How Do Smart Beta ETFs Affect the Asset Management Industry?

Evidence from Mutual Fund Flows*

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Abstract

We examine the impact of non-market-tracking (smart beta) equity exchange-traded funds (ETFs) on how investors evaluate mutual fund performance. We rely on mutual fund flow sensitivity to alphas from different asset pricing models to measure investor behavior. Our empirical results show that when such ETFs are actively traded, fund flow sensitivity to alphas from multi-factor models increases. The dominance of CAPM alpha weakens and even disappears during the high-trading volume period of such ETFs. The results, which are robust to different empirical methods, are not caused by market-tracking ETFs or index mutual funds. The evidence is more pronounced among funds with high exposure to non-market risks and funds with more sophisticated investors.

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Abstract

We examine the impact of non-market-tracking (smart beta) equity exchange-traded funds (ETFs) on how investors evaluate mutual fund performance. We rely on mutual fund flow sensitivity to alphas from different asset pricing models to measure investor behavior. Our empirical results show that when such ETFs are actively traded, fund flow sensitivity to alphas from multi-factor models increases. The dominance of CAPM alpha weakens and even disappears during the high-trading volume period of such ETFs. The results, which are robust to different empirical methods, are not caused by market-tracking ETFs or index mutual funds. The evidence is more pronounced among funds with high exposure to non-market risks and funds with more sophisticated investors.

Keywords: Mutual fund flows; ETFs; smart beta; asset pricing models; investor behavior

JEL Classification: G11; G23; G02; O3

1. Introduction

"Active managers will now have to demonstrate that they can outperform after deducting the influence of easily measurable factor exposures."

-- Hortense Bioy, Morningstar, 2015

The last two decades have witnessed a boom in exchange-traded funds (ETFs). With higher transparency, better liquidity, and lower transaction costs, ETFs have attracted a large number of investors—especially after the creation of strategic beta, or smart beta strategies[1]—who had previously invested in equity mutual funds. In 2015, actively managed equity mutual funds lost $124 billion in fund flows. In contrast, flows to ETFs totaled $200 billion (*Financial Times*, 2016). As the competition from passive asset management has intensified, the traditional mutual fund industry continues to experience dramatic changes. As pointed out in a Morningstar research report (Greggory Warren (2014)), "*It has been easy for most of the traditional asset managers to ignore the growth of ETFs, as it has had little impact on their economic moats, that will change as we move forward.*" In this paper, we examine the impact of ETFs on the traditional mutual fund industry. Specifically, we investigate whether the trading of smart beta equity ETFs, which track multiple non-market risks, could change investors' way of evaluating active mutual fund managers' performance.

How do investors assess mutual fund managers' skills? Superior mutual fund returns can be decomposed into two components: (1) exposures to factor returns, and (2) superior abnormal performance (i.e., alpha) after controlling for factor exposures. In theory, investors should only reward fund managers for alphas, the risk-adjusted returns (Pastor and Stambaugh (2002a)). If a mutual fund manager fails to generate alphas, investors should turn to other managers or other investment vehicles with lower fees. Although mutual fund flows should be sensitive to risk-adjusted returns only, in practice, mutual fund investors tend to act differently. The fact that mutual fund flows are more sensitive to the CAPM model alpha than alphas from multi-factor (APT) models (see e.g., Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2015))

[1] Smart beta (also known as strategic beta, fundamental indexing, factor investing, among others) is a catchall term for rules-based strategies that aim to deliver better risk-adjusted returns than traditional market-cap-weighted indexes. From 2008 to June 2016, the AUM of smart beta ETFs had a significant increase from US$160 billion to US$429 billion. In 2016, BlackRock, the world's largest ETF provider, projected that smart beta ETF assets will reach US$1 trillion globally by 2020.

indicates that investors seem to reward mutual fund managers for exposures to non-market risk factors such as SMB, HML, and MOM (momentum factor). Even though models such as the Fama-French (1993) three-factor model and the Carhart (1997) four-factor model have been well recognized for two decades, the application of such models seems to be more limited compared with that of the CAPM model. We argue that one of the reasons is an insufficiency of investment vehicles, such as ETFs, that enable investors to gain exposure to such non-market risks.[2]

