Active Mutual Funds: Beware of Smart Beta ETFs![*]

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Abstract

Smart beta ETFs have gained tremendous prevalence among investors in recent years. This study provides empirical evidence that a proportion of this fast-paced growth can be attributed to the investor migration from closet factor active mutual funds to smart beta ETFs. Using a sample of US domestic equity active mutual funds and smart beta ETFs from 2000 to 2019, we find that smart beta ETFs offer higher returns and factor exposures at lower fees than closet factor funds. Therefore, investors replace closet factor funds with smart beta ETFs. The replacement impact intensifies with investor sophistication and market share of smart beta ETFs. Our findings illustrate the dynamic changes in investor preference towards investment products that bring similar or greater benefits at a lower price.

JEL Classifications: G11; G23

Keywords: ETFs; mutual funds; active mutual funds; smart beta ETFs; replacement; factor investing

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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[3]. 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, Goetzmann, and Schaefer, 2009). Strikingly, Bender, Hammond, and Mok (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 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[4].

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, Frazzini, and Pedersen, 2019; Frazzini and Pedersen, 2014; Ang et al. 2006). Prior to the arrival of smart beta ETFs,

[3]J.P. Morgan Asset Management Global ETF Study 2020
[4]FTSE Russell Smart Beta: 2019 Global Survey

investors were neither aware of factor investing nor able to harvest the 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 (Mossawi, Shen, and Velthuis, 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, Scholz, and Grim, 2020), and 25% of surveyed global investors respond that they have already replaced their actively managed mutual funds with smart beta ETFs[5].

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

[5] Brown Brothers Harriman 2020 Global ETF Investor Survey

vehicles that can replace closet factor mutual funds in investors' portfolios since these factor ETFs deliver higher factor exposures and returns at lower costs. Net flows of smart beta ETFs have a significantly negative relation with net flows of closet factor funds. Additionally, we find supporting evidence that investors are substituting closet factor funds with smart beta ETFs, but not vice versa. Using three different proxies for investor sophistication: market sentiment, broker-sold and direct-sold funds, and institutional and retail share classes, we illustrate that more sophisticated investors are more likely to substitute closet factor funds with smart beta ETFs. In addition, when smart beta ETFs market share increases and therefore these funds become more salient, closet factor funds are at higher risks of being replaced. Consistent with the substantial growth of smart beta ETFs in recent years, we document a more significant replacement effect after 2012. Finally, the placebo test results demonstrate that only closet factor funds lose investors to smart beta ETFs. There is no replacement impact of smart beta ETFs on non-closet factor funds, even though these funds' names may explicitly include specific factors. Investors appear to understand the benefits of factor investing, and therefore, we do not observe a similar impact on closet factor funds from 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. Splitting net flows of smart beta ETFs into positive net flows (net inflows) and negative net flows (net outflows), we reinforce our result of the unidirectional replacement impact by showing that only positive net flows of smart beta ETFs have a negative relation with net flows of closet factor mutual funds.

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 will make 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, Mateus, and Soggiu (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. Brown, Cederburg, and Towner (2020) 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, Song, and Xiang (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 2 describes our data sample and methodology to identify closet factor funds. Section 3 presents the empirical results of the replacement impact of smart beta ETFs on closet factor mutual funds. Section 4 contains the placebo and robustness tests. Finally, Section 5 summarizes and concludes this study.

2. Data and Methodology

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 because 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, Gormley, and Keim (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, Song, and Xiang (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. Regarding the funds classified as multi-factor ETFs, we rely on the fund prospectus to identify which factor exposures the funds offer to investors. 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[6].

Our paper's analysis is at the fund group level, i.e., closet factor funds (smart beta ETFs) that target the same factor 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 switching from closet factor funds to these new investment funds. Therefore, we believe fund group comparison is appropriate. Second, our approach is consistent

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

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.

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, Hammond, and Mok, 2014; Zorina, Scholz, and Grim, 2020) and academic researchers (Sharpe, 1992; 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, we can estimate the proportion of fund returns explained by factor premia using the adjusted R-squared from regression analysis.

Following Barber, Huang, and Odean (2016) and Song (2017), we estimate each fund monthly factor exposures by 36-month rolling regressions, using the following 6-factor model as in Frazzini, Kabiller, and Pedersen (2018):

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,1}(R_{m,t} - R_{f,t}) + \beta_{i,2}SMB_t + \beta_{i,3}HML_t \\ + \beta_{i,4}UMD_t + \beta_{i,5}QMJ_t + \beta_{i,6}BAB_t + \epsilon_{i,t} \end{aligned} \tag{1}$$

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, Huij, and Kyosev (2019) and Patton and Weller (2020), we define a fund as targeting a specific factor if the factor exposure is positive (except for Growth factor) and its t-statistic exceeds 2 in absolute value. The only exception is a fund will target the Growth factor if $\beta_3 < 0$ since Glushkov (2016) and Huang, Song, and Xiang (2020) show that the smart beta ETFs or indexes that aim to capture the Growth factor have negative and statistically significant exposure to the HML. The adjusted R-squared shows the percentage of fund returns variance 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[7]. A closet factor fund can target multiple factors simultaneously.

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 closet factor fund that targets 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.

[7]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`

2.3. Descriptive statistics

Figure 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.

In Table 1, we present the number of funds, total net assets, and the corresponding proportions of active equity mutual funds that are classified as closet factor funds each year from 2003 to 2019. The fraction of closet factor funds grew over time and peaked in 2011 when 40% of active equity funds were identified as closet factor funds. However, the fraction of closet factor funds significantly dropped after 2012, when smart beta ETFs started growing tremendously and became more prevalent among investors, as exhibited in Figure 1 and the extant literature (Cao et al., 2020; Johansson, Sabbatucci, and Tamoni, 2020).

Table 2 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. Interestingly, 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 also observe in Figure 3 that while smart beta ETFs took in more than $200 billion, around $600 billion came out of closet factor mutual funds during the period from 2003 to 2019.

[Insert Table 2 here]

2.4. Factor exposures of closet factor funds and smart beta ETFs

One of the main benefits of smart beta ETFs is that investors can have factor exposures at a lower cost compared to closet factor funds. We find in the previous section that smart beta ETFs charge lower fees compared to closet factor funds. Therefore, in this section, we examine whether investors also benefit from higher exposures to priced factors by using these new investment products. Specifically, we form portfolios of closet factor funds and smart beta ETFs that target each of the factors (Growth, Momentum, Quality, Risk-oriented, and Value) and estimate the exposures of closet factor funds and smart beta ETFs by regressing portfolio returns on factor returns. In Panel A of Table 3, we form value-weighted portfolios of funds and document that smart beta ETFs deliver higher exposures to each of the target factors, except Quality. One possible reason 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 beta on the Value factor of smart beta ETFs is 0.415, higher than 0.206 of closet factor funds. The results remain qualitatively similar when we estimate equally-weighted portfolio returns in Panel B. However, it appears that larger smart beta ETFs offer better factor exposures than small funds since the benefits are more significant in value-weighted portfolios. This finding is consistent with Brown, Cederburg, and Towner (2020) that investors allocate more capital to smart beta ETFs that can effectively deliver their promised factor tilts.

