Three Essays on Exchanged-traded funds and Institutional ownership

by

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Abstract

The first essay examines the replacement effect of smart beta ETFs on closet-factor active mutual funds. The results show that smart beta ETFs offer factor exposures at lower fees and, therefore, higher risk-adjusted returns than closet factor funds. Investors notice the benefits of smart beta ETFs and replace closet factor funds with these ETFs. Closet factor funds are at higher risks of being replaced when investors are sophisticated, when the market share of smart beta ETFs increases, and after 2012. The findings illustrate the dynamic changes in investor preference towards investment products that bring similar or greater benefits at a lower price.

Actively managed ETFs are new but fast-growing products in the financial markets. The second essay studies whether these funds employ active management and deliver better risk-adjusted returns to the investors than their passive peers. The sample consists of ETFs investing in US equity and international equity from 2008 to 2021. The results suggest that actively managed ETFs investing in US equity, including non-transparent funds, neither significantly differ in their management style nor deliver better risk-adjusted returns to the investors than their passive counterparts. However, there is some evidence of outperformance from active ETFs that invest in international markets. Based on net flows to these funds, active ETF flows do not seem to have a stronger response to the "skill" components of the fund returns, suggesting that flows to active ETFs may not be as "smart" as expected.

The prior literature documents that institutional investors, especially those with large and persistent holdings, play an essential role in the corporate governance of their investee firms. The third essay examines whether institutional ownership stability can enhance product quality management. Using a sample of product recall incidents from 2012 to 2021, we find that firms with more stable institutional investors have a lower probability, frequency, and severity of recall incidents and adopt a proactive product-recall strategy. The findings support the monitoring theory of stable institutional investors that they can effectively reduce product failures, which jeopardize a firm long-term performance and value.

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List of Abbreviations

3SLS	Three Stage Least Squares
ANT	Active Non-Transparent
CalPERS	California Public Employees' Retirement System
CAPM	Capital Asset Pricing Model
CEO	Chief Executive Officer
CIC	Census Industry Classification
CPSC	Consumer Product Safety Commission
CUSIP	Committee on Uniform Securities Identification Procedures
ETF	Exchange-Traded Fund
ETN	Exchange-Traded Note
FDA	Food and Drug Administration
FRR	Factor-Related Return
GM	General Motors
IOP	Institutional Ownership Persistence
MSCI	Morgan Stanley Capital International
N-SAR	Semi-Annual Report (for investment companies)

NAV	Net Asset Value
NHTSA	National Highway Traffic Safety Administration
OLS	Ordinary Least Squares
S&P 500	Standard and Poor 500
SEC	Securities and Exchange Commission
SIC	Standard Industrial Classification
TE	Tracking Error
US	United States
USA	United States of America

Chapter 1

Active mutual funds: Beware of smart beta ETFs!

1.1 Introduction

Smart beta exchange-traded funds (ETFs) have experienced significant growth in recent years and received greater attention from academic researchers and industry practitioners. As of year-end 2019, assets invested in smart beta ETFs accounted for 22% of total assets in the US ETF industry. A recent survey by J.P. Morgan Asset Management demonstrates that investors expect smart beta ETFs will grow at a higher rate than traditional passive ETFs and account for 20% of an ETF portfolio[1]. These low-cost factor ETFs bring disruptions to the traditional active management for several reasons. First, a significant proportion of active mutual fund returns can be attributed to systematic factor exposures (Kahn and Lemmon, 2016; Ang et al., 2009). Strikingly, (Bender et al., 2014) find that factor premia can account for up to 80% of active fund CAPM alpha. Second, both institutional and retail investors have become increasingly aware of factor investing. Large institutional investors such as GM Asset Management, The Government Pension Fund of Norway, and California Public Employees' Retirement System (CalPERS) have already embraced multi-factor models as the benchmarks for fund managers (Ang, 2014; Bioy, 2015). In addition, a growing number of global investors consider smart beta funds more aligned with active management, and therefore, these funds can serve as replacements for expensive active funds[2].

The academic literature provides evidence that systematic factors such as Size, Value, Momentum, Quality, and Low Volatility can generate abnormal returns (Fama and French, 1992; Jegadeesh and Titman, 1993; Asness et al., 2019; Frazzini et al., 2018; Frazzini and Pedersen,

[1] J.P. Morgan Asset Management Global ETF Study 2020

[2] FTSE Russell Smart Beta: 2019 Global Survey

2014; Ang et al., 2006). Prior to the arrival of smart beta ETFs, investors were not able to harvest factor premia in a cheap and systematic manner. Therefore, active mutual fund managers were able to tilt their portfolios to the traditional factors to outperform the market benchmark and collect high fees without exerting efforts in stock picking or market/factor timing. However, the availability and prevalence of smart beta ETFs allow investors to reproduce the returns of active mutual funds that rely heavily on well-known factor exposures at much lower costs. Besides, these smart beta funds offer the benefits of ETFs, such as intraday liquidity, transparency, and tax benefits (Moussawi et al., 2020). Investing in smart beta ETFs with predefined factor tilts helps the investors choose the desired exposures and control portfolio risk. Therefore, it is reasonable to expect investors to replace the expensive active mutual funds that aim to harvest factor premia with smart beta ETFs. In practice, Vanguard has suggested a framework to replicate the equity fund performance using factor strategies (Zorina et al., 2020), and 25% of surveyed global investors respond that they have already replaced their actively managed mutual funds with smart beta ETFs[3].

Even though the industry reports suggest that smart beta funds have attracted investor money from active funds, we expect that not all active funds suffer from this issue. Active mutual funds that provide the unique benefits that investors cannot obtain from smart beta ETFs, such as factor timing or stock-picking within a factor theme, may not lose investors to smart beta funds. In this study, we denote the active funds whose returns are primarily the result of a combination of passive factor tilts as closet factor funds. Our primary research purpose is to provide empirical evidence that only active mutual funds that are closet factor funds lose investors to smart beta ETFs.

Our results show that smart beta ETFs have gained acceptance as new investment vehicles that can replace closet factor mutual funds in investors' portfolios since these factor ETFs deliver higher risk-adjusted returns and factor exposures at lower costs. Net flows of smart beta ETFs have a significantly negative relation with net flows of closet factor funds. Importantly, there is supporting evidence that investors are substituting closet factor funds with smart beta ETFs, but not vice versa. First, splitting net flows of smart beta ETFs into positive ner

[3]Brown Brothers Harriman 2020 Global ETF Investor Survey

flows (net inflows) and negative net flows (net outflows), we find that only positive net flows of smart beta ETFs have a negative relation with net flows of closet factor mutual funds. Second, tests using inflows and outflows from N-SAR filings reinforce our results of the unidirectional replacement impact. Next, using fund distribution channels as a proxy for investor sophistication, we illustrate that more sophisticated investors are more likely to substitute closet factor funds with smart beta ETFs. Our findings are consistent with the recent empirical evidence that more sophisticated investors better understand the contributions of factors when evaluating active fund performance (Barber et al., 2016; Cao et al., 2020). Furthermore, when smart beta ETFs market share increases and these funds become more salient, closet factor funds are at higher risk of being replaced. Consistent with the substantial growth of smart beta ETFs in recent years, we document the replacement effect only after 2012. Finally, the placebo tests demonstrate no replacement impact of smart beta ETFs on non-closet factor funds. In addition, investors appear to understand the benefits of factor investing, and therefore, we do not observe a similar migration from closet factor funds to traditional passive ETFs. Our findings of the replacement impact remain robust when we focus on the group of smart beta ETFs that successfully deliver the intended factor exposures.

Our study is related to two main strains of literature. First, it contributes to the analysis of the potential impacts of ETFs on the mutual fund industry. Cremers et al. (2016) find that higher competition from low-cost indexed funds makes actively managed funds more active and charge lower fees. Sherrill and Upton (2018) document the substitutability between active mutual funds and actively managed ETFs. Closely related to our study is Cao et al. (2020) finding that mutual fund flows are driven more by multi-factor alphas than CAPM alpha when smart beta ETFs become available. Their results highlight the effects of smart beta ETFs on the criteria that investors use to make investment decisions. We further elaborate that smart beta ETFs are gaining market share by attracting investor money from closet factor active mutual funds.

Second, our paper relates to the understandings of the newly emerged smart beta ETFs. Previous studies focus on the performance, investor behaviors, and concerns associated with these funds. Glushkov (2016) documents no conclusive evidence of smart beta ETF outperformance relative to a risk-adjusted benchmark. Besides, smart beta ETFs may expose investors to unintended factors that can offset the performance from intended factor tilts. Mateus et al. (2020) find that smart beta ETFs outperform related traditional cap-weighted ETFs after expenses, and there is short-term persistence in the performance of these funds. Broman and Shum (2018) show that investors, especially institutions, appear to identify and invest in smart beta ETFs that capture exposures to only one or two factors. However, there are also concerns associated with factor investing and smart beta ETFs. Huang et al. (2020) warn investors of data mining in smart beta indexes. Specifically, they find a significant reduction in index performance after the smart beta ETFs tracking these indexes become listed and available for investment, and investors seem to chase the fund backtest returns. Backgrounds of factor investing and the skepticisms of expected factor returns are well summarized in White and Haghani (2020). We extend the literature by showing that smart beta ETFs outperform closet factor funds and offer higher factor exposures to investors while charging much lower fees. In addition, investors recognize these benefits and replace closet factor funds with smart beta ETFs.

The structure of the paper is as follows. Section 1.2 describes our data sample and methodology to identify closet factor funds. Section 1.3 compares the risk-adjusted performance and factor exposures of smart beta ETFs and closet factor funds. Section 1.4 presents the empirical results of the replacement impact of smart beta ETFs on closet factor mutual funds. Section 1.5 contains the placebo and robustness tests. Finally, Section 1.6 summarizes and concludes this study.

1.2 Data and methodology

1.2.1 Active mutual funds and smart beta ETFs data

We obtain mutual funds and ETFs data from the Center for Research in Security Prices (CRSP) Mutual Fund Database and Morningstar Direct. To serve the purpose of our study, we construct two samples: US domestic equity active mutual funds and smart beta ETFs, covering the period from 2000 to 2019. The reason for our choice of sample period is that the first smart beta ETF was available in 2000. We use the CRSP style variable *crsp_obj_cd* to identify US domestic equity funds and eliminate funds with an average equity investment of less than 80%. Following Appel et al. (2016), and Dannhauser and Pontiff (2019), we detect index funds and ETFs by fund names and the indicators *index_fund_flag* and *et_flag* in the CRSP database. The active mutual fund data are merged to the Morningstar Direct database by CUSIP and Ticker to gather monthly fund styles and monthly fund new sales and redemptions (inflows and outflows from hereon) from N-SAR filings. To create the smart beta ETFs sample, we follow the search criteria in Huang et al. (2020) to extract the list of US equity smart beta ETFs from the Morningstar database. We obtain the *Strategic Beta Group* for each fund, which shows the fund's target factor tilt. Our study includes the smart beta ETFs that are in the *Strategic Beta Group* of Value, Growth, Momentum, Quality, Risk-Oriented, and Multifactor. The main reason is that these factors have been studied extensively in the academic literature and are widely accepted by the industry. Besides, the assets in smart beta ETFs that fall into these themes account for, on average, 80% of the total net assets of all domestic equity smart beta ETFs. We also gather ETF monthly inflows and outflows from N-SAR filings and monthly fund styles from Morningstar and then merge the ETF sample to CRSP by CUSIP and Ticker. The results of the CRSP and Morningstar merge are verified manually to ensure matching accuracy.

Following Sirri and Tufano (1998) and Agapova (2011), we calculate monthly net flows of a fund in million dollars as

$$Net\ Flow_{i,t} = TNA_{i,t} - TNA_{i,t-1} * (1 + R_{i,t}),$$

where $TNA_{i,t}$ is fund *i*'s total net assets at time *t*, and $R_{i,t}$ is the fund's return over month *t*. Finally, we collect monthly factor returns from Kenneth French's and AQR Capital Management's websites[4].

Our paper's analysis is at the fund group level, i.e., closet factor funds (smart beta ETFs) that are in the same factor theme and are in the same Morningstar style box form a fund group because of the following reasons. First, investors have a wide choice of smart beta ETFs when

[4] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`
`https://www.aqr.com/Insights/Datasets`

switching from closet factor funds to these new investment funds. Therefore, we believe fund group comparison is appropriate. Second, our approach is consistent with Agapova (2011), who studies the substitutability between index mutual funds and ETFs tracking the same index at the fund group level. Accordingly, we construct the fund-group level variables by calculating the sum or weighted average values across all funds in the same group. Even though there are 6 factor themes (Growth, Momentum, Quality, Risk-Oriented, Value, Multifactor) and 9 Morningstar styles (Large Value, Large Growth, Large Blend, Mid Value, Mid Growth, Mid Blend, Small Value, Small Growth, Small Blend), our sample has 38 fund groups in total. The reason is that there are groups that do not have any smart beta ETFs or closet factor funds. For example, there are no smart beta ETFs that target the Growth factor in Large Value, Mid Value, and Small Value styles.

1.2.2 Closet factor funds

Since our paper focuses on a subsample of active mutual funds, i.e., closet factor funds, it is essential to detect these funds in the active domestic equity mutual funds universe. Our approach is to rely on the regression-based method to identify closet factor funds and their target factor exposures. A possible alternative is to utilize fund holdings to classify the target factor of a fund. However, we choose the return-based analysis as it is widely used by industry practitioners (Bender et al., 2014; Zorina et al., 2020) and academic researchers (Sharpe, 1991; Patton and Weller, 2020). Additionally, while the holdings of most mutual funds are only reported quarterly, monthly fund returns help us identify the fund factor exposures each month. Importantly, from regression analysis, we can estimate the proportion of fund returns explained by factor premia using the adjusted R-squared, which is an important criterion that we use to detect closet factor funds.

Following Barber et al. (2016) and Song (2020), we estimate each fund monthly factor exposures by 36-month rolling regressions, using the following 6-factor model as in Frazzini et al. (2018):

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,MKT}(R_{m,t} - R_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t \\ + \beta_{i,UMD}UMD_t + \beta_{i,QMJ}QMJ_t + \beta_{i,BAB}BAB_t + \epsilon_{i,t}, \end{aligned} \tag{1.1}$$

where $R_{i,t}$ is the mutual fund *i* return in month *t*, $R_{f,t}$ is the risk-free rate , $R_{m,t}$ is the market return, SMB_t is the return on size factor, HML_t is the return on the value factor, UMD_t is the return on the momentum factor, QMJ_t is the return on the quality factor, BAB_t is the return on the betting-against-beta factor in month *t*.

Following (Van Gelderen et al., 2019) and Patton and Weller (2020), we classify a fund as targeting a specific factor if the factor exposure is positive (except for Size and Growth factor) and its t-statistic exceeds 2 in absolute value. There are two exceptions to identify the funds that target the Size and Growth factors. First, a fund will target the Size factor if $\beta_{SMB} > 0.7$, as Chen and Bassett (2014) show that a positive β_{SMB} cannot separate large-cap and small-cap portfolios, and a portfolio with 80% Small has a β_{SMB} of 0.73. Second, Growth is classified as a fund's target factor if $\beta_{HML} < 0$ since Glushkov (2016) and Huang et al. (2020) show that the smart beta ETFs or indexes that aim to capture the Growth factor have negative and statistically significant HML exposures. The adjusted R-squared shows the percentage of fund returns variation that can be explained by factor exposures. Even though there is no consensus on the R-squared threshold, we choose the 95% level to classify an active mutual fund as a closet factor fund as it is used by Vanguard and other industry participants[5].

From regression (1.1), we identify whether a closet factor fund targets the Size factor. However, we do not include Size as a separate factor theme in our analysis because of the following reasons. First, Blitz and Hanauer (2020) show that the Size premium has not materialized since its discovery and appears to be not accessible to investors. However, the authors suggest that Size factor exposures benefit a multifactor investment approach. Second, Morningstar does not have a stand-alone Strategic Beta Group for the Size factor, as there are still very few smart beta ETFs that explicitly offer Size exposure. In our study, closet factor funds that target multiple factors simultaneously are classified as Multifactor funds.

We hypothesize that investors who seek exposure to specific factors replace the closet factor funds with smart beta ETFs that offer similar target factor exposures. For example, a

[5] Vanguard Research suggests that investors can replicate the performance of active mutual funds by factor strategies if adjusted R-squared is higher than 95%, available at `https://advisors.vanguard.com/iwe/pdf/ISGCAEM.pdf`; Supervisory Work on Potential Closet Index Tracking (ESMA, 2016), available at `www.esma.europa.eu/document/public-statement-supervisory-work-potential-closet-index-tracking`

closet factor fund that targets the Value factor can be substituted by smart beta ETFs that offer exposure to Value. Investors can easily compare funds within a specific style when making investment decisions. The industry standard, Morningstar style box, for example, represents an easy tool for investors to compare investment styles of mutual funds and ETFs. Therefore, we consider only smart beta ETFs with similar investment styles as a possible replacement.

1.2.3 Descriptive statistics

Figure 1.1 illustrates the total net assets and investor interest in smart beta ETFs, measured by the Google Trends' Search Volume Index. Smart beta ETFs grew over time and gained significant popularity in recent years. Specifically, the assets invested in these factor ETFs increased by almost six times from 2012 to 2019.

Table 1.1 compares some characteristics between groups of closet factor funds and smart beta ETFs with the same target factor. Closet factor funds charge higher fees, have larger assets under management, and belong to larger families than smart beta ETFs. Both closet factor funds and smart beta ETFs earn comparable gross returns (i.e., fund returns before expenses) since they both aim to harvest the same factor premia. However, the net returns are higher in smart beta ETFs, thanks to lower expenses of these funds. The monthly net flows of closet factor funds are negative, while smart beta ETFs experience positive monthly net flows, suggesting a potential investor migration from closet factor funds to smart beta ETFs. Consistent with this analysis, we observe in Figure 1.3 that while smart beta ETFs took in more than $200 billion, closet factor mutual funds experienced outflows of around $600 billion during the period from 2003 to 2019.

[Please insert Table 1.1 here]

1.3 Risk-adjusted performance and factor exposures of smart beta ETFs and closet factor funds

1.3.1 Risk-adjusted performance of smart beta ETFs and closet factor funds

Smart beta or factor investing strategies are investment approaches that deviate from traditional market-cap weighted indexes to deliver higher risk-adjusted returns. Therefore, we start our analysis of the benefits of investing in smart beta ETFs instead of closet factor funds by comparing the CAPM and multifactor (Fama French 3 factor and Fama French Carhart 4 factor) alphas of these two types of funds. Each month, we form value-weighted portfolios of smart beta ETFs and closet factor funds in each factor theme and estimate the risk-adjusted performance by regressing the portfolio returns on factor returns. In Table 1.2, we find that neither smart beta ETFs nor closet factor funds can deliver positive risk-adjusted returns to the investors in all factor themes, as shown by negative and even significantly negative (for closet factor funds) CAPM and multifactor alphas. These findings are consistent with the recent empirical evidence on the underperformance of smart beta ETFs relative to their risk-adjusted benchmarks (Glushkov, 2016; Huang et al., 2020). However, we document that smart beta ETFs outperform closet factor funds in the same factor theme. Specifically, the outperformance in Growth, Risk-Oriented, and Value are statistically significant and range from 0.097% to 0.316% per month. The differences in risk-adjusted performance in Momentum and Multifactor are also positive but not significantly different from zero. Lastly, even though we observe an underperformance of smart beta ETFs relative to closet factor funds in Quality, the difference is not statistically significant.

[Please insert Table 1.2 here]

1.3.2 Factor exposures of smart beta ETFs and closet factor funds

One of the main benefits of smart beta ETFs is that investors can capture factor exposures at lower costs compared to closet factor funds. In this section, we examine whether investors also achieve higher exposures to priced factors from using smart beta ETFs than closet factor funds. We carry out the analysis by forming value-weighted portfolios of closet factor funds and smart beta ETFs in each factor theme (Growth, Momentum, Quality, Risk-oriented, Value, and Multifactor) and estimate the exposures of closet factor funds and smart beta ETFs using regression (1). In Table 1.3, we show that smart beta ETFs deliver higher target factor exposures in every factor theme, except Quality. One possible explanation is that the construction of the academic Quality factor (QMJ) is different from the Quality strategies that smart beta ETFs actually implement. For example, the HML beta of Value smart beta ETFs is 0.348, significantly higher than 0.196 of closet factor mutual funds; the UMD beta of Momentum smart beta ETFs is 0.238, much larger than 0.078 of closet factor funds. Finally, Multifactor smart beta ETFs offer more factor exposures than closet factor funds.

[Please insert Table 1.3 here]

Overall, our findings so far illustrate that investors will be better off investing in smart beta ETFs since these funds offer higher risk-adjusted returns and factor exposures than closet factor funds. To conclude this section, we compare the growth of $1,000 investment in smart beta ETFs and in closet factor funds during our sample period in Figure 1.2. Consistent with the previous findings, $1,000 investments in smart beta ETFs will grow into larger amounts than those in closet factor funds. Interestingly, investments in both smart beta ETFs and closet factor funds outperform an investment in the S&P 500 index, suggesting that factor investing can still benefit investors by offering higher returns than a prevalent market-cap weighted index.

As smart beta ETFs offer more significant benefits than closet factor funds, we will investigate the replacement impact of smart beta ETFs on closet factor funds in the following parts of this study.

1.4 Smart beta ETFs replace closet factor funds

1.4.1 Main results

1.4.1.1 The replacement impact of smart beta ETFs on closet factor funds

Our first analysis examines the replacement effect of smart beta ETFs on closet factor funds, using the following regression

$$\begin{aligned} CMF\ Net\ Flow_{i,t} = {} & \beta_0 + \beta_1 ETF\ Net\ Flow_{i,t} + \beta_2 CMF\ Net\ Flow_{i,t-1} \\ & + \beta_3 ETF\ Net\ Flow_{i,t-1} + \beta_4 Return_{i,t} + \beta_5 Return_{i,t-1} + \beta_6 Expense_{i,t-1} \\ & + \beta_7 Log(Size)_{i,t-1} + \beta_8 Log(Family\ Size)_{i,t-1} \\ & + (Year - Month\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t}. \end{aligned} \tag{1.2}$$

The dependent variable is net flows of closet factor funds group *i* in month *t*. The main independent variable is $ETF\ Net\ Flow_{i,t}$, which is net flows of smart beta ETFs group *i* in month *t*. The coefficient of interest is β_1, which shows the relation between net flows of smart beta ETFs and net flows of closet factor funds. If investors are substituting closet factor funds with smart beta ETFs, we expect β_1 to be negative. The regression includes the following control variables: lagged fund flows, contemporaneous and lagged fund returns, expenses, the natural log of lagged fund total net assets, and the natural log of lagged fund family total net assets. We also control for the month-year (time) fixed effects and factor fixed effects.

The regression results are presented in Table 1.4. Consistent with our hypothesis, the coefficient β_1 is negative and statistically significant in all specifications where we include factor fixed effects (columns 2 and 4) and control variables (columns 3 and 4). Overall, the findings suggest that higher net flows of smart beta ETFs are associated with lower net flows of closet factor funds. Specifically, columns 3 and 4 show that \$1 million of net inflows to smart beta ETFs are associated with \$0.206 and \$0.162 million net outflows from closet factor funds. Controlling for the determinants of fund flows does not seem to affect our results, as we still observe a negative relation between net flows of closet factor funds and smart beta ETFs in columns 3 and 4. However, the magnitude of the replacement impact is slightly smaller in the presence of the fund flow determinants. Other control variables have signs consistent with the extant literature. Funds with lower expenses attract higher net flows. Fund size negatively affects the net flows of mutual funds.

[Please insert Table 1.4 here]

1.4.1.2 Direction of the replacement impact

The previous section documents the negative relation between net flows of smart beta ETFs and net flows of closet factor funds. Even though the result suggests investor migration from closet factor funds to smart beta ETFs, we can possibly interpret this negative relation as investors are replacing smart beta ETFs with closet factor funds. In order to investigate this possibility, we split net flows of smart beta ETFs into positive net flows (net inflows) and negative net flows (net outflows) and include both variables, as in regression (1.3) below.

$$\begin{aligned} CMF\ Net\ Flow_{i,t} = \beta_0 &+ \beta_1 ETF\ Net\ Flow\ Positive_{i,t} + \beta_2 ETF\ Net\ Flow\ Negative_{i,t} \\ &+ \beta_3 CMF\ Net\ Flow_{i,t-1} + \beta_4 ETF\ Net\ Flow\ Positive_{i,t-1} \\ &+ \beta_5 ETF\ Net\ Flow\ Negative_{i,t-1} + \beta_6 Return_{i,t} + \beta_7 Return_{i,t-1} \\ &+ \beta_8 Expense_{i,t-1} + \beta_9 Log(Size)_{i,t-1} + \beta_{10} Log(Family\ Size)_{i,t-1} \\ &+ (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t}. \end{aligned} \tag{1.3}$$

The results are presented in Table 1.5. In detail, there is a negative relation between positive ETF net flows and closet factor fund net flows, but a positive relation between negative ETF net flows and closet factor fund net flows. These results suggest that higher net inflows to smart beta ETFs are associated with lower net flows to closet factor funds. However, more net outflows from smart beta ETFs are associated with lower net flows to closet factor funds. This finding supports the unidirectional replacement impact that investors migrate from closet factor funds to smart beta ETFs, but not vice versa.

[Please insert Table 1.5 here]

We also attempt to collect inflows and outflows of smart beta ETFs and closet factor funds from N-SAR filings to provide more empirical evidence on the direction of the replacement impact. In regression (1.4), we examine the relation between inflows of closet factor mutual funds and outflows of smart beta ETFs, and the relation between inflows of smart beta ETFs and outflows of closet factor funds in regression (1.5). Both regressions include lagged inflows and outflows of smart beta ETFs and closet factor funds and the known determinants of fund flows. In the case of a unidirectional impact, we expect that the coefficient β_1 is positive and statistically significant only in regression (1.5).

$$\begin{aligned} CMF\ Inflow_{i,t} &= \beta_0 + \beta_1 ETF\ Outflow_{i,t} + \beta_2 CMF\ Inflow_{i,t-1} \\ &+ \beta_3 ETF\ Outflow_{i,t-1} + \beta_4 Return_t + \beta_5 Return_{i,t-1} \\ &+ \beta_6 Expense_{i,t-1} + \beta_7 Log(Size)_{i,t-1} + \beta_8 Log(Family\ Size)_{i,t-1} \\ &+ (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t}, \end{aligned} \tag{1.4}$$

$$\begin{aligned} ETF\ Inflow_{i,t} &= \beta_0 + \beta_1 CMF\ Outflow_{i,t} + \beta_2 ETF\ Inflow_{i,t-1} \\ &+ \beta_3 CMF\ Outflow_{i,t-1} + +\beta_4 Return_t + \beta_5 Return_{i,t-1} \\ &+ \beta_6 Expense_{i,t-1} + \beta_7 Log(Size)_{i,t-1} + \beta_8 Log(Family\ Size)_{i,t-1} \\ &+ (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t}. \end{aligned} \tag{1.5}$$

Table 1.6 presents the regression results. On the one hand, we document that outflows of smart beta ETFs have no significant relation with inflows of closet factor funds. The coefficient estimates are positive but not statistically significant in all specifications. On the other hand, there is a positive and statistically significant relation (at the 1% level) between outflows of closet factor funds and inflows of smart beta ETFs. The results remain robust in all regressions where we include factor fixed effects (columns 6 and 8) and the determinants of fund flows (columns 7 and 8). Specifically, the β_1 estimate in column 8 displays that \$1 million outflows from closet factor funds are associated with \$0.062 million inflows to smart beta ETFs. These findings suggest that investors redeem their shares from closet factor mutual funds and invest a proportion (6%) of the proceeds in smart beta ETFs, but not vice versa. One caveat is that not all ETFs are required to report monthly inflows and outflows using N-SAR filings since ETFs structured as unit investment trusts do not have to file these forms to the SEC. In addition, we are not able to obtain inflows and outflows for all closet factor funds in our sample. Consequently, we have a smaller number of observations and the results may be subject to selection bias.