Suppose an investor learns that, on average, small-cap stocks outperform large-cap stocks due to the higher risk exposure to the SMB factor. She then wants to gain exposure to such risk with sufficient diversification.[3] Without actively traded ETFs tracking small-cap and large-cap stocks, the investor's demand could only be satisfied by investing in well-diversified mutual fund portfolios.[4] Therefore, her fund flow is sensitive to the return of the SMB-factor exposure. The higher return generated through exposure to certain risk factors would then be attributed to fund manager skills. However, after the introduction of small-cap ETFs and large-cap ETFs, the fund investor could gain risk exposure to SMB by investing in ETFs with a much lower cost.[5] Therefore, her flow to the mutual fund manager will be more sensitive to more purified alphas, SMB, and market risk-adjusted returns. Similar logic applies for risk factors such as HML and MOM.

This simple example shows how ETFs, particularly ETFs tracking non-market risk factors, change fund flow sensitivity to alphas from different risk-factor models. Our paper tests the argument directly. Relying on a manually categorized data set of ETFs and a comprehensive data set covering nearly 4,000 unique U.S. domestic equity mutual funds from 2000 to 2015, our empirical evidence shows that the trading of non-market-tracking ETFs has indeed changed the mutual fund flow sensitivity to alphas. Specifically, we find significant increases of flow

[2] The first ETF was launched by State Street Global Advisors in 1993. The very first ETF that tracks Standard & Poor's 500 stock index is known as the SPDR. In the early days, ETFs were marketed mostly to institutional investors for sophisticated strategies such as hedging, or for keeping cash active during a change in investment managers. Only recently, with the rise of fee-only financial advisors and access to online financial advisory services, individual investors could gain broader exposure in one trade. ("History of ETFs," n.d.)

[3] The same outcome applies for hedging demand and style chasing. To be consistent, we refer to "gain the risk exposure" only in our paper.

[4] Currently, largest and most actively traded small cap is iShare Russell 2000 ETF (IWM), which was launched on May 22, 2000. However, the trading of iShare Russell 2000 ETF was quite sparse until 2006 and peaked in August 2007. After the financial crisis, the trading volume dropped again. ("IWM," 2016)

[5] While the average U.S. domestic equity mutual fund charges 1.42% in annual expenses, the average equity ETF charges just 0.53%. ("Why Are ETFs So Cheap?" n.d.).

sensitivity to the Fama-French three-factor alpha, the Carhart four-factor alpha, and the seven-factor alpha in high non-market-tracking ETFs trading period. More importantly, in the period in which non-market-tracking ETFs' average trading volume is high, the dominance of the CAPM model over the multi-factor models weakens and even disappears.

Our results are robust to alternative ways of splitting the sample based on different measures of ETF trading volumes, including total trading volume and average dollar trading volume. Different empirical methods, including simultaneous panel regression and a pairwise model horserace competition, also confirm our main findings. One may argue that we might have captured the effect of some unobservable changes or time trends in the financial market. To confirm that our documented evidence indeed comes from the impact of ETFs' tracking non-market risks, we conduct two placebo tests. We split the sample again, conditional on ETFs' tracking the total stock market or on the index mutual funds that track non-market risks. We find no impact on the fund flow sensitivity to alphas from the multi-factor models. Furthermore, our analysis shows that the impact of non-market-tracking ETFs is more significant for funds with higher exposure to non-market risks (SMB and HML) and funds with more sophisticated investors, who are more likely to use smart beta ETFs as investment tools. Finally, we decompose fund returns into components related to manager skill (alpha) and risk exposures. The trading of non-market-tracking ETFs increases the sensitivity of mutual fund flows to alpha, and reduces the sensitivity to returns arising from risk exposure, particularly for returns attributed to more exotic risks such as momentum.

Our paper contributes to the literature in the following ways. First, our paper documents a new and important impact of ETFs. The major role of ETFs is known to be indexing and tracking. Previous literature largely focuses on tracking errors and concludes that ETFs generally stay close to their benchmarks (See, for example, Elton, Gruber, and Busse (2004); Poterba and Shoven (2002); Johnson (2009)). Yet recently, the competition between ETFs and mutual funds is discussed frequently in the news media. For example, anecdotal evidence shows that the popularity of ETFs is due to the poor performance of active asset management.[6] Academic literature has also investigated the relationship between ETFs and mutual funds. Guedj and Huang (2010) argue that ETFs could not fully replace the index mutual fund because of the