Overall, our findings so far illustrate that investors will be better off investing in smart beta ETFs since these funds offer higher factor exposures and returns at lower fees compared to closet factor funds. We visualize the benefits in Figure 2, where we compare the growth of $1,000 investment in smart beta ETFs and in closet factor funds that capture the same factor exposure. We observe that the investment values are higher if investor money has been put in smart beta ETFs rather than in closet factor funds. Specifically, investors can earn $175 to $2,478 more when switching from closet factor funds to smart beta ETFs. Consequently, we will investigate the replacement impact of smart beta ETFs on closet factor funds in the following parts of this study.

[Insert Table 3 here]

3. Smart beta ETFs replace closet factor funds

3.1. Main results

3.1.1. 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

$$\begin{aligned} CMF\ Net\ Flow_{i,t} = \beta_0 &+ \beta_1 ETF\ Net\ Flow_{i,t} + \beta_2 CMF\ Net\ Flow_{i,t-1} \\ &+ \beta_3 ETF\ Net\ Flow_{i,t-1} + \beta_4 Return_{i,t-1} + \beta_5 Expense_{i,t-1} \\ &+ \beta_6 Log(Size)_{i,t-1} + \beta_7 Log(Family\ Size)_{i,t-1} \\ &+ (Year - Month\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t} \end{aligned} \tag{2}$$

The dependent variable is net flows of closet factor funds group i in month t. $ETF\ Net\ Flow_{i,t}$ 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, 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 year-month fixed effects and factor fixed effects.

The regression results are presented in Table 4. Consistent with our hypothesis, the coefficient β_1 is negative and statistically significant in all specifications where we include 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 1 and 2 show that $1 million of net inflows to smart beta ETFs are associated with $0.194 and $0.191 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 higher returns and lower expenses attract higher net flows. Fund size negatively affects the net flows of mutual funds.

[Insert Table 4 here]

3.1.2. 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 analyze the relations between inflows and outflows of closet factor funds and smart beta ETFs in the following regressions

$$\begin{aligned} CMF\ Inflow_{i,t} = & \beta_0 + \beta_1 ETF\ Outflow_{i,t} + \beta_2 CMF\ Inflow_{i,t-1} \\ & + \beta_3 ETF\ Outflow_{i,t-1} + +\beta_4 Return_{i,t-1} + \beta_5 Expense_{i,t-1} \\ & + \beta_6 Log(Size)_{i,t-1} + \beta_7 Log(Family\ Size)_{i,t-1} \\ & + (Year - Month\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t} \end{aligned} \tag{3}$$

$$\begin{aligned} ETF\ Inflow_{i,t} = & \beta_0 + \beta_1 CMF\ Outflow_{i,t} + \beta_2 ETF\ Inflow_{i,t-1} \\ & + \beta_3 CMF\ Outflow_{i,t-1} + +\beta_4 Return_{i,t-1} + \beta_5 Expense_{i,t-1} \\ & + \beta_6 Log(Size)_{i,t-1} + \beta_7 Log(Family\ Size)_{i,t-1} \\ & + (Year - Month\ Fixed\ Effects) + (Factor\ Fixed\ Effects) + \epsilon_{i,t} \end{aligned} \tag{4}$$

In regression 3, 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 4. Both regressions include lagged inflows and outflows of smart beta ETFs and closet factor funds and the known determinants of fund flows. With the potential benefits of smart beta ETFs, we expect a unidirectional replacement impact, i.e., investors replace closet factor funds with smart beta ETFs, but not otherwise. In that case, the coefficient β_1 is positive and statistically significant only in regression 4.

Table 5 presents the regression results. On the one hand, we document that outflows of smart beta ETFs have no statistically significant relation with inflows of closet factor funds. In detail, the positive relation is statistically significant (at the 10% level) only in column 1 but not in columns 2, 3, and 4, where we include the year-month and factor fixed effects and the control variables. 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 specifications where we include the fixed effects (in columns 6 and 8) and the determinants of fund flows (in columns 7 and 8). Specifically, the β_1 estimate in column 8 displays that \$1 million outflows from closet factor funds are associated with \$0.08 million inflows to smart beta ETFs. These findings suggest that investors redeem their shares from closet factor mutual funds and invest a proportion (6-8%) of the proceeds in smart beta ETFs, but not vice versa. Overall, our findings demonstrate the investor migration from closet factor funds to smart beta ETFs.

[Insert Table 5 here]

3.2. Investor sophistication

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. 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 to be more likely to replace closet factor funds with smart beta ETFs. Accordingly, our subsequent analyses focus on analyzing the variation of the replacement impact with investor sophistication using three different proxies for investor sophistication: market sentiment, fund distribution channels, and types of mutual fund share classes.

3.2.1. High and Low market sentiment

First, we utilize the sentiment index in Baker and Wurgler (2006) as a proxy for investor sophistication. The authors construct the index by taking the first principal component of 6 sentiment proxies: closed-end fund discount, lagged NYSE share turnover, number of IPOs, lagged average first-day return on IPOs, equity share in new issues, and the dividend premium. There are two versions of the sentiment index, and we use the index that has been orthogonalized to the macroeconomic conditions. We classify a month as high (low) market sentiment if the index value is higher (lower) than the median of the time-series index level. We hypothesize that during the months that investors are optimistic about the market, i.e., when the market sentiment is high, they tend to be less sophisticated and may ignore whether a fund is a closet factor fund. Conversely, in months of low market sentiment, closet factor funds are at a higher risk of being replaced by smart beta ETFs.

Table 6 presents our regression results, where the dependent variables are net flows of closet factor funds (columns 1 and 2) and inflows of smart beta ETFs (columns 3 and 4). Even though the coefficients are negative in both high and low market sentiments, the impact is statistically significant and more considerable in low market sentiment periods. Specifically, in months of low market sentiment, \$1 million net flows to smart beta ETFs are associated with \$0.419 million net flows out of closet factor funds, much larger than in high sentiment months. Consistent with the results using net flows, we observe a positive and statistically significant relation between outflows of closet factor funds and inflows of smart beta ETFs only in low market sentiment periods. Our findings are consistent with the evidence in Cao et al. (2020) that the increase in flow sensitivity to multi-factor alphas due to smart beta ETFs exists only in low sentiment months.

[Insert Table 6 here]

3.2.2. Direct-sold and Broker-sold funds

The second proxy for investor sophistication in our 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 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, Chalmers, and Tufano (2009), we identify broker-sold funds as those that charge a front or rear load or a 12b-1 fee greater than 25 bps. The remaining funds are classified as direct-sold funds.

Table 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. In columns 1 and 2, where the dependent variable is net flows of closet factor funds, the negative relation is statistically significant only in direct-sold funds. In addition, the magnitude of the coefficient β_1 in the direct-sold funds double that in the broker-sold funds. When the outcome variable is inflows of smart beta ETFs in columns 3 and 4, we observe the positive correlations in both fund distribution channels. However, the replacement impact is more extensive in direct-sold funds.

