
| $Fund\ performance_{t-2}$ | −0.004 | −0.004 | −0.267* | 0.010 | −0.182* |
| | (−0.09) | (−0.03) | (−1.91) | (0.22) | (−1.85) |
| $Spread_{t-1}$ | 0.073 | 0.056 | 0.064 | 0.251 | 0.063 |
| | (0.77) | (0.60) | (0.36) | (1.14) | (0.46) |
| $Premium_{t-1}$ | −0.100 | −0.098 | −0.230* | −0.046 | −0.521** |
| | (−1.64) | (−1.49) | (−1.65) | (−0.71) | (−2.12) |
| $Family\ inflow_{t-1}$ | 0.003 | 0.014 | 0.056 | 0.010 | 0.101 |
| | (0.10) | (0.45) | (0.75) | (0.28) | (1.37) |
| $Family\ inflow_{t-2}$ | −0.03 | 0.025 | −0.619 | −0.041 | −0.158** |
| | (−0.65) | (0.86) | (−0.71) | (−0.72) | (−2.09) |
| $Family\ performance_{t-1}$ | −0.02 | −0.002 | 0.024 | 0.013 | −0.201*** |
| | (−0.31) | (0.04) | (0.22) | (0.29) | (−2.61) |
| $Family\ performance_{t-2}$ | −0.04 | −0.033 | 0.075 | −0.011 | −0.155** |
| | (−0.53) | (−0.47) | (0.71) | (−0.18) | (−2.22) |
| $Obj\ performance_{t-1}$ | −0.053 | 0.018 | 0.002 | −0.067 | 0.215** |
| | (−1.11) | (0.32) | (0.01) | (−1.15) | (2.29) |
| $Obj\ performance_{t-2}$ | 0.106 | 0.006 | −0.353 | 0.140* | 0.047 |
| | (1.56) | (0.09) | (−0.95) | (1.78) | (0.79) |
| $Obj\ inflow_{t-1}$ | −0.002 | 0.004 | 0.126 | −0.335 | 0.434 |
| | (−0.01) | (0.15) | (1.19) | (−1.61) | (0.48) |
| $Obj\ inflow_{t-2}$ | 0.015 | 0.019 | 0.154 | −0.093 | 0.572 |
| | (0.83) | (0.99) | (1.36) | (−1.43) | (0.67) |
| $Family\ no.\ of\ funds_{t-1}$ | −0.132 | −0.112 | −0.258 | −0.099 | −0.563** |
| | (−0.64) | (−0.51) | (−1.05) | (−0.47) | (−2.41) |
| $Obj\ no.\ of\ funds_{t-1}$ | −0.135 | −0.093 | −0.147 | −0.216 | −0.481** |
| | (−0.65) | (−0.42) | (−0.73) | (−0.92) | (−2.06) |
| $Team\ mgmt.$ | −0.302 | −0.424 | 0.373 | −0.593* | −0.317 |
| | (−1.13) | (−1.43) | (0.79) | (−1.81) | (−0.52) |
| No. of obs | 8302 | 6398 | 1904 | 5403 | 2899 |
| Pseudo $R^2$ | 0.347 | 0.335 | 0.268 | 0.339 | 0.410 |

This table uses quarterly observations to show the coefficients and $t$-statistics of the binomial logit model for AETFs from 03/2008 to 12/2022. The dependent variable takes 1 if an AETF is alive and 2 if it dies for every quarter. The standard errors are clustered by fund family and the $t$-statistics are robust to heteroskedasticity. All the explanatory variables are described in Section 3.3.3. The $spread_{t-1}$ and $premium_{t-1}$ are added for AETFs because they are traded on exchanges. Quarter fixed effects have been added.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

in size results in a remarkable 70.59% reduction in the likelihood of liquidation, with its impact weakening post-2020 due to the inclusion of smaller, newer funds.[26] Fund expenses positively affect the liquidation likelihood after 2020, but not before. This result is consistent with investors' growing sensitivity to fees, particularly in recent years.[27] Fund inflow in the most recent quarter is another significant driver of AETF liquidation, with its impact intensifying post-2020, indicating a stronger connection between lower inflow and higher liquidation likelihood. This is reflected in the likelihood of liquidation jump from 20.71% to 71.55%, with a one SD decrease in fund inflow. The impact of excess return at $t-2$ becomes significant after 2020, suggesting an increasing role of prior returns when assessing liquidation risk. The coefficients for premium-to-NAV are negative, significantly so for the period after 2020. That is, AETFs that are traded at a premium (discount) have a lower (higher) chance of being terminated.