[Please insert Table 1.6 here]

Overall, the results in Table 1.5 and Table 1.6 demonstrate the investor migration from closet factor funds to smart beta ETFs.

1.4.2 Investor sophistication: Distribution channels

Our baseline results illustrate the competitive threat of smart beta ETFs to active mutual funds that depend primarily on exposures to well-known factors. Factor investing has attracted greater investor attention and dollars in recent years. However, investing in smart beta ETFs requires a thorough understanding of the underlying factors and the wise choice of funds due to the proliferation of fund offerings. Barber et al. (2016) document that more sophisticated investors respond less to factor-related returns when evaluating active fund performance. In addition, the empirical evidence in Cao et al. (2020) shows that less sophisticated fund flows do not exhibit higher sensitivity to multi-factor alphas even in the presence of smart beta ETFs. Therefore, we expect investors with investment expertise are more likely to replace closet factor funds with smart beta ETFs. Accordingly, our subsequent analysis focuses on analyzing the variation of the replacement impact with investor sophistication.

Our proxy investor sophistication in this study is based on the fund distribution channels, i.e., whether funds shares are sold through brokers (broker-sold funds) or investors can directly invest in the funds (direct-sold funds). Chalmers and Reuter (2020) document that investors with a lower level of sophistication tend to rely on brokers' advice for investment decisions. Consistent with this finding, direct-sold fund flows are less responsive to factor-related returns (Barber et al., 2016) and more sensitive to multi-factor alphas during periods of high smart beta liquidity (Cao et al., 2020). Thus, we predict that investors in direct-sold funds possess better understandings of factor investing and are more likely to replace closet factor funds with smart beta ETFs. Following Bergstresser et al. (2008), we identify broker-sold funds as those that have at least 75% of assets held in a share class that charges a front-end load or a back-end load, or a 12b-1 fee greater than 25 bps. On the contrary, a fund is classified as a direct-sold fund if at least 75% of its assets are held in a share class that does not charge any front-end load, back-end load, and 12b-1 fee.

In order to test our hypothesis, we interact each of the independent variables in regressions (1.2) and (1.3) with a dummy variable equal to one if the fund is broker-sold.

Table 1.7 shows the difference in the replacement impacts of smart beta ETFs on closet factor funds offered to investors through brokers and those that can be directly purchased. Columns 1 and 2 present the coefficient estimates from regression (2) for direct-sold and broker-sold funds. The coefficient estimates for broker-sold funds are the sum of the coefficient estimates of direct-sold funds and the estimates of the interaction terms with the broker-sold dummy. Similarly, columns 3 and 4 summarize the regression results from regression (3) for direct-sold and broker-sold channels. Consistent with our hypothesis, the replacement impact of smart beta ETFs on closet factor funds is only significant in direct-sold funds. In fact, the coefficient estimates of *ETF Net Flow* and *ETF Net Flow Positive* are insignificantly positive for the broker-sold channel, and the differences (the estimated interaction terms) between direct-sold and broker-sold funds are statistically significant. In summary, the empirical evidence strongly supports the notion that more sophisticated investors better understand factor investing and will replace closet factor funds with smart beta ETFs.

[Please insert Table 1.7 here]

1.4.3 Competition intensity

In this section, we examine the difference in the replacement impact when the competition pressure from smart beta ETFs intensifies. Following Cremers et al. (2016), we measure the competition intensity based on the market share of smart beta ETFs, i.e., the proportion of these funds' total net assets in the entire ETF industry. We classify a month as high (low) competition if the last month-end market share of smart beta ETFs is above (below) the time-series median. We expect that when smart beta ETFs gain market share in the ETF industry and become more salient to the investors, these factor funds will represent a more significant threat to closet factor mutual funds.

Columns 1 and 2 of Table 1.8 display a statistically significant replacement impact only in months of high competition when we examine the relation between net flows of closet factor funds and smart beta ETFs. Turning to the results using positive and negative net flows of smart beta ETFs in columns 3 and 4, we document that investors replace closet factor funds with smart beta ETFs only in periods of high competition.

[Please insert Table 1.8 here]

1.4.4 Sub-period results

Even though the first smart beta ETF was available on the market in 2000, these factor funds have become an emerging phenomenon in recent years. Figure 1 exhibits that smart beta ETFs grew tremendously after 2012, and the attention to these funds surged in the later period. In addition, Cao et al. (2020) and Johansson et al. (2021) highlight the increasingly important role of smart beta ETFs after 2012. Therefore, we analyze the replacement impact of smart beta ETFs on closet factor funds in two sub-periods: before and after 2012. Table 1.9 illustrates that the negative relations between net flows of smart beta ETFs and net flows of closet factor funds are statistically significant only after 2012. When splitting net flows of smart beta ETFs into positive and negative net flows, we find that investors migrate from closet factor funds to smart beta ETFs mainly after 2012. Overall, our findings are consistent with the recent massive growth of these factor ETFs in the asset management industry.

[Please insert Table 1.9 here]

1.5 Placebo and robustness tests

1.5.1 Do investors replace non-closet factor funds with smart beta ETFs?

The findings so far support our hypothesis that investors are increasingly attracted to smart beta investment products and replacing the expensive closet factor mutual funds with these low-cost factor ETFs. To further support our empirical evidence, we carry out the placebo analysis by focusing on the active mutual funds that are not classified as closet factor funds (non-closet factor funds). Since non-closet factor funds may generate excess returns on top of the factor premia for the investors and thus add value to the investment portfolios, we do not expect investors to redeem their investments from non-closet factor funds and invest in smart beta

ETFs. In our sample, there are some active mutual funds that do not meet both the criteria to be classified as closet factor funds but still have an adjusted R-squared above 95%. These funds are not non-closet factor funds in our study because the majority of variation in fund returns can still be explained by factor exposures. In this placebo analysis, we group smart beta ETFs and non-closet factor funds by Morningstar style only since a non-closet factor fund will be a non-closet factor fund to all smart beta ETFs. Therefore, the number of observations is smaller than in the previous tests in our study.

Table 1.10 presents the regression results. Neither net flows nor positive net flows of smart beta ETFs have significant relations with net flows of non-closet factor funds. In summary, the findings demonstrate that investors do not substitute non-closet factor funds with smart beta ETFs.

[Please insert Table 1.10 here]

1.5.2 Do investors replace closet-factor funds with traditional passive ETFs?

There has been a substantial migration of investor money out of mutual funds and into ETFs in recent years. Therefore, the negative relation between net flows of closet factor funds and smart beta ETFs documented in our study can also be due to this migration from active to passive investing or from mutual funds to ETFs. If it is the case, net flows and positive net flows of traditional passive ETFs should also negatively relate to net flows of closet factor funds. We carry out the second placebo test to investigate this possible implication. Similar to the previous placebo test, we also group closet factor funds and passive ETFs by Morningstar style. In column 2 of Table 1.11, net flows of traditional passive ETFs have a significantly negative relation with net flows of closet factor funds. However, columns 3 and 4 present that only the coefficient estimates of *Passive Net Flow Negative* are negative and statistically significant, suggesting higher net outflows from passive ETFs are associated with higher net flows of closet factor funds. Importantly, positive net flows of passive ETFs have a positive relation with net flows of closet factor funds, contradicting the expected sign in the case of migration from closet factor funds to traditional passive ETFs. Combining all the results, we can conclude that there is some evidence that investors are leaving passive ETFs for closet factor funds. This finding is consistent with the analysis in Figure 1.2 that closet factor funds historically outperform the S&P 500 index. Therefore, investors may switch from passive ETFs to closet factor funds.

The findings in this section suggest that investors understand the potential benefits of smart beta ETFs relative to traditional passive ETFs. As a result, they substitute closet factor funds with smart beta ETFs, but not the ETFs that track broad market-cap-weighted indexes.

[Please insert Table 1.11 here]

1.5.3 Robustness: Smart beta ETFs that deliver the stated factor exposures

In the previous sections, we rely on the fund investment objectives and Morningstar classification to identify smart beta ETFs' target factors. However, there are concerns that smart beta ETFs might not provide the intended factor exposures (Glushkov, 2016). Consequently, in this robustness analysis, we include only the ETFs that successfully deliver the stated factors in our sample. Specifically, we use regression (1.1) and all available historical return observations of each smart beta ETF to identify its target factor. We follow the criteria in Section 1.2.2, except that we do not use the adjusted R-squared threshold. For multifactor ETFs, we include only the funds that successfully deliver multiple factor exposures. The results are presented in Table 1.12. In columns 1 and 2, we find a significantly negative relation between net flows of smart beta ETFs and net flows of closet factor funds. Besides, positive net flows of smart beta ETFs are negatively associated with net flows of closet factor funds in columns 3 and 4. These findings are consistent with our previous empirical evidence.

[Please insert Table 1.12 here]

1.6 Conclusions

This study examines the replacement impact of smart beta ETFs on closet factor funds, i.e., active equity mutual funds that mainly load up on well-known systematic factors. Specifically, we find that smart beta ETFs offer higher risk-adjusted returns and factor exposures to investors at much lower fees. We document that investors notice these advantages and replace closet factor funds with the newly emerged smart beta ETFs. In addition, closet factor funds are at higher risks of replacement when investors are sophisticated, when competition from beta ETFs increases, and after 2012.

Our findings highlight the dynamic changes in investor preference in the asset management industry. In the investment product innovation era, investors can identify the funds that fail to deliver what they promise to offer and replace them with other investment funds that provide similar or even greater benefits at a lower price. In the context of our study, active mutual funds that primarily focus on harvesting factor premia are at risk of losing investors to smart beta ETFs.

Figure 1.1: Smart beta ETFs: Total Net Assets and Investor Attention

This figure illustrates the growth in total net assets of smart beta ETFs ($ million) and investor attention to these funds, as measured by the Google Trends' Search Volume Index from 2000 to 2019.

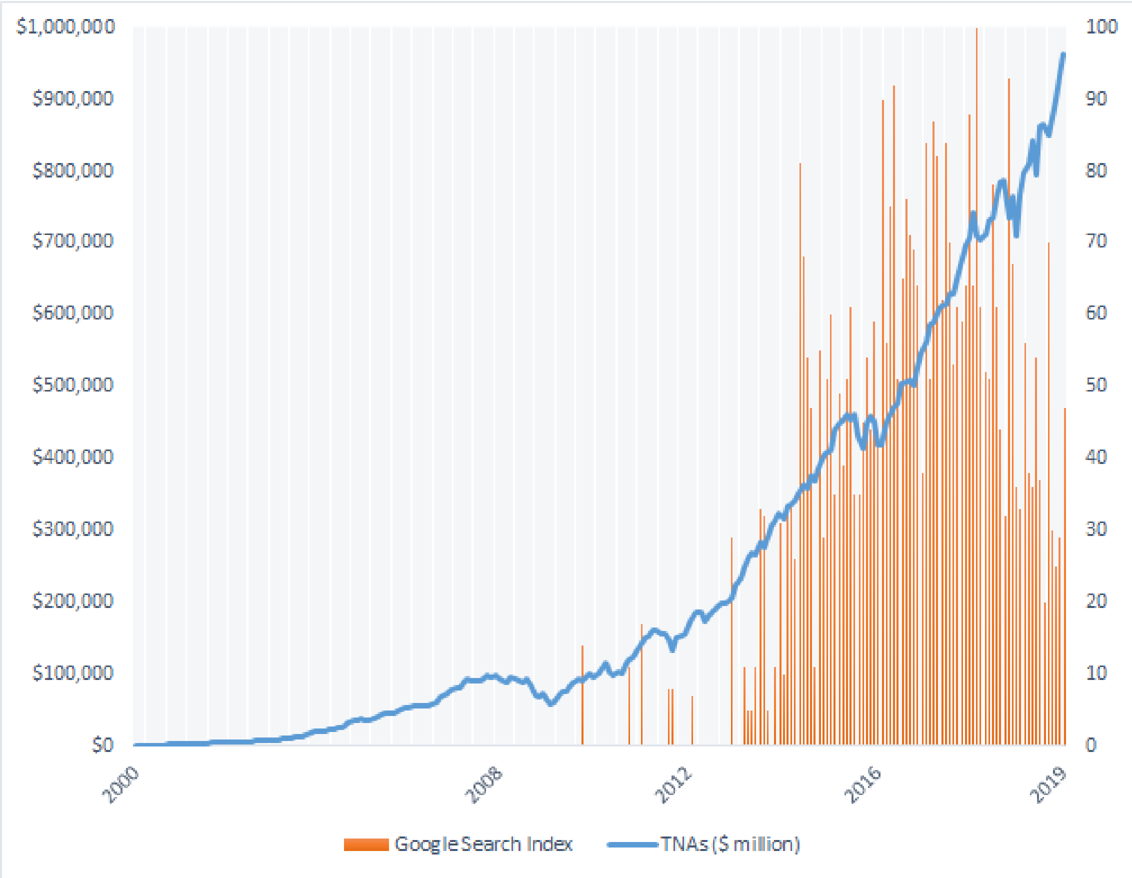

Figure 1.2: Investments in Smart beta ETFs vs. Closet factor funds vs. S&P 500

This figure compares the growth of $1,000 invested in smart beta ETFs and in closet factor funds with the same target factor, and in S&P 500 from 2003 to 2019.

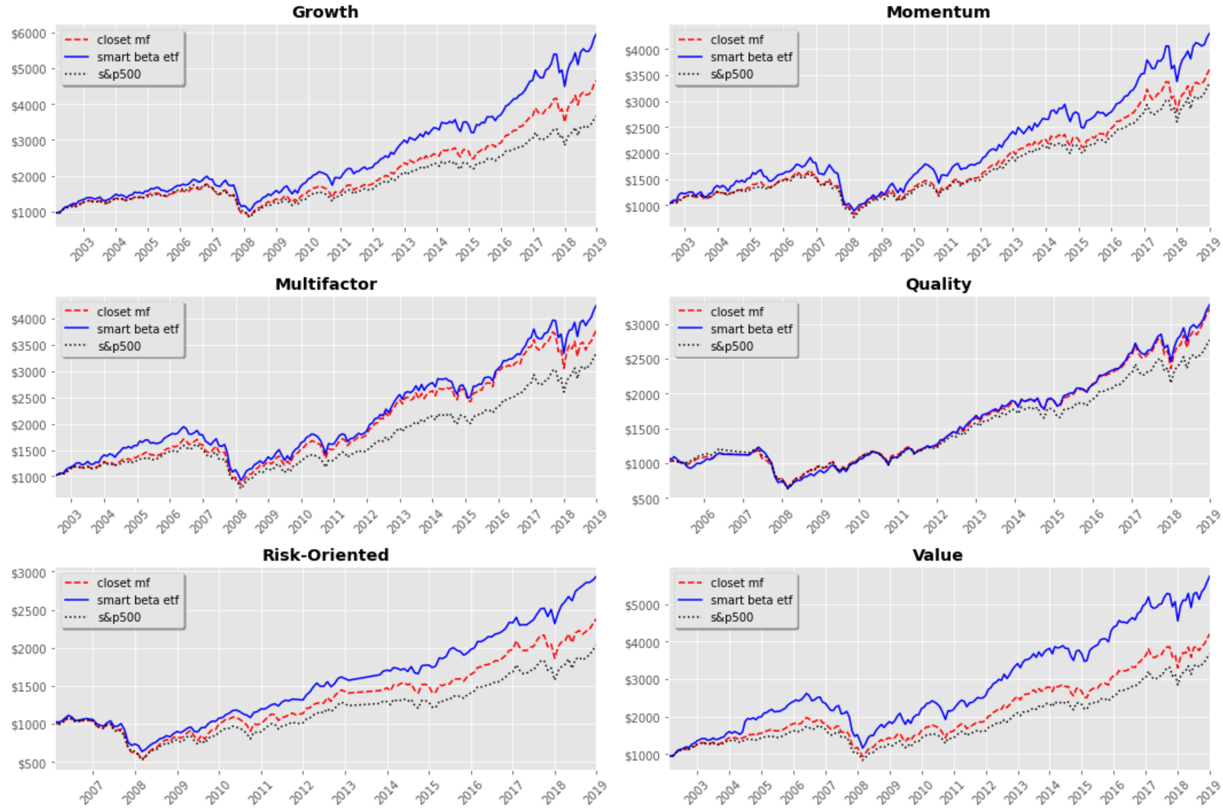

Figure 1.3: Cumulative net flows to Closet factor funds and Smart beta ETFs

This figure presents cumulative net flows ($ million) to closet factor funds and smart beta ETFs from 2003 to 2019.

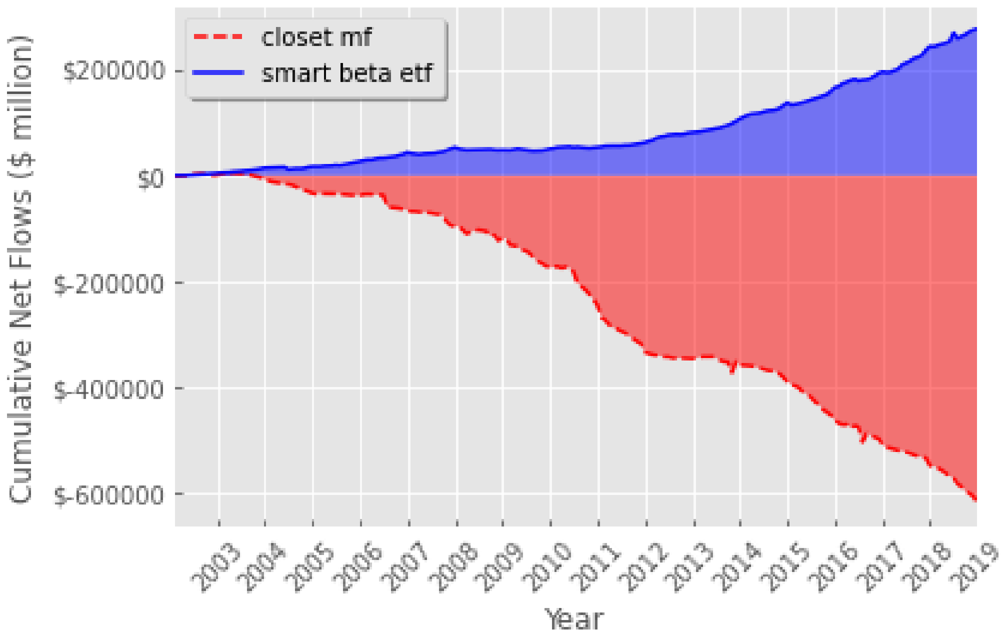

Table 1.1: Descriptive Statistics

This table contains summary statistics for closet factor funds and smart beta ETFs groups. The observation is at the fund group-month level. *Net Flow* is the total monthly net flows in million dollars to a fund group. *Gross Return* is the weighted average of gross returns (returns before expenses) of all funds in a group; *Net Return* is the weighted average of net returns of all funds in a group; *Expense* is the weighted average of expense ratio of all funds in a group. *Size* and *Family Size* are aggregate fund and fund family total net assets of all funds in a group. *Outflow* and *Inflow* are aggregate redemptions and new sales from N-SAR filings in million dollars of all funds in a group. Reported levels of statistical significance of the t-test between the means of groups; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Growth	**Number of obervations**	**Smart beta ETFs**	**Closet factor funds**	**Difference**
Net Flow($ million)	483	152.05	-545.71	697.76***
Gross Return(%)	483	0.968	1.002	-0.034
Net Return(%)	483	0.951	0.933	0.019
Expense(%)	483	0.201	0.832	-0.631***
Size ($ million)	483	27170.49	88248.92	-61078.43***
Family Size ($ million)	483	10242028	8186939	2055089***
Outflow NSAR ($ million)	423	524.89	1875.14	-1350.26***
Inflow NSAR ($ million)	423	697.21	1359.75	-662.55***
Panel B: Momentum	**Number of obervations**	**Smart beta ETFs**	**Closet factor funds**	**Difference**
Net Flow($ million)	442	15.64	-38.43	54.078***
Gross Return(%)	442	0.797	0.852	-0.055
Net Return(%)	442	0.753	0.775	-0.022
Expense(%)	442	0.524	0.921	-0.397***
Size ($ million)	442	1377.12	11071.40	-9694.28***
Family Size ($ million)	442	490058	1572224	-1082166***
Outflow NSAR ($ million)	216	34.52	119.32	-84.81***
Inflow NSAR ($ million)	216	35.44	118.260	-82.82***
Panel C: Multifactor	**Number of obervations**	**Smart beta ETFs**	**Closet factor funds**	**Difference**
Net Flow($ million)	1230	15.54	-53.96	69.50***
Gross Return(%)	1230	0.841	0.878	-0.037
Net Return(%)	1230	0.79	0.804	-0.014
Expense(%)	1230	0.608	0.880	-0.272***
Size ($ million)	1230	849.19	28867.57	-28018.38***
Family Size ($ million)	1230	440477	3883498	-3443021***
Outflow NSAR ($ million)	916	19.52	513.52	-494.00***
Inflow NSAR ($ million)	916	25.51	463.380	-437.86***
Panel D: Quality	**Number of obervations**	**Smart beta ETFs**	**Closet factor funds**	**Difference**
Net Flow($ million)	259	50.23	29.81	20.42
Gross Return(%)	259	1.121	1.067	0.054
Net Return(%)	259	1.08	0.999	0.081
Expense(%)	259	0.489	0.813	-0.324***
Size ($ million)	259	1463.66	10745.36	-9281.70***
Family Size ($ million)	259	346313	1370442	-1024130***
Outflow NSAR ($ million)	122	31.89	241.160	-209.27***
Inflow NSAR ($ million)	122	53.30	256.800	-203.50***
Panel E: Risk-Oriented	**Number of obervations**	**Smart beta ETFs**	**Closet factor funds**	**Difference**
Net Flow($ million)	227	134.32	-205.52	339.84***
Gross Return(%)	227	0.977	0.919	0.058
Net Return(%)	227	0.95	0.844	0.106
Expense(%)	227	0.326	0.903	-0.576***
Size ($ million)	227	6688.93	6045.36	643.57
Family Size ($ million)	227	922095	1442947	-520852***
Outflow NSAR ($ million)	108	153.16	126.94	26.22
Inflow NSAR ($ million)	108	174.07	111.760	62.31*
Panel F: Value	**Number of obervations**	**Smart beta ETFs**	**Closet factor funds**	**Difference**
Net Flow($ million)	645	157.62	-245.12	402.73***
Gross Return(%)	645	1.074	0.850	0.225
Net Return(%)	645	1.058	0.775	0.283
Expense(%)	645	0.199	0.896	-0.698***
Size ($ million)	645	19811.16	57578.08	-37766.92***
Family Size ($ million)	645	8024780	6246274	1778506***
Outflow NSAR ($ million)	527	381.43	923.18	-541.76***
Inflow NSAR ($ million)	527	558.11	776.760	-218.65***

Table 1.2: Risk-adjusted returns of closet factor funds and smart beta ETFs

This table reports CAPM, Fama French 3 factor, and Fama French Carhart 4 factor alphas of closet factor funds and smart beta ETFs in the same factor group. For each factor group in a given month, we form value-weighted portfolios of closet factor funds and smart beta ETFs and calculate portfolio returns. We then estimate the portfolio alphas by regressing portfolio returns on factor returns. Newey-West standard errors with 12 lags are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Factor Theme	Performance measure	Smart beta ETFs	Closet factor funds	Difference
Growth	CAPM alpha (%)	0.020	-0.094	0.114**
		(0.058)	(0.060)	(0.045)
	FF alpha (%)	-0.019	-0.129***	0.110**
		(0.030)	(0.046)	(0.042)
	FFC alpha (%)	-0.026	-0.123**	0.097**
		(0.028)	(0.048)	(0.041)
Momentum	CAPM alpha (%)	-0.080	-0.153***	0.073
		(0.105)	(0.034)	(0.101)
	FF alpha (%)	-0.115	-0.165***	0.050
		(0.119)	(0.035)	(0.115)
	FFC alpha (%)	-0.174**	-0.183***	0.009
		(0.086)	(0.034)	(0.091)
Quality	CAPM alpha (%)	-0.043	-0.041	-0.003
		(0.112)	(0.061)	(0.099)
	FF alpha (%)	-0.085	-0.063	-0.021
		(0.127)	(0.058)	(0.117)
	FFC alpha (%)	-0.091	-0.064	-0.027
		(0.116)	(0.058)	(0.106)
Risk-Oriented	CAPM alpha (%)	0.229	-0.086*	0.316**
		(0.140)	(0.044)	(0.121)
	FF alpha (%)	0.186	-0.084	0.271**
		(0.131)	(0.052)	(0.111)
	FFC alpha (%)	0.184	-0.084	0.268**
		(0.128)	(0.052)	(0.107)
Value	CAPM alpha (%)	-0.008	-0.133***	0.125
		(0.121)	(0.049)	(0.093)
	FF alpha (%)	0.063	-0.097***	0.160*
		(0.097)	(0.029)	(0.093)
	FFC alpha (%)	0.063	-0.096***	0.159*
		(0.093)	(0.027)	(0.089)
Multifactor	CAPM alpha (%)	-0.098	-0.154**	0.056
		(-1.427)	(-2.532)	(0.785)
	FF alpha (%)	-0.069	-0.134***	0.065
		(-1.078)	(-2.704)	(0.927)
	FFC alpha (%)	-0.082	-0.140***	0.058
		(-1.473)	(-2.906)	(0.912)