[Insert Table 7 here]

3.2.3. Institutional and Retail share classes

Our last proxy for investor sophistication is based on the two common types of mutual fund share classes: institutional and retail share classes. Anecdotal evidence suggests a growing number of institutional investors have switched from active management to factor investing. In addition, the institutional class of mutual funds typically requires large initial investments, e.g., a minimum of $100,000. As a result, investors buying these shares are generally assumed to be more sophisticated than retail investors. Since inflows and outflows data are only available at the fund level, our analysis in this section focuses on the different impacts of net flows of smart beta ETFs on net flows of closet factor fund institutional and retail share classes. Consistent with the previous findings, we document a statistically significant and negative relation between net flows of smart beta ETFs and net flows of institutional class in columns 1 and 3 of Table 8. Similar impacts do not seem to exist in retail flows as the coefficients β_1 are negative but not statistically significant in columns 2 and 4.

Overall, using three different proxies for investor sophistication, we find consistent evidence that more sophisticated investors can identify and substitute closet factor funds in their portfolios with smart beta ETFs.

[Insert Table 8 here]

3.3. Competition intensity

This section examines 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 9 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 inflows of smart beta ETFs and outflows of closet factor funds, we document that investors replace closet factor funds with smart beta ETFs in both periods of high and low competition. However, the magnitude is larger in months when smart beta ETFs become more salient.

[Insert Table 9 here]

3.4. 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, Sabbatucci, and Tamoni (2020) 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 10 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. In columns 3 and 4, we observe that investors redeem their investment in closet factor funds and invest in smart beta ETFs both before and after 2012 but more considerably in recent years. Our findings are consistent with the recent massive growth of these factor ETFs in the asset management industry.

[Insert Table 10 here]

4. Placebo and robustness tests

4.1. Do investors replace non-closet factor funds and closet factor funds with smart beta ETFs offering different factor exposures?

The findings so far have supported 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) and the closet factor funds that do not target the same factors as smart beta ETFs. First, 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. Second, investors will not replace closet factor funds with smart beta ETFs that do not capture the same factor exposures. Consequently, we expect no replacement impact of smart beta ETFs on these mutual funds.

Table 11 presents the regression results. Net flows of smart beta ETFs have a positive relation with net flows of non-closet factor funds and closet factor funds that do not target the same factors, contradicting the expected sign in the case of replacement.

The coefficients are statistically significant in columns 1 and 2, suggesting that smart beta ETFs can complement non-closet factor funds and closet factor funds targeting different factors. However, the relationship is neither statistically nor economically significant in regressions where the dependent variable is inflows to smart beta ETFs. In summary, the findings demonstrate that investors do not substitute non-closet factor funds and closet factor funds with smart beta ETFs that do not offer similar factor exposures.

[Insert Table 11 here]

4.2. Do investors replace factor-based active funds with smart beta ETFs?

Some active mutual funds explicitly mention a factor in their names, such as GuideStone Value Equity Fund, Invesco Low Volatility Equity Fund. However, these funds can offer benefits that investors cannot attain by using smart beta ETFs such as stock-picking ability within some factor-oriented stock segments (e.g., value-oriented, momentum-oriented). Consequently, we expect that investors do not replace factor-based active funds with smart beta ETFs since these funds still employ active management, and their performance is thus not replicable by using smart beta ETFs. We follow Johansson, Sabbatucci, and Tamoni (2020) to identify factor-based funds by fund names[8]. After filtering out these funds, we follow the same procedure in Section 2.2 and identify the factor-based active funds that are not classified as closet factor funds. More than 90% of factor-based funds in our sample are not closet factor funds. In columns 1 and 2 of Table 12, even though

[8] VALUE if fund names contain “value”, “book”, or “low p/e”; GROWTH if fund names contain “growth”; MOMENTUM if fund names contain “mom”, or “trend”; QUALITY if fund names contain “quality”; RISK-ORIENTED if fund names contain “low risk”, “volatility”, or “risk”.

the relation between net flows of factor-based active funds and smart beta ETFs are negative, it is not statistically significant. In addition, we observe that outflows of factor-based active funds positively correlate with inflows of smart beta ETFs in columns 3 and 4. However, this relation is not statistically significant. Overall, we do not find evidence of the replacement impact of smart beta ETFs on factor-based active funds, consistent with our expectations.

[Insert Table 12 here]

4.3. 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 of traditional passive ETFs should also negatively correlate with net flows of closet factor funds, and there is a positive relation between inflows of passive ETFs and outflows of mutual funds. We carry out the second placebo test to investigate this possible implication. Table 13 shows that net flows of traditional passive ETFs do not negatively correlate with net flows of closet factor funds. Similarly, there is no statistically significant relation between outflows from closet factor funds and inflows to traditional passive ETFs. These findings provide supporting evidence 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.

[Insert Table 13 here]

4.4. Robustness

In the previous sections, we rely on the fund investment objectives to identify smart beta ETFs' target factors. However, there are concerns that smart beta ETFs might not provide the intended factor exposures (Glushkov 2016). Therefore, in this robustness analysis, we include only the ETFs that successfully deliver the stated factors in our sample. Specifically, we use regression (1) and all available historical return observations of each smart beta ETF to identify its target factor. We follow the criteria in section 2.2, except that we do not use the adjusted R-squared threshold. For multi-factor funds, we rely on the identified target factors instead of the fund's stated exposures. Consequently, we find that 73% of smart beta ETFs can deliver the promised factor tilts. The results are presented in Table 14. 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, outflows from closet factor funds positively correlate with inflows to smart beta ETFs in columns 3 and 4. These findings are consistent with our previous empirical evidence.

[Insert Table 14 here]

Another concern 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. Consequently, the empirical evidence of unidirectional replacement impact in Table 5 may be subject to selection bias, as we cannot observe the inflows and outflows of some ETFs that do not report this information. In order to deal with this issue, we split net flows of smart beta ETFs into positive net flows (net inflows) and negative net flows (net outflows) and include both variables in regression 2. The results are presented in Table 15. In detail, we observe a negative (positive) relation between net inflows (net outflows) of smart beta ETFs and net flows of closet factor funds, suggesting that investors withdraw the money from closet factor funds and invest in smart beta ETFs but not vice versa. This finding is consistent with and supports the unidirectional replacement impact that we have documented previously.

[Insert Table 15 here]

5. Conclusions

This study examines the replacement impact of smart beta ETFs on closet factor funds, i.e., active equity mutual funds that mostly load up on well-known systematic factors. Specifically, we find that smart beta ETFs offer higher returns and factor exposures to investors at much lower fees. Therefore, investors replace closet factor funds with the newly emerged smart beta ETFs. The impact intensifies with investor sophistication and market share of these factor ETFs.

Our findings highlight the dynamic changes in investor preference in the asset management industry. In the investment product innovation era, investors will identify the funds that fail to deliver what they purport 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.

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Figure 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.