The results on the likelihood of liquidation in equity and fixed-income categories reveal varying dynamics. Two factors significantly impact both categories – size and fund inflow in the most recent quarter. Size has a negative effect; i.e., larger funds are less likely to be terminated. The effect is more pronounced for fixed-income AETFs. Fund inflow in the most recent quarter, but not before, also has a negative effect, especially for the period after 2020. Some other factors are significant only for fixed-income AETFs. For example, excess returns in both the most recent quarter and the one before play a significantly negative role in the termination of fixed-income AETFs but not for equity AETFs. Objective returns

[26] The reduction in the probability of liquidation is calculated as $e^{-1.224}-1$, where $-1.224$ is the regression coefficient for the whole sample period.

[27] Investors' sensitivity to high fund fees has recently been regularly reported in the press. See, for example, a newspaper article entitled "Investors Pull Hugh Sums from Expensive Investment Funds" in the August 8, 2023 edition of the *Financial Times*.

in the past quarter also significantly increase the likelihood of liquidation for fixed-income AETFs. In addition, the premium-to-NAV ratio emerges as a substantial factor for liquidation, characterized by a coefficient of $-0.521$. This phenomenon aligns with the findings of Petajisto (2017) that fixed-income ETFs tend to exhibit higher and more persistent premiums compared to equity ETFs. This can be attributed to limited creation and redemption arbitrage activities in fixed-income markets relative to equities, rendering the premium-to-NAV ratio more impactful for fixed-income ETFs.

Finally, a greater number of managed funds within the family lowers the likelihood of liquidation of fixed-income AETFs, contradicting the findings in Audretsch (1994) that independent business units are less likely to exit than those that belong to larger entities. Similarly, a greater number of managed funds with the same investment objective lowers the fund's closure risk, consistent with the idea that there is "safety in numbers." Investors tend to judge poorly performing funds less harshly if many other funds with the same objective also perform poorly.

In contrast, some factors are significant only for equity AETFs. In particular, team management emerges as a weakly significant determinant, negatively impacting the likelihood of liquidation. This is consistent with the finding of Bliss et al. (2008) that team management attracts fund inflows and curbs the probability of liquidation.[28]

[28] Team management can limit irrational investment decisions and thus prevent the funds from taking extreme risks.

### 3.5.2 Active Management – AETFs and AMFs

Table 3.6 shows the multinomial logit regression results for AETFs and AMFs in two exit forms (liquidation and mergers) and the final two columns illustrate the differences in the effects of factors. The results indicate that fund size remains pivotal across both fund types. The larger the size of a fund, the less likely it is to be closed. The impact of size is most pronounced for AETFs, followed by liquidated AMFs and merged AMFs. Expense ratios are not a significant factor for the closure of AETFs, likely because the fees of AETFs are already generally low. However, they are a significant factor in the liquidation and more so for the merger of AMFs, consistent with the finding in Zhao (2005). In particular, for merged AMFs, a coefficient of 0.203 indicates that a one SD increase in expenses elevates the likelihood of mutual funds being merged by 22.51%. This finding aligns with English et al. (2011) insight that portfolios with higher expenses are more likely to be merged within the fund family to sustain revenue.

The age of a fund is consistently found to be significant for both active fund closures. Greater longevity is associated with reduced liquidation likelihood. For instance, a coefficient of $-0.699$ for liquidated AMFs implies that a one SD increase in age lowers the likelihood of liquidation by about half (50.29%). This result is consistent with an argument by Brown and Goetzmann (1995) that older funds have longer track records with which to judge current performance.

Fund inflow continues to be a substantial negative factor for both fund types, and this is especially pronounced for AETFs, which further shows a significant difference (shown in the last two columns) between AETFs and AMFs terminations.