Table 1.3: Factor exposures of closet factor funds and smart beta ETFs

This table reports the factor exposures of closet factor funds and smart beta ETFs in the same factor group. For each factor group in a given month, we form value-weighted portfolio of closet factor funds and smart beta ETFs and calculate portfolio returns. We then estimate portfolio factor exposures on a set of factors, including market ($R_m - R_f$), size (SMB), value (HML), momentum (UMD), quality (QMJ), and betting-against-beta (BAB). Newey-West standard errors with 12 lags are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Factor Theme	Type	MKTRF	SMB	HML	UMD	QMJ	BAB
Growth	Smart beta ETFs	1.038***	0.155***	**-0.236*** **	0.037	-0.034	-0.006
		(0.011)	(0.026)	**(0.019)**	(0.024)	(0.025)	(0.022)
	Closet factor funds	1.005***	0.024	**-0.228*** **	-0.016	-0.101***	-0.006
		(0.016)	(0.024)	**(0.024)**	(0.020)	(0.034)	(0.021)
	Difference	0.033**	0.131***	**-0.008**	0.054***	0.067**	-0.000
		(0.016)	(0.034)	**(0.014)**	(0.010)	(0.032)	(0.013)
Momentum	Smart beta ETFs	1.023***	0.285***	-0.230***	**0.238*** **	-0.215***	0.036
		(0.035)	(0.063)	(0.048)	**(0.038)**	(0.051)	(0.041)
	Closet factor funds	1.000***	-0.014	-0.047**	**0.078*** **	-0.078**	-0.022
		(0.018)	(0.033)	(0.023)	**(0.011)**	(0.031)	(0.014)
	Difference	0.023	0.299***	-0.182***	**0.160*** **	-0.138***	0.058
		(0.032)	(0.068)	(0.052)	**(0.034)**	(0.050)	(0.041)
Quality	Smart beta ETFs	0.987***	0.103	-0.079**	0.042	**0.035**	0.122*
		(0.023)	(0.089)	(0.034)	(0.034)	**(0.055)**	(0.062)
	Closet factor funds	1.003***	-0.097***	-0.006	-0.018	**0.182*** **	0.015
		(0.016)	(0.034)	(0.021)	(0.015)	**(0.026)**	(0.016)
	Difference	-0.015	0.200**	-0.073*	0.060	**-0.148*** **	0.107
		(0.028)	(0.098)	(0.041)	(0.039)	**(0.055)**	(0.069)
Risk-Oriented	Smart beta ETFs	0.764***	-0.061	-0.006	-0.015	0.109	**0.259*** **
		(0.042)	(0.049)	(0.047)	(0.024)	(0.069)	**(0.038)**
	Closet factor funds	0.970***	-0.019	0.027	-0.008	-0.061*	**0.110*** **
		(0.025)	(0.028)	(0.025)	(0.016)	(0.033)	**(0.022)**
	Difference	-0.207***	-0.042	-0.034	-0.007	0.171***	**0.150*** **
		(0.057)	(0.052)	(0.051)	(0.031)	(0.060)	**(0.050)**
Value	Smart beta ETFs	0.956***	0.179***	**0.348*** **	-0.007	-0.039	0.068
		(0.020)	(0.053)	**(0.060)**	(0.019)	(0.029)	(0.059)
	Closet factor funds	0.970***	-0.020	**0.196*** **	-0.005	-0.009	0.001
		(0.009)	(0.024)	**(0.013)**	(0.012)	(0.017)	(0.020)
	Difference	-0.015	0.199***	**0.152*** **	-0.002	-0.029	0.067
		(0.021)	(0.049)	**(0.058)**	(0.014)	(0.032)	(0.052)
Multifactor	Smart beta ETFs	0.999***	0.269***	0.106***	0.038**	0.038	0.049*
		(0.016)	(0.027)	(0.039)	(0.016)	(0.031)	(0.028)
	Closet factor funds	1.006***	0.247***	0.060	0.006	0.067	0.073**
		(0.019)	(0.050)	(0.055)	(0.021)	(0.045)	(0.028)
	Difference	-0.007	0.021	0.046	0.032	-0.029	-0.024
		(0.022)	(0.070)	(0.057)	(0.028)	(0.050)	(0.036)

Table 1.4: The replacement impact of smart beta ETFs on closet factor funds

This table presents the results of panel regressions of net flows of closet factor funds on net flows of smart beta ETFs and the determinants of mutual fund flows:

$$\begin{aligned} CMF\ Net\ Flow_{i,t} = {} & \beta_0 + \beta_1 ETF\ Net\ Flow_{i,t} + \beta_2 CMF\ Net\ Flow_{i,t-1} \\ & + \beta_3 ETF\ Net\ Flow_{i,t-1} + \beta_4 Return_{i,t} + \beta_5 Return_{i,t-1} \\ & + \beta_6 Expense_{i,t-1} + \beta_7 Log(Size)_{i,t-1} + \beta_7 Log(Family\ Size)_{i,t-1} \\ & + (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t} \end{aligned}$$

where *Return* is the net return of closet factor funds; *Expense* is the expense of closet factor funds; *Log(Size)* is the natural log of closet factor funds total net assets; *Log(Family Size)* is the natural log of closet factor funds fund family total net assets. The regression includes year-month and factor fixed effects. Standard errors are in parentheses and clustered at the fund group-year level. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$
ETF Net Flow$_t$	-0.206**	-0.162**	-0.168**	-0.134*
	(0.082)	(0.079)	(0.072)	(0.072)
CMF Net Flow$_{t-1}$	0.061	0.036	0.015	0.000
	(0.199)	(0.193)	(0.188)	(0.184)
ETF Net Flow$_{t-1}$	-0.201***	-0.155**	-0.152**	-0.116
	(0.065)	(0.068)	(0.066)	(0.071)
Return$_t$			-4.773	-2.335
			(15.616)	(15.717)
Return$_{t-1}$			11.691	13.157
			(13.482)	(13.395)
Expense$_{t-1}$			-169.830*	-160.697*
			(89.695)	(87.014)
Log(Size)$_{t-1}$			-142.709***	-139.283***
			(34.696)	(34.482)
Log(Family Size)$_{t-1}$			18.972	19.960
			(17.276)	(19.493)
Constant	-135.942***	-147.484***	1038.131***	973.474***
	(33.430)	(34.956)	(312.035)	(282.879)
Month-Year Fixed Effects	Yes	Yes	Yes	Yes
Factor Fixed Effects	No	Yes	No	Yes
Number of observations	3047	3047	3047	3047
Adj. R-squared	0.009	0.030	0.049	0.062

Table 1.5: Direction of the replacement impact - Positive and negative net flows

The table presents the results of panel regressions of net flows of closet factor funds on positive net flows and negative net flows of smart beta ETFs and the determinants of mutual fund flows.

$$
\begin{aligned}
CMF\ Net\ Flow_{i,t} = {} & \beta_0 + \beta_1 ETF\ Net\ Flow\ Positive_{i,t} + \beta_2 ETF\ Net\ Flow\ Negative_{i,t} \\
& + \beta_3 CMF\ Net\ Flow_{i,t-1} + \beta_4 ETF\ Net\ Flow\ Positive_{i,t-1} \\
& + \beta_5 ETF\ Net\ Flow\ Negative_{i,t-1} + \beta_6 Return_{i,t} + \beta_7 Return_{i,t-1} \\
& + \beta_8 Expense_{i,t-1} + \beta_9 Log(Size)_{i,t-1} + \beta_{10} Log(Family\ Size)_{i,t-1} \\
& + (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t}
\end{aligned}
$$

where *Return* is the net return of closet factor funds; *Expense* is the expense of closet factor funds; *Log(Size)* is the natural log of closet factor funds total net assets; *Log(Family Size)* is the natural log of closet factor funds fund family total net assets. The regression includes year-month and factor fixed effects. Standard errors are in parentheses and clustered at the fund group-year level. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$
ETF Net Flow Positive$_t$	-0.482***	-0.425***	-0.417***	-0.377***
	(0.112)	(0.123)	(0.127)	(0.136)
ETF Net Flow Negative$_t$	0.376**	0.324*	0.341**	0.304*
	(0.174)	(0.175)	(0.164)	(0.167)
CMF Net Flow$_{t-1}$			-0.014	-0.020
			(0.185)	(0.182)
ETF Net Flow Positive$_{t-1}$	-0.248*	-0.209	-0.179*	-0.153
	(0.140)	(0.138)	(0.097)	(0.105)
ETF Net Flow Negative$_{t-1}$	0.585***	0.480***	0.493**	0.423**
	(0.168)	(0.180)	(0.195)	(0.210)
Return$_t$			-2.642	-1.343
			(15.792)	(15.841)
Return$_{t-1}$			14.646	15.251
			(12.705)	(12.774)
Expense$_{t-1}$			-150.531*	-151.477*
			(85.316)	(83.724)
Log(Size)$_{t-1}$			-127.255***	-131.844***
			(33.033)	(34.204)
Log(Family Size)$_{t-1}$			19.364	22.998
			(16.582)	(18.197)
Constant	-50.635*	-68.770*	945.982***	923.408***
	(27.407)	(36.471)	(283.112)	(255.164)
Month-Year Fixed Effects	Yes	Yes	Yes	Yes
Factor Fixed Effects	No	Yes	No	Yes
Number of observations	3047	3047	3047	3047
Adj. R-squared	0.046	0.053	0.075	0.079

Table 1.6: Direction of the replacement impact - N-SAR inflows and outflows

This table presents the results of panel regressions of inflows of closet factor funds on outflows of smart beta ETFs (columns 1-4) and inflows of smart beta ETFs on outflows of closet factor funds (columns 5-8) and the determinants of fund flows:

$$\begin{aligned}
CMF\ Inflow_{i,t} &= \beta_0 + \beta_1 ETF\ Outflow_{i,t} + \beta_2 CMF\ Inflow_{i,t-1} \\
&+ \beta_3 ETF\ Outflow_{i,t-1} + \beta_4 Return_t + \beta_5 Return_{i,t-1} \\
&+ \beta_6 Expense_{i,t-1} + \beta_7 Log(Size)_{i,t-1} + \beta_8 Log(Family\ Size)_{i,t-1} \\
&+ (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t}
\end{aligned}$$

$$\begin{aligned}
ETF\ Inflow_{i,t} &= \beta_0 + \beta_1 CMF\ Outflow_{i,t} + \beta_2 ETF\ Inflow_{i,t-1} \\
&+ \beta_3 CMF\ Outflow_{i,t-1} + +\beta_4 Return_t + \beta_5 Return_{i,t-1} \\
&+ \beta_6 Expense_{i,t-1} + \beta_7 Log(Size)_{i,t-1} + \beta_8 Log(Family\ Size)_{i,t-1} \\
&+ (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t}
\end{aligned}$$

where *Return* is the net return of closet factor funds or smart beta ETFs; *Expense* is the expense of closet factor funds or smart beta ETFs; *Log(Size)* is the natural log of closet factor funds or smart beta ETFs total net assets; *Log(Family Size)* is the natural log of closet factor funds or smart beta ETFs fund family total net assets. The regression includes year-month and factor fixed effects. Standard errors are in parentheses and clustered at the fund group-year level. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CMF Inflow$_t$	CMF Inflow$_t$	CMF Inflow$_t$	CMF Inflow$_t$	ETF Inflow$_t$	ETF Inflow$_t$	ETF Inflow$_t$	ETF Inflow$_t$
ETF Outflow$_t$	0.039	0.020	0.031	0.017				
	(0.059)	(0.066)	(0.057)	(0.065)				
CMF Outflow$_t$					0.066***	0.064***	0.062***	0.062***
					(0.019)	(0.019)	(0.019)	(0.019)
Inflow$_{t-1}$	0.924***	0.922***	0.885***	0.886***	0.711***	0.599***	0.582***	0.571***
	(0.017)	(0.018)	(0.026)	(0.025)	(0.032)	(0.039)	(0.038)	(0.039)
ETF Outflow$_{t-1}$	0.055	0.037	0.053	0.038				
	(0.051)	(0.056)	(0.050)	(0.057)				
MF Outflow$_{t-1}$					-0.018	-0.017	-0.018	-0.018
					(0.016)	(0.016)	(0.016)	(0.016)
Return$_t$			-8.489	-8.881			1.106	0.982
			(7.102)	(7.298)			(1.297)	(1.266)
Return$_{t-1}$			9.529	9.039			23.463***	23.013***
			(8.120)	(7.992)			(6.945)	(6.879)
Expense$_{t-1}$			1.576	-1.837			-96.098*	68.497
			(24.900)	(24.890)			(53.728)	(65.784)
Log(Size)$_{t-1}$			46.235***	46.006***			40.454***	38.064***
			(10.960)	(10.435)			(7.194)	(7.648)
Log(Family Size)(t-1)			-6.124	-7.063			0.848	-5.641
			(5.062)	(5.722)			(5.495)	(6.849)
Constant	35.479**	44.853**	-283.658***	-258.454***	48.386***	82.265***	-189.401**	-154.807
	(13.755)	(19.592)	(89.977)	(89.891)	(8.992)	(11.868)	(75.541)	(94.268)
Month-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factor Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	2121	2121	2121	2121	2118	2118	2117	2117
Adj. R-squared	0.862	0.862	0.864	0.864	0.633	0.656	0.663	0.665

Table 1.7: Investor sophistication: Distribution channels

This table presents the results of panel regressions of net flows of closet factor funds on net flows of smart beta ETFs (columns 1-2) and net flows of closet factor funds on positive and negative net flows of smart beta ETFs (columns 3-4) and the determinants of fund flows. Difference shows the difference between coefficient estimates of $ETF\ Net\ Flow_t$ in columns 1 and 2; and the difference between coefficient estimates of $ETF\ Net\ Flow\ Positive_t$ in columns 3 and 4.

$$\begin{aligned} CMF\ Net\ Flow_{i,t} &= \beta_0 + \beta_1 ETF\ Net\ Flow_{i,t} + \beta_2 CMF\ Net\ Flow_{i,t-1} \\ &+ \beta_3 ETF\ Net\ Flow_{i,t-1} + \beta_4 Return_{i,t} + \beta_5 Return_{i,t-1} \\ &+ \beta_6 Expense_{i,t-1} + \beta_7 Log(Size)_{i,t-1} + \beta_7 Log(Family\ Size)_{i,t-1} \\ &+ (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t} \end{aligned}$$

$$\begin{aligned} CMF\ Net\ Flow_{i,t} &= \beta_0 + \beta_1 ETF\ Net\ Flow\ Positive_{i,t} + \beta_2 ETF\ Net\ Flow\ Negative_{i,t} \\ &+ \beta_3 CMF\ Net\ Flow_{i,t-1} + \beta_4 ETF\ Net\ Flow\ Positive_{i,t-1} \\ &+ \beta_5 ETF\ Net\ Flow\ Negative_{i,t-1} + \beta_6 Return_{i,t} + \beta_7 Return_{i,t-1} \\ &+ \beta_8 Expense_{i,t-1} + \beta_9 Log(Size)_{i,t-1} + \beta_{10} Log(Family\ Size)_{i,t-1} \\ &+ (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t} \end{aligned}$$

where *Return* is the net return of closet factor funds or smart beta ETFs; *Expense* is the expense of closet factor funds or smart beta ETFs; *Log(Size)* is the natural log of closet factor funds or smart beta ETFs total net assets; *Log(Family Size)* is the natural log of closet factor funds or smart beta ETFs fund family total net assets. The regression includes year-month and factor fixed effects. Standard errors are in parentheses and clustered at the fund group-year level. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Direct	Broker	Direct	Broker
	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$
ETF Net Flow$_t$	-0.089*	0.002		
	(0.047)	(0.019)		
ETF Net Flow Positive$_t$			-0.215***	0.022
			(0.081)	(0.047)
ETF Net Flow Negative$_t$			0.209	-0.051
			(0.147)	(0.046)
CMF Net Flow$_{t-1}$	-0.311**	0.358***	-0.321**	0.373***
	(0.136)	(0.125)	(0.128)	(0.128)
ETF Net Flow$_{t-1}$	-0.005	-0.024		
	(0.066)	(0.022)		
ETF Net Flow Positive$_{t-1}$			-0.021	-0.061
			(0.092)	(0.053)
ETF Net Flow Negative$_{t-1}$			0.341*	-0.009
			(0.201)	(0.025)
Return$_t$	6.916	4.951	7.221	5.372
	(8.088)	(7.497)	(8.334)	(7.669)
Return$_{t-1}$	-2.503	-3.388	-2.112	-2.190
	(7.762)	(8.930)	(7.629)	(8.688)
Expense$_{t-1}$	-6.801	-77.648***	-21.298	-63.653**
	(38.268)	(28.939)	(32.837)	(26.054)
Log(Size)$_{t-1}$	-32.529**	-31.593***	-28.180**	-29.776***
	(14.098)	(11.053)	(13.712)	(11.059)
Log(Family Size)$_{t-1}$	-6.467	-1.156	-3.778	-2.086
	(7.158)	(5.633)	(6.700)	(5.466)
Month-Year Fixed Effects	Yes	Yes	Yes	Yes
Factor Fixed Effects	Yes	Yes	Yes	Yes
Difference	0.091* (0.052)		0.237** (0.098)	
Number of observations	4374		4374	
Adj. R-squared	0.087		0.099	

Table 1.8: Periods of high and low competition

This table presents the results of panel regressions of net flows of closet factor funds on net flows of smart beta ETFs (columns 1-2) and net flows of closet factor funds on positive and negative net flows of smart beta ETFs (columns 3-4) and the determinants of fund flows. Difference shows the difference between coefficient estimates of $ETF\ Net\ Flow_t$ in columns 1 and 2; and the difference between coefficient estimates of $ETF\ Net\ Flow\ Positive_t$ in columns 3 and 4.

$$\begin{aligned} CMF\ Net\ Flow_{i,t} = & \beta_0 + \beta_1 ETF\ Net\ Flow_{i,t} + \beta_2 CMF\ Net\ Flow_{i,t-1} \\ & + \beta_3 ETF\ Net\ Flow_{i,t-1} + \beta_4 Return_{i,t} + \beta_5 Return_{i,t-1} \\ & + \beta_6 Expense_{i,t-1} + \beta_7 Log(Size)_{i,t-1} + \beta_7 Log(Family\ Size)_{i,t-1} \\ & + (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t} \end{aligned}$$

$$\begin{aligned} CMF\ Net\ Flow_{i,t} = & \beta_0 + \beta_1 ETF\ Net\ Flow\ Positive_{i,t} + \beta_2 ETF\ Net\ Flow\ Negative_{i,t} \\ & + \beta_3 CMF\ Net\ Flow_{i,t-1} + \beta_4 ETF\ Net\ Flow\ Positive_{i,t-1} \\ & + \beta_5 ETF\ Net\ Flow\ Negative_{i,t-1} + \beta_6 Return_{i,t} + \beta_7 Return_{i,t-1} \\ & + \beta_8 Expense_{i,t-1} + \beta_9 Log(Size)_{i,t-1} + \beta_{10} Log(Family\ Size)_{i,t-1} \\ & + (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t} \end{aligned}$$

where *Return* is the net return of closet factor funds or smart beta ETFs; *Expense* is the expense of closet factor funds or smart beta ETFs; *Log(Size)* is the natural log of closet factor funds or smart beta ETFs total net assets; *Log(Family Size)* is the natural log of closet factor funds or smart beta ETFs fund family total net assets. The regression includes year-month and factor fixed effects. Standard errors are in parentheses and clustered at the fund group-year level. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Low	High	Low	High
	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$
ETF Net Flow$_t$	-0.107	-0.145*		
	(0.418)	(0.075)		
ETF Net Flow Positive$_t$			-0.069	-0.413***
			(0.693)	(0.125)
ETF Net Flow Negative$_t$			-0.167	0.332*
			(0.787)	(0.173)
CMF Net Flow$_{t-1}$	0.305	-0.111	0.296	-0.141
	(0.341)	(0.175)	(0.353)	(0.165)
ETF Net Flow$_{t-1}$	-0.264	-0.134*		
	(0.418)	(0.075)		
ETF Net Flow Positive$_{t-1}$			-0.951	-0.184*
			(0.664)	(0.109)
ETF Net Flow Negative$_{t-1}$			0.990	0.481**
			(0.824)	(0.201)
Return$_t$	-25.626	7.711	-25.981	8.166
	(18.260)	(20.728)	(20.467)	(21.055)
Return$_{t-1}$	40.547**	-1.880	42.075**	2.102
	(16.673)	(17.464)	(16.604)	(16.653)
Expense$_{t-1}$	-96.677	-195.149*	-136.846	-166.409*
	(130.169)	(102.012)	(134.572)	(91.387)
Log(Size)$_{t-1}$	-131.045**	-115.390***	-122.538***	-101.044***
	(53.276)	(31.734)	(45.037)	(29.725)
Log(Family Size)$_{t-1}$	26.042	3.118	23.732	5.819
	(21.545)	(23.993)	(19.256)	(22.797)
Month-Year Fixed Effects	Yes	Yes	Yes	Yes
Factor Fixed Effects	Yes	Yes	Yes	Yes
Difference	-0.038 (0.426)		-0.344 (0.698)	
Number of observations	3047		3047	
Adj. R-squared	0.090		0.112	

Table 1.9: Before and after 2012

This table presents the results of panel regressions of net flows of closet factor funds on net flows of smart beta ETFs (columns 1-2) and net flows of closet factor funds on positive and negative net flows of smart beta ETFs (columns 3-4) and the determinants of fund flows. Difference shows the difference between coefficient estimates of $ETF\ Net\ Flow_t$ in columns 1 and 2; and the difference between coefficient estimates of $ETF\ Net\ Flow\ Positive_t$ in columns 3 and 4.

$$\begin{aligned} CMF\ Net\ Flow_{i,t} &= \beta_0 + \beta_1 ETF\ Net\ Flow_{i,t} + \beta_2 CMF\ Net\ Flow_{i,t-1} \\ &+ \beta_3 ETF\ Net\ Flow_{i,t-1} + \beta_4 Return_{i,t} + \beta_5 Return_{i,t-1} \\ &+ \beta_6 Expense_{i,t-1} + \beta_7 Log(Size)_{i,t-1} + \beta_7 Log(Family\ Size)_{i,t-1} \\ &+ (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t} \end{aligned}$$

$$\begin{aligned} CMF\ Net\ Flow_{i,t} &= \beta_0 + \beta_1 ETF\ Net\ Flow\ Positive_{i,t} + \beta_2 ETF\ Net\ Flow\ Negative_{i,t} \\ &+ \beta_3 CMF\ Net\ Flow_{i,t-1} + \beta_4 ETF\ Net\ Flow\ Positive_{i,t-1} \\ &+ \beta_5 ETF\ Net\ Flow\ Negative_{i,t-1} + \beta_6 Return_{i,t} + \beta_7 Return_{i,t-1} \\ &+ \beta_8 Expense_{i,t-1} + \beta_9 Log(Size)_{i,t-1} + \beta_{10} Log(Family\ Size)_{i,t-1} \\ &+ (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t} \end{aligned}$$

where *Return* is the net return of closet factor funds or smart beta ETFs; *Expense* is the expense of closet factor funds or smart beta ETFs; *Log(Size)* is the natural log of closet factor funds or smart beta ETFs total net assets; *Log(Family Size)* is the natural log of closet factor funds or smart beta ETFs fund family total net assets. The regression includes year-month and factor fixed effects. Standard errors are in parentheses and clustered at the fund group-year level. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Before	After	Before	After
	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$
ETF Net Flow$_t$	0.012	-0.178**		
	(0.142)	(0.086)		
ETF Net Flow Positive$_t$			0.032	-0.490***
			(0.346)	(0.134)
ETF Net Flow Negative$_t$			0.006	0.502**
			(0.103)	(0.206)
CMF Net Flow$_{t-1}$	0.213	-0.137	0.214	-0.175
	(0.242)	(0.198)	(0.247)	(0.181)
ETF Net Flow$_{t-1}$	-0.232	-0.137*		
	(0.254)	(0.078)		
ETF Net Flow Positive$_{t-1}$			-0.622**	-0.128
			(0.312)	(0.113)
ETF Net Flow Negative$_{t-1}$			0.692	0.467**
			(0.588)	(0.200)
Return$_t$	-27.923	13.791	-28.078	12.414
	(17.143)	(22.782)	(17.586)	(23.110)
Return$_{t-1}$	34.613**	-1.481	35.714**	0.266
	(15.334)	(17.505)	(14.319)	(17.025)
Expense$_{t-1}$	-78.064	-257.819**	-109.503	-224.006**
	(149.012)	(111.418)	(149.901)	(95.753)
Log(Size)$_{t-1}$	-162.583***	-107.408***	-161.540***	-88.641***
	(54.160)	(29.840)	(52.394)	(26.278)
Log(Family Size)$_{t-1}$	59.731*	-18.454	62.008*	-17.240
	(32.654)	(20.224)	(32.234)	(17.621)
Month-Year Fixed Effects	Yes	Yes	Yes	Yes
Factor Fixed Effects	Yes	Yes	Yes	Yes
Difference	-0.190 (0.167)		-0.522 (0.363)	
Number of observations	3047		3047	
Adj. R-squared	0.086		0.110	

Table 1.10: Non-closet factor funds and smart beta ETFs

This table presents the results of panel regressions of net flows of non-closet factor funds on net flows of smart beta ETFs (columns 1-2) and net flows of non-closet factor funds on positive and negative net flows of smart beta ETFs (columns 3-4) and the determinants of fund flows.