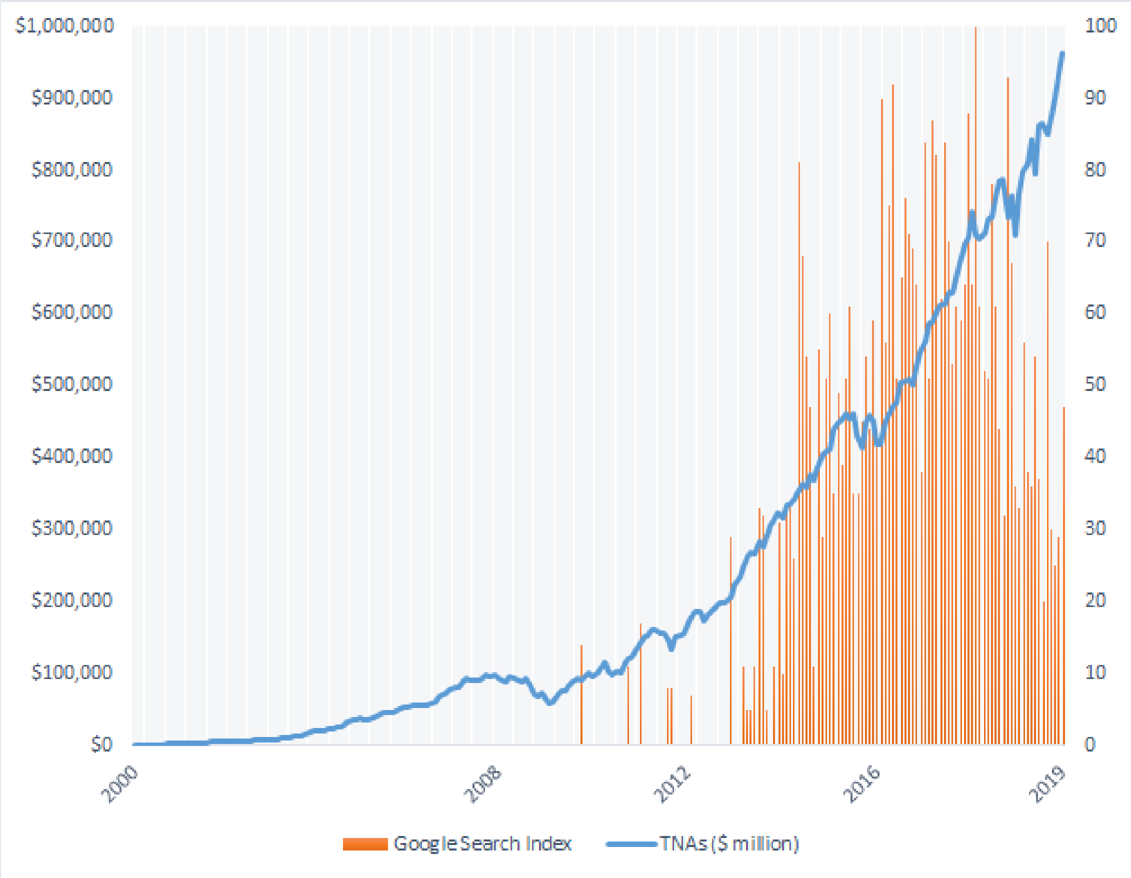

Figure 2: Investment in Smart beta ETFs vs. Closet factor funds

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

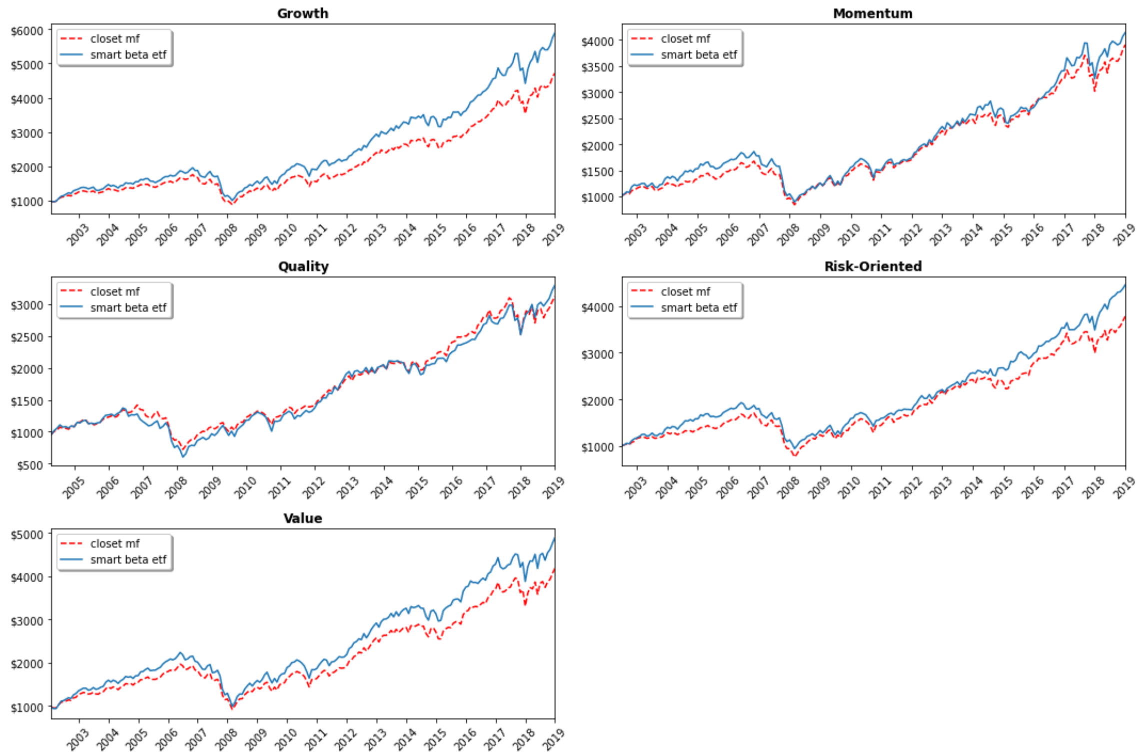

Figure 3: Cumulative net flows to Closet factor funds and Smart beta ETFs

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

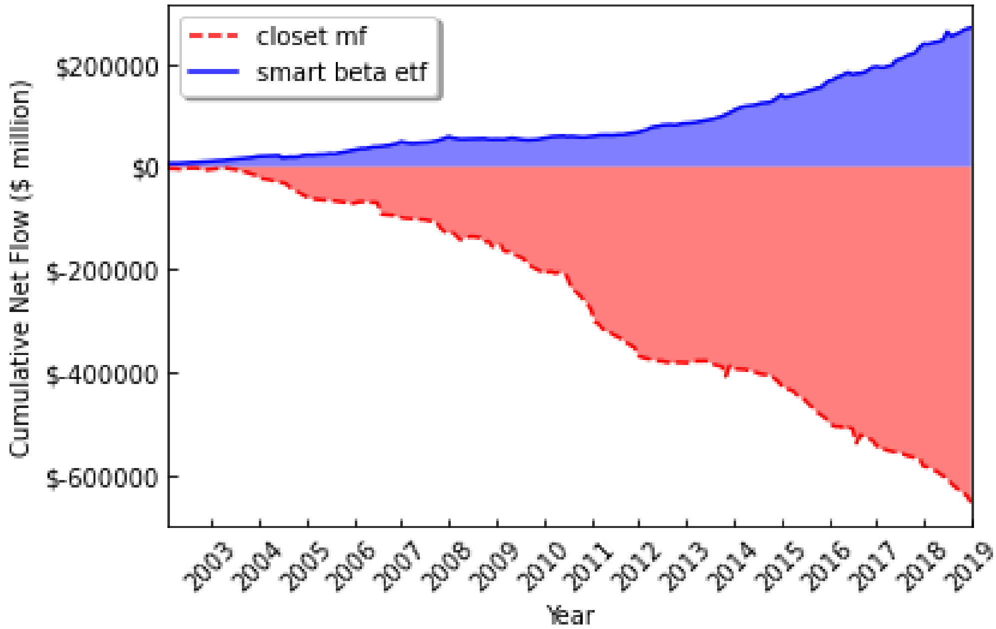

Table 1: Number and total net assets of closet factor funds and active equity mutual funds

This table reports the number and total net assets of closet factor funds and active equity mutual funds each year from 2003 to 2019.

	Number of funds			Total Net Assets ($ million)		
Year	**Closet factor**	**Active**	**% of Active**	**Closet factor**	**Active**	**% of Active**
2003	181	1,453	12.46	386,644.46	1,602,167.37	24.13
2004	305	1,614	18.90	730,266.63	2,026,277.28	36.04
2005	276	1,645	16.78	747,248.23	2,262,765.14	33.02
2006	124	1,635	7.58	263,505.36	2,494,675.89	10.56
2007	118	1,616	7.30	191,958.54	2,796,692.82	6.86
2008	262	1,572	16.67	444,571.84	2,225,859.8	19.97
2009	545	1,555	35.05	853,098.99	1,703,316.33	50.08
2010	611	1,634	37.39	1,081,828.23	2,048,102.85	52.82
2011	655	1,610	40.68	1,192,624.07	2,262,483.12	52.71
2012	448	1,570	28.54	828,683.32	2,294,053.17	36.12
2013	364	1,510	24.11	853,309.62	2,747,655.1	31.06
2014	352	1,528	23.04	971,058.53	3,249,402.56	29.88
2015	291	1,572	18.51	868,583.01	3,338,397.11	26.02
2016	385	1,578	24.40	1,161,777.05	3,241,314.56	35.84
2017	327	1,571	20.81	1,092,953.56	3,652,728.28	29.92
2018	282	1,555	18.14	892,996.58	3,925,905.35	22.75
2019	419	1,542	27.17	1,014,892.29	3,989,914.57	25.44

Table 2: 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 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	**Closet factor funds**	**Smart beta ETFs**	**Difference**
Net Flow($ million)	-410.01	90.07	-500.08***
Gross Return(%)	1.13	1.20	-0.08**
Net Return(%)	1.05	1.17	-0.12***
Expense(%)	0.89	0.39	0.50***
Size ($ million)	76,050	15,763	60,287***
Family Size ($ million)	7,694,506	6,022,762	1,671,744***
Outflow ($ million)	1,599.92	320.36	1,279.56***