**Table 3.6:** Active Funds Liquidations Determinants

| | AETFs | AMFs Liq. | AMFs Merge | Differences | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (1) − (2) | (1) − (3) |
| $Fund\ size_{t-1}$ | −0.701*** | −0.380*** | −0.294*** | −0.321** | −0.407** |
| | (−5.08) | (−5.87) | (−3.21) | (−2.07) | (−2.42) |
| $Fund\ expense_{t-1}$ | 0.011 | 0.145* | 0.203*** | | |
| | (0.04) | (1.89) | (3.02) | | |
| $Fund\ age$ | −0.296** | −0.699*** | −0.199** | 0.403*** | |
| | (−2.08) | (−11.32) | (−2.07) | (3.56) | |
| $Fund\ inflow_{t-1}$ | −1.366** | −0.017* | −0.021*** | −1.349** | −1.345** |
| | (−2.24) | (−1.79) | (−2.71) | (−2.29) | (−2.28) |
| $Fund\ inflow_{t-2}$ | −0.281 | −0.023*** | −0.022*** | | |
| | (−1.26) | (−2.99) | (−3.36) | | |
| $Fund\ performance_{t-1}$ | 0.008 | −0.135*** | −0.089*** | 0.143*** | 0.097*** |
| | (0.41) | (−8.48) | (−5.65) | (4.06) | (3.50) |
| $Fund\ performance_{t-2}$ | 0.003 | −0.085*** | −0.077*** | 0.088*** | 0.080*** |
| | (0.15) | (−6.21) | (−5.36) | (3.81) | (3.64) |
| $Family\ inflow_{t-1}$ | −0.035 | −0.015* | 0.002 | | |
| | (−0.11) | (−1.81) | (0.15) | | |
| $Family\ inflow_{t-2}$ | −1.324 | −0.017* | −0.002 | | |
| | (−1.93) | (−1.67) | (−0.13) | | |
| $Family\ performance_{t-1}$ | −0.052* | −0.071*** | −0.052 | | |
| | (−1.75) | (−4.40) | (−1.20) | | |
| $Family\ performance_{t-2}$ | −0.067* | −0.069*** | −0.062 | | |
| | (−1.71) | (−3.15) | (−1.23) | | |
| $Obj\ performance_{t-1}$ | 0.098*** | 0.012 | 0.058*** | 0.086*** | |
| | (3.43) | (1.25) | (4.58) | (2.86) | |
| $Obj\ performance_{t-2}$ | 0.076** | −0.014 | 0.041*** | | |
| | (2.30) | (−1.40) | (3.58) | | |
| $Obj\ inflow_{t-1}$ | −0.204 | −0.012 | 0.027* | | |
| | (−0.95) | (−1.11) | (1.87) | | |
| $Obj\ inflow_{t-2}$ | −0.38 | −0.022 | 0.015*** | | |
| | (−0.69) | (−1.42) | (2.70) | | |
| $Family\ no.\ of\ funds_{t-1}$ | −0.048 | −0.092 | 0.249*** | | |
| | (−0.30) | (−1.62) | (3.54) | | |
| $Obj\ no.\ of\ funds_{t-1}$ | −0.409*** | 0.031 | 0.047 | −0.439*** | −0.456*** |
| | (−4.51) | (0.73) | (0.75) | (−4.41) | (−4.14) |
| $Team\ mgmt.$ | 0.229 | −0.310** | 0.019 | | |
| | (0.79) | (−2.37) | (0.12) | | |
| No. of obs | | 159,776 | | | |
| Pseudo $R^2$ | | 0.208 | | | |

This table uses quarterly observations to show the coefficients and $t$-statistics of the multinomial logit model for the whole sample (AETFs and AMFs combined) from 03/2008 to 12/2022. The dependent variable takes 1 if the fund is alive, 2 if an AETF dies in a quarter, 3 if an AMF is liquidated in a quarter, and 4 if an AMF is merged in a quarter. The standard errors are clustered by fund family and are robust to heteroskedasticity. All the explanatory variables are described in Section 3.3.3. Quarter fixed effects have been added.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

An increase in $t-1$ fund flow by one SD reduces the probability of liquidation for AETFs by 74.5% (12.63% for liquidated AMFs and 8.52% for merged MFs). This finding is consistent with the expectation that funds with reduced fund inflows will shrink in size, leading to a higher chance of termination.

Note, however, that fund performance (objective excess return) plays a disparate role, impacting AETFs and AMFs differently. In specific, excess returns do not matter for AETFs liquidation and merges, but they become a significant driver for AMFs' liquidation. The commonly observed relationship between fund inflow and past performance indicates that fund flows respond rationally to historical performance (e.g., Berk and Green 2004; Sirri and Tufano 1998). Thus, it is expected that a higher performance will bring more fund inflow, increase fund size, and lower the chance of liquidation. However, in the case of AETFs, poor performance may not necessarily reduce the fund flows and lead to a higher chance of closure. This might be due to investors' psychology bias that prevents them from switching out of poorly performing funds, as explored by Goetzmann and Peles (1997).[29]

At the family level, family performance in the most recent two quarters emerges as a determinant of the closure of AETFs and some AMFs (those that were closed by liquidation).[30] However, I do not find family performance relevant to mutual fund mergers. Aligned with the findings of Zhao (2005), the merging decisions are influenced by the number of funds within the family, as evidenced by a coefficient of +0.249.[31] The more funds a family has, the greater the likelihood that a poorly performing fund will be merged.

[29] Goetzmann and Peles (1997) explain that investors' aversion to switching poor performers could be attributed to their overly optimistic perceptions of past fund performance and their recollections are therefore consistently biased above actual past performance. As a result, the recollection bias makes the investors remain in poorly performing funds.

[30] Even though the effect of family excess return is weaker for AETFs in terms of significance, there is no statistical difference in the AETFs and AMFs liquidation.