$$\begin{aligned} NCMF\ Net\ Flow_{i,t} &= \beta_0 + \beta_1 ETF\ Net\ Flow_{i,t} + \beta_2 NCMF\ Net\ Flow_{i,t-1} \\ &+ \beta_3 ETF\ Net\ Flow_{i,t-1} + \beta_4 Return_{i,t} + \beta_5 Return_{i,t-1} \\ &+ \beta_6 Expense_{i,t-1} + \beta_7 Log(Size)_{i,t-1} + \beta_7 Log(Family\ Size)_{i,t-1} \\ &+ (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t} \end{aligned}$$

$$\begin{aligned} NCMF\ Net\ Flow_{i,t} &= \beta_0 + \beta_1 ETF\ Net\ Flow\ Positive_{i,t} + \beta_2 ETF\ Net\ Flow\ Negative_{i,t} \\ &+ \beta_3 NCMF\ Net\ Flow_{i,t-1} + \beta_4 ETF\ Net\ Flow\ Positive_{i,t-1} \\ &+ \beta_5 ETF\ Net\ Flow\ Negative_{i,t-1} + \beta_6 Return_{i,t} + \beta_7 Return_{i,t-1} \\ &+ \beta_8 Expense_{i,t-1} + \beta_9 Log(Size)_{i,t-1} + \beta_{10} Log(Family\ Size)_{i,t-1} \\ &+ (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t} \end{aligned}$$

where *Return* is the net return of non-closet factor funds or smart beta ETFs; *Expense* is the expense of non-closet factor funds or smart beta ETFs; *Log(Size)* is the natural log of non-closet factor funds or smart beta ETFs total net assets; *Log(Family Size)* is the natural log of aggregate non-closet factor funds or smart beta ETFs fund family total net assets. The regression includes year-month and style fixed effects. Standard errors are in parentheses and clustered at the fund group-year level. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	NCMF Net Flow$_t$	NCMF Net Flow$_t$	NCMF Net Flow$_t$	NCMF Net Flow$_t$
ETF Net Flow$_t$	0.044	0.067		
	(0.110)	(0.118)		
ETF Net Flow Positive$_t$			-0.059	-0.044
			(0.123)	(0.129)
ETF Net Flow Negative$_t$			0.250	0.246
			(0.316)	(0.324)
CMF Net Flow$_{t-1}$	0.266***	0.216***	0.261***	0.212***
	(0.066)	(0.064)	(0.070)	(0.068)
ETF Net Flow$_{t-1}$	0.028	0.060		
	(0.076)	(0.085)		
ETF Net Flow Positive$_{t-1}$			-0.147	-0.121
			(0.164)	(0.171)
ETF Net Flow Negative$_{t-1}$			0.523**	0.520**
			(0.258)	(0.258)
Return$_t$	-13.088	-17.487	-6.721	-9.588
	(38.915)	(37.151)	(38.540)	(37.128)
Return$_{t-1}$	108.616**	102.286**	113.017**	109.277**
	(43.654)	(42.243)	(45.129)	(43.703)
Expense$_{t-1}$	-913.053*	-1230.082	-1105.025**	-1178.783
	(522.699)	(905.067)	(544.466)	(881.494)
Log(Size)$_{t-1}$	-541.816***	-575.487***	-498.298***	-496.699***
	(158.372)	(178.001)	(141.361)	(165.831)
Log(Family Size)$_{t-1}$	108.034	223.671*	94.655	194.030*
	(92.091)	(113.448)	(85.790)	(105.753)
Constant	4919.970**	3769.746	4942.547***	3393.068
	(1900.715)	(2836.289)	(1831.483)	(2766.778)
Month-Year Fixed Effects	Yes	Yes	Yes	Yes
Style Fixed Effects	No	Yes	No	Yes
Number of observations	1746	1746	1746	1746
Adj. R-squared	0.276	0.302	0.282	0.307

Table 1.11: Closet factor funds and passive ETFs

This table presents the results of panel regressions of net flows of closet factor funds on net flows of passive ETFs (columns 1-2) and net flows of closet factor funds on positive and negative net flows of passive ETFs (columns 3-4) and the determinants of fund flows.

$$\begin{aligned} CMF\ Net\ Flow_{i,t} = {} & \beta_0 + \beta_1 Passive\ Net\ Flow_{i,t} + \beta_2 CMF\ Net\ Flow_{i,t-1} \\ & + \beta_3 Passive\ Net\ Flow_{i,t-1} + \beta_4 Return_{i,t} + \beta_5 Return_{i,t-1} \\ & + \beta_6 Expense_{i,t-1} + \beta_7 Log(Size)_{i,t-1} + \beta_7 Log(Family\ Size)_{i,t-1} \\ & + (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t} \end{aligned}$$

$$\begin{aligned} CMF\ Net\ Flow_{i,t} = {} & \beta_0 + \beta_1 Passive\ Net\ Flow\ Positive_{i,t} + \beta_2 Passive\ Net\ Flow\ Negative_{i,t} \\ & + \beta_3 CMF\ Net\ Flow_{i,t-1} + \beta_4 Passive\ Net\ Flow\ Positive_{i,t-1} \\ & + \beta_5 Passive\ Net\ Flow\ Negative_{i,t-1} + \beta_6 Return_{i,t} + \beta_7 Return_{i,t-1} \\ & + \beta_8 Expense_{i,t-1} + \beta_9 Log(Size)_{i,t-1} + \beta_{10} Log(Family\ Size)_{i,t-1} \\ & + (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t} \end{aligned}$$

where *Return* is the net return of closet factor funds or traditional passive ETFs; *Expense* is the expense of closet factor funds ortraditional passive ETFs; *Log(Size)* is the natural log of closet factor funds or traditional passive ETFs total net assets; *Log(Family Size)* is the natural log of closet factor funds or traditional passive ETFs fund family total net assets. The regression includes month-year and style fixed effects. Standard errors are in parentheses and clustered at the fund group-year level. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$
Passive Net Flow$_t$	-0.003	-0.020**		
	(0.009)	(0.009)		
Passive Net Flow Positive$_t$			0.025**	0.004
			(0.012)	(0.016)
Passive Net Flow Negative$_t$			-0.060**	-0.049*
			(0.023)	(0.025)
CMF Net Flow$_{t-1}$	-0.000	-0.070	-0.021	-0.074
	(0.194)	(0.189)	(0.195)	(0.190)
Passive Net Flow$_{t-1}$	0.030**	0.012		
	(0.012)	(0.010)		
Passive Net Flow Positive$_{t-1}$			0.047***	0.028*
			(0.016)	(0.016)
Passive Net Flow Negative$_{t-1}$			-0.026	-0.017
			(0.019)	(0.019)
Return$_t$	-42.291	-28.555	-40.450	-27.626
	(38.679)	(40.501)	(39.022)	(40.534)
Return$_{t-1}$	-8.975	5.056	-6.179	5.677
	(50.646)	(47.527)	(49.975)	(47.535)
Expense$_{t-1}$	-158.815	-733.921*	-75.679	-718.891*
	(264.660)	(384.737)	(262.255)	(380.500)
Log(Size)$_{t-1}$	-336.610***	-223.398**	-363.012***	-230.469**
	(98.448)	(105.466)	(101.468)	(104.982)
Log(Family Size)$_{t-1}$	-5.689	27.107	-16.568	33.653
	(71.664)	(79.543)	(71.790)	(78.743)
Constant	3438.584***	2166.779*	3720.012***	2068.649*
	(997.944)	(1151.544)	(1020.633)	(1133.101)
Month-Year Fixed Effects	Yes	Yes	Yes	Yes
Style Fixed Effects	No	Yes	No	Yes
Number of observations	1509	1509	1509	1509
Adj. R-squared	0.105	0.149	0.115	0.149

Table 1.12: Robustness: Smart beta ETFs that deliver the stated factor exposures

This table presents the results of panel regressions of net flows of closet factor funds on net flows of smart beta ETFs (columns 1-2) and net flows of closet factor funds on positive and negative net flows of smart beta ETFs (columns 3-4) and the determinants of fund flows.

$$\begin{aligned}CMF\ Net\ Flow_{i,t} = &\ \beta_0 + \beta_1 ETF\ Net\ Flow_{i,t} + \beta_2 CMF\ Net\ Flow_{i,t-1}\\ &+ \beta_3 ETF\ Net\ Flow_{i,t-1} + \beta_4 Return_{i,t} + \beta_5 Return_{i,t-1}\\ &+ \beta_6 Expense_{i,t-1} + \beta_7 Log(Size)_{i,t-1} + \beta_7 Log(Family\ Size)_{i,t-1}\\ &+ (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t}\end{aligned}$$

$$\begin{aligned}CMF\ Net\ Flow_{i,t} = &\ \beta_0 + \beta_1 ETF\ Net\ Flow\ Positive_{i,t} + \beta_2 ETF\ Net\ Flow\ Negative_{i,t}\\ &+ \beta_3 CMF\ Net\ Flow_{i,t-1} + \beta_4 ETF\ Net\ Flow\ Positive_{i,t-1}\\ &+ \beta_5 ETF\ Net\ Flow\ Negative_{i,t-1} + \beta_6 Return_{i,t} + \beta_7 Return_{i,t-1}\\ &+ \beta_8 Expense_{i,t-1} + \beta_9 Log(Size)_{i,t-1} + \beta_{10} Log(Family\ Size)_{i,t-1}\\ &+ (Month - Year\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t}\end{aligned}$$

where *Return* is the net return of closet factor funds or smart beta ETFs; *Expense* is the expense of closet factor funds or smart beta ETFs; *Log(Size)* is the natural log of closet factor funds or smart beta ETFs total net assets; *Log(Family Size)* is the natural log of closet factor funds or smart beta ETFs fund family total net assets. The regression includes month-year and factor fixed effects. Standard errors are in parentheses and clustered at the fund group-year level. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$
ETF Net Flow$_t$	-0.162**	-0.123*		
	(0.073)	(0.072)		
ETF Net Flow Positive$_t$			-0.431***	-0.386***
			(0.131)	(0.139)
ETF Net Flow Negative$_t$			0.357**	0.321*
			(0.165)	(0.167)
CMF Net Flow$_{t-1}$	-0.003	-0.018	-0.031	-0.035
	(0.189)	(0.186)	(0.187)	(0.185)
ETF Net Flow$_{t-1}$	-0.136*	-0.093		
	(0.069)	(0.075)		
ETF Net Flow Positive$_{t-1}$			-0.146	-0.116
			(0.103)	(0.112)
ETF Net Flow Negative$_{t-1}$			0.475**	0.406*
			(0.199)	(0.212)
Return$_t$	3.546	5.606	7.167	8.176
	(20.805)	(21.075)	(21.081)	(21.320)
Return$_{t-1}$	4.233	5.341	10.876	10.988
	(18.393)	(18.153)	(16.826)	(16.811)
Expense$_{t-1}$	-33.869	-63.387	-44.837	-69.218
	(93.957)	(94.012)	(90.759)	(91.376)
Log(Size)$_{t-1}$	-166.008***	-163.924***	-148.344***	-153.761***
	(40.411)	(40.959)	(39.259)	(40.799)
Log(Family Size)$_{t-1}$	25.540	20.908	25.771	26.401
	(22.352)	(24.662)	(21.440)	(22.628)
Constant	1009.439***	1067.925***	931.849***	977.407***
	(346.645)	(327.317)	(316.257)	(289.849)
Month-Year Fixed Effects	Yes	Yes	Yes	Yes
Factor Fixed Effects	No	Yes	No	Yes
Number of observations	2517	2517	2517	2517
Adj. R-squared	0.060	0.072	0.085	0.088

Chapter 2

Actively managed ETFs: Are they really active?

2.1 Introduction

Actively managed ETFs are relatively new but fast-growing products in financial markets. They provide many similar benefits as traditional ETFs, such as intraday liquidity, low-cost investing, and tax efficiency, but also allow managers to employ active investment strategies and opportunities to outperform passive benchmarks.

The main concern regarding active ETFs has been the efficiency of their pricing. The arbitrage pricing mechanism that ensures ETF shares trade close to their NAV relies mainly on the transparency of their holdings. To address this concern, SEC requires that all actively managed ETFs disclose the identities and weightings of their holdings daily. Studies of premiums and discounts associated with active ETFs find that their long-term mean premium is close to zero, with relatively low diffusion volatility (Hilliard, 2014). This finding suggests that the arbitrage process remains efficient for these funds despite their decreased transparency.

The newest development in actively managed ETFs is the debut of actively managed non-transparent ETFs, ANTs, approved by the SEC at the end of 2019. These actively managed ETFs have the same features as other ETFs, except they disclose their holdings to the public only quarterly, not daily. This feature ensures that they can meaningfully pursue an active investment strategy but comes with a more severe lack of transparency. To address this issue, the SEC limits the fund investments to only securities that trade simultaneously as the funds themselves. This requirement means that ANTs can trade only in US stocks, the American Depositary Receipts and Global Depositary Receipts of foreign companies, US Treasuries, US-listed ETFs, and foreign stocks that trade during US market hours. To ensure that the in-kind creation and redemption process can function, the SEC requires ANT sponsors to provide additional information on the creation and redemption baskets and their intraday NAVs.

Assets under the management of actively managed ETFs account for a small part of total ETF assets, around 4.03% as of December 2021. However, the money invested in actively managed ETFs has increased exponentially, especially in recent years (Figure 1). Specifically, the amount of money invested in active ETFs rose from $562 million in December 2008 to $292 billion in December 2021.

Despite the structural challenges that actively managed ETFs face, they represent an attractive alternative to passive funds for ETF investors and active mutual fund managers. According to the data compiled by Bloomberg, the number of newly launched actively managed ETFs (68 funds) in the first half of 2020 surpassed, for the first time in history, the number of recently launched traditional ETFs (63 funds)[1]. More recently, actively managed ETFs dominated ETF launches in 2021[2]. These facts suggest that investors are starting to turn towards ETFs not only as a form of efficient diversification but also in their search for abnormal returns. Indeed, Sherrill et al. (2020) document that the use of non-benchmark ETFs enhances active fund performance and lower portfolio risk.

In this paper, we examine actively managed ETFs, both transparent and non-transparent funds, that invest in US equity and International equity and answer three research questions. (1) Do active ETFs employ active investment strategies? (2) Do they offer better returns to investors than their passive peers? (3) Are the flows to these funds determined by the same factors as the flows to passive funds?

We find that neither transparent nor non-transparent active ETFs have higher tracking errors than passive funds in the same category. The evidence suggests that active management does not represent a substantial investment strategy for these funds. Instead, they tend to adhere to the underlying index, as do their passive peers. Using the activeness measure suggested by Amihud and Goyenko (2013), we document similar results that active ETFs appear to be

[1]https://www.bloomberg.com/news/articles/2020-07-16/active-etf-launches-are-outstripping-passive-for-first-time

[2]https://www.wsj.com/articles/etf-inflows-top-1-trillion-for-first-time-11639257534

active in their names only since their levels of activeness are not significantly higher than those of passive funds. Overall, our result indicates that less frequent portfolio disclosure requirement in ANTs does not successfully induce fund managers to deviate significantly from the benchmarks.

Regarding the performance of these funds, the previous empirical evidence is not conclusive. Some studies support the idea that actively managed ETFs indeed add value to investors' portfolios by enhancing risk-adjusted returns (Beck et al., 2017; Meziani, 2015; Schizas, 2014; Garyn-Tal, 2013). Other studies attest to their failure to deliver positive alphas while exposing investors to higher volatility (Rompotis, 2015). Our results support the later studies. We find that both transparent and non-transparent US Equity active ETFs do not offer better risk-adjusted returns to their investors. However, we find evidence that active funds investing in international equity can outperform passive peers. In addition, we compare the performance of active and passive ETFs in different equity market conditions and find that only International Equity active ETFs outperform passive peers when the market is volatile or experiences positive returns.

To answer our last question, we examine the flows to actively managed ETFs. On average, demand for active ETFs is not higher than for passive funds. Flows to active ETFs are lower or not significantly different from flows to passive funds. Following the recent literature on fund flows (Barber et al., 2016; Song, 2020), we decompose fund returns into skill (alphas) and non-skill (factor-related returns) components. We document the performance-chasing behavior of their investors, consistent with the findings of Clifford et al. (2014), Broman and Shum (2018), and Dannhauser and Pontiff (2019).

However, alphas and benchmark-adjusted returns do not have a more substantial impact on net flows to active funds. This finding is somewhat surprising because it is the active ETFs, not passive index-tracking funds, that rely on managers' skills to search for outperformance.

Finally, we also document that flows to active non-transparent ETFs chase CAPM alphas, but not Fama-French 3-factor or Fama-French-Carhart 4-factor alphas. As Barber et al. (2016)

document that more sophisticated investors rely on multi-factor alpha to evaluate fund performance, our findings suggest that active ETF investors may not be more sophisticated than their passive peers.

We make several contributions to the literature. First, prior studies show that active ETFs and mutual funds do not appear to be more active than their passive peers (Schizas, 2014; Cremers and Petajisto, 2009). More recently, Akey et al. (2021) and Easley et al. (2021) document that passive funds become more active and thus emphasize the increasingly blurred line between active and passive management. Our evidence generally supports these findings and further suggests that allowing active ETF managers to conceal their holdings does not seem to incentivize them to make active investment decisions.

Second, even though our results agree with the previous literature on the underperformance of active to passive investment management (Rompotis, 2015; French, 2008), we show that there is no difference in performance between active and passive ETFs in various market states, contradicting the findings that active funds outperform in adverse market conditions (Kosowski, 2011; Kacperczyk et al., 2016). However, we document that active ETFs in the International Equity category outperform their passive peers in a highly volatile market. Moreover, while Pástor and Vorsatz (2020) document that active mutual funds perform poorly during the Covid-19 pandemic, we extend the evidence to the ETF universe by demonstrating that US equity active ETFs do not outperform their passive peers in periods of negative market returns and high volatility.

Lastly, prior studies examine the determinants of active mutual fund and ETF flows and document the return-chasing behaviors of investors (Dannhauser and Pontiff, 2019; Clifford et al., 2014) and that more sophisticated investors tend to adjust for factor-related returns when evaluating active managers (Barber et al., 2016). We contribute to this literature by showing that active and passive ETF flows chase returns, but active ETF investors do not appear to be "smarter" than their passive peers.

The remainder of the paper is structured as follows. Section 2.2 describes our data sample and methods used in the analyses in this paper. Section 2.3 analyzes whether active ETFs deviate more from the benchmark than passive funds. Next, Section 2.4 compares the performance measures of active and passive funds. Section 2.5 investigates the determinants of flows, specifically, the difference in flow performance relations in active and passive ETFs. Section 2.6 presents the robustness checks using propensity-score-matched samples. Finally, section 2.7 concludes the paper.

2.2 Data

The data in this study come from the Center for Research in Security Prices (CRSP) and Morningstar Direct. We merge the two databases by fund's CUSIP and Ticker. We focus on ETFs that are domiciled in the US and have Morningstar US Category classification as either US Equity or International Equity. Active ETFs and active non-transparent ETFs (ANTs) are identified by the *Actively Managed* and *Active Non Transparent* indicators. We exclude leveraged ETFs, smart beta, and exchange-traded notes (ETNs) using *Leveraged Fund*, *Strategic Beta*, and *Exchange Traded Notes* indicators and funds' names. We then collect the fund's returns, characteristics, and exchange activities data from the CRSP database. To be included in the sample, each fund must have at least 30 monthly return observations and available data on all the variables used in the analyses. For active non-transparent funds, we only apply the data availability requirement since these funds have been offered to the market only in recent years.

We construct three separate samples for transparent active ETFs investing in US equity (US Equity), international equity (International Equity), and non-transparent active ETFs (US Equity (ANT)). Most active non-transparent funds invest in US equity, so the ANT sample includes only these funds.

Following Clifford et al. (2014), Broman and Shum (2018), and the mutual fund literature, we remove all ETFs that are less than six months old to avoid issues with incubation bias and outliers in the number of shares outstanding during the early life of a fund. We classify ETFs that invest only internationally but not domestically as International Equity (e.g., Japan, Europe, Diversified Emerging Markets, Foreign Large Core). We exclude active and passive ETFs that invest in both international and US equity (e.g., World Large Growth, World Large Core) since there are very few active ETFs in these categories. Finally, as our purpose is to compare active and passive ETFs that belong to the same Morningstar Institutional Category, we require that for passive ETFs to be included in the sample, they must have at least one active ETF within the same Morningstar Institutional Category in the month.

Our US Equity sample consists of 52 active and 88 passive funds, covering the period from October 2008 to December 2021. The International Equity sample spans the period from April 2011 to December 2021 and includes 23 active and 138 passive funds. Lastly, there are 8 active and 78 passive ETFs in the US Equity (ANT) sample that starts in April 2020 and ends in December 2021. Figure 2.2 and Figure 2.3 illustrate the number of funds and total net assets of transparent and non-transparent active ETFs in our study. The majority of funds and net assets in active ETFs belong to transparent funds that invest in domestic equity since these funds have existed on the market for a longer time. However, there are increasing numbers of active ETFs that invest in international equity and non-transparent ETFs, and these funds seem to gradually attract investor money.

Previous literature has shown that a fund's prospectus benchmark often does not match the fund's actual investment styles (Sensoy, 2009; Cremers and Petajisto, 2009). Therefore, we do not use the self-declared benchmark when evaluating the fund tracking error and performance. Instead, we rely on the Morningstar equity style box for funds that invest in US equity to define a fund's benchmark each month. The Morningstar equity box is based on the fund's actual holdings. It classifies a fund's style into nine categories: Large Blend, Large Growth, Large Value, Mid Blend, Mid Growth, Mid Value, Small Blend, Small Growth, and Small Value with the following corresponding benchmarks: Russell 1000, Russell 1000 Growth, Russell 1000 Value, Russell Mid Cap, Russell Mid Cap Growth, Russell Mid Cap Value, Russell 2000, Russell 2000 Growth, and Russell 2000 Value. For International Equity funds, we use Morningstar FTSE/Russell benchmark assigned to each fund. This assignment is also based on the fund's holdings. Monthly fund return volatility is calculated based on a 24-month rolling standard deviation of the fund's returns. In our study, we rely on tracking errors to measure the level of fund active management. Following Drenovak et al. (2014), we estimate three types of fund tracking errors using daily returns each month. The first tracking error, TE1, is the mean of the absolute value of the difference between the return of an ETF and the benchmark index.

$$TE1 = \frac{\sum_{t=1}^{n} |r_{i,t} - r_{b,t}|}{n}$$

The second type, TE2, is the standard deviation of the difference between the fund's return and its benchmark's return,

$$TE2 = \sqrt{\sigma_i^2 + \sigma_b^2 - 2\sigma_i \sigma_b \rho_{i,b}}$$

The last measure, TE3, is the standard deviation of the residuals from the OLS regression of the fund's returns on the benchmark's returns,

$$r_{i,t} = \alpha_i + \beta_i r_{b,t} + \epsilon_{i,t}$$

where $r_{i,t}$ is the return of fund *i* on day *t*, $r_{b,t}$ is the return of the relevant benchmark on day *t*, and $\epsilon_{i,t}$ is the residual. The standard deviation of the residuals from the above regression is our last measure of tracking error. We require a fund to have at least 15 daily return observations in a month to calculate monthly tracking errors.

We measure the fund's performance as the adjusted returns using the Fama-French-Carhart (4 factors), Fama-French (3 factors), and CAPM models. Following Breloer et al. (2014), we utilize the international version of these models for funds in the International Equity category. The market factor for International Equity funds is the excess return of the MSCI ACWI ex USA All Cap index. The size factor is the average return of the MSCI ACWI Ex USA Small Value index and the MSCI ACWI Ex USA Small Growth index minus the average return of the MSCI ACWI Ex USA Large Value and the MSCI ACWI Ex USA Large Growth index. The value factor is the difference between the average return of the MSCI ACWI Ex USA Small Value and the MSCI ACWI Ex USA Large Value index and the average return of the MSCI ACWI Ex USA Small Growth and the MSCI ACWI Ex USA Large Growth index. The momentum factor is proxied by the returns of the MSCI World ex US Momentum index.

We decompose the fund's monthly excess returns into two components following the recent literature (Barber et al., 2016; Song, 2020; Dannhauser and Pontiff, 2019). Specifically, we estimate the factor sensitivities of fund *i* in month *t* by 24-month rolling regression, using model F_N with N factor as:

$$r_{i,t} - r_{f,t} = \alpha_{i,t}^{F_N} + \sum_{n=1}^{N} \beta_{i,t}^{n} F_{n,t} + \epsilon_{i,t}.$$

We calculate the fund's factor-related return (FRR) in month *t* using each fund's estimates of factor exposures as:

$$FRR_{i,t}^{F_N} = \sum_{n=1}^{N} \hat{\beta}_{i,n,t-1}^{F_N} F_{n,t},$$

and the factor-adjusted component (alpha) as

$$\hat{\alpha}_{i,t}^{F_N} = (r_{i,t} - r_{f,t}) - FRR_{i,t}^{F_N}.$$

In order to calculate alphas and factor-related returns for funds in the ANT sample, we rely on daily fund returns and factor returns to estimate monthly factor exposures. These factor exposures are used to calculate daily alpha and factor-related returns for the next month. The monthly alphas and factor-related returns are computed as the compounded daily alpha and factor-related return during the month.

We also calculate monthly net fund flows as:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + r_{i,t})}{TNA_{i,t-1}},$$

Clifford et al. (2014) and Broman and Shum (2018) document that exchange and trading characteristics can also affect ETF flows. Therefore, we include the following variables in the regressions that examine ETFs flow determinants: standard deviation of daily volume, average daily spread, standard deviation of daily spread, price-NAV ratio (at the end of the month), and share turnover (average daily volume in a month divided by the beginning of month shares outstanding). All variables are winsorized at the 1st and 99th percentiles to mitigate the impact of outliers or data error issues. In all regressions, we control for year-month and fund category fixed effects (using Morningstar Institutional Category). Standard errors are clustered at the fund level.

Table 2.1 compares some characteristics of active and passive ETFs. First, the total net assets of active ETFs are much smaller compared to those of passive peers in all samples. This finding is expected since active ETFs have just recently been introduced to the market. Both transparent and non-transparent US Equity active ETFs are larger than International Equity funds.

Next, all three tracking error measures show that active ETFs deviate more from the benchmark and hold fewer stocks than their passive peers. Although active ETFs charge significantly higher fees to their investors, they do not seem to outperform their passive peers on both performance measures. Strikingly, transparent active ETFs that invest in US equity charge the highest fees (0.78 percent) but significantly underperform passive ETFs.

Regarding the trading characteristics, active ETFs have lower liquidity than passive funds, as shown by higher average daily spread and standard deviation of daily spread. Only non-transparent active ETFs appear to trade more actively than passive funds, with an average share turnover of 0.64 versus 0.19 of passive ETFs. The result suggests that investors use these non-transparent funds to make short-term investment horizon bets on the US equity market.

[Please insert Table 2.1 here]

2.3 Are active ETFs really active?

This section addresses our first question of whether active ETFs employ active investment strategies. We use tracking error as a proxy for active management. Tracking error measures how much the fund's returns deviate from the returns of the benchmark. Passive funds aim to replicate the benchmark and should have low tracking errors. On the other hand, actively managed funds aim to beat the underlying benchmark by strategic asset allocation or stock selection. Thus, if they indeed employ active management, we should observe higher tracking errors in active ETFs than in passive funds.

Tracking errors have been shown to be related to other fund characteristics, such as fund size, age, expense ratio, fund returns volatility, and the number of assets in the fund's holdings (Vardharaj et al., 2004; Rompotis, 2015). To closely examine tracking errors of active versus passive funds, we regress tracking errors on a dummy variable *Active* that takes the value of one for actively managed ETF and zero otherwise, and control for other fund's characteristics:

$$\begin{aligned}TE_{i,t} = {} & \beta_0 + \beta_1 Active_{i,t} + \beta_2 Log(Age)_{i,t-1} + \beta_3 Log(TNA)_{i,t-1} \\ & + \beta_4 Expense_{i,t-1} + \beta_5 Fund\ volatility_{i,t-1} + \beta_6 Log(Holdings)_{i,t-1} \\ & + (Category\ Fixed\ Effects) + (Time\ Fixed\ Effects) + \epsilon_{i,t}\end{aligned} \tag{2.1}$$

where *TE* is tracking error, *Log(Age), Log(TNA), Expense, Volatility,* and *Holdings* are control variables depicting the natural log of fund age, the natural log of fund total net assets, fund expense, fund return volatility, and the natural log of the number of stocks in fund's portfolios, respectively.