Inflow ($ million)	1,212.84	424.99	787.84***
Panel B: Momentum	**Closet factor funds**	**Smart beta ETFs**	**Difference**
Net Flow($ million)	-55.79	19.15	-74.94***
Gross Return(%)	0.88	0.89	-0.00
Net Return(%)	0.80	0.84	-0.04
Expense(%)	0.96	0.52	0.44***
Size ($ million)	16,186	1,032	15153***
Family Size ($ million)	2,588,336	538,342	2,049,994***
Outflow ($ million)	277.29	25.65	251.64***
Inflow ($ million)	246.43	27.44	219.29***
Panel C: Quality	**Closet factor funds**	**Smart beta ETFs**	**Difference**
Net Flow($ million)	17.24	50.54	-33.30**
Gross Return(%)	1.07	1.05	0.01
Net Return(%)	1.00	1.02	-0.02
Expense(%)	0.83	0.46	0.37***
Size ($ million)	17,973	1,479	16,493***
Family Size ($ million)	1,686,799	829,137	857,662***
Outflow ($ million)	311.88	25.29	286.58***
Inflow ($ million)	325.93	38.78	287.16
Panel D: Risk-Oriented	**Closet factor funds**	**Smart beta ETFs**	**Difference**
Net Flow($ million)	-133.36	109.39	-242.75***
Gross Return(%)	0.74	0.82	-0.08
Net Return(%)	0.67	0.79	-0.12
Expense(%)	0.85	0.32	0.53***
Size ($ million)	16,823	4,803	12,020
Family Size ($ million)	3,508,969	1,090,107	2,418,863***
Outflow ($ million)	237.75	104.59	133.16***
Inflow ($ million)	213.58	120.65	92.93***
Panel E: Value	**Closet factor funds**	**Smart beta ETFs**	**Difference**
Net Flow($ million)	-152.72	100.93	-253.65***
Gross Return(%)	0.86	1.08	-0.22
Net Return(%)	0.79	1.05	-0.25*
Expense(%)	0.83	0.38	0.45***
Size ($ million)	55,464	11,961	43,503***
Family Size ($ million)	6,815,473	5,084,031	1,731,442***
Outflow ($ million)	871.68	244.8	626.88***
Inflow ($ million)	784.63	351.29	433.35***

Table 3: Factor exposures of closet factor funds and smart beta ETFs

This table reports the loadings of closet factor funds and smart beta ETFs on their target factors. For each target factor in a given month, we form a value-weighted portfolio (Panel A) or an equally-weighted portfolio (Panel B) of closet factor funds and smart beta ETFs and calculate the portfolio gross returns. We then estimate the portfolio's loadings 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.