[31] In specific, Zhao (2005) finds that the number of funds in the family plays a positive and significant role for within-family mergers, rather than across-family mergers.

At the objective level, higher objective returns over the most recent two quarters increase the likelihood of AETFs to be terminated and AMFs to be merged, yet the difference is significant only in the prior quarter ($t-1$). This suggests that funds are more likely to be terminated when the returns on their benchmarks (against which they are judged) have been high. Note, however, that the coefficient for the number of funds with the same objective is negative and significant for AETFs. This negative effect is similar to what was observed in AETF closures alone, reinforcing the idea that a higher number of AETFs sharing the same investment objective reduces their probability of termination. This implies that there is "safety in numbers," where poorly performing funds tend to be judged less harshly by investors if many other funds also have bad performance.[32] Finally, team management is a key driver of liquidated AMFs, affirming the hypothesized connection (refer to Table 3.1) that team management lowers the chance of closure.

### 3.5.3 Small Funds

The significance of size as a determinant for fund liquidation calls for an examination of how smaller funds can sustain themselves and whether the factors influencing them differ. To explore this, I ranked funds based on their TNA (total net assets) and focused on the bottom tercile sample of funds. For this purpose, I choose to include only the AMFs that were terminated by liquidation, but not those that were terminated by being merged into other funds. The reason is that the size of the latter group is, on average, much larger than the size in the bottom

[32] This is similar to the idea of herding by fund managers. One possible explanation of herding is that fund managers are concerned about their career and reputation (e.g., Chevalier and Ellison 1999; Jiang and Verardo 2018). By herding, fund managers can minimize the deviation between their performance and their peers'.

tercile of the former group and of AETFs. As a result, the latter group should not be included in the comparison. All variables were standardized with a mean of 0 and a standard deviation of 1, and quarter fixed effects were incorporated.

**Table 3.7:** Small Active Funds Liquidations Determinants

| | AETFs | AMFs Liq. | Differences |
|---|---|---|---|
| | (1) | (2) | (1) − (2) |
| $Fund\ size_{t-1}$ | −0.077* | −0.142** | 0.064** |
| | (−1.89) | (−2.02) | (1.96) |
| $Fund\ expense_{t-1}$ | −0.236 | 0.078 | |
| | (−0.68) | (0.82) | |
| $Fund\ age$ | −0.099 | −0.708*** | 0.609*** |
| | (−0.59) | (−10.42) | (3.36) |
| $Fund\ inflow_{t-1}$ | −0.029 | −0.047* | |
| | (−0.42) | (−1.90) | |
| $Fund\ inflow_{t-2}$ | −0.217 | −0.044* | |
| | (−0.56) | (−1.67) | |
| $Fund\ performance_{t-1}$ | 0.006 | −0.024 | |
| | (0.13) | (−1.33) | |
| $Fund\ performance_{t-2}$ | 0.034 | −0.008 | |
| | (0.75) | (−0.51) | |
| $Family\ inflow_{t-1}$ | 0.013 | −0.014 | |
| | (0.20) | (−1.12) | |
| $Family\ inflow_{t-2}$ | −1.238 | 0.011 | |
| | (−0.78) | (1.15) | |
| $Family\ performance_{t-1}$ | −0.061** | −0.020 | |
| | (−2.16) | (−1.55) | |
| $Family\ performance_{t-2}$ | −0.012 | −0.033** | |
| | (−0.36) | (−2.31) | |
| $Obj\ performance_{t-1}$ | 0.176*** | 0.055*** | 0.121*** |
| | (4.77) | (4.67) | (3.13) |
| $Obj\ performance_{t-2}$ | 0.131*** | 0.068*** | 0.063* |
| | (3.79) | (5.9) | (1.74) |
| $Obj\ inflow_{t-1}$ | −0.072 | 0.021 | |
| | (−1.11) | (1.05) | |
| $Obj\ inflow_{t-2}$ | −0.091 | 0.018 | |
| | (−0.9) | (0.92) | |
| $Family\ no.\ of\ funds_{t-1}$ | −0.380 | −0.184** | |
| | (−1.61) | (−1.99) | |
| $Obj\ no.\ of\ funds_{t-1}$ | −0.491*** | 0.079 | −0.570*** |
| | (−4.49) | (1.02) | (−4.25) |
| $Team\ mgmt.$ | 0.306 | 0.342 | |
| | (0.78) | (1.43) | |
| No. of obs | 34,142 | | |
| Pseudo $R^2$ | 0.268 | | |