The results are presented in Table 2.2, Panel A. Using three different tracking error measures, we find that the coefficient estimates of the dummy variable *Active* are not statistically significant for US equity funds. This evidence suggests that active ETFs do not deviate more from their benchmarks than their passive peers and hence do not employ active management. For international equity funds, we find negative and statistically significant coefficient estimates on the dummy variable *Active*. Therefore, these funds do not appear to be active, but they, in fact, follow the benchmarks more closely than their passive peers. Regarding the control variables, funds with more stocks in their portfolio can achieve lower tracking errors. Finally, fund expense and volatility positively affect ETFs' tracking errors.

The finance literature also suggests other measures of active management. One standard measure is 1-R^2 (Amihud and Goyenko, 2013), where R^2 is obtained from the regression of the fund daily excess returns on different multifactor models (CAPM, Fama French 3 factor, and Fama French and Carhart 4 factor models). (Amihud and Goyenko, 2013) suggest that this measure can indicate active management and predict mutual fund returns. In the context of active ETFs, Garyn-Tal (2013) identifies that active ETFs with low R^2 (higher 1-R^2) can achieve higher returns. Therefore, we use this alternative measure of active management in regression 1 to reexamine our first research question. Consistent with the previous result, active ETFs do not have higher *Activeness* than passive peers in any category. In addition, non-transparent and international equity funds have significantly lower activeness levels than passive ETFs.

Overall, our evidence is consistent with the results of Schizas (2014) that active ETFs have not been more active than their corresponding passive funds. Complementing the striking findings in Cremers and Petajisto (2009) that some active mutual funds are "closet indexers", our evidence shows that active ETFs appear to be active by names only. Importantly, our finding that non-transparent active ETFs do not employ active management suggests that less frequent portfolio disclosure requirements may not successfully induce fund managers to deviate significantly from the benchmark. However, a possible explanation for this indifference in the degree of activeness between active and passive ETFs is the increasingly blurred line between active and passive management as documented by Akey et al. (2021), and Easley et al. (2021). Since passive funds are becoming increasingly active, it may be challenging for active managers to demonstrate their efforts in making informed investment decisions to investors.

[Please insert Table 2.2 here]

2.4 Performance of active and passive ETFs

2.4.1 Do active ETFs outperform passive peers?

The previous section finds that active ETFs do not deviate more from the benchmarks than passive funds despite charging higher expense ratios to investors. Our subsequent analysis examines whether they bring significantly higher returns to their investors than passive funds. We regress different performance measures on a dummy variable *Active* while controlling for other confounding variables of fund performance:

$$
\begin{aligned}
Performance_{i,t} = \beta_0 &+ \beta_1 Active_{i,t} + \beta_2 Log(Age)_{i,t-1} + \beta_3 Log(TNA)_{i,t-1} \\
&+ \beta_4 Expense_{i,t-1} + \beta_5 Flow_{i,t-1} + \beta_6 Activeness_{i,t-1} \\
&+ \beta_7 Turnover_{i,t-1} + (Category\ Fixed\ Effects) \\
&+ (Time\ Fixed\ Effects) + \epsilon_{i,t}
\end{aligned}
\tag{2.2}
$$

where *Performance* is expressed as benchmark-adjusted returns and alphas from the Fama-French-Carhart (4 factors) model. The coefficient of interest is β_1. If active ETFs outperform passive peers, β_1 will be positive and statistically significant.

Regression results are reported in Table 2.3. We find that neither transparent nor non-transparent actively managed ETFs investing in US equity can outperform passive funds in the same categories, as shown by insignificant coefficient estimates. We use alphas from Fama French (3 factors) and CAPM models as performance measures in unreported results and reach similar conclusions.

The results of active ETFs investing in international stock markets illustrate that these funds outperform passive peers by 0.21 percent (4-factor alphas) or 0.35 percent (benchmark-adjusted returns) per month. This outperformance is equivalent to 2.52 percent (4-factor alphas) or 4.2 percent (benchmark-adjusted returns) per year.

Turning to the control variables, we find that funds with higher portfolio turnover and *Activeness* deliver significantly lower performance. The negative relation between *Activeness* and fund performance contradicts the findings in Amihud and Goyenko (2013) and Garyn-Tal (2013).

In summary, we document that active ETFs investing in US equity, including ANTs, do not significantly outperform their passive peers. This is consistent with our previous findings that their investment strategy does not significantly differ from their passive peers. For the International Equity category, however, we find that active ETFs significantly outperform passive funds. Recalling the results from Table 2.2 that tracking errors and activeness of passive ETFs are significantly larger than active funds in this category, we can explain the outperformance of active ETFs by the findings of Akey et al. (2021) that more active passive index funds tend to underperform.

[Please insert Table 2.3 here]

Proponents of active investment generally suggest that active fund managers can exhibit their skills and make portfolio choices that can deliver higher performance than passive funds in adverse market conditions. In fact, several studies have documented the outperformance of active funds in recession periods (Kosowski, 2011; Kacperczyk et al., 2016). Therefore, we examine whether active ETFs can outperform passive funds under different market states in the following two sections.

As active non-transparent ETFs have been offered to the market since 2019, there is not much variation in market conditions during our sample period. Consequently, we only examine the performance of US Equity transparent active ETFs and International Equity active ETFs when the market experiences high and low volatility and positive and negative returns.

2.4.2 Performance comparison in periods of high and low market volatility

We measure the US and international market volatility by the 24-month rolling standard deviation of returns of the S&P 500 and MSCI ACWI ex USA All Cap indexes. A month is classified as high(low) volatility if the volatility is above(below) the time series median. We then compare the performance of active and passive ETFs using regression 2 in two separate samples, i.e., in high market volatility and low market volatility months.

Table 2.4 presents the results. On the one hand, there is only weak evidence of the outperformance of US Equity active ETFs when the equity market is not highly volatile, as shown by a positive and significant (at 10 % level) coefficient estimate. On the other hand, active ETF managers specializing in international markets deliver higher returns during months of high market volatility. Specifically, active ETFs outperform passive peers by 0.36 percent (alphas) and 0.57 percent (benchmark-adjusted returns) per month, which translates into 4.32 percent and 6.84 percent annually.

[Please insert Table 2.4 here]

2.4.3 Performance comparison in periods of up and down market

This section examines whether active ETFs can deliver better returns than passive funds when the markets perform well or poorly. Specifically, we split our sample into Up (positive market returns) and Down (negative market returns) months. Consistent with the result in the previous section, we document in Table 2.5 that active ETFs that invest in US equity do not generate higher returns than passive peers in either market condition. However, it is interesting to note that International Equity active funds significantly benefit investors when the equity market is trending upward. The coefficient estimates of the dummy variable *Active* are positive and statistically significant at the 5% level in both performance measures.

[Please insert Table 2.5 here]

Overall, we document that active ETFs investing in the US stock market fail to deliver better performance to investors in different market conditions. Nevertheless, investors may benefit from their investment in International Equity active funds during volatile and up markets. Our evidence regarding the US Equity active funds indicates that investors would generally benefit by investing in passively-managed funds (Sharpe, 1991; French, 2008). We also extend the results of Pástor and Vorsatz (2020) to the ETF universe by showing that active funds still do not outperform passive peers in adverse market states. However, our findings also suggest that investors may benefit from investing in International Equity active ETFs, especially during periods of high market volatility or positive market returns.

2.5 Determinants of flows

This final section studies the determinants of flows to active and passive ETFs and compares the flow-performance relations in these two types of funds. Following Clifford et al. (2014), we control for various previously documented determinants of fund flows, including fund's characteristics, e.g., age, size, expense, and turnover and exchanged related variables. Specifically, we use the following regression:

$$\begin{aligned} Flow_{i,t} = \beta_0 + \beta_1 Active_{i,t} + \beta_1 Performance_{i,t-1} + \beta_2 Performance_{i,t-1}.Active_{i,t} \\ + \sum_j \beta_j Fund\ Variables_{i,t-1} + \sum_k \beta_k Exchange\ Variables_{i,t-1} \\ + (Category\ Fixed\ Effects) + (Time\ Fixed\ Effects) + \epsilon_{i,t} \end{aligned} \tag{2.3}$$

where *Flow* is monthly ETF net flows, *Active* is a dummy variable indicating the actively managed fund, and *Performance* is benchmark-adjusted returns or alphas from the Fama-French-Carhart (4 factors), Fama-French (3 factors), and CAPM models. Table 2.6 presents the results for the US Equity (Panel A), US Equity ANT (Panel B), and International Equity (Panel C) samples, respectively. We find that active ETFs have not been entirely successful in attracting investor flows. Monthly net flows into active funds are approximately 2.4 percentage points (equivalent to $1.5 million per month) lower than the flows to their passive peers in the International Equity sample and not statistically different in the other two samples. These findings are consistent with the dominance of passive investing in recent years and that these funds still account for a small proportion of total ETF assets. However, it is surprising that even though active ETFs investing in international stock markets outperform their passive peers, investors do not seem to allocate more money to these funds.

Consistent with the previous studies (Clifford et al., 2014; Dannhauser and Pontiff, 2019), we document the performance-chasing behavior of ETF investors. In detail, the coefficient estimates of *Alpha* and *Benchmark adjusted returns* are positive and statistically significant in Panel A and Panel B of Table 2.6. The sum of coefficient estimates of fund performance measure and the interaction term between performance measures and *Active*, which illustrates the flow-performance relationship in active ETFs, are also positive and statistically significant. We expect, however, different responses to performance between investors of active and passive ETFs. The skill component of fund returns, i.e., alpha and benchmark-adjusted returns, should be stronger determinants of flows to active ETFs since it depicts the manager's ability. Nevertheless, as shown in Table 2.6, none of the coefficient estimates of the interaction terms between performance measures and the dummy *Active* is significantly different from zero. In addition, investors in active non-transparent ETFs only adjust fund returns for market risk and chase factor-related returns to a larger extent than passive fund investors.

Overall, these results illustrate that flows to both active and passive ETFs chase past performance. However, active ETF investors do not seem to pay more attention to the managers' skill-related returns. There is also evidence that non-transparent active ETF investors treat returns from exposures to size, value, and momentum factors as alphas, and their response to this *misperceived* alpha is even stronger than passive peers.

The impacts of the control variables are consistent with the previous literature (Clifford et al., 2014). Fund age and expense negatively affect net flows to ETFs. ETFs with lower fees and more exchange activity (share turnover, price-NAV) attract more cash flows.

[Please insert Table 2.6 here]

2.6 Robustness: Propensity-score-matched sample

Even though we include many control variables in our regression models, other confounding factors may affect tracking errors, activeness, or fund performance but have not been controlled for. To alleviate this concern, we apply the propensity score matching strategy and match (without replacement) each active ETF to one passive ETF on the control variables, fund category, and month. We then reexamine our two research questions using this propensity-score-matched sample. Table 2.7 summarizes the results and confirms that active ETFs do not appear to employ active management.

[Please insert Table 2.7 here]

In Table 2.8, we compare the performance of active ETFs with the matched passive peers in the whole sample and various market conditions. Similar to the results in section 4, there is only evidence that International Equity active ETFs outperform passive peers. This outperformance is more pronounced during periods of high market volatility and positive market returns.

[Please insert Table 2.8 here]

2.7 Conclusions

Actively managed ETFs are relatively new ETF offerings in the financial markets. So far, they manage only a small proportion of assets in the ETF industry. Nevertheless, the number of newly launched funds in this category has recently exceeded the number of newly launched passive funds. In this paper, we examine three essential aspects of actively managed ETFs. Specifically, we compare the level of active management, risk-adjusted returns, and flow determinants of actively managed ETFs with those of traditional passive ETFs in the same category. First, despite their names, actively managed ETFs do not seem to depart from their benchmarks significantly. Their tracking errors and activeness, ceteris paribus, are not significantly different from their passive peers. Second, actively managed ETFs investing in US equity, including non-transparent funds, do not deliver better returns to their investors. However, investors may benefit from investing in International Equity active funds, especially when the market is highly volatile and experiences positive returns. Finally, an analysis of flows reveals that net flows to active funds are equally sensitive to alpha to net flows of passive funds. The finding is surprising because these funds' purpose is to deliver returns above the benchmark, and therefore investors should pay attention to the "skill" of these managers. In short, our analysis illustrates that putting active management under the ETF wrapper does not overturn the long-standing underperformance of active to passive investment.

Figure 2.1: Active and passive ETFs total net assets ($ million)

This figure illustrates the total net assets of active and passive ETFs from 2008 to 2021.

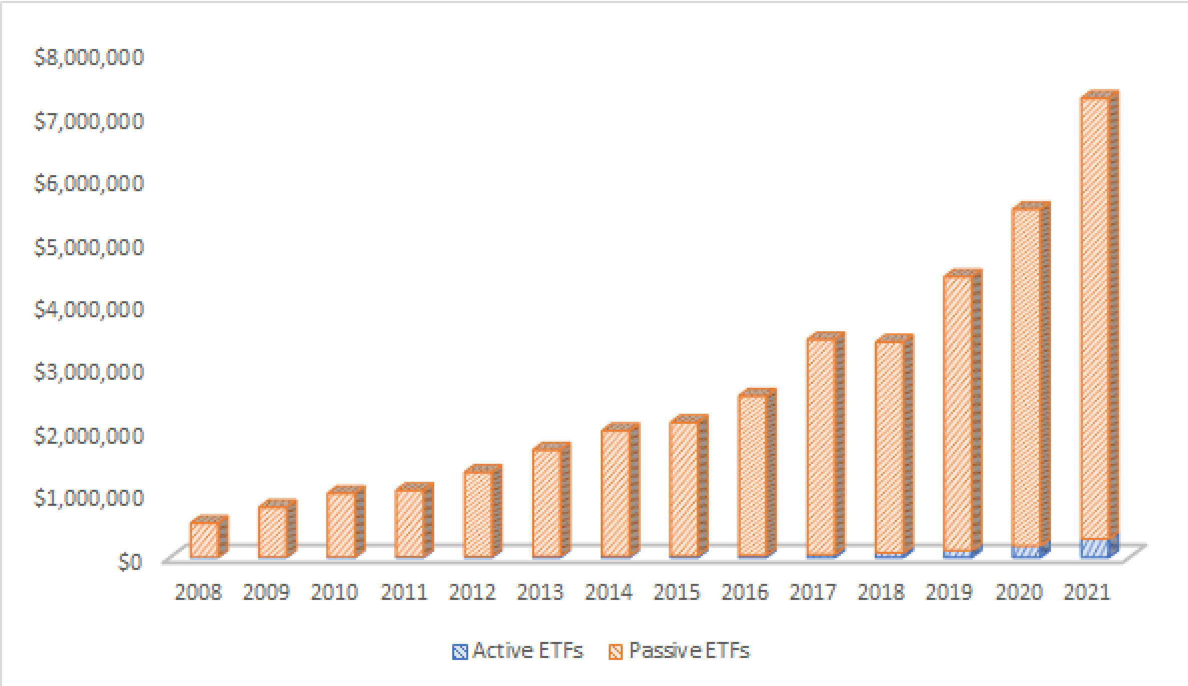

Figure 2.2: Number of US equity and international equity active ETFs

This figure illustrates the number of active ETFs from 2008 to 2021.

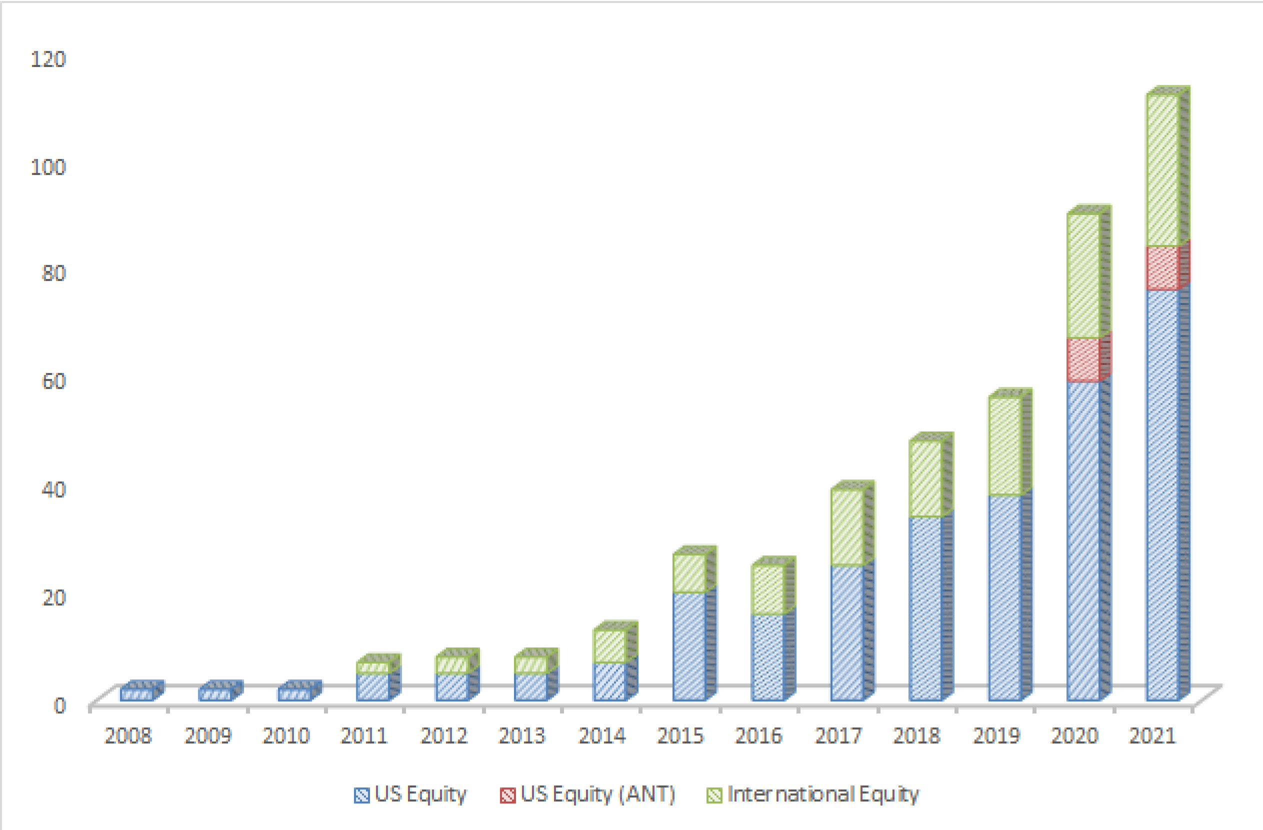

Figure 2.3: Total net assets ($ million) of US equity and international equity active ETFs

This figure illustrates the total net assets of active and passive ETFs from 2008 to 2021.

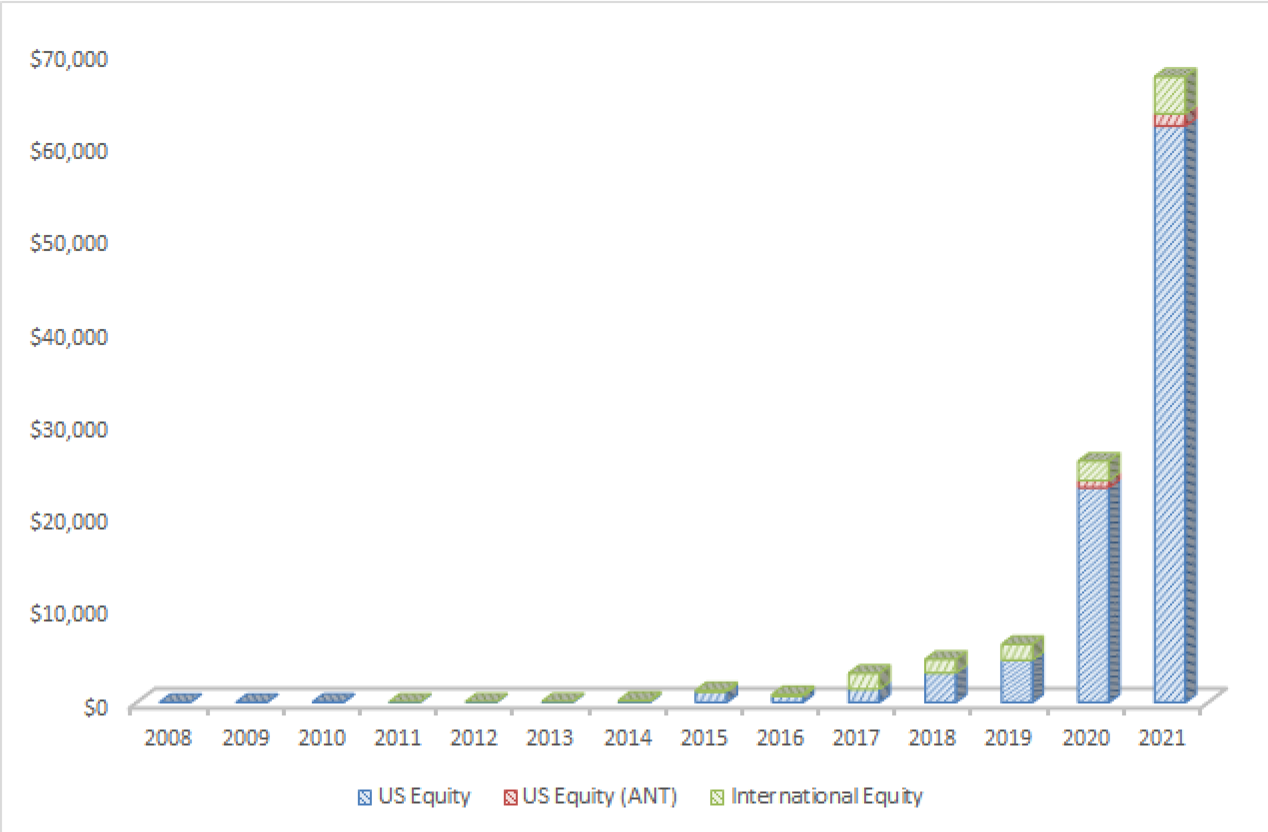

Table 2.1: Summary statistics

This table contains summary statistics for actively managed and passive ETFs within th US equity, International Equity and World Equity categories.*TNA* the monthly total net assets in millions of dollars, *Benchmark adjusted returns* is the difference between fund net returns and style or benchmark returns in percentage; *Alpha(FFC)* is alpha from Fama-French-Carhart 4-factor model; *Tracking error* are measured by three different methods and in percentage ; *Activess (FFC)* is 1-R^2 from regressions of fund returns on factor returns *Fund volatility* is 24-month rolling standard deviations of fund net returns in percentage; *Age* in months is the difference between the current month and the fund's inception month; *Expense ratio* is the stated annual expense ratio in percent; *Turnover ratio* is the stated annual turnover in decimals; *Holdings* is the number of stocks in the fund portfolio; *Flow* is a fund's dollar flow divided by the total net assets of the previous period; *Std. dev. Daily volume* is calculated using daily volume over the entire month; *Average daily spread* and *Std. dev. Daily spread* are calculated using each day's bid-ask spread for the entire month; *Price-NAV ratio* is the price to NAV ratio at the end of the month; *Share turnover* is calculated as the average of daily volume over the entire month divided the number of shares outstanding at the beginning of the month. Reported levels of statistical significance of the t-test between the means of group; *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

	US Equity			**US Equity (ANT)**			**International Equity**		
	Active	Passive	Difference	Active	Passive	Difference	Active	Passive	Difference
TNA ($ million)	350.17	9514.23	-9164.06***	120.51	6197.65	-6077.14***	61.54	6966.49	-6904.95***
Benchmark adj. Return (%)	-0.31	-0.09	-0.22***	0.23	0.11	0.12	-0.04	-0.17	0.13
Alpha (FFC) (%)	-0.28	-0.12	-0.16***	-0.11	0.09	-0.20*	-0.12	-0.06	-0.06
Tracking Error (TE1) (%)	0.34	0.18	0.16***	0.32	0.27	0.05***	0.40	0.43	-0.03*
Tracking Error (TE2) (%)	0.44	0.22	0.22***	0.40	0.34	0.06***	0.52	0.55	-0.03*
Tracking Error (TE3) (%)	0.36	0.20	0.16***	0.38	0.30	0.08***	0.48	0.51	-0.03
Activeness (FFC)	0.11	0.03	0.08***	0.08	0.05	0.03***	0.27	0.27	0.00
Fund volatility (%)	4.66	4.75	-0.09	4.84	4.46	0.36**	4.91	4.93	-0.02
Age (months)	59.38	120.97	-61.59***	10.86	70.60	-59.74***	57.18	110.95	-53.77***
Expense Ratio (%)	0.78	0.23	0.55***	0.49	0.32	0.17***	0.71	0.37	0.34***
Turnover Ratio	2.46	0.35	2.11***	0.47	0.47	0.00	0.90	0.22	0.68***
Number of stocks	123.94	1014.95	-891.02***	93.61	539.35	-445.74***	169.93	838.17	-668.24***
Flow (%)	0.39	1.80	-1.41***	7.71	4.13	3.58***	-0.55	1.09	-1.64***
Std. dev. Daily volume	536.35	3619.28	-3082.93***	284.30	1154.83	-870.53***	134.52	9410.74	-9276.21***
Average daily spread	0.14	0.07	0.07***	0.08	0.09	-0.01	0.16	0.08	0.08***
Std. dev. Daily spread	0.06	0.04	0.02***	0.04	0.04	0.00	0.07	0.03	0.04***
Price-NAV ratio	1.00	1.00	0.00	1.00	1.00	-0.00***	1.00	1.00	0.00
Share turnover	0.16	0.18	-0.02*	0.64	0.19	0.45***	0.13	0.30	-0.17***

Table 2.2: Are active ETFs really active?