Panel A: Fund Loadings on the Target Factors (Value-weighted)			
Target Factor	**Closet factor funds**	**Smart beta ETFs**	**Difference**
Growth (HML Factor)	-0.222***	-0.252***	-0.030**
	(0.026)	(0.020)	(0.014)
Momentum (UMD Factor)	0.063***	0.208***	0.145***
	(0.012)	(0.035)	(0.031)
Quality (QMJ Factor)	0.213***	0.063	-0.150
	(0.047)	(0.063)	(0.102)
Risk-Oriented (BAB Factor)	0.119***	0.189***	0.070
	(0.017)	(0.043)	(0.046)
Value (HML Factor)	0.206***	0.415***	0.209*
	(0.020)	(0.123)	(0.121)

Panel B: Fund Loadings on the Target Factors (Equally-weighted)			
Target Factor	**Closet factor funds**	**Smart beta ETFs**	**Difference**
Growth (HML Factor)	-0.218***	-0.237***	-0.018
	(0.024)	(0.025)	(0.018)
Momentum (UMD Factor)	0.075***	0.182***	0.107***
	(0.016)	(0.026)	(0.019)
Quality (QMJ Factor)	0.207***	0.117**	-0.090
	(0.035)	(0.045)	(0.068)
Risk-Oriented (BAB Factor)	0.140***	0.169***	0.028
	(0.020)	(0.026)	(0.033)
Value (HML Factor)	0.240***	0.396***	0.156**
	(0.022)	(0.065)	(0.061)

Table 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:

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

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$_t$	-0.194**	-0.191**	-0.153**	-0.162**
	(0.084)	(0.086)	(0.075)	(0.078)
CMF Net Flow$_{t-1}$	0.067	0.054	0.018	0.016
	(0.189)	(0.185)	(0.180)	(0.177)
ETF Net Flow$_{t-1}$	-0.162**	-0.167**	-0.122*	-0.128*
	(0.068)	(0.065)	(0.067)	(0.067)
Return$_{t-1}$			8.250**	27.091**
			(3.405)	(11.736)
Expense$_{t-1}$			-262.596***	-259.556***
			(79.502)	(87.733)
Log(Size)$_{t-1}$			-134.703***	-149.273***
			(32.587)	(35.463)
Log(Family Size)$_{t-1}$			4.385	28.766
			(16.331)	(17.998)
Constant	-127.725***	-129.615***	1269.532***	1044.960***
	(30.283)	(29.835)	(286.440)	(276.948)
Fixed Effects	No	Yes	No	Yes
Number of observations	3840	3840	3840	3840
Adj. R-squared	0.016	0.039	0.060	0.074

Table 5: Direction of the replacement impact

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:

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

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

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$_t$	0.112*	0.057	0.098	0.047				
	(0.064)	(0.065)	(0.063)	(0.065)				
CMF Outflow$_t$					0.082***	0.070***	0.077***	0.064***
					(0.019)	(0.018)	(0.018)	(0.018)
Inflow$_{t-1}$	0.929***	0.932***	0.904***	0.909***	0.689***	0.666***	0.593***	0.602***
	(0.016)	(0.015)	(0.022)	(0.021)	(0.034)	(0.033)	(0.038)	(0.036)
ETF Outflow$_{t-1}$	0.014	0.059	0.006	0.052				
	(0.061)	(0.058)	(0.061)	(0.057)				
CMF Outflow$_{t-1}$					-0.039**	-0.027*	-0.041**	-0.030*
					(0.016)	(0.015)	(0.016)	(0.015)
Return$_{t-1}$			3.725**	10.983			2.762**	3.057
			(1.593)	(7.779)			(1.262)	(2.520)
Expense$_{t-1}$			74.913**	46.756			-129.417***	-178.208***
			(32.653)	(33.685)			(38.000)	(52.601)
Log(Size)$_{t-1}$			42.211***	43.101***			35.088***	30.324***
			(9.632)	(10.028)			(5.454)	(5.865)
Log(Family Size)$_{t-1}$			-4.410	-8.312*			-3.682	-6.187
			(3.342)	(4.657)			(3.006)	(4.374)
Constant	28.565**	28.805**	-353.972***	-291.340***	46.724***	53.266***	-69.548	14.293
	(11.850)	(13.765)	(92.153)	(96.390)	(7.703)	(8.434)	(48.190)	(58.551)
Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	2582	2582	2582	2582	2588	2588	2588	2588
Adj. R-squared	0.885	0.889	0.886	0.890	0.600	0.650	0.623	0.663

Table 6: The replacement impact in periods of high and low market sentiment

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 inflows of smart beta ETFs on outflows of closet factor funds (columns 3-4) and the determinants of fund flows:

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

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

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)
	High	Low	High	Low
	CMF Net Flow$_t$	CMF Net Flow$_t$	ETF Inflow$_t$	ETF Inflow$_t$
ETF Net Flow$_t$	-0.066	-0.419***		
	(0.072)	(0.151)		
CMF Outflow$_t$			0.072	0.058***
			(0.049)	(0.016)
CMF Net Flow$_{t-1}$	0.090	-0.102		
	(0.108)	(0.234)		
ETF Net Flow$_{t-1}$	-0.160**	-0.020		
	(0.064)	(0.114)		
ETF Inflow$_{t-1}$			0.480***	0.640***
			(0.059)	(0.042)
CMF Outflow$_{t-1}$			-0.039	-0.022
			(0.040)	(0.015)
Return$_{t-1}$	19.326*	36.983**	0.592	20.024***
	(11.114)	(15.661)	(1.001)	(6.817)
Expense$_{t-1}$	-194.236*	-301.020***	-323.772***	-96.111*
	(100.562)	(115.725)	(107.003)	(54.905)
Log(Size)$_{t-1}$	-176.270***	-142.343***	34.101***	26.668***
	(57.805)	(41.399)	(9.507)	(6.555)
Log(Family Size)$_{t-1}$	77.140**	3.893	-2.851	-4.864
	(33.129)	(18.196)	(9.239)	(4.662)
Constant	604.611**	1354.117***	50.992	-44.678
	(256.059)	(372.147)	(128.989)	(61.449)
Fixed Effects	Yes	Yes	Yes	Yes
Number of observations	1223	2279	912	1644
Adj. R-squared	0.107	0.082	0.643	0.697

Table 7: The replacement impact in broker-sold and direct-sold funds

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 inflows of smart beta ETFs on outflows of closet factor funds (columns 3-4) and the determinants of fund flows:

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

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

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)
	Broker	Direct	Broker	Direct
	CMF Net Flow$_t$	CMF Net Flow$_t$	ETF Inflow$_t$	ETF Inflow$_t$
ETF Net Flow$_t$	-0.056	-0.104**		
	(0.038)	(0.048)		
CMF Outflow$_t$			0.074***	0.119***
			(0.023)	(0.035)
CMF Net Flow$_{t-1}$	0.261	-0.297**		
	(0.18)	(0.14)		
ETF Net Flow$_{t-1}$	-0.08***	-0.08		
	(0.03)	(0.05)		
ETF Inflow$_{t-1}$			0.597***	0.608***
			(0.036)	(0.037)
CMF Outflow$_{t-1}$			-0.024	-0.040
			(0.021)	(0.035)
Return$_{t-1}$	25.368***	-0.535	2.999	3.627
	(5.968)	(8.872)	(2.598)	(3.095)
Expense$_{t-1}$	-84.530	-185.592***	-166.429***	-153.684**
	(56.276)	(55.800)	(60.560)	(60.647)
Log(Size)$_{t-1}$	-66.725***	-53.337***	29.850***	36.893***
	(18.129)	(15.381)	(6.295)	(8.097)
Log(Family Size)$_{t-1}$	13.035	-12.770*	-4.794	-6.233
	(9.587)	(7.591)	(4.958)	(5.293)
Constant	402.171***	686.242***	-3.621	-34.946
	(115.972)	(158.365)	(67.393)	(71.324)
Fixed Effects	Yes	Yes	Yes	Yes
Number of observations	3675	3302	2434	2109
Adj. R-squared	0.117	0.111	0.666	0.654