This table uses quarterly observations to show the coefficients and $t$-statistics of the multinomial logit model for the small funds (bottom tercile of TNA) from the AETFs and AMFs in liquidations from 03/2008 to 12/2022. The dependent variable takes 1 if the fund is alive, 2 if an AETF dies in a quarter, 3 if an AMF is liquidated in a quarter. The standard errors are clustered by fund family and are robust to heteroskedasticity. All the explanatory variables are described in Section 3.3.3. Quarter fixed effects have been added.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The results are reported in Table 3.7, and the changes in the impact of underlying factors on the liquidation of small AETFs and small AMFs are observed. First, there is a significant reduction in the impact of previously identified crucial drivers on small funds. For example, the significance of size diminishes for both active funds (compared to Table 3.6), although the difference between the impacts remains significant. This suggests that size has a more pronounced effect on small AMFs than small AETFs. This is likely due to the fact that mutual funds generally have higher expenses than AETFs do and, thus, are more sensitive to size because the fees that they generate are proportional to their size.[33] Secondly, fund inflows in the two most recent quarters have a mildly significant impact on small AMFs, but not AETFs. Again, this is likely because mutual funds are more expensive to operate, and so small mutual funds are unlikely to survive if their inflows are low. Other relevant factors include age, which is now a significant factor only for the liquidation of small AMFs, but not for AETFs. As before, older AMFs have a smaller chance of being liquidated.

Stronger family excess returns reduce the likelihood of liquidation for both types of small active funds. As mentioned above, the performance of the whole family can help to cushion the poor performance of a family member. Next, similar to the case of the whole sample, the objective return exerts a more pronounced positive effect on the liquidation of small AETFs compared to small AMFs, and this difference is statistically significant and larger in magnitude, compared to Table 3.6. This suggests that objective return plays a critical role in the closure risk, especially when funds are small. When the objective return is positive, it creates

[33] Mutual fund fees are generally higher than those of AETFs because they have to deal directly with the investors who want to buy and/or redeem the funds' units.

more pressure on small funds (especially small AETFs) to survive, as investors can easily switch to other better-performing investment alternatives.

### 3.5.4 Funds by Objective Returns

The significance of objective performance (i.e., an asset-weighted average of the returns of other funds with the same objective) in determining AETFs liquidation prompts an examination of how different factors react under varying objective return scenarios.[34] To achieve this, I first categorize funds into two subsamples based on their CRSP objective returns during their survival periods, distinguishing between positive and negative objective returns for AETFs and AMFs. Then, I reexamine the multinomial logit model within each subsample and present results in Table 3.8.

The results, in general, show that the impact of some fund-specific characters changes in response to the performance of the objective. Consistent with prior findings, size still remains a significant determinant of termination risk, regardless of the performance of the investment objective. The larger the size is, the less likely the fund is to be shut down. Notably, size has a greater impact on both fund types under the condition of a positive objective return. Moreover, the differences in the size impact between the AETFs and AMFs are positive (+0.331) and significant, suggesting that AETFs rely more heavily on assets than AMFs when the overall objective is generating positive returns.

When the objective return is positive, age emerges as a significant negative factor for AETFs liquidation, while the impact on mutual funds is the same as

[34] I focus on AMFs in liquidation (not mergers) to be consistent with Sherrill and Stark (2018).