The table presents the results of panel regression of fund activeness measures: Tracking errors (Panel A) and Activeness (Panel B) on a dummy variable indicating whether a fund is an actively managed ETFs and the determinants of tracking error as control variables:

$$\begin{aligned} TE_{i,t} &= \beta_0 + \beta_1.Active_{i,t} + \beta_2.Log(Age)_{i,t-1} + \beta_3.Log(TNA)_{i,t-1} \\ &+ \beta_4.Expense_{i,t-1} + \beta_5.Fund\ volatility_{i,t-1} + \beta_6.Log(Holdings)_{i,t-1} \\ &+ (CategoryFixedEffects) + (TimeFixedEffects) + \epsilon_{i,t} \end{aligned}$$

where *Active* is a dummy variable with the value of 1 if the fund is an actively managed ETF; *Log(Age)* is the natural log of the fund's age in months; *Log(TNA)* is the natural log of the fund's total net assets; *Expense* is the fund's expense ratio; *Fund volatility* is the volatility of fund's net return; *Log(Holdings)* is the natural log of the number of stocks in the fund's portfolio. The regression includes calendar month and category fixed effects. Standard errors are in parentheses and clustered at the fund level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

Panel A: Tracking Error									
	US Equity			**US Equity (ANT)**			**International Equity**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	TE1	TE2	TE3	TE1	TE2	TE3	TE1	TE2	TE3
Active_t	0.0002	0.0003	0.0004	-0.0009*	-0.0011*	-0.0005	-0.0012***	-0.0015***	-0.0010***
	(0.0003)	(0.0003)	(0.0003)	(0.0005)	(0.0006)	(0.0005)	(0.0003)	(0.0004)	(0.0004)
Log(Age)_{t-1}	-0.0001	-0.0001	0.0000	0.0001	0.0002	0.0002	0.0001	0.0001	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.0003)
Log(TNA)_{t-1}	0.0001*	0.0001**	0.0001	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Expense_{t-1}	0.1786***	0.2314***	0.1499***	0.0334	0.0431	-0.0632	0.1191*	0.1510*	0.0743
	(0.0467)	(0.0610)	(0.0417)	(0.0624)	(0.0788)	(0.0840)	(0.0618)	(0.0785)	(0.0757)
$\text{Fund volatility}_{t-1}$	0.0665***	0.0811***	0.0804***	0.0602***	0.0725***	0.0745***	0.0639***	0.0829***	0.0845***
	(0.0180)	(0.0227)	(0.0177)	(0.0124)	(0.0155)	(0.0145)	(0.0143)	(0.0182)	(0.0183)
$\text{Log(Holdings)}_{t-1}$	-0.0003***	-0.0004***	-0.0003***	-0.0006***	-0.0008***	-0.0007***	-0.0008***	-0.0010***	-0.0009***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
Constant	0.0000	0.0002	-0.0008	0.0028***	0.0037***	0.0032***	0.0048***	0.0061***	0.0044**
	(0.0011)	(0.0014)	(0.0010)	(0.0009)	(0.0011)	(0.0011)	(0.0017)	(0.0022)	(0.0020)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	4778	4778	4778	1312	1312	1312	5393	5393	5393
R-squared	0.640	0.626	0.653	0.621	0.615	0.632	0.564	0.558	0.541

Table 2.2: Are active ETFs really active? (continued)

Panel B: Activeness (1-R^2)									
	US Equity			**US Equity (ANT)**			**International Equity**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Activeness(FFC)	Activeness(FF)	Activeness(CAPM)	Activeness(FFC)	Activeness(FF)	Activeness(CAPM)	Activeness(FFC)	Activeness(FF)	Activeness(CAPM)
Active_t	-0.0093	-0.0093	-0.0033	-0.0215*	-0.0266*	-0.0013	-0.0747***	-0.0561*	-0.0803**
	(0.0094)	(0.0123)	(0.0226)	(0.0117)	(0.0155)	(0.0256)	(0.0279)	(0.0291)	(0.0309)
Log(Age)_{t-1}	-0.0073	-0.0094	-0.0011	0.0029	0.0023	0.0133	-0.0153	-0.0171	-0.0281
	(0.0056)	(0.0067)	(0.0117)	(0.0045)	(0.0055)	(0.0090)	(0.0228)	(0.0234)	(0.0242)
Log(TNA)_{t-1}	0.0054***	0.0062***	0.0062**	0.0006	0.0016	0.0026	-0.0016	0.0000	0.0020
	(0.0016)	(0.0019)	(0.0031)	(0.0020)	(0.0024)	(0.0044)	(0.0060)	(0.0062)	(0.0065)
Expense_{t-1}	7.6502***	8.5106***	13.4148***	1.1768	1.9966	7.7829	9.1635*	9.0844*	11.0606*
	(2.2139)	(2.4576)	(4.0538)	(3.1198)	(3.8793)	(6.4731)	(4.8473)	(5.0296)	(5.6114)
$\text{Fund volatility}_{t-1}$	-0.0628	-0.1744	3.5166***	0.4868	0.6510	2.9405***	2.3531*	2.1420	2.0509
	(0.3634)	(0.4429)	(0.8813)	(0.4895)	(0.6496)	(0.7755)	(1.2302)	(1.3772)	(1.4349)
$\text{Log(Holdings)}_{t-1}$	-0.0250***	-0.0287***	-0.0352***	-0.0290***	-0.0336***	-0.0651***	-0.0431***	-0.0449***	-0.0559***
	(0.0048)	(0.0053)	(0.0082)	(0.0054)	(0.0064)	(0.0132)	(0.0106)	(0.0108)	(0.0117)
Constant	0.1747***	0.2107***	0.1075	0.1757***	0.1987***	0.3010***	0.4333***	0.5071***	0.6796***
	(0.0436)	(0.0498)	(0.0805)	(0.0353)	(0.0417)	(0.0789)	(0.1406)	(0.1433)	(0.1511)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	4778	4778	4778	1312	1312	1312	5393	5393	5393
R-squared	0.491	0.493	0.600	0.450	0.449	0.621	0.372	0.395	0.415

Table 2.3: OLS regressions of performance measures

The table presents the results of panel regressions of fund's performance measure on a dummy variable indicating whether a fund is an actively managed ETFs and the determinants of fund's performance as control variables:

$$
\begin{aligned}
Performance_{i,t} = \beta_0 &+ \beta_1 Active_{i,t} + \beta_2 Log(Age)_{i,t-1} + \beta_3 Log(TNA)_{i,t-1} + \beta_4 Expense_{i,t-1} \\
&+ \beta_5 Flow_{i,t-1} + \beta_6 Activeness_{i,t-1} + \beta_7 Turnover_{i,t-1} \\
&+ (CategoryFixedEffects) + (TimeFixedEffects) + \epsilon_{i,t}
\end{aligned}
$$

where *Active* is a dummy variable with the value of 1 if the fund is an actively managed ETF; *Log(Age)* is the natural log of the fund's age in months; *Log(TNA)* is the natural log of the fund's total net assets; *Expense* is the fund's expense ratio; *Flow* is the fund's net flow; *Performance* is the fund's performance measured by factor model alphas and benchmark adjusted returns. *TE* is the fund's tracking error. *Turnover* is the fund's turnover ratio. The regression includes calendar month and category fixed effects. Standard errors are in parentheses and clustered at the fund level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

	US Equity		**US Equity (ANT)**		**International Equity**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret
Active	-0.0006	0.0005	-0.0012	-0.0016	0.0021*	0.0035**
	(0.0006)	(0.0007)	(0.0013)	(0.0014)	(0.0011)	(0.0014)
Log(Age)$_{t-1}$	0.0000	-0.0005	-0.0008*	-0.0002	0.0001	-0.0005
	(0.0004)	(0.0005)	(0.0004)	(0.0006)	(0.0007)	(0.0006)
Log(TNA)$_{t-1}$	-0.0000	-0.0001	0.0003	0.0003	-0.0001	0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Expense$_{t-1}$	-0.0613	-0.1985*	0.1066	0.3715	-0.1061	-0.2057
	(0.1132)	(0.1059)	(0.2389)	(0.3039)	(0.1246)	(0.1343)
Flow$_{t-1}$	-0.0028	0.0070*	0.0060*	0.0043	0.0034	0.0029
	(0.0030)	(0.0038)	(0.0036)	(0.0057)	(0.0038)	(0.0034)
Activeness$_{t-1}$	-0.0104***	-0.0122***	-0.0072	-0.0317***	-0.0026	-0.0048***
	(0.0038)	(0.0041)	(0.0114)	(0.0101)	(0.0020)	(0.0018)
Turnover$_{t-1}$	-0.0002	-0.0009***	0.0002	0.0018	-0.0035***	-0.0031*
	(0.0002)	(0.0001)	(0.0010)	(0.0012)	(0.0013)	(0.0016)
Constant	-0.0005	0.0032*	0.0016	-0.0001	0.0012	0.0027
	(0.0016)	(0.0018)	(0.0014)	(0.0022)	(0.0026)	(0.0026)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	4728	4728	1286	1286	5384	5384
R-squared	0.106	0.120	0.065	0.107	0.072	0.072

Table 2.4: Performance in periods of High and Low market volatility

The table presents the results of panel regressions of fund's performance measure on a dummy variable indicating whether a fund is an actively managed ETFs and the determinants of fund's performance as control variables, in periods of high and low market volatility:

$$
\begin{aligned}
Performance_{i,t} = &\ \beta_0 + \beta_1 Active_{i,t} + \beta_2 Log(Age)_{i,t-1} + \beta_3 Log(TNA)_{i,t-1} + \beta_4 Expense_{i,t-1} \\
&+ \beta_5 Flow_{i,t-1} + \beta_6 Activeness_{i,t-1} + \beta_7 Turnover_{i,t-1} \\
&+ (CategoryFixedEffects) + (TimeFixedEffects) + \epsilon_{i,t}
\end{aligned}
$$

where *Active* is a dummy variable with the value of 1 if the fund is an actively managed ETF; *Log(Age)* is the natural log of the fund's age in months; *Log(TNA)* is the natural log of the fund's total net assets; *Expense* is the fund's expense ratio; *Flow* is the fund's net flow; *Performance* is the fund's performance measured by factor model alphas and benchmark adjusted returns. *TE* is the fund's tracking error. *Turnover* is the fund's turnover ratio. The regression includes calendar month and category fixed effects. Standard errors are in parentheses and clustered at the fund level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

	US Equity				**International Equity**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High	High	Low	Low	High	High	Low	Low
	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret
Active_t	-0.0013	0.0002	0.0006	0.0015*	0.0036**	0.0057***	0.0004	0.0005
	(0.0009)	(0.0009)	(0.0010)	(0.0008)	(0.0017)	(0.0019)	(0.0012)	(0.0013)
Log(Age)_{t-1}	-0.0001	-0.0001	0.0007	-0.0008	-0.0005	-0.0004	0.0004	-0.0006
	(0.0005)	(0.0007)	(0.0005)	(0.0005)	(0.0011)	(0.0009)	(0.0006)	(0.0007)
Log(TNA)_{t-1}	0.0001	-0.0001	-0.0003*	0.0000	0.0002	0.0003*	-0.0003**	-0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Expense_{t-1}	0.3095*	-0.1171	-0.4827***	-0.3342***	0.0811	0.1095	-0.3970***	-0.5589***
	(0.1866)	(0.1692)	(0.1373)	(0.1076)	(0.2224)	(0.2148)	(0.1266)	(0.1679)
Flow_{t-1}	-0.0036	0.0098**	-0.0013	0.0022	0.0047	0.0062	0.0009	-0.0009
	(0.0037)	(0.0049)	(0.0034)	(0.0040)	(0.0054)	(0.0056)	(0.0050)	(0.0034)
Activeness_{t-1}	-0.0281***	-0.0265***	0.0040	-0.0032	-0.0000	-0.0066**	-0.0048*	-0.0052**
	(0.0050)	(0.0073)	(0.0047)	(0.0052)	(0.0032)	(0.0029)	(0.0027)	(0.0025)
Turnover_{t-1}	0.0000	-0.0010***	-0.0005***	-0.0007***	-0.0052***	-0.0052**	-0.0009	0.0003
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0017)	(0.0023)	(0.0011)	(0.0013)
Constant	-0.0015	0.0020	-0.0007	0.0038*	0.0008	0.0005	0.0029	0.0055*
	(0.0020)	(0.0025)	(0.0018)	(0.0019)	(0.0041)	(0.0041)	(0.0027)	(0.0028)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	2634	2634	2094	2094	2399	2399	2985	2985
R-squared	0.114	0.120	0.130	0.145	0.070	0.085	0.088	0.064

Table 2.5: Performance in Up and Down markets

The table presents the results of panel regressions of fund's performance measure on a dummy variable indicating whether a fund is an actively managed ETFs and the determinants of fund's performance as control variables, in periods of up and down market:

$$
\begin{aligned}
Performance_{i,t} = \beta_0 + \beta_1 Active_{i,t} + \beta_2 Log(Age)_{i,t-1} + \beta_3 Log(TNA)_{i,t-1} + \beta_4 Expense_{i,t-1} \\
+ \beta_5 Flow_{i,t-1} + \beta_6 Activeness_{i,t-1} + \beta_7 Turnover_{i,t-1} \\
+ (CategoryFixedEffects) + (TimeFixedEffects) + \epsilon_{i,t}
\end{aligned}
$$

where *Active* is a dummy variable with the value of 1 if the fund is an actively managed ETF; *Log(Age)* is the natural log of the fund's age in months; *Log(TNA)* is the natural log of the fund's total net assets; *Expense* is the fund's expense ratio; *Flow* is the fund's net flow; *Performance* is the fund's performance measured by factor model alphas and benchmark adjusted returns. *TE* is the fund's tracking error. *Turnover* is the fund's turnover ratio. The regression includes calendar month and category fixed effects. Standard errors are in parentheses and clustered at the fund level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

	US Equity				**International Equity**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Up	Up	Down	Down	Up	Up	Down	Down
	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret
$Active_t$	-0.0009	0.0011	-0.0004	-0.0012	0.0024**	0.0042**	0.0019	0.0012
	(0.0008)	(0.0010)	(0.0017)	(0.0014)	(0.0012)	(0.0017)	(0.0024)	(0.0018)
$Log(Age)_{t-1}$	-0.0000	-0.0000	0.0001	-0.0023**	0.0001	0.0018**	-0.0046***	0.0001
	(0.0004)	(0.0006)	(0.0011)	(0.0010)	(0.0009)	(0.0008)	(0.0017)	(0.0011)
$Log(TNA)_{t-1}$	0.0001	-0.0002	-0.0003	0.0004	-0.0002	-0.0002	0.0007**	0.0000
	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
$Expense_{t-1}$	0.1853	-0.1863	-0.6626**	-0.1076	-0.2009	-0.0961	-0.4549	0.0634
	(0.1928)	(0.1562)	(0.3127)	(0.2623)	(0.1608)	(0.2089)	(0.3328)	(0.2128)
$Flow_{t-1}$	-0.0018	0.0078*	-0.0026	0.0082	0.0027	0.0042	0.0006	0.0049
	(0.0031)	(0.0040)	(0.0061)	(0.0060)	(0.0047)	(0.0041)	(0.0063)	(0.0062)
$Activeness_{t-1}$	-0.0296***	-0.0253***	0.0348***	0.0143	-0.0035	-0.0109***	0.0070**	-0.0009
	(0.0053)	(0.0059)	(0.0088)	(0.0088)	(0.0030)	(0.0030)	(0.0028)	(0.0030)
$Turnover_{t-1}$	-0.0002	-0.0016***	-0.0002	0.0010***	-0.0039***	-0.0046**	0.0007	-0.0025
	(0.0003)	(0.0002)	(0.0004)	(0.0003)	(0.0013)	(0.0020)	(0.0028)	(0.0023)
Constant	-0.0005	0.0026	-0.0005	0.0060*	0.0025	-0.0041	0.0141**	-0.0013
	(0.0017)	(0.0021)	(0.0038)	(0.0035)	(0.0031)	(0.0033)	(0.0067)	(0.0041)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	3384	3384	1344	1344	3470	3470	1914	1914
R-squared	0.129	0.161	0.129	0.166	0.057	0.079	0.096	0.108

Table 2.6: Determinants of flows

The table presents the results of panel regressions of fund's flows on a dummy variable indicating whether a fund is an actively managed ETFs and the determinants of fund's performance as control variables:

$$\begin{aligned} Flow_{i,t} &= \beta_0 + \beta_1 Active_{i,t} + \beta_1 Performance_{i,t-1} + \beta_2 Performance_{i,t-1}.Active_{i,t} \\ &+ \sum_j \beta_j FundVariables_{i,t-1} + \sum_k \beta_k ExchangeVariables_{i,t-1} \\ &+ (CategoryFixedEffects) + (TimeFixedEffects) + \epsilon_{i,t} \end{aligned}$$

where *Active* is a dummy variable with the value of 1 if the fund is an actively managed ETF; *Performance* is the fund's performance measured by factor model alphas and benchmark adjusted returns. Fund variables include the fund's tracking errors, fund's flows in the previous three months, fund age and total net assets, expense and turnover ratios, and fund's return volatility. Exchange variables are standard deviation of daily volumes, average and standard deviation of daily bid-ask spreads, price-nav ratio and share turnover. The regression includes calendar month and category fixed effects. Standard errors are in parentheses and clustered at the fund level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

Panel A: US Equity				
	(1)	(2)	(3)	(4)
	Flow(FFC)	Flow(FF)	Flow(CAPM)	Flow(benchmark adj. ret)
Active$_t$	-0.0030	-0.0024	-0.0028	-0.0039
	(0.0055)	(0.0055)	(0.0055)	(0.0055)
Alpha$_{t-1}$	0.4541***	0.3856***	0.4562***	
	(0.1456)	(0.1361)	(0.1140)	
Alpha$_{t-1} * Active_t$	0.0334	0.1609	0.0255	
	(0.1770)	(0.1703)	(0.1675)	
Benchmark adj. ret$_{t-1}$				0.3444**
				(0.1536)
Benchmark adj.rett-1*Active$_t$				0.1271
				(0.2179)
FRR$_{t-1}$	0.3940***	0.3676***	0.1379	
	(0.1024)	(0.1137)	(0.1646)	
FRR$_{t-1} * Active_t$	-0.0437	-0.0604	-0.0519	
	(0.0647)	(0.0657)	(0.0628)	
Log(Age)$_{t-1}$	-0.0176***	-0.0176***	-0.0174***	-0.0174***
	(0.0047)	(0.0047)	(0.0047)	(0.0047)
Log(TNA)$_{t-1}$	0.0006	0.0006	0.0005	0.0007
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Expense$_{t-1}$	-3.7748***	-3.7899***	-3.8469***	-3.7468***
	(1.0349)	(1.0375)	(1.0379)	(1.0473)
Turnover$_{t-1}$	0.0010	0.0010	0.0010	0.0012
	(0.0014)	(0.0014)	(0.0014)	(0.0015)
Fund volatility$_{t-1}$	0.7033**	0.7018**	0.8155***	0.7264***
	(0.2762)	(0.2776)	(0.2914)	(0.2703)
Std. daily volume$_{t-1}$	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ave. daily spread$_{t-1}$	0.0190	0.0192	0.0185	0.0208
	(0.0278)	(0.0278)	(0.0280)	(0.0276)
Std. daily spread$_{t-1}$	0.0169	0.0168	0.0169	0.0163
	(0.0131)	(0.0131)	(0.0131)	(0.0131)
Price-NAV$_{t-1}$	3.4198***	3.4072***	3.3716***	3.5656***
	(0.9847)	(0.9805)	(0.9794)	(0.9922)
Share turnover$_{t-1}$	0.0590***	0.0589***	0.0592***	0.0601***
	(0.0170)	(0.0170)	(0.0170)	(0.0173)
Constant	-3.3655***	-3.3528***	-3.3190***	-3.5089***
	(0.9872)	(0.9829)	(0.9818)	(0.9947)
Fixed Effects	Yes	Yes	Yes	Yes
Coefficient sum	0.4875***	0.5465***	0.4817***	0.4715***
Number of observations	4876	4876	4876	4876
R-squared	0.137	0.137	0.138	0.134

Table 2.6: Determinants of Flows (continued)

Panel B: US Equity (ANT)				
	(1)	(2)	(3)	(4)
	Flow(FFC)	Flow(FF)	Flow(CAPM)	Flow(benchmark adj. ret)
Active$_t$	-0.0219	-0.0251	-0.0234	-0.0114
	(0.0218)	(0.0220)	(0.0219)	(0.0228)
Alpha$_{t-1}$	0.7554***	0.6884***	0.5012***	
	(0.2498)	(0.2255)	(0.1776)	
Alpha$_{t-1} * Active_t$	0.2259	-0.0973	0.6281	
	(0.7860)	(0.8183)	(0.5622)	
Benchmark adj. ret$_{t-1}$				0.4329**
				(0.2111)
Benchmark adj.ret$_{t-1} * Active_t$				1.2566
				(1.1573)
FRR$_{t-1}$	0.4615*	0.4055*	0.6645*	
	(0.2382)	(0.2181)	(0.3620)	
FRR$_{t-1} * Active_t$	0.6518***	0.7459***	0.6845***	
	(0.2327)	(0.2336)	(0.1475)	
Log(Age)$_{t-1}$	-0.0157**	-0.0159**	-0.0162**	-0.0154**
	(0.0062)	(0.0062)	(0.0062)	(0.0061)
Log(TNA)t-1	-0.0023	-0.0022	-0.0021	-0.0022
	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Expense$_{t-1}$	-6.2052*	-6.0539*	-6.0281*	-5.9830*
	(3.1369)	(3.1465)	(3.1211)	(3.1221)
Turnover$_{t-1}$	0.0147**	0.0144**	0.0144**	0.0145**
	(0.0064)	(0.0065)	(0.0064)	(0.0064)
Fund volatility$_{t-1}$	-0.7009*	-0.7727**	-0.7981**	-0.7869**
	(0.3810)	(0.3846)	(0.3594)	(0.3802)
Std. daily volume$_{t-1}$	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ave. daily spread$_{t-1}$	-0.0778	-0.0762	-0.0739	-0.0847
	(0.0569)	(0.0567)	(0.0564)	(0.0569)
Std. daily spread$_{t-1}$	0.0153	0.0145	0.0162	0.0246
	(0.0219)	(0.0222)	(0.0220)	(0.0215)
Price-NAV$_{t-1}$	10.1654***	10.1064***	10.2380***	10.4229***
	(3.2579)	(3.2932)	(3.3028)	(3.3156)
Share turnover$_{t-1}$	0.0347**	0.0349**	0.0352**	0.0374**
	(0.0168)	(0.0170)	(0.0170)	(0.0170)
Constant	-10.0256***	-9.9623***	-10.0992***	-10.2707***
	(3.2475)	(3.2834)	(3.2934)	(3.3070)
Fixed Effects	Yes	Yes	Yes	Yes
Coefficient sum	0.9813	0.5911	1.1293**	1.6895
Number of observations	1372	1372	1372	1372
R-squared	0.148	0.148	0.147	0.142

Table 2.6: Determinants of flows (continued)

Panel C: International Equity				
	(1)	(2)	(3)	(4)
	Flow(FFC)	Flow(FF)	Flow(CAPM)	Flow(benchmark adj. ret)
Active$_t$	-0.0243***	-0.0241***	-0.0242***	-0.0242***
	(0.0072)	(0.0071)	(0.0071)	(0.0072)
Alpha$_{t-1}$	0.4497***	0.4076***	0.4044***	
	(0.0762)	(0.0707)	(0.0735)	
Alpha$_{t-1} * Active_t$	0.1011	0.1747	0.2244	
	(0.1784)	(0.1790)	(0.1696)	
Benchmark adj. ret$_{t-1}$				0.4326***
				(0.0811)
Benchmark adj.ret$_{t-1} * Active_t$				0.0424
				(0.1902)
FRR$_{t-1}$	0.3450***	0.4183***	0.4720**	
	(0.0964)	(0.1133)	(0.1855)	
FRR$_{t-1} * Active_t$	0.0715	0.0569	0.0475	
	(0.0998)	(0.0985)	(0.0990)	
Log(Age)$_{t-1}$	-0.0179***	-0.0178***	-0.0179***	-0.0179***
	(0.0049)	(0.0049)	(0.0049)	(0.0049)
Log(TNA)$_{t-1}$	0.0004	0.0004	0.0004	0.0003
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Expense$_{t-1}$	-2.5334**	-2.5470***	-2.5263**	-2.4892**
	(0.9722)	(0.9725)	(0.9721)	(0.9682)
Turnover$_{t-1}$	0.0084	0.0085	0.0085	0.0075
	(0.0062)	(0.0062)	(0.0061)	(0.0062)
Fund volatility$_{t-1}$	0.1612	0.1503	0.1580	0.1940
	(0.2349)	(0.2359)	(0.2301)	(0.2340)
Std. daily volume$_{t-1}$	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ave. daily spread$_{t-1}$	-0.0183	-0.0183	-0.0185	-0.0194
	(0.0211)	(0.0212)	(0.0212)	(0.0212)
Std. daily spread$_{t-1}$	0.0642**	0.0643**	0.0655**	0.0653**
	(0.0259)	(0.0259)	(0.0259)	(0.0262)
Price-NAV$_{t-1}$	3.1833***	3.1959***	3.1717***	3.0964***
	(0.4304)	(0.4307)	(0.4313)	(0.4365)
Share turnover$_{t-1}$	0.0409***	0.0410***	0.0409***	0.0410***
	(0.0110)	(0.0110)	(0.0110)	(0.0111)
Constant	-3.1048***	-3.1179***	-3.0939***	-3.0162***
	(0.4316)	(0.4318)	(0.4326)	(0.4378)
Fixed Effects	Yes	Yes	Yes	Yes
Coefficient sum	0.5508***	0.5823***	0.6288***	0.4750***
Number of observations	5509	5509	5509	5509
R-squared	0.128	0.127	0.127	0.126

Table 2.7: Propensity-score-matched sample: Are active ETFs really active?