Table 8: The replacement impact on institutional and retail net flows

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

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

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)
	Institutional	Retail	Institutional	Retail
	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$	CMF Net Flow$_t$
ETF Net Flow$_t$	-0.106***	-0.051	-0.093***	-0.064
	(0.034)	(0.070)	(0.034)	(0.070)
CMF Net Flow$_{t-1}$	0.015	0.034	0.026	0.029
	(0.085)	(0.224)	(0.079)	(0.215)
ETF Net Flow$_{t-1}$	0.004	-0.131**	-0.001	-0.131***
	(0.051)	(0.052)	(0.050)	(0.050)
Return$_{t-1}$	1.243	5.216*	7.763	14.811
	(1.388)	(2.974)	(6.491)	(9.854)
Expense$_{t-1}$	-52.451	-148.585*	-69.204	-166.167**
	(50.313)	(75.937)	(44.046)	(81.582)
Log(Size)$_{t-1}$	3.432	-107.333***	5.731	-122.237***
	(8.180)	(28.050)	(9.236)	(30.150)
Log(Family Size)$_{t-1}$	-9.465	-2.947	-12.338*	22.170*
	(6.399)	(11.468)	(6.986)	(11.535)
Constant	161.352	950.849***	188.273	742.048***
	(137.501)	(298.155)	(123.275)	(261.381)
Fixed Effects	No	No	Yes	Yes
Number of observations	3690	3741	3690	3741
Adj. R-squared	0.005	0.072	0.042	0.090

Table 9: The replacement impact in 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 inflows of smart beta ETFs on outflows of closet factor funds (columns 3-4) and the determinants of fund flows:

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

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

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)
	High	Low	High	Low
	CMF Net Flow$_t$	CMF Net Flow$_t$	ETF Inflow$_t$	ETF Inflow$_t$
ETF Net Flow$_t$	-0.171**	-0.156		
	(0.082)	(0.398)		
CMF Outflow$_t$			0.114***	0.038***
			(0.027)	(0.010)
CMF Net Flow$_{t-1}$	-0.097	0.331		
	(0.177)	(0.308)		
ETF Net Flow$_{t-1}$	-0.150**	-0.201		
	(0.069)	(0.464)		
ETF Inflow$_{t-1}$			0.514***	0.579***
			(0.047)	(0.061)
CMF Outflow$_{t-1}$			-0.020	-0.016*
			(0.031)	(0.009)
Return$_{t-1}$	14.848	44.726***	2.137	14.123***
	(15.669)	(14.623)	(2.013)	(4.177)
Expense$_{t-1}$	-276.911***	-177.651*	-203.196**	-201.117***
	(106.630)	(105.562)	(80.262)	(60.827)
Log(Size)$_{t-1}$	-127.943***	-118.188**	39.113***	20.770***
	(34.994)	(48.847)	(8.695)	(4.696)
Log(Family Size)$_{t-1}$	19.684	7.868	-4.655	-4.524
	(22.927)	(18.455)	(6.499)	(4.057)
Constant	1001.766***	989.063**	-72.763	65.196
	(303.116)	(419.917)	(96.504)	(57.904)
Fixed Effects	Yes	Yes	Yes	Yes
Number of observations	2511	1329	1501	1087
Adj. R-squared	0.073	0.156	0.659	0.753

Table 10: The replacement impact 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 inflows of smart beta ETFs on outflows of closet factor funds (columns 3-4) and the determinants of fund flows:

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

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

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$_t$	ETF Inflow$_t$	ETF Inflow$_t$
ETF Net Flow$_t$	-0.089	-0.177*		
	(0.065)	(0.094)		
CMF Outflow$_t$			0.033***	0.105***
			(0.012)	(0.028)
CMF Net Flow$_{t-1}$	0.069	-0.017		
	(0.169)	(0.240)		
ETF Net Flow$_{t-1}$	-0.022	-0.156**		
	(0.106)	(0.073)		
ETF Inflow$_{t-1}$			0.634***	0.532***
			(0.049)	(0.050)
CMF Outflow$_{t-1}$			-0.020*	-0.033
			(0.011)	(0.026)
Return$_{t-1}$	33.441**	19.254	1.162	21.383**
	(13.158)	(17.428)	(1.247)	(9.521)
Expense$_{t-1}$	-177.386*	-335.935***	-250.473***	-207.194***
	(106.609)	(121.497)	(75.772)	(71.061)
Log(Size)$_{t-1}$	-172.443***	-135.051***	13.989*	34.432***
	(59.372)	(44.180)	(7.778)	(7.871)
Log(Family Size)$_{t-1}$	74.064**	4.194	-2.480	-3.714
	(37.148)	(19.533)	(5.710)	(6.077)
Constant	574.987**	1311.062***	129.937	-74.291
	(274.558)	(389.812)	(78.805)	(86.796)
Fixed Effects	Yes	Yes	Yes	Yes
Number of observations	1423	2417	1107	1481
Adj. R-squared	0.074	0.084	0.727	0.662

Table 11: Do investors replace non-closet factor funds or closet factor funds with smart beta ETFs offering different factor exposures?

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

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

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

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 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)
	NCMF Net Flow$_t$	NCMF Net Flow$_t$	ETF Inflow$_t$	ETF Inflow$_t$
ETF Net Flow$_t$	0.206*	0.264**		
	(0.118)	(0.107)		
NCMF Outflow$_t$			0.002*	0.000
			(0.001)	(0.001)
NCMF Net Flow$_{t-1}$	0.080*	0.078*		
	(0.043)	(0.042)		
ETF Net Flow$_{t-1}$	0.025	0.121		
	(0.106)	(0.091)		
ETF Inflow$_{t-1}$			0.650***	0.646***
			(0.033)	(0.033)
NCMF Outflow$_{t-1}$			0.000	0.001
			(0.001)	(0.001)
Return(t-1)	22.197***	127.498***	2.029**	2.292
	(6.853)	(42.358)	(0.901)	(1.891)
Expense$_{t-1}$	-215.967	-2480.391***	-105.251***	-179.505***
	(358.942)	(634.661)	(26.451)	(39.699)
Log(Size)$_{t-1}$	-455.754***	-1286.448***	32.916***	33.121***
	(106.297)	(169.542)	(4.429)	(4.872)
Log(Family Size)$_{t-1}$	-752.95***	9.15	-1.68	-5.20*
	(142.091)	(133.979)	(2.068)	(3.077)
Constant	17308.193***	16503.808***	-91.920**	-13.075
	(2211.875)	(1981.846)	(36.335)	(42.005)
Fixed Effects	No	Yes	No	Yes
Number of observations	5354	5354	3565	3564
Adj. R-squared	0.173	0.346	0.615	0.645

Table 12: Do investors replace factor-based active funds with smart beta ETFs?