**Table 3.8:** Active Funds Liquidations by Objectives

| | **Negative** Objective Returns | | | **Positive** Objective Returns | | |
|---|---|---|---|---|---|---|
| | Active ETFs | Active MFs Liq. | Difference | Active ETFs | Active MFs Liq. | Difference |
| | (1) | (2) | (1) − (2) | (3) | (4) | (3) − (4) |
| $Fund\ size_{t-1}$ | $-0.530^{***}$ | $-0.262^{***}$ | | $-0.681^{***}$ | $-0.351^{***}$ | $-0.331^{*}$ |
| | $(-3.37)$ | $(-3.59)$ | | $(-3.80)$ | $(-4.83)$ | $(-1.71)$ |
| $Fund\ expense_{t-1}$ | $0.062$ | $0.556^{***}$ | | $0.065$ | $0.203^{***}$ | |
| | $(0.19)$ | $(6.63)$ | | $(0.22)$ | $(3.15)$ | |
| $Fund\ age$ | $0.079$ | $-0.816^{***}$ | $0.896^{***}$ | $-0.261^{*}$ | $-0.909^{***}$ | $0.648^{***}$ |
| | $(0.40)$ | $(-7.17)$ | $(3.88)$ | $(-1.91)$ | $(-15.95)$ | $(4.36)$ |
| $Fund\ inflow_{t-1}$ | $-1.343$ | $-0.033$ | | $-1.988^{**}$ | $0.002$ | $-1.990^{**}$ |
| | $(-1.43)$ | $(-0.97)$ | | $(-1.99)$ | $(0.21)$ | $(-1.99)$ |
| $Fund\ inflow_{t-2}$ | $-1.088$ | $0.016$ | | $-0.623$ | $0.010$ | |
| | $(-0.79)$ | $(0.36)$ | | $(-0.45)$ | $(1.04)$ | |
| $Fund\ performance_{t-1}$ | $0.019$ | $-0.021$ | | $0.015$ | $-0.066^{***}$ | $0.081^{***}$ |
| | $(0.41)$ | $(-0.72)$ | | $(0.94)$ | $(-5.67)$ | $(4.05)$ |
| $Fund\ performance_{t-2}$ | $0.016$ | $-0.031$ | | $0.024$ | $-0.050^{***}$ | $0.074^{***}$ |
| | $(1.21)$ | $(-1.25)$ | | $(1.46)$ | $(-4.27)$ | $(3.68)$ |
| $Family\ inflow_{t-1}$ | $-0.59$ | $-0.006$ | | $-0.716$ | $-0.004$ | |
| | $(-0.61)$ | $(-0.51)$ | | $(-0.47)$ | $(-0.59)$ | |
| $Family\ inflow_{t-2}$ | $-1.522$ | $0.007$ | | $-1.859$ | $0.007$ | |
| | $(-1.17)$ | $(0.42)$ | | $(-0.92)$ | $(1.23)$ | |
| $Family\ performance_{t-1}$ | $-0.029$ | $-0.021$ | | $-0.017$ | $-0.054^{***}$ | $0.037^{*}$ |
| | $(-0.52)$ | $(-0.94)$ | | $(-0.99)$ | $(-5.15)$ | $(1.82)$ |
| $Family\ performance_{t-2}$ | $-0.001$ | $-0.032$ | | $-0.014$ | $-0.044^{***}$ | |
| | $(-0.01)$ | $(-1.64)$ | | $(-0.74)$ | $(-4.24)$ | |
| $Obj\ performance_{t-1}$ | $0.034$ | $-0.099^{***}$ | $0.133^{*}$ | $0.124^{***}$ | $0.029^{***}$ | $0.095^{***}$ |
| | $(0.53)$ | $(-3.92)$ | $(1.93)$ | $(4.18)$ | $(3.59)$ | $(3.07)$ |
| $Obj\ performance_{t-2}$ | $0.040$ | $-0.095^{***}$ | $0.135^{**}$ | $0.078^{**}$ | $0.027^{***}$ | |
| | $(0.64)$ | $(-4.05)$ | $(2.03)$ | $(2.26)$ | $(3.74)$ | |
| $Obj\ inflow_{t-1}$ | $-0.108$ | $-0.063$ | | $-0.056$ | $0.016$ | |
| | $(-1.23)$ | $(-1.52)$ | | $(-0.83)$ | $(1.07)$ | |
| $Obj\ inflow_{t-2}$ | $-0.033$ | $-0.049$ | | $-0.068$ | $-0.002$ | |
| | $(-0.46)$ | $(-1.31)$ | | $(-0.46)$ | $(-0.17)$ | |
| $Family\ no.\ of\ funds_{t-1}$ | $0.151$ | $-0.015$ | | $-0.036$ | $-0.070$ | |
| | $(0.81)$ | $(-0.18)$ | | $(-0.19)$ | $(-1.30)$ | |
| $Obj\ no.\ of\ funds_{t-1}$ | $-0.416^{***}$ | $0.068$ | $-0.484^{***}$ | $-0.382^{***}$ | $0.071^{*}$ | $-0.452^{***}$ |
| | $(-4.16)$ | $(0.75)$ | $(-3.60)$ | $(-3.71)$ | $(1.81)$ | $(-4.11)$ |
| $Team\ mgmt.$ | $0.526$ | $-0.187$ | $0.713^{*}$ | $0.022$ | $-0.374^{***}$ | |
| | $(1.56)$ | $(-0.91)$ | $(1.81)$ | $(0.07)$ | $(-2.69)$ | |
| No. of obs | 27,314 | | | 119,900 | | |
| Pseudo $R^2$ | 0.326 | | | 0.244 | | |

This table uses quarterly observations to show the coefficients and $t$-statistics of the multinomial logit model for AETFs and AMFs from 03/2008 to 12/2022, with respect to positive and negative objective performance. The dependent variable takes 1 if the fund is alive, 2 if an AETF dies in a quarter, and 3 if an AMF is liquidated in a quarter. The standard errors are clustered by fund family and are robust to heteroskedasticity. All the explanatory variables are described in Section 3.3.3. Quarter fixed effects have been added.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

before, which is that older funds are less likely to be terminated. Also, higher fund inflow in the previous quarter significantly reduces AETFs liquidation under the positive objective return.