The table presents the results of panel regressions Tracking errors (Panel A) and Activeness (Panel B) on a dummy variable indicating whether a fund is an actively managed ETFs and the determinants of tracking error as control variables:

$$\begin{aligned} TE_{i,t} &= \beta_0 + \beta_1.Active_{i,t} + \beta_2.Log(Age)_{i,t-1} + \beta_3.Log(TNA)_{i,t-1} \\ &+ \beta_4.Expense_{i,t-1} + \beta_5.Fund\ volatility_{i,t-1} + \beta_6.Log(Holdings)_{i,t-1} \\ &+ (CategoryFixedEffects) + (TimeFixedEffects) + \epsilon_{i,t} \end{aligned}$$

where *Active* is a dummy variable with the value of 1 if the fund is an actively managed ETF; *Log(Age)* is the natural log of the fund's age in months; *Log(TNA)* is the natural log of the fund's total net assets; *Expense* is the fund's expense ratio; *Fund volatility* is the volatility of fund's net return; *Number of stocks* is the number of holdings in the fund's portfolio. The regression includes calendar month and category fixed effects. Standard errors are in parentheses and clustered at the fund level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

Panel A: Tracking error									
	US Equity			**US Equity (ANT)**			**International Equity**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	TE1	TE2	TE3	TE1	TE2	TE3	TE1	TE2	TE3
$Active_t$	-0.0000	-0.0000	0.0001	-0.0010*	-0.0013**	-0.0005	-0.0015***	-0.0020***	-0.0016***
	(0.0002)	(0.0003)	(0.0002)	(0.0005)	(0.0006)	(0.0006)	(0.0003)	(0.0003)	(0.0003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	711	711	711	179	179	179	648	648	648
R-squared	0.717	0.713	0.753	0.659	0.662	0.656	0.670	0.663	0.655

Panel B: Activeness (1-R^2)									
	US Equity			**US Equity (ANT)**			**International Equity**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Activeness(FFC)	Activeness(FF)	Activeness(CAPM)	Activeness(FFC)	Activeness(FF)	Activeness(CAPM)	Activeness(FFC)	Activeness(FF)	Activeness(CAPM)
$Active_t$	-0.0200***	-0.0229**	-0.0212	-0.0294*	-0.0427*	-0.0393	-0.0906***	-0.0682***	-0.0996***
	(0.0068)	(0.0091)	(0.0228)	(0.0171)	(0.0229)	(0.0343)	(0.0248)	(0.0254)	(0.0273)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	711	711	711	179	179	179	648	648	648
R-squared	0.524	0.513	0.592	0.453	0.423	0.617	0.505	0.499	0.563

Table 2.8: Propensity-score-matched sample: OLS regressions of performance measures

The table presents the results of panel regressions of fund's performance measure on a dummy variable indicating whether a fund is an actively managed ETFs and the determinants of fund's performance as control variables. The regression includes calendar month and category fixed effects. Standard errors are in parentheses and clustered at the fund level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

Panel A: Whole sample

	US Equity		**US Equity (ANT)**		**International Equity**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret
Active_t	-0.0007	-0.0010	-0.0034	-0.0033	0.0040*	0.0039
	(0.0010)	(0.0012)	(0.0033)	(0.0037)	(0.0024)	(0.0024)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	785	785	209	209	1024	1024
R-squared	0.152	0.162	0.127	0.217	0.162	0.137

Table 2.8: Propensity-score-matched sample: OLS regressions of performance measures (continued)

Panel B: High vs Low volatility

	US Equity				International Equity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High	High	Low	Low	High	High	Low	Low
	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret
$Active_t$	-0.0017	-0.0004	0.0013	0.0008	0.0047	0.0074**	0.0027	0.0006
	(0.0014)	(0.0017)	(0.0017)	(0.0012)	(0.0030)	(0.0031)	(0.0027)	(0.0023)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	579	579	206	206	495	495	529	529
R-squared	0.139	0.139	0.280	0.319	0.140	0.138	0.225	0.171

Panel C: Up vs. Down market

	US Equity				International Equity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Up	Up	Down	Down	Up	Up	Down	Down
	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret	Alpha(FFC)	Benchmark adj. ret
$Active_t$	-0.0003	-0.0004	-0.0018	-0.0014	0.0040*	0.0049*	0.0028	0.0016
	(0.0014)	(0.0015)	(0.0023)	(0.0021)	(0.0022)	(0.0027)	(0.0039)	(0.0037)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	570	570	213	213	672	672	352	352
R-squared	0.187	0.187	0.219	0.291	0.139	0.131	0.230	0.213

Chapter 3

Institutional ownership stability and product quality failures

3.1 Introduction

Product recalls have been rising (Bapuji, 2012) and attracted greater attention from researchers in multiple disciplines in recent years (Li et al., 2022). In the US, federal regulations require that a firm reports the defects to the relevant regulating agency and immediately stops selling the product once the firm detects a safety defect or a fundamental failure[1]. Thus, product recalls manifest failures in the firm product quality management (Kini et al., 2022).

Prior studies suggest that recall incidents are highly costly to the recalling firms. These firms have to bear the direct costs, including the costs of repairing or replacing the defective products, the shipping and transaction costs of the recall process, the costs arising from potential lawsuits, and the costs to improve product quality (Jarrell and Peltzman, 1985; Barber and Darrough, 1996). Moreover, product quality deficiencies reduce the credibility and legitimacy of the recalling firms to customers (Liu et al., 2020), leading to a significant decline in their intention to purchase products (Yu et al., 2018) and, therefore, lower future sales revenues (Topaloglu and Gokalp, 2018).

Market participants generally perceive product recalls as negatively affecting future performance and risk of recalling firms. Chen and Nguyen (2013) document that financial analysts revise their earnings forecasts downward after recall announcements. Banks consider firms involved in product recalls to have higher default risk and charge higher interest rates (Zhang et al., 2022). Govindaraj et al. (2004) and Unsal et al. (2017) consistently document that markets negatively react to product recall announcements. Moreover, the negative impact

[1]Consumer Product Safety Commission (CPSC), Food and Drug Administration (FDA), and National Highway Traffic Safety Administration (NHTSA) are the US agencies regulating safety for the different types of products.

of product recalls on firm values can linger for up to two months (Pruitt and Peterson, 1986) and even twelve months (Liu et al., 2017).

Given the adverse long-term effects of product recalls on various perspectives of firm performance, the frequency and severity of recall incidence seriously concern all stockholders[2], especially institutional investors. Therefore, this study examines whether stable institutional investors, by their monitoring efforts, mitigate product quality failures, as measured by the firm's propensity, number, and severity of product recall incidents.

Institutional investors are the largest owners of US firms and can effectively shape corporate policies. The prior literature suggests that institutional investors with persistent holdings exhibit greater commitment and monitor the investee firms more effectively. Elyasiani and Jia (2010) find that institutional ownership stability increases firm performance by reducing information asymmetry and using incentive-based compensation. Other studies document that firms with stable institutional investors manage their earnings less (Sakaki et al., 2017); have lower cost of debt (Elyasiani et al., 2010); lower future stock price crash risk (Callen and Fang, 2013); higher propensity to pay dividends (Jory et al., 2017); and higher level of innovation (Sakaki and Jory, 2019). Regarding non-financial performance, stable institutional ownership enhances corporate social performance (Wang and Sun, 2022) and reduces workplace injury (Amin and Sakaki, 2022).

Overall, the empirical evidence highlights the significant monitoring benefits of stable institutional investors. Therefore, we expect that stable institutional investors can effectively improve product quality in investee firms, thereby reducing recall incidents. In addition, as the costs and reputation damage increase with the severity of product recalls (Pozo and Schroeder, 2016; Ni et al., 2016), the performance of stable institutional investors is more heavily affected in more severe recall incidents. Consequently, they will also aim to mitigate the severity of product quality failures through monitoring channels. Lastly, firms can take a proactive approach to minimize the devastating effect of recall incidents (Zhao et al., 2013; Zhang et al.,

[2]https://www.reuters.com/business/healthcare-pharmaceuticals/dutch-shareholders-threaten-sue-philips-over-recall-media-2022-09-12/

2022). As a result, we hypothesize that institutional investors with persistent holdings will encourage their investee firms to make voluntary and prompt responses to product defects.

Using data on recall incidents covered by the Food and Drug Administration (FDA), Consumer Product Safety Commission (CPSC), and National Highway Traffic Safety Administration (NHTSA) from 2012 to 2021, we document the empirical evidence supporting our hypotheses. First, stable institutional investors reduce the propensity and the frequency of product recall incidents of investee firms. Second, we rely on the FDA classification of recall severity and find that institutional ownership stability is negatively associated with the severity of product quality failures. Finally, tests using CPSC recall announcements confirm that firms with larger stable institutional ownership are more likely to adopt a proactive recall strategy.

As stable institutional investors tend to maintain their holdings for an extended period, their investment performance will be heavily affected by recall incidents. Our results align with the expectation that these institutional investors have strong incentives and motives to effectively monitor their investee firms to maintain appropriate quality management and avoid product issues. The empirical findings remain robust when we carry out several robustness checks to address the endogeneity concerns and when we use alternative measures of institutional ownership stability.

Next, we examine the channel through which stable institutional investors can improve quality management of their investee firms. Prior studies suggest that over-investment could distort product quality (Shah et al., 2017; Thirumalai and Sinha, 2011) as an excessive pursuit of product variety without adequate focus can lead to the trade-off between quality and quantity. Therefore, one possible mechanism is that institutional investors with large and persistent holdings can enhance the investment efficiency of their investee firms. Consistent with our hypothesis, we document a negative relationship between institutional ownership stability and over-investment.

As managers play an essential role in product quality management and recall decisions (Li et al., 2022), we extend our analysis to investigate the heterogeneous effect of ownership stability on recall incidence based on managerial ability and experience. The previous literature suggests that more able and generalist CEOs demonstrate better management efficiency and benefit firms in various aspects (Demerjian et al., 2012; Bonsall IV et al., 2017; Custódio et al., 2013; Betzer et al., 2020). Therefore, we expect that stable institutional investors may exhibit weaker monitoring efforts in firms with high managerial ability and generalist CEOs. The empirical results support our hypothesis.

Finally, we document that stable ownership by active investors such as investment companies and investment advisors can more effectively enhance product quality management of their investee firms than passive and other types of stable institutional holdings. This finding is consistent with the prior evidence that passive investors, such as banks and insurance companies, may not be able to intensely monitor management due to their deep business relations with the firms (Elyasiani et al., 2010; Sakaki et al., 2017; Jory et al., 2017). Furthermore, banks likely adjust loan pricing upward for recalling firms (Zhang et al., 2022) and, therefore, may not have strong incentives to reduce product failures of investee firms.

We contribute to two main strands of literature. First, we extend the empirical evidence on the impact of institutional ownership stability on firm outcomes. Prior studies generally support the monitoring theory of stable institutional investors that they can push management toward maximizing long-term value rather than meeting short-term earnings goals (Dobrzynski, 1993; Monks and Minow, 1995). We add to the literature by showing that firms with more stable institutional ownership experience lower likelihood, number, and less severe product deficiencies and are more likely to adopt a proactive approach in dealing with recall incidence.

Second, we complement the literature on the determinants of product quality failures. Li et al. (2022) summarize the extensive literature on product recall research and suggest that both firm internal and external stakeholders can affect product quality management. Managers' risk-taking and ownership weaken quality management and make firms more susceptible to product failures (Kashmiri et al., 2017; Wowak et al., 2015). Moreover, employee characteristics such as production experience (Haunschild and Rhee, 2004) and unionization rate (Kini et al., 2022) can affect the likelihood of recall incidents. Finally, Kashmiri and Brower (2016) find that firms with higher family ownership are less likely to experience product recalls. External stakeholders such as suppliers and competitors also affect the propensity for product recalls (Steven et al., 2014; Ball et al., 2018). We demonstrate that institutional investors with large and persistent holdings also play an essential role in preventing product quality failures of their investee firms.

The remainder of the paper proceeds as follows. Section 3.2 describes the data and variable construction. Section 3.3 presents our main empirical findings. Section 3.4 and 3.5 contain the robustness checks and cross-sectional heterogeneity tests. Finally, Section 3.6 concludes the paper.

3.2 Data and variables

3.2.1 Product recalls

Following Kini et al. (2022), we collect product recall incidents from three primary sources. The food, drug, and medical device recalls are from the Food and Drug Administration (FDA). The consumer product recalls are from the Consumer Product Safety Commission (CPSC). Finally, automobile recalls are from the National Highway Traffic Safety Administration (NHTSA). From each source, we collect information on the manufacturers, the recalled products, the number of units recalled, the reasons for recalls, and the recall dates. Our sample includes 6,793 recall events during the period 2012-2021. Table 3.1 provides a detailed description of the number of recall incidents covered by each regulator over time.

[Please insert Table 3.1 here]

Our primary dependent variable, *Recall*, is a dummy variable that takes a value of 1 if a firm is a recalling firm and 0 if the firm is the control firm. A recalling firm is a firm that has at least one recall incident in a particular year. For each recalling firm, we select the control firms as those that are in the same 3-digit SIC industry code as the recalling firm in the same year but do not have any recall incidents during the whole sample period. We also examine the relationship between institutional ownership stability and the frequency of recalls, denoted as *#Recall*. For control firms, *#Recall* has a value of 0.

Additionally, the FDA classification allows us to collect data on the level of recall severity. The agency classifies recall incidents into three classes based on the severity of product failures. Class I recalls are considered the most severe, likely to "cause adverse health consequences or death," class II likely to "cause temporary or medically reversible adverse health consequences," and class III the least severe incidents. Consequently, we create a variable *Severity*, which has discrete values from 0 to 3[3], showing the increasing level of recall severity.

3.2.2 Institutional ownership stability

The institutional ownership stability measure is constructed based on data from the Thompson-Reuters Institutional (13f) Holdings database. Following Elyasiani and Jia (2008) and Amin and Sakaki (2022), we use institutional ownership persistence (IOP) as our main proxy for institutional ownership stability. IOP is calculated as the ratio of the average percentage ownership to the standard deviation of percentage ownership over a five-year period (20 quarters) that include the current year and the previous four years. Finally, we average across all institutional investors in the firm to create a firm-level measure of institutional ownership stability.

In detail, for each firm-year observation, institutional ownership persistence is calculated as:

$$IOP_{i,t} = \sum_{j=1}^{J_i} [(\sum_{t=1}^{20} \frac{p_{i,t}^j}{20})/Std(p_{i,t}^j)]/J_i \tag{3.1}$$

where $p_{i,t}^j$ is the proportion of firm i held by investor j at time t, J_i is the number of institutional investors in firm i, and $Std(p_{i,t}^j)$ is the standard deviation of $p_{i,t}^j$ over the previous 20 quarters (i.e., the current year and the previous 4 years).

3.2.3 Firm-related variables

We use several financial and non-financial control variables that can relate to the product recall probability. Firm-level financial data are from Compustat. Kini et al. (2017) report that leverage can be an essential determinant of recall incidents. Therefore, we include firm leverage as a control variable in our analysis. *Leverage* is the sum of the long-term debt and debt in current liabilities (Compustat item DLTT+ Compustat item DLC) divided by total assets (Compustat

[3] *Severity* has values of 3 for class I recalls, values of 2 for class II recalls, and values of 1 for class III recalls. For control firms, *Severity* has values of 0.

item AT). We also control other financial factors like cash, firm size, asset turnover, tangible assets, capital expenditure, market-to-book value, and R&D activity, which are defined as follows. *Cash* is total cash and equivalents (Compustat item CHE) divided by total assets. *Log(Size)* is the natural logarithm of total assets. *Turnover* is total sales (Compustat item REVT) divided by total assets. *Tangibility* is net property, plant, and equipment (Compustat item PPENT) scaled by total assets. *CAPEX* is capital expenditure (Compustat item CAPX) divided by total assets. *Market to book* is the market value of equity (Compustat item PRCC_F * Compustat item CSHO) divided by the book value of equity (Compustat item CEQ). *RD intensity* is measured as the ratio of the research and development expenditure (Compustat item XRD) to total assets.

We calculate *Total factor productivity* following Kini et al. (2017) and Faleye et al. (2006). Specifically, for each two-digit SIC industry and year, we regress the natural logarithm of firm sales on the natural logarithm of the number of employees (Compustat item EMP) and the natural logarithm of net property, plant, and equipment. *Total factor productivity* is the residual from this regression. Also, *HHI* is the sales-based Herfindahl index for the three-digit SIC industry of the recalling (control) firm.

Finally, we obtain data from the Union Stats website[4] to construct the *Unionization* variable. This database reports industry unionization rates for each three-digit Census Industry Classification (CIC) industry. Following Kini et al. (2017), we identify the corresponding four-digit SIC codes for each three-digit CIC code and then assign industry unionization rates to all firms in our sample. When we are unable to assign a four-digit SIC industry, we impute the unionization rates at the three-digit SIC industry level.

The independent variables in the regressions are lagged by one year. Table 3.2 provides summary statistics for all variables in our analysis. All continuous variables are winsorized at their 1st and 99th percentiles to mitigate the impact of possible outliers.

[Please insert Table 3.2 here]

[4]http://www.unionstats.com

3.3 Empirical results

3.3.1 The impact of institutional ownership stability on recall incidence

We start our empirical analysis by examining the effect of institutional ownership stability on the probability of a firm having recall incidents, using the following Probit regression model:

$$Prob(Recall_{i,t} = 1) = F(\beta_0 + \beta_1 IOP_{i,t-1} + \sum_k \gamma_k Controls_{i,t-1} + \delta_t + \theta_i + \epsilon_{i,t}). \quad (3.2)$$

where the dependent variable is the dummy variable *Recall*, which takes the value of 1 if at least 1 recall takes place for firm *i* in year *t*; and 0 if the firm is a control firm. The primary independent variable of interest is the 1-year lagged institutional ownership stability *IOP*. Other control variables include *Leverage*, *Cash*, *Log(Size)*, *Turnover*, *Tangibility*, *Capex*, *Market to book*, *RD intensity*, *Total factor productivity*, *HHI*, and *Unionization*. We also include year dummies and/or industry dummies in different regression specifications.

Table 3.3 summarizes the results and reports marginal effects. We control for industry dummies in Column (1), for year dummies in Column (2), and year and industry dummies in Column (3). As presented, the relation between *IOP* and *Recall* is negative and significant at the 1% level in all three columns. The results indicate that firms with more stable institutional investors have a lower likelihood of product recall incidents. Specifically, a one standard deviation increase in IOP is associated with a 2.10-percentage-point decrease in the probability of a recall (Column (3)). The impact is economically meaningful, given the sample mean for *Recall* is 7.8 percent in Table 3.1.

[Please insert Table 3.3 here]

3.3.2 The impact of institutional ownership stability on the frequency of recall incidence

To further assess the impacts of institutional ownership stability on recall incidents, we extend our analysis to the frequency of recalls, using the following regression model:

$$\#Recall = F(\beta_0 + \beta_1 IOP_{i,t-1} + \sum_k \gamma_k Controls_{i,t-1} + \delta_t + \theta_i + \epsilon_{i,t}). \quad (3.3)$$

Our new dependent variable is *#Recall*, which is the number of recalls of each firm per year. Since the number of recall incidents (#Recall) is a count variable with dispersed and excessive zero values, the Negative Binomial regression model is the appropriate framework. The independent variables are the same as those in the previous regression.

The results are presented in Table 3.4. Consistent with our findings in the previous section, we document that institutional ownership stability is negatively and significantly correlated with the frequency of recalls. These findings are robust to all three different regression specifications.

Overall, the empirical evidence confirms our hypothesis that institutional investors with large and persistent holdings can effectively reduce the propensity and number of product recall of investee firms.

[Please insert Table 3.4 here]

3.3.3 The impact of institutional ownership stability on recall severity

In this section, we examine our second hypothesis on whether stable institutional investors, through their monitoring activities, can mitigate the severity of recall incidents. Even though we collect recall events from the FDA, CPSC, and NHTSA, only the FDA assigns the severity to product failures. Therefore, we limit our analysis to the FDA sample and use the following regression model:

$$Severity_{i,t} = \beta_0 + \beta_1 IOP_{i,t-1} + \sum_k \gamma_k Controls_{i,t-1} + \delta_t + \theta_i + \epsilon_{i,t} \tag{3.4}$$

where *Severity* is the severity level of each recall incident of firm *i* in year *t*. Table 3.5 reports the Ordered Probit regression results on the relation between institutional holdings stability (*IOP*) and the severity of recall incidents. The results support our expectation of the benefits of institutional ownership stability in enhancing product quality. Specifically, the coefficient estimates of the variable *IOP* are negative and statistically significant at the 1% level in all specifications.

[Please insert Table 3.5 here]

3.3.4 The impact of institutional ownership stability on recall strategy

The previous literature suggests that the approach adopted by recalling firms in response to product deficiencies can affect the market reaction to these incidents. On the one hand, a proactive or preventive strategy implies that a firm frequently conducts quality checks and inspections to identify defects that may pose significant dangers to consumers and recall these products before any injury is reported. On the other hand, firms can choose a passive approach and only recall their products after product-related accidents have already occurred. A responsive and proactive recall can signal firms' responsibility and commitment to the safety of their consumers and, therefore, can help alleviate the negative impacts of recall incidence on firm value and performance. On the contrary, a passive recall strategy can significantly damage customer trust and confidence in the brand and company (Smith et al., 1997). Consistent with these reasonings, Zhao et al. (2013) document that the market reacts more negatively to passive than proactive recall strategy. In addition, recalling firms that adopt a passive approach experience a larger increase in bank loan interest rates than those that proactively responds to product quality concerns (Zhang et al., 2022). Consequently, we expect that firms with more stable institutional investors are more likely to act proactively in recall incidence.

Following Chen et al. (2009) and Zhang et al. (2022), we examine the impact of institutional ownership stability on the choice of product-recall strategy using the data from CPSC. Since each CPSC recall announcement specifies the number of reported incidents related to the recalled products by the time the recall was issued, we classify that a firm has adopted a proactive strategy if a recall was issued, but the firm and the CPSC did not receive any incident report. Control firms are also classified as proactive since these firms have actively maintained product quality checks and inspections to prevent any product deficiency that could potentially endanger consumers. We then create a dummy variable *Proactive* that takes values of 1 for proactive firms and 0 otherwise.

Consistent with our hypothesis, the results in Table 3.6 demonstrate that firms with larger institutional ownership stability are more likely to adopt a proactive and preventive strategy to avoid the devastating consequence of recall incidents.

Overall, we provide evidence that stable institutional investors help reduce the propensity, frequency, and severity of investee firms' product recall incidents. In addition, these investors also push the firms to adopt a proactive approach when responding to product deficiencies. Our findings suggest that institutional shareholders with significant and persistent holdings have a strong incentive to monitor the firm management more effectively so that their investee firms experience less severe damage to long-term value and reputation from product quality failures.

[Please insert Table 3.6 here]

3.3.5 Potential channel through which institutional ownership stability affects product quality failures

The prior literature shows that managers' excessive pursuit of value creation makes firms more susceptible to product failures (Shah et al., 2017; Thirumalai and Sinha, 2011). Intuitively, when firms engage in a substantive number of projects that broaden product offerings, it is likely that they cannot ensure the quality of each product and consequently experience more recalls. Therefore, we expect that stable institutional investors, with their efficient monitoring, can discipline managers and prevent the over-investment issues of investee firms, leading to a lower propensity for product failures.

We follow Biddle et al. (2009) to create a dummy variable *Over_investment* that takes a value of 1 if the firm is an over-investing firm, and a value of 0 otherwise. Specifically, we run the following cross-sectional regression for firms within each industry-year based on the 2-digit SIC codes for all industries with at least 20 observations in a given year.

$$Investment_{i,t} = \beta_0 + \beta_1 Sales\_Growth_{i,t-1} + \epsilon_{i,t} \tag{3.5}$$

where $Investment_{i,t}$ is calculated as the sum of research and development expenditure (Compustat item XRD), capital expenditure (Compustat item CAPEX), and acquisitions (Compustat item AQC) less cash receipts from sale of property, plant, and equipment (Compustat item SPPE) and depreciation and amortization (Compustat item DPC), scaled by lagged total assets. $Sales\_Growth_{i,t}$ is the percentage change in sales over the year.

We then use the magnitude of the residuals from this regression (i.e., deviations from expected investment) to identify the over-investing firms as those in the top quartile of each industry-year group.

Using *Over-investment* as the dependent variable and the Probit regression framework, we examine the relation between institutional ownership stability and over-investment in the following regression model.

$$Prob(Over-investment_{i,t}=1)=F(\beta_0+\beta_1 IOP_{i,t-1}+\sum_k \gamma_k Controls_{i,t-1}+\delta_t+\theta_i+\epsilon_{i,t}) \tag{3.6}$$

The results in Table 3.7 show that institutional ownership stability is negatively associated with over-investment. These findings remain robust in all specifications, where we control for different combinations of industry and year fixed effects. In summary, we find that institutional stable institutional owners can effectively enhance product quality management of their investee firms by mitigating the over-investment problems.

[Please insert Table 3.7 here]

3.4 Robustness tests

This section presents two robustness checks of our findings. First, we conduct two tests to deal with the endogeneity issue. Second, we reexamine our results using alternative measures of institutional ownership stability. We also conduct an additional analysis to investigate the various impacts of institutional ownership stability on product quality failures among different institutional investors.

3.4.1 Endogeneity

Reverse causality is a potential concern that could bias our findings. Specifically, product recall incidents may lead to a reduction in institutional ownership stability. We partially mitigate this issue by using lagged values of *IOP* in all previous regressions. In this section, we further address the endogeneity concern by conducting two additional tests.

First, suppose stable institutional investors enhance product quality control, thereby reducing recall incidents of investee firms and not vice versa. In that case, we expect that future *IOP* should be unrelated to the propensity for a recall. Following Kini et al. (2017), we include both the future and past values of *IOP* in regression (3). The result in Column (1) of Table 3.7 shows that only the lag of *IOP* has a significantly negative relation with the dummy variable *Recall*.

Second, we employ the three-stage least-squares (3SLS) method following the prior literature (Amin and Sakaki, 2022; Wang and Sun, 2022) and run a simultaneous regression of the recall probability, *Recall*, and institutional ownership stability, *IOP*. The control variables for *IOP* are *firm size*, *the number of shares outstanding*, *share turnover*, and *stock return volatility*. Columns (2) and (3) of Table 3.8 demonstrate that while lagged *IOP* is negatively associated with the propensity to recall, there is no significant relation between past recall incidents and future institutional ownership stability.

Overall, the empirical evidence suggests that stable institutional investors strengthen product quality control of their investee firms, leading to a lower probability of product recall incidents, and the effect is likely causal.

[Please insert Table 3.8 here]

3.4.2 Alternative measures of institutional ownership stability

According to Bushee (2001), "transient" institutional investors with short-term investment horizons could pressure managers to excessively focus on near-term earnings and less on long-term performance. Meanwhile, "dedicated" institutional investors, who have large and persistent ownership, focus on the long-term performance and monitor the investee firms more effectively (Bushee, 1998; An and Zhang, 2013). Following Callen and Fang (2013), we use the percentage ownership by "dedicated" institutional investors (*DED*) and "transient" institutional investors (*TRA*) as two alternative proxies for institutional ownership stability and reexamine our main hypotheses. The higher the *DED*, the higher the institutional investor stability, and the higher the *TRA*, the lower the institutional investor stability.

Table 3.9 summarizes the results from Model (2) (Columns 1, 2, and 3) and Model (3) (Columns 3, 4, and 6) using the two different measures of institutional ownership stability. The results demonstrate that firms with greater dedicated institutional ownership are less prone to product failures and experience fewer recall incidents. In contrast, transient institutional investors tend to be less vigilant to long-term quality risk, making firms more susceptible to product quality issues.

Our findings extrapolate Bushee (2001)'s and Callen and Fang (2013)'s viewpoints by providing evidence that the level of institutional holdings by transient (dedicated) investors is positively (negatively) associated with the propensity and the frequency of product recall incidents of investee firms. A possible explanation is that dedicated institutional owners have more incentive to control and monitor management toward long-term and more sustainable performance targets. Meanwhile, transient investors are more likely to focus on more myopic short-term earnings targets that can potentially harm the firm's reputation.

[Please insert Table 3.9 here]

3.5 Cross-sectional heterogeneity tests

3.5.1 Managerial ability and generalist CEOs

CEOs or managers are responsible for managing the firm daily operations and business performance. Therefore, they play an essential role in product quality management and decision-making during recall incidents (Li et al., 2022).

Demerjian et al. (2012) develop a measure of managerial ability and find that more able managers can achieve better firm performance as they understand the industry trends and manage firm resources more efficiently. In addition, CEOs who have diverse skills and experience across various industries, i.e., generalist CEOs, can perform more complex tasks (Custódio et al., 2013), enhance firm innovation (Custódio et al., 2019), and are beneficial to shareholders (Betzer et al., 2020).