This table presents the results of panel regressions of net flows of factor-based funds on net flows of smart beta ETFs (columns 1-2) and inflows of smart beta ETFs on outflows of factor-based funds (columns 3-4) and the determinants of fund flows:

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

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

where *Return* is the net return of factor-based funds or smart beta ETFs; *Expense* is the expense of factor-based funds or smart beta ETFs; *Log(Size)* is the natural log of factor-based funds or smart beta ETFs total net assets; *Log(Family Size)* is the natural log of factor-based 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)
	FBMF Net Flow$_t$	FBMF Net Flow$_t$	ETF Inflow$_t$	ETF Inflow$_t$
ETF Net Flow$_t$	-0.095	-0.074		
	(0.058)	(0.060)		
FBMF Outflow$_t$			0.003	0.001
			(0.002)	(0.002)
FBMF Net Flow$_{t-1}$	0.128	0.106		
	(0.082)	(0.080)		
ETF Net Flow$_{t-1}$	-0.034	-0.008		
	(0.052)	(0.056)		
ETF Inflow$_{t-1}$			0.627***	0.622***
			(0.035)	(0.035)
FBMF Outflow$_{t-1}$			0.002	0.001
			(0.002)	(0.001)
Return$_{t-1}$	3.489	23.774**	3.140**	5.640
	(2.328)	(11.749)	(1.332)	(4.337)
Expense$_{t-1}$	159.197***	-114.914	-80.367*	-210.947***
	(53.737)	(73.310)	(44.232)	(80.786)
Log(Size)$_{t-1}$	-43.821**	-85.826***	42.211***	53.897***
	(17.205)	(25.615)	(8.836)	(10.827)
Log(Family Size)$_{t-1}$	4.035	1.957	-2.732	-17.158**
	(7.054)	(8.693)	(4.151)	(6.639)
Constant	72.998	750.985***	-143.971**	8.528
	(103.166)	(239.047)	(66.972)	(99.957)
Fixed Effects	No	Yes	No	Yes
Number of observations	3253	3253	2381	2381
Adj. R-squared	0.045	0.093	0.595	0.647

Table 13: Do investors replace closet-factor funds with traditional passive ETFs?

This table presents the results of panel regressions of net flows of closet factor funds on net flows of traditional passive ETFs (columns 1-2) and inflows of traditional passive ETFs on outflows of closet factor funds (columns 3-4) and the determinants of fund flows:

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

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

where *Return* is the net return of closet factor funds 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 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$_t$	Passive Inflow$_t$	Passive Inflow$_t$
Passive Net Flow$_t$	-0.003	0.002		
	(0.003)	(0.003)		
CMF Outflow$_t$			0.096	0.018
			(0.059)	(0.058)
CMF Net Flow$_{t-1}$	0.036	0.032		
	(0.192)	(0.191)		
Passive Net Flow$_{t-1}$	0.006**	0.012***		
	(0.003)	(0.004)		
Passive Inflow$_{t-1}$			0.795***	0.814***
			(0.029)	(0.019)
CMF Outflow$_{t-1}$			-0.148**	-0.064
			(0.059)	(0.059)
Return$_{t-1}$	7.898**	20.204	-6.607	-10.966
	(3.966)	(15.899)	(6.181)	(7.294)
Expense$_{t-1}$	-241.320***	-216.737**	1563.648***	2172.278***
	(90.321)	(94.857)	(443.630)	(540.544)
Log(Size)$_{t-1}$	-157.903***	-170.972***	112.017***	128.717***
	(37.290)	(40.708)	(26.217)	(31.798)
Log(Family Size)$_{t-1}$	8.049	31.016	193.088***	203.915***
	(19.763)	(21.844)	(40.081)	(43.380)
Constant	1394.032***	1153.773***	-3133.985***	-3626.706***
	(327.074)	(326.928)	(677.188)	(665.388)
Fixed Effects	No	Yes	No	Yes
Number of observations	3320	3318	2468	2466
Adj. R-squared	0.058	0.069	0.717	0.796

Table 14: Robustness analysis

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 inflows of smart beta ETFs on outflows of closet factor funds (columns 3-4) and the determinants of fund flows:

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

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

where *Return* is the net return of closet factor funds 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$_t$	ETF Inflow$_t$	ETF Inflow$_t$
ETF Net Flow$_t$	-0.166**	-0.164**		
	(0.078)	(0.080)		
CMF Outflow$_t$			0.067***	0.057***
			(0.017)	(0.017)
CMF Net Flow$_{t-1}$	0.010	0.006		
	(0.180)	(0.177)		
ETF Net Flow$_{t-1}$	-0.130*	-0.134*		
	(0.071)	(0.071)		
ETF Inflow$_t$			0.589***	0.602***
			(0.039)	(0.037)
CMF Outflow$_{t-1}$			-0.033**	-0.023
			(0.015)	(0.015)
Return$_{t-1}$	8.950**	17.484	3.618**	4.858
	(4.087)	(17.703)	(1.450)	(4.117)
Expense$_{t-1}$	-276.202***	-310.153***	-17.572	59.850
	(94.145)	(105.499)	(51.301)	(77.795)
Log(Size)$_{t-1}$	-140.034***	-163.371***	35.478***	34.819***
	(36.049)	(39.743)	(6.194)	(6.970)
Log(Family Size)$_{t-1}$	6.981	28.406	6.582*	5.993
	(19.151)	(18.890)	(3.891)	(5.969)
Constant	1276.281***	1216.195***	-242.876***	-266.125***
	(303.050)	(320.084)	(76.122)	(92.947)
Fixed Effects	No	Yes	No	Yes
Number of observations	3263	3263	2205	2205
Adj. R-squared	0.060	0.081	0.621	0.663

Table 15: Robustness analysis

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.

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

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$_t$	-0.479***	-0.488***	-0.402***	-0.436***
	(0.154)	(0.148)	(0.140)	(0.135)
ETF Net Flow Negative$_t$	0.414*	0.422**	0.343*	0.375*
	(0.219)	(0.203)	(0.202)	(0.192)
ETF Net Flow Positive$_{t-1}$	-0.177	-0.189*	-0.138	-0.138
	(0.116)	(0.109)	(0.117)	(0.112)
ETF Net Flow Negative$_{t-1}$	0.390**	0.378**	0.314*	0.315*
	(0.188)	(0.187)	(0.174)	(0.173)
CMF Net Flow$_{t-1}$	0.027	0.018	-0.008	-0.009
	(0.186)	(0.181)	(0.177)	(0.174)
Return$_{t-1}$			7.447**	31.002***
			(3.247)	(11.264)
Expense$_{t-1}$			-291.476***	-246.918***
			(77.630)	(83.477)
Log(Size)$_{t-1}$			-121.684***	-134.957***
			(31.575)	(33.869)
Log(Family Size)$_{t-1}$			7.889	31.019*
			(15.589)	(17.053)
Constant	-56.878**	-55.955**	1185.916***	930.744***
	(24.702)	(25.204)	(266.031)	(240.948)
Fixed Effects	No	Yes	No	Yes
Number of observations	3840	3840	3840	3840
Adj. R-squared	0.049	0.070	0.081	0.096