Similar to prior findings, fund performance (i.e., the objective excess return) has no relation to the likelihood of AETFs liquidation under either positive or negative objective returns. Instead, fund excess return exclusively impacts AMFs liquidation during positive objective returns, suggesting that the impact of better fund performance is more important in reducing mutual funds termination when the objective return is positive. Objective return remains significantly positive for both AETFs and AMFs during favorable overall objective return periods, indicating that higher positive category returns create pressure on fund managers to outperform and consequently elevate the likelihood of liquidation. However, as the objective turns bearish, the objective return's relationship with AMFs liquidations becomes negative, with no effect on AETFs liquidations. The number of funds under the objective remains significant for AETFs irrespective of positive or negative objective returns, with the difference being statistically significant.

### 3.5.5 Family Decisions

The results of decision-making in launching and closing different funds within the family are reported in Table 3.9. The probit models are run at the family and the family objective level respectively.[35] At the family level, there is a trend observed among AETFs and AMFs within the same fund family, where their actions in the previous quarter tend to persist. For instance, if an AETF was liquidated in the previous quarter, there is a notable increase of approximately 154% (accompanied by a coefficient of 0.934 in column (1)) in the likelihood of another AETF in the same family being liquidated in the subsequent quarter. In a similar fashion, if an

[35] To get a more detailed classification of the fund's investment objective, I use the full four-digit CRSP objective code to group funds at the family objective level.

AMF was launched in the previous quarter, the chance of creating a new mutual fund in the subsequent quarter is 34.72% (coefficient of 0.298 in column (4)).

At the family objective level, some mutual interaction between the births and liquidation of AETFs and AMFs is observed. For instance, an AMF creation in a certain investment objective in the previous quarter raises the likelihood of introducing an AETF with the same investment objective by 29.17% (coefficient of 0.256 in column (6)) in the following quarter. This indicates that fund companies are more likely to launch an AETF with the same objective after introducing an AMF. This strategy potentially allows for shared research costs and expanded avenues to attract assets, considering the popularity of AETFs among investors. Conversely, launching an AETF in the prior quarter raises the probability of introducing a new AMF with the same objective by 57.93% (coefficient of 0.457 in column (8)) in the subsequent quarter. The higher likelihood of creating an AETF to the creation of an AMF in the following quarter aligns with the findings of Sherrill and Stark (2018) that fund companies may use ETFs within an investment objective to test investor demand before launching a mutual fund in the same category.

Lastly, I do not find a significant negative relationship between AETF births and AMF liquidations (or between AETF liquidation and AMF births). This may indicate that companies that issue both AETFs and AMFs do not take these two types of products as competitors.

**Table 3.9:** Family Decisions between AETFs and AMFs

| | Family Level | | | | Family Objective Level | | | |
|---|---|---|---|---|---|---|---|---|
| Dummies | *AETFs Liq.* | *AETFs Birth* | *AMFs Liq.* | *AMFs Birth* | *AETFs Liq.* | *AETFs Birth* | *AMFs Liq.* | *AMFs Birth* |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $AMFs\ Liq._{t-1}$ | 0.021 | 0.093 | 0.918*** | 0.019 | 0.046 | 0.267 | 0.924*** | 0.098 |
| | (0.09) | (0.65) | (7.02) | (0.13) | (0.80) | (0.98) | (5.59) | (0.34) |
| $AMFs\ Birth_{t-1}$ | −0.493 | 0.265 | 0.446*** | 0.298** | 0.073 | 0.256** | 0.348 | −0.177 |
| | (−1.59) | (1.17) | (3.15) | (2.20) | (1.49) | (2.11) | (1.46) | (−0.68) |
| $AETFs\ Liq._{t-1}$ | 0.934*** | 0.268 | 0.262 | −0.035 | 0.668* | 0.184 | −0.308 | 0.142 |
| | (3.04) | (0.96) | (0.98) | (−0.12) | (1.79) | (0.35) | (−0.67) | (0.26) |
| $AETFs\ Birth_{t-1}$ | −0.059 | 0.645*** | −0.213 | 0.112 | 0.416 | 0.482** | −0.067 | 0.457** |
| | (−0.24) | (5.08) | (−1.39) | (0.79) | (1.43) | (2.03) | (−0.30) | (2.07) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of obs | 784 | 784 | 784 | 784 | 1067 | 1067 | 1067 | 1067 |
| Pseudo $R^2$ | 0.087 | 0.061 | 0.114 | 0.070 | 0.147 | 0.055 | 0.089 | 0.051 |