[6] U.S. investors are increasingly dissatisfied with what they perceive as the poor financial value that active fund managers provide, and passive funds are the main beneficiaries of their switching from such managers (Owen Walker (2013)).

heterogeneity in investor liquidity demands. Our paper explores the popular question from a different perspective. We show that the trading of smart beta ETFs has led to a structural change in the mutual fund industry by altering the way investors assess mutual fund managers' skills. Investors no longer reward managers for being exposed to common risk factors when ETFs, which could replicate the return to such risk factors, are actively traded. In contrast, we fail to find a similar impact by non-market (smart beta) index mutual funds. Other studies show that ETFs might have adverse impacts on the financial market. For example, Israeli, Lee, and Sridharan (2016) show that firms with an increased ETF ownership experience a decline in pricing efficiency because of higher trading costs and lower benefits of information acquisition. Using data from one large German brokerage firm, Bhattacharya, Loos, Meyer, and Hackethal (2016) document that individual investing in passive ETFs does not improve portfolio performance. Our paper shows that ETFs are not just simple indexing and tracking tools, but can also provide more options to investors with exposure to multiple non-market risks. Currently, mutual fund managers must offer outperformance because of the competition from smart beta ETFs. In this way, ETFs have changed the asset management industry in a constructive way.

In this paper, we add to the studies on the fund flow-return relation. Though the theory has proposed that fund flows should not be sensitive to the return that is related to various systematic risks, the practice diverges. Literature has shown that fund flows are sensitive to fund performance, defined as from raw return to multi-factor alphas (Ippolito (1992); Chevalier and Ellison (1997); Sirri and Tufano (1998); Huang, Wei, and Yan (2012); Agarwal, Green, and Ren (2017)). In recent studies, mutual fund flows have been documented to be more sensitive to CAPM alpha than to other multi-factor alphas. (see e.g., Barber et al. (2016); Berk and van Binsbergen (2015)). Barber et al. (2016) conclude that as investors cannot understand all of the risk factors, on average, they use the simplest model, which is CAPM. Berk and Van Binsbergen (2015) point out that the CAPM preference indicates that CAPM is the true asset pricing model. By illustrating the relation between fund flow sensitivity and non-market-tracking ETF trading activities, we provide an important yet unexplored alternative explanation. We argue that mutual fund investors reward managers for exposure to non-market risk factors, such as SMB or HML, because they do not have sufficient investment tools to gain (or hedge) the risk by themselves. Once investors gain access to these non-market risks by low-cost ETFs, their investment behavior changes. Agarwal et al. (2017) study hedge fund flow-return relation and find that investors increase their response to exotic return components over traditional return components. It is consistent with our finding that investors decrease their response to traditional return components because they have relatively more substitutive tools (ETFs) to acquire returns related to market, size, and value, than returns related to more exotic risk factors such as momentum. Our study highlights the importance of financial innovation in shaping investor decisions.[7]

The rest of our paper proceeds as follows. Section 2 describes our data and sample construction. We introduce the baseline empirical results, robustness checks, and placebo tests in Section 3. Section 4 shows the channels. Section 5 investigates how flows react to different components of fund returns. Finally, we discuss and conclude.

2. Data and Sample Construction

2.1. Mutual funds flows

We obtain mutual fund data from the Center for Research in Security Prices (CRSP) mutual fund database. The CRSP database contains monthly data beginning from 1991. Since relatively few ETFs traded in the 1990s, we start our analysis from 2000. To construct alphas, we use an estimate window of five years. We exclude funds identified as index funds or ETFs (ETNs) by CRSP.[8]

We calculate fund flows following standard literature. The fund flow F_{pt} for fund p in month *t is* measured as Eq. (1):

$$F_{pt} = \frac{TNA_{pt}}{TNA_{p,t-1}} - \left(1 + R_{pt}\right) \tag{1}$$

where TNA_{pt} is the total net assets under management of fund p at the end of month *t*, and R_{it} is the total return of fund p in month t.[9] For funds with multiple share classes, we calculate flows by adding up all the flows and calculate returns as the value-weighted returns of different

[7] Khan and Lemmon (2016) argue that smart beta is a "disruptive innovation" with the potential to significantly affect the market for investment products, particularly traditional active products. The goal of disruptive innovation in investment management is to deliver superior investment outcomes and meet investors' needs (as opposed to requests).