Therefore, we examine in this section whether the impact of institutional ownership stability on product quality failures varies among firms with high managerial ability and generalist

CEOs. We use the managerial ability index from Demerjian et al. (2012) and the general ability index from Custódio et al. (2013) and identify firms with more able or generalist CEOs as those with index values above the time-series median.

In columns 1 and 2 of Table 3.10, we find no significant difference in the effect of stable institutional ownership on recall incidence between firms with high and low managerial ability, and between firms with generalist and specialist CEOs. More importantly, the negative relation between institutional ownership stability and the probability of recall remains robust when we control for the effect of managerial ability and generalist CEOs. Additionally, the results from columns 3 and 4 show that both institutional ownership stability and managerial ability can help reduce the recall frequency. Finally, institutional shareholders with large and persistent ownership exhibit stronger product quality monitoring in firms with low managerial ability or specialist CEOs, as shown by the positive and significant coefficient estimates of the interaction terms. One possible explanation is that since highly able and generalist CEOs can effectively improve operational efficiency and maintain adequate attention to product quality, stable institutional investors may not necessarily exhibit as strong a monitoring function as in firms with low managerial ability or specialist CEOs.

[Please insert Table 3.10 here]

3.5.2 Institutional investor types

Due to the business relationship with the investee firms and investment schemes, different types of institutional investors have various incentives to monitor. Elyasiani et al. (2010) document that even though all types of stable institutional investors reduce the firm cost of debt, the effect is of larger magnitudes for active investors (investment companies and investment advisors) than passive investors (banks and insurance companies). In the same vein, banks and insurance companies monitor their investee firms less effectively as they do not impact earnings management (Sakaki et al., 2017) or tend to rely on dividend payout to reduce agency conflicts and discipline management (Jory et al., 2017).

Therefore, we examine whether the effect of institutional ownership stability on product quality failures varies among different types of institutions. Following Elyasiani et al. (2010), we classify institutional investors into three categories: active investors (investment companies and independent advisors), passive investors (banks and insurance companies), and other investors (pension funds, hedge funds, endowment funds...). We then estimate *IOP* for each investor type and reexamine our main hypothesis on the relation between institutional ownership stability and product quality failures, using regression model (2). Columns 1, 2, and 3 of Table 3.11 suggest that all types of stable institutional investors can significantly reduce the likelihood of recall incidence of their investee firms. The impact magnitudes are slightly larger for active investors and other investors. However, when we include all three types of stable institutional ownership in column 4, only the coefficient estimate for active investors remains statistically significant. These findings are consistent with the previous literature that institutional investors that do not have a business relationship with firms demonstrate better monitoring efficiency. In contrast, stable holdings by banks and insurance companies do not seem to have significant relation with the recall incidence of investee firms. Two possible reasons can explain this result. First, banks and insurance companies tend to have a deeper business relationship with firms and, therefore, cannot pressure management as effectively as other institutional investors. Second, Zhang et al. (2022) find that banks tend to increase the loan interest rates of firms after recalls. Therefore, banks may not have strong incentives to improve the quality control of their investee firms.

[Please insert Table 3.11 here]

3.6 Conclusions

Given the social and economic consequences of recall incidents, we investigate whether stable institutional ownership influences the investee firm's product quality failures. Using a sample of 6,793 recall incidents from the FDA, CPSC, and NHTSA from 2012 to 2021, we document empirical evidence that institutional ownership stability is negatively associated with the probability and frequency of product failures and reduces the severity of product recall incidents. A possible channel for this negative relation is the limitation of the over-investment issues.

In addition, we find that firms with larger institutional ownership persistence tend to adopt a proactive and preventive recall strategy.

The results from our cross-sectional heterogeneity analyses demonstrate that the impact of institutional ownership stability on product quality failures is slightly weaker in firms with high managerial ability and generalists CEOs. Finally, stable holdings by active investors such as independent advisors and investment companies have a more substantial influence in enhancing the product quality management of their investee firms than passive and other types of stable institutional holdings.

In summary, our findings suggest that stable institutional investors play an essential role in preventing product quality failures that could significantly damage a firm's long-term reputation and value. These results support the monitoring benefits of stable institutional investors, who have the incentives to push management toward pursuing long-term goals.

Table 3.1: Frequency of recall events

This table presents the frequency of recall events by public firms during our sample period of 2012–2021. The table reports product recalls covered by the Food and Drug Administration (FDA), the Consumer Product Safety Commission (CPSC), and the National Highway Traffic Safety Administration (NHTSA).

	Number of observations			
Year of recall	NHTSA	FDA	CPSC	Overall
2012	146	360	34	540
2013	175	559	46	780
2014	298	485	47	830
2015	251	384	41	676
2016	222	433	52	707
2017	205	394	48	647
2018	240	410	30	680
2019	270	338	28	636
2020	284	347	35	666
2021	363	232	36	631
Total	2,454	3,942	397	6,793

Table 3.2: Summary statistics

This table presents the summary statistics of the variables for the sample of public firms included in our study during the 2012-2021 period. Recalls data is from FDA, CPSC, and NHTSA. Firm-level institutional ownership stability measures are constructed based on data from Thompson-Reuters 13F, CRSP databases, and `https://accounting-faculty.wharton.upenn.edu/bushee`. Firm-level control variables are from Compustat and `http://unionstats.com`.

	N	Mean	Median	SD	P25	P75
Recall	6546	0.094	0	0.292	0	0
#Recall	6546	0.477	0	3.191	0	0
IOP	6546	10.063	3.444	27.102	2.012	6.515
DED	6546	0.056	0.031	0.066	0.008	0.085
TRA	6546	0.114	0.104	0.082	0.045	0.167
Leverage	6546	0.201	0.138	0.23	0.001	0.318
Cash	6546	0.366	0.277	0.295	0.109	0.608
Log (Assets)	6546	5.984	5.857	2.091	4.49	7.359
Turnover	6546	0.881	0.736	0.728	0.361	1.197
Tangibility	6546	0.137	0.091	0.142	0.04	0.188
CAPEX	6546	0.036	0.023	0.041	0.01	0.046
Market to book	6546	4.681	2.97	9.768	1.547	5.608
RD intensity	6546	0.147	0.069	0.204	0.016	0.192
Total factor productivity	6546	0.051	0.116	1.032	-0.298	0.568
HHI	6546	0.094	0.048	0.097	0.045	0.088
Unionization (%)	6546	7.054	5.418	5.618	4.05	8.05

Table 3.3: Probit regressions: Impact of institutional ownership stability on recall incidence

This table presents the marginal effects from Probit model regressions for the impact of institutional ownership stability on the probability of a firm being recalled from 2012 to 2021. The dependent variable is the dummy variable *Recall*. This variable has a value of zero for all control firms and 1 for recalling firms. Marginal effects are reported in the table. Robust standard errors are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	Recall	Recall	Recall
IOP_{t-1}	-0.0009***	-0.0008***	-0.0009***
	(0.0002)	(0.0002)	(0.0002)
Leverage_{t-1}	-0.0093	-0.0123	-0.0048
	(0.0155)	(0.0170)	(0.0155)
Cash_{t-1}	-0.0318	-0.0722***	-0.0292
	(0.0223)	(0.0226)	(0.0223)
Log(Size)_{t-1}	0.0409***	0.0351***	0.0407***
	(0.0018)	(0.0018)	(0.0018)
Turnover_{t-1}	0.0198***	0.0178***	0.0191***
	(0.0055)	(0.0053)	(0.0055)
Tangibility_{t-1}	0.0018	-0.0550**	0.0047
	(0.0322)	(0.0278)	(0.0321)
Capex_{t-1}	0.0518	0.1208	0.0474
	(0.1013)	(0.1043)	(0.1009)
Market to book_{t-1}	-0.0003	0.0002	-0.0003
	(0.0003)	(0.0004)	(0.0003)
RD intensity_{t-1}	-0.0026	-0.0597	-0.0023
	(0.0460)	(0.0472)	(0.0458)
Total factor $\text{productivity}_{t-1}$	0.0059	-0.0019	0.0060
	(0.0053)	(0.0048)	(0.0053)
HHI_{t-1}	-0.1704	0.0689**	-0.1410
	(0.1078)	(0.0296)	(0.1099)
$\text{Unionization}_{t-1}$	-0.0016**	0.0038***	-0.0010
	(0.0008)	(0.0009)	(0.0012)
Number of observations	6546	6546	6546
Year dummies	No	Yes	Yes
Industry dummies	Yes	No	Yes
Pseudo R-squared	0.4178	0.2275	0.4197

Table 3.4: Negative Binomial regressions: Impact of institutional ownership stability on the frequency of recall incidence

This table presents the results from Negative binomial regressions for the impact of institutional ownership stability on the number of recall incidences per year from 2012 to 2021. The dependent variable is *#Recall*. This variable has values of zero for all control firms. Robust standard errors are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	#Recall	#Recall	#Recall
IOP_{t-1}	-0.0110***	-0.0136***	-0.0124***
	(0.0031)	(0.0035)	(0.0030)
Leverage_{t-1}	-0.5327*	-0.5577*	-0.3582
	(0.2912)	(0.3063)	(0.2942)
Cash_{t-1}	-0.9632**	-1.7630***	-0.8217**
	(0.3944)	(0.4074)	(0.3799)
Log(Size)_{t-1}	0.7329***	0.5980***	0.7252***
	(0.0431)	(0.0341)	(0.0436)
Turnover_{t-1}	0.6247***	0.1605*	0.5984***
	(0.1321)	(0.0872)	(0.1320)
Tangibility_{t-1}	0.7479	-1.2208**	0.8442
	(0.6111)	(0.5503)	(0.6042)
Capex_{t-1}	-1.4891	2.2792	-2.3173
	(1.8318)	(1.9095)	(1.8646)
Market to book_{t-1}	-0.0184***	-0.0075	-0.0151**
	(0.0062)	(0.0077)	(0.0063)
RD intensity_{t-1}	-1.1653	-2.2657**	-1.1029
	(0.8573)	(0.9210)	(0.8582)
Total factor $\text{productivity}_{t-1}$	-0.1655	-0.1861*	-0.1383
	(0.1409)	(0.1074)	(0.1450)
HHI_{t-1}	-2.4639	-1.5635***	-1.3691
	(1.5134)	(0.5115)	(1.6441)
$\text{Unionization}_{t-1}$	-0.0148	0.1405***	0.0149
	(0.0125)	(0.0206)	(0.0220)
Number of observations	6546	6546	6546
Year dummies	No	Yes	Yes
Industry dummies	Yes	No	Yes
Pseudo R-squared	0.276	0.138	0.280

Table 3.5: Ordered Probit regressions: Impact of institutional ownership stability on recall severity

This table presents the results from the Ordered Probit model regressions for the impact of institutional ownership stability on the severity level of recall incidences reported by the FDA from 2012 to 2021. The dependent variable is *Severity*. This variable has values of zero for all control firms. Robust standard errors are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	Severity	Severity	Severity
IOP_{t-1}	-0.0112***	-0.0100***	-0.0114***
	(0.0033)	(0.0026)	(0.0031)
Leverage_{t-1}	-0.2505	-0.2688*	-0.1689
	(0.1806)	(0.1553)	(0.1820)
Cash_{t-1}	-0.5872***	-0.7562***	-0.5494**
	(0.2255)	(0.1880)	(0.2260)
Log(Size)_{t-1}	0.3526***	0.2752***	0.3504***
	(0.0193)	(0.0158)	(0.0193)
Turnover_{t-1}	0.0481	0.0153	0.0165
	(0.0606)	(0.0524)	(0.0610)
Tangibility_{t-1}	0.0087	0.2756	0.1401
	(0.4181)	(0.3183)	(0.4170)
Cape_{t-1}	2.1155*	1.5281	2.0210
	(1.2496)	(1.0828)	(1.2633)
$\text{Market to book}_{t-1}$	-0.0049	-0.0026	-0.0037
	(0.0035)	(0.0030)	(0.0035)
$\text{RD intensity}_{t-1}$	-0.5004	-0.8591**	-0.4809
	(0.4933)	(0.4213)	(0.4912)
$\text{Total factor productivity}_{t-1}$	-0.0012	-0.0438	0.0045
	(0.0398)	(0.0297)	(0.0401)
HHI_{t-1}	-2.2617	-1.4777***	-0.8106
	(2.0645)	(0.5261)	(2.1093)
$\text{Unionization}_{t-1}$	-0.0149**	-0.0170*	-0.0132
	(0.0065)	(0.0103)	(0.0117)
Number of observations	4459	4459	4459
Year dummies	No	Yes	Yes
Industry dummies	Yes	No	Yes
Pseudo R-squared	0.382	0.234	0.388

Table 3.6: Probit regressions: Impact of institutional ownership stability on recall strategy

This table presents the marginal effects from Probit model regressions for the impact of institutional ownership stability on recall strategy from 2012 to 2021. The dependent variable is *Proactive*. This variable has values of 1 for proactive recalls and for control firms. Marginal effects are reported in the table. Robust standard errors are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	Proactive	Proactive	Proactive
IOP_{t-1}	0.0013***	0.0012**	0.0013***
	(0.0005)	(0.0006)	(0.0005)
$Leverage_{t-1}$	-0.0098	-0.0191	-0.0095
	(0.0175)	(0.0187)	(0.0178)
$Cash_{t-1}$	0.0110	0.0656**	0.0099
	(0.0372)	(0.0329)	(0.0366)
$Log(Size)_{t-1}$	-0.0280***	-0.0238***	-0.0281***
	(0.0037)	(0.0027)	(0.0037)
$Turnover_{t-1}$	-0.0268***	-0.0329***	-0.0266***
	(0.0087)	(0.0057)	(0.0087)
$Tangibility_{t-1}$	-0.0230	0.0217	-0.0268
	(0.0432)	(0.0301)	(0.0428)
$Capex_{t-1}$	-0.1064	-0.1855*	-0.0998
	(0.1254)	(0.0970)	(0.1264)
Market to $book_{t-1}$	-0.0005	-0.0002	-0.0006
	(0.0004)	(0.0004)	(0.0004)
RD $intensity_{t-1}$	-0.0239	0.0164	-0.0280
	(0.0977)	(0.0725)	(0.1002)
Total factor $productivity_{t-1}$	-0.0254**	-0.0136	-0.0258**
	(0.0123)	(0.0095)	(0.0120)
HHI_{t-1}	0.1023	-0.1454***	0.1063
	(0.0882)	(0.0222)	(0.0924)
$Unionization_{t-1}$	-0.0028	-0.0050***	-0.0043
	(0.0032)	(0.0013)	(0.0036)
Number of observations	2413	2620	2413
Year dummies	No	Yes	Yes
Industry dummies	Yes	No	Yes
Pseudo R-squared	0.4675	0.3811	0.4734

Table 3.7: Potential channel through which institutional ownership stability affects product quality failures

This table presents the marginal effects from Probit model regressions for the impact of institutional ownership stability on the probability of over-investment from 2012 to 2021. The dependent variable is *Over-investment*. This variable has a value of 1 for over-investing firms. Marginal effects are reported in the table. Robust standard errors are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	Over-investment	Over-investment	Over-investment
IOP_{t-1}	-0.0004**	-0.0005**	-0.0004**
	(0.0002)	(0.0002)	(0.0002)
Cash_{t-1}	0.3976***	0.3537***	0.3984***
	(0.0249)	(0.0226)	(0.0250)
Log(Size)_{t-1}	-0.0328***	-0.0239***	-0.0327***
	(0.0031)	(0.0030)	(0.0031)
Leverage_{t-1}	0.0742***	0.0536**	0.0768***
	(0.0236)	(0.0239)	(0.0239)
Tangibility_{t-1}	-0.2361***	-0.1733***	-0.2326***
	(0.0570)	(0.0465)	(0.0571)
$\text{Market to book}_{t-1}$	0.0021***	0.0018***	0.0022***
	(0.0005)	(0.0005)	(0.0005)
Turnover_{t-1}	-0.0257***	0.0041	-0.0254***
	(0.0097)	(0.0089)	(0.0098)
HHI_{t-1}	-0.1626	0.2996***	-0.1597
	(0.2134)	(0.0584)	(0.2166)
$\text{Unionization}_{t-1}$	-0.0008	-0.0017	0.0023
	(0.0010)	(0.0016)	(0.0019)
Number of observations	6282	6301	6282
Year dummies	No	Yes	Yes
Industry dummies	Yes	No	Yes
Pseudo R-squared	0.1214	0.0902	0.1234

Table 3.8: Robustness: Endogeneity

This table presents the results from Probit (Column 1) and 3SLS (Columns 2 and 3) model regressions. The dependent variables are *Recall* (Columns 1 and 2) and *IOP* (Column 3). Marginal effects are reported in column 1. Robust standard errors are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	Probit	3SLS	
	Recall	Recall	IOP
IOP_{t-1}	-0.0010***	-0.0002*	
	(0.0002)	(0.0001)	
IOP_{t+1}	-0.0003		
	(0.0002)		
$Recall_{t-1}$			-1.1092
			(1.1796)
$Leverage_{t-1}$	-0.0144	-0.0210	
	(0.0176)	(0.0152)	
$Cash_{t-1}$	-0.0225	-0.0502***	
	(0.0262)	(0.0170)	
$Log(Size)_{t-1}$	0.0455***	0.0516***	-0.8041***
	(0.0020)	(0.0019)	(0.2785)
$Turnover_{t-1}$	0.0226***	0.0213***	
	(0.0063)	(0.0066)	
$Tangibility_{t-1}$	0.0051	0.0227	
	(0.0379)	(0.0365)	
$Capex_{t-1}$	0.0243	-0.0590	
	(0.1177)	(0.1048)	
Market to $book_{t-1}$	0.0000	-0.0003	
	(0.0003)	(0.0003)	
RD $intensity_{t-1}$	-0.0060	0.0632***	
	(0.0590)	(0.0212)	
Total factor $productivity_{t-1}$	0.0060	-0.0040	
	(0.0064)	(0.0035)	
HHI_{t-1}	-0.2015	-0.2580**	
	(0.1284)	(0.1187)	
$Unionization_{t-1}$	0.0009	-0.0001	
	(0.0024)	(0.0011)	
$Log(Shares)_{t-1}$			-0.2162
			(0.3194)
Share $turnover_{t-1}$			-164.7261***
			(34.7497)
Stock return $volatility_{t-1}$			28.4298
			(25.4129)
Number of observations	5387	6377	6377
Year dummies	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
Pseudo R-squared (R-squared)	0.4193	0.2714	0.0313

Table 3.9: Robustness: Alternative measures of institutional ownership stability

This table presents the results from Probit model regressions (Columns 1 and 2) and Negative binomial regressions (Columns 3 and 4). The dependent variables are *Recall* (Columns 1 and 2) and *#Recall* (Columns 3 and 4). Marginal effects are reported in columns 1 and 2. Robust standard errors are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Recall	Recall	Recall	#Recall	#Recall	#Recall
DED_{t-1}	-0.1514**		-0.1729***	-5.2657***		-5.8826***
	(0.0598)		(0.0623)	(1.3959)		(1.4834)
TRA_{t-1}		0.0424	0.0644*		0.4710	1.2902*
		(0.0379)	(0.0382)		(0.6600)	(0.6694)
Leverage_{t-1}	-0.0002	-0.0052	-0.0002	-0.1906	-0.3649	-0.1746
	(0.0156)	(0.0156)	(0.0156)	(0.3144)	(0.2929)	(0.3150)
Cash_{t-1}	-0.0263	-0.0261	-0.0267	-0.8170**	-0.7846**	-0.8148**
	(0.0221)	(0.0224)	(0.0222)	(0.3769)	(0.3797)	(0.3779)
Log(Size)_{t-1}	0.0420***	0.0409***	0.0416***	0.7520***	0.7273***	0.7527***
	(0.0017)	(0.0018)	(0.0017)	(0.0409)	(0.0441)	(0.0414)
Turnover_{t-1}	0.0191***	0.0189***	0.0193***	0.6161***	0.5984***	0.6144***
	(0.0055)	(0.0056)	(0.0055)	(0.1272)	(0.1330)	(0.1284)
Tangibility_{t-1}	0.0069	0.0050	0.0057	0.8513	0.9311	0.8485
	(0.0315)	(0.0318)	(0.0317)	(0.5791)	(0.5941)	(0.5785)
Capex_{t-1}	0.0392	0.0518	0.0395	-2.4917	-2.3675	-2.4437
	(0.0994)	(0.1011)	(0.1004)	(1.8295)	(1.8558)	(1.8342)
$\text{Market to book}_{t-1}$	-0.0003	-0.0003	-0.0003	-0.0155**	-0.0149**	-0.0161**
	(0.0003)	(0.0003)	(0.0003)	(0.0062)	(0.0062)	(0.0063)
$\text{RD intensity}_{t-1}$	0.0017	0.0023	0.0042	-0.9307	-1.0012	-0.8567
	(0.0441)	(0.0454)	(0.0440)	(0.8035)	(0.8386)	(0.7954)
$\text{Total factor productivity}_{t-1}$	0.0067	0.0054	0.0058	-0.1087	-0.1353	-0.1238
	(0.0053)	(0.0053)	(0.0053)	(0.1413)	(0.1454)	(0.1421)
HHI_{t-1}	-0.1340	-0.1321	-0.1273	-1.2314	-1.2011	-1.1309
	(0.1107)	(0.1088)	(0.1113)	(1.7364)	(1.6611)	(1.7683)
$\text{Unionization}_{t-1}$	-0.0011	-0.0011	-0.0011	0.0077	0.0103	0.0079
	(0.0012)	(0.0012)	(0.0012)	(0.0213)	(0.0210)	(0.0214)
Number of observations	6546	6546	6546	6546	6546	6546
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.417	0.4157	0.4176	0.2807	0.2779	0.2811

Table 3.10: Cross-sectional heterogeneity: Managerial ability and generalist CEOs

This table presents the results from Probit model regressions (Columns 1 and 2) and Negative binomial regressions (Columns 3 and 4). The dependent variables are *Recall* (Columns 1 and 2) and *#Recall* (Columns 3 and 4). Marginal effects are reported in columns 1 and 2. Robust standard errors are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Recall	Recall	#Recall	#Recall
IOP_{t-1}	-0.0015***	-0.0030*	-0.0229***	-0.0310**
	(0.0005)	(0.0017)	(0.0066)	(0.0129)
High_MA	-0.0121		-0.4931***	
	(0.0116)		(0.1440)	
High_GAI		-0.0338		-0.2309
		(0.0361)		(0.2695)
IOP_{t-1} x High_MA	0.0004		0.0131*	
	(0.0006)		(0.0077)	
IOP_{t-1} x High_GAI		0.0024		0.0298*
		(0.0021)		(0.0156)
$Leverage_{t-1}$	-0.0171	-0.1440*	-0.5544*	-1.4792**
	(0.0230)	(0.0868)	(0.3098)	(0.7230)
$Cash_{t-1}$	-0.0593*	0.0329	-0.7455*	-1.2559
	(0.0326)	(0.1052)	(0.4013)	(0.8637)
$Log(Size)_{t-1}$	0.0530***	0.1194***	0.7064***	0.8415***
	(0.0026)	(0.0073)	(0.0563)	(0.0647)
$Turnover_{t-1}$	0.0182**	0.1458***	0.4884***	1.2201***
	(0.0087)	(0.0319)	(0.1661)	(0.2709)
$Tangibility_{t-1}$	0.0057	-0.1206	1.0708	1.0992
	(0.0518)	(0.1921)	(0.6668)	(1.3333)
$Capex_{t-1}$	0.1122	0.0167	-2.2351	0.5509
	(0.1650)	(0.5704)	(2.0726)	(4.7858)
Market to $book_{t-1}$	-0.0007	-0.0026*	-0.0173***	-0.0351**
	(0.0005)	(0.0015)	(0.0061)	(0.0147)
RD $intensity_{t-1}$	0.0083	-0.2572	-0.7255	-4.5698
	(0.0691)	(0.3210)	(0.9509)	(2.8514)
Total factor $productivity_{t-1}$	0.0161*	0.0672***	-0.0319	0.0498
	(0.0083)	(0.0235)	(0.1716)	(0.1856)
HHI_{t-1}	-0.1294	-1.3019*	-0.3218	-1.8790
	(0.1840)	(0.6687)	(1.7259)	(4.0716)
$Unionization_{t-1}$	0.0028	0.0265***	0.1288***	0.3268***
	(0.0034)	(0.0087)	(0.0462)	(0.0643)
Number of observations	4114	714	4114	714
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Pseudo R-squared	0.386	0.417	0.249	0.213

Table 3.11: Cross-sectional heterogeneity: Institutional investor types

This table presents the marginal effects from Probit model regressions for the impact of institutional ownership stability on the probability of a firm being recalled from 2012 to 2021. The dependent variable is the dummy variable *Recall*. This variable has a value of zero for all control firms and 1 for recalling firms. Marginal effects are reported in the table. Robust standard errors are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Recall	Recall	Recall	Recall
IOP_Active$_{t-1}$	-0.0007***			-0.0006***
	(0.0001)			(0.0002)
IOP_Passive$_{t-1}$		-0.0006**		-0.0001
		(0.0003)		(0.0003)
IOP_Others$_{t-1}$			-0.0007***	-0.0002
			(0.0002)	(0.0002)
Leverage$_{t-1}$	-0.0051	-0.0050	-0.0042	-0.0050
	(0.0155)	(0.0156)	(0.0156)	(0.0156)
Cash$_{t-1}$	-0.0293	-0.0273	-0.0277	-0.0295
	(0.0223)	(0.0223)	(0.0223)	(0.0223)
Log(Size)$_{t-1}$	0.0410***	0.0411***	0.0408***	0.0408***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Turnover$_{t-1}$	0.0192***	0.0188***	0.0192***	0.0192***
	(0.0055)	(0.0055)	(0.0055)	(0.0055)
Tangibility$_{t-1}$	0.0059	0.0066	0.0042	0.0060
	(0.0320)	(0.0317)	(0.0320)	(0.0320)
Capex$_{t-1}$	0.0438	0.0476	0.0498	0.0433
	(0.1006)	(0.1003)	(0.1007)	(0.1007)
Market to book$_{t-1}$	-0.0003	-0.0003	-0.0003	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
RD intensity$_{t-1}$	-0.0005	-0.0015	-0.0019	-0.0016
	(0.0456)	(0.0455)	(0.0458)	(0.0457)
Total factor productivity$_{t-1}$	0.0062	0.0062	0.0060	0.0062
	(0.0053)	(0.0053)	(0.0053)	(0.0053)
HHI$_{t-1}$	-0.1402	-0.1379	-0.1385	-0.1405
	(0.1096)	(0.1093)	(0.1099)	(0.1099)
Unionization$_{t-1}$	-0.0011	-0.0011	-0.0010	-0.0011
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Number of observations	6546	6546	6546	6546
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Pseudo R-squared	0.4198	0.4162	0.4179	0.4199

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