This table shows the family decision interactions between AETFs and AMFs. Only fund families that manage both AETFs and AMFs are considered. The control variables include *size*, *expense*, *age*, $fund\ inflow$, and $fund\ performance$ and they are average across the family for ETFs and mutual funds, respectively. The dummy variables at time $t$ are 1 for the following choices: if an AETF is liquidated at $t-1$, if an AETF is liquidated at $t-1$, if an AMF is liquidated at $t-1$, and if an AMF is created at $t-1$, respectively.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

## 3.6 Conclusion

This study investigates the factors underlying the closures of actively managed ETFs (AETFs) from 03/2008 to 12/2022 and how the decisions are affected by various subsamples based on size and overall objective performance. Further, this paper compares the effects of these determinants in the liquidation between AETFs and actively managed mutual funds (AMFs). The research finds that AETFs and AMFs exhibit commonalities in certain fund-level influencing factors, particularly size and fund inflow, which negatively correlate with the probability of liquidation. The effect, however, is statistically and significantly more pronounced for AETFs. In addition, expense appear to hold limited significance for AETFs, in contrast to their positive influence on AMFs terminations. This could be because AETFs already charge a lower expense compared to AMFs.

Intriguingly, the absence of a discernible impact of fund performance (i.e., objective excess return) on the liquidation likelihood of AETFs is observed, unlike the significant and negative role it plays for AMFs. This phenomenon could partially explain why AETFs have maintained a relatively lower closure rate than AMFs during the sample period. In other words, the underperformance does not punish AETFs in the same way as AMFs, and as a result, fund families might be inclined to continue launching AETFs to attract assets, potentially without being concerned about achieving exceptional performance.

When funds are small, AMF liquidations are more heavily reliant on size and fund flow, while the influence is limited to AETFs. This suggests that AETFs may not need a comparable fund size to operate as the AMFs do.

In a broader context, the performance of the objective category holds more substantial influence over the likelihood of AETFs liquidation than that of AMFs. A higher objective return significantly increases the chance of AETFs closure. Moreover, fund-specific and family-level characteristics tend to affect both AETFs and AMFs more when the objective return is positive.

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# Appendix A

# Chapter 2 Supplement

## A1 How to construct the MPPs

Below, I show the steps of constructing a matching passive portfolio (MPP) for each single security held in a fund.

First, the characteristics used to construct the benchmark portfolios include the firm's size (market value), value (book-to-market ratio), and momentum (previous years' stock return). These factors are commonly employed as regressors in returns-based multi-factor models. Studies like Carhart (1997), Fama and French (1993), Grinblatt and Titman (1989), and Jegadeesh and Titman (1993) have demonstrated that these attributes serve as strong predictors of expected returns across stocks.

Second, DGTW's approach to constructing benchmark portfolios involves categorizing all stocks listed on the New York Stock Exchange (NYSE), Nasdaq, and American Stock Exchange (AMEX) into three quintiles based on their size, value, and momentum characteristics. They assign a score ranging from 1 to 5 (from lowest to highest) to each dimension. This process yields 125 DGTW passive characteristic-based benchmark portfolios across the three dimensions (5 * 5 * 5). Each portfolio is represented by a unique three-digit port number that corresponds to the order of size, value, and momentum. This port number effectively signifies the portfolio's style with respect to these three characteristics. Therefore, the weighted average of the quintile scores (ranging from 1 to 5) for all stocks within the portfolio is the style of each benchmark portfolio. For instance, in a scenario where a fund holds two stocks, A and B, each with a 50% weight, and stock A falls in the bottom quintile for size, value, and momentum (assigned a port number of 111), while stock B belongs to the top quintile for all three characteristics (assigned a port number of 555), the calculated style for this fund would be 333-indicating size, value, and momentum quintiles of 3 each.

Third, following this methodology, the style of all funds can be computed, provided each security corresponds to a port number across the size, value, and momentum dimensions. To calculate the average style for all funds in the sample, I calculated the cross-sectional mean of the styles for each year (with rebalancing in June). Then, the time-series average of these cross-sectional mean styles throughout the entire sample period yields the average style of the sample.

Finally, the benchmark portfolio return is computed to further calculate the fund's benchmark-adjusted return (excess return over the benchmark) at time t. This involves determining the value-weighted returns of all stocks included at that time. As previously mentioned, each stock held by the fund is assigned a port number based on the three quintiles of size, value, and momentum. Each stock is then matched (based on the same port number) with one of the 125 DGTW characteristic-based benchmark portfolios. Consequently, the fund's benchmark-adjusted return is the value-weighted average of the excess return for each stock, where the excess return is the difference between the stock's return and its characteristic benchmark's return. Overall, for each measurement period (monthly for AETFs and quarterly for CMFs), I calculate the cross-sectional mean excess return for all funds at time t, and the total sample's excess return is the time-series average of these cross-sectional means during the entire sample period.