[8] We exclude funds with index_fund_flag identified as "B (Index-based fund)", "D (Pure Index Fund)" or "E (Index fund enhanced)". We also exclude funds with et_flag identified as "E (ETF)" or "N (ETN)".

[9] Here we assume all fund flows change at the end of the month.

categories. In cases of fund mergers, we sum up the TNA of each component fund as the TNA before the merger. We restrict our sample to funds with a minimum $TNA_{p,t-1}$ of $10 million and flows ranging from -90% to 1000%.

After applying the restrictions, our sample contains 397,352 fund-month observations from 4,587 unique domestic equity funds over the period of January 2000 to December 2015. Table 1 Panel A presents summary statistics for mutual fund characteristics. The monthly average fund flow is about 0.34% with a standard deviation of 13.28%, indicating considerable variation in fund flows. The average fund size is around $1,434.02 million, while the median value is only $281.90 million. The average fund age is 4.81 (log (months)), which is approximately 123 months (about 10 years). Our sample is a little tilted toward older funds. The average fund flow volatility over the past 12 months is about 4.53% and the average annual expense ratio is about 1.25%. We classify a fund as having a load if any subclass of it charges a load fee. About 74% funds in our sample have either a front-end or rear-end load.

[Insert Table 1 about here]

To classify the fund styles, we also calculate the funds' exposures to different risk factors. For the scope of our paper, we mainly consider the Fama-French three risk factors. Table 1 Panel B presents the summary statistics for funds' risk exposure. On average, the exposure to market factor is the largest, about 0.89. The average exposure to SMB is about 0.11, while average exposure to HML is only 0.05, which is the smallest.

2.2. Exchange traded funds data

Our objective is to investigate the impact of ETFs on the mutual fund industry. To show the *availability* and *liquidity* of such investment tools, we rely on the monthly trading volume.[10] The ETFs' data is obtained from CRSP, and ETFs have a historical share code of "73." We restrict our sample to ETFs that are mainly investing in U.S. domestic equity stocks.[11] For each ETF, we obtain the monthly trading volume, return, and size (AUM) over our sample period. We merge

[10] We use monthly average trading volume of ETFs as the main measure to split the sample. For robustness, we also rely on the monthly total trading volume or the average ETF dollar volume.

[11] We use CSRP Style Coding to do the first filtering. To ensure the data quality, we later manually check our sample and exclude ETFs that do not satisfy the condition.

ETFs with the Bloomberg ETF database to identify ETF categories. Our final ETF sample consists of 747 domestic equity ETFs. As we build our story on non-market-tracking, or so-called "smart beta" ETFs, we then classify the 747 ETFs into different categories based on two methods. In our first method (Categorization I), we manually collect descriptions for every ETF from *Yahoo Finance* and *Bloomberg Markets*. We then read these descriptions carefully to identify ETFs that track the market risk. Specifically, market-tracking ETFs are defined as either 1) ETFs tracking the absolute market index or 2) ETFs tracking large stocks such as S&P 500 Index. In this setting, we identify 42 pure market-tracking ETFs[12] and 705 non-market-tracking ETFs.[13] To further clean our sample of non-market-tracking ETFs, we combine our manual identification with the Bloomberg classification as our second method (Categorization II). Finally, we get 227 market tracking ETFs (185 more than the initially identified 42 purely market-tracking ETFs) and 520 non-market-tracking ones.[14] Our main results hold in both classification methods. As Categorization II offers a more purified sample of non-market-tracking ETFs, we use it as the main specification in this paper. Consistent with anecdotal evidence, the number of ETFs increases over years. In 2015, there were approximately 599 domestic equity ETFs with total assets under management (AUM) of $1.20 trillion.

Table 1 Panel C presents the descriptive statistics of market and non-market-tracking ETFs under Categorization I and Categorization II. Market-tracking ETFs generate higher monthly return in both categorizations, which is about 0.66% or 0.60%. Non-market ETFs only get 0.47% or 0.43% per month. The average size of market-tracking ETFs is about $2,106.89 million (Categorization II), while the average size of non-market-tracking ETFs is only

[12] The 42 purely market tracking ETFs are listed in Appendix 5. According to www.etf.com, 16 out of these 42 market-tracking ETFs are also classified as smart beta ETFs as they use different weighting schemes other than value weighting. To obtain a clean sample of non-market-tracking ETFs, we do not count the 16 ETFs as non-market-tracking (smart beta) ETFs in the main specification. The main results are consistent even if we classify the 16 ETFs as non-market-tracking ETFs.

[13] Our list of non-market-tracking equity ETFs is free of survivor bias and highly overlaps with the smart beta channel (for domestic equity ETFs) from www.etf.com, after taking the survivorship bias into account.

[14] Bloomberg first identifies 69 ETFs as industry-related ETFs. Remaining ETFs are further classified based on market cap or strategy Market-tracking ETFs are defined within the market-cap based ETFs. If we follow the definition of Bloomberg, our sample contains 208 market-tracking ETFs. In our second specification, we combine the manually identified market-tracking ETFs and the ones identified as market-tracking ETFs by Bloomberg. Appendix 4 lists 20 largest ETFs in our sample in December 2015, together with their descriptions in Yahoo Finance and their classifications under the two methods. We think our manual identification (Categorization I) is more accurate than Bloomberg classification. For example, the VNQ ETF (VANGUARD REIT IDX VIPERS ETF), the eighth largest ETF in December 2015, is identified as non-market taking one by us but as market tracking one by Bloomberg. Based on its description, VNQ ETF follows MSCI REIT Index, which is designed to cover about two-thirds of the value of the entire U.S. REIT market.

$1,060.87 million (Categorization II). In addition, the average trading volume of market-tracking ETFs (428,105.40, number of shares (in hundreds)) is larger than that of non-market-tracking ETFs (337,046.20, number of shares (in hundreds)). The non-market-tracking ETFs' trading volume is the main measure for us to split our sample into two sub-periods. The "high" non-market-tracking ETFs trading volume periods indicate a high liquidity and availability of investment vehicles, and thus investors gain exposure to non-market risks by investing in such ETFs easily. Conversely, the "low" non-market-tracking ETFs trading volume period should have less impact on investors' behavior.

Figure 1 shows the details of ETF development over the 192 months from January 2000 to December 2015 under the two categorizations. The total number of non-market-tracking ETFs has grown much faster than that of market-tracking ETFs. In terms of total net assets, non-market-tracking ETFs have exceeded market-tracking ETFs since 2009, which is consistent with the ongoing boom for smart beta strategies.

[Insert Figure 1 about here]

Table 1 Panel D presents the correlations between ETF returns and risk factors (MKTRF, SMB, and HML) *ex post* under the two different categorizations. Specifically, for each individual ETF covered in our sample, we use all the available periods to calculate its return correlations with the three risk factors. To benchmark against market returns, for each ETF we also calculate the correlations between contemporaneous market returns and the three risk factors during the same period for that ETF covered in our sample. If our classifications of ETFs are correct, then we expect that market-tracking ETF returns should closely mimic market returns, as well as similar correlations with SMB or HML. On the contrary, non-market-tracking ETF returns will deviate from market returns and should have very dispersed correlations with SMB or HML.

Panel D confirms our expectations. Column (1) shows the correlations between ETF returns and the three risk factors. Column (2) shows the average correlations between contemporaneous market returns and the risk factors during the same period for each ETF. Column (3) shows the differences between these two correlations and the significance. As we can see, under both categorizations, market-tracking ETF returns have very similar correlations with the risk factors when compared with the correlations between the contemporaneous market returns and the risk factors. For example, the average correlation between market-tracking ETF returns and SMB is 0.25 (Categorization II), while the correlation between the contemporaneous market return and SMB is 0.26, which are very close. However, for non-market-tracking ETFs, the average return correlation with SMB is 0.27, which is 0.06 less than the correlation between the contemporaneous market return and SMB, as well as statistically significant. In Columns (5), (6), and (7), we report the cross-ETF distributions of the differences in correlations with the risk factors, compared with the contemporaneous market returns.[15] The results show that under Categorization I, the market-tracking ETF returns closely mimic contemporaneous market returns in the correlation with the three risk factors, with a small cross-ETF variation. However, the non-market-tracking ETF returns show very large absolute deviations from market returns in the correlation with the three risk factors. The evidence suggests that our ETFs' classification is reasonable. Since non-market-tracking ETFs have a big cross-sectional variation in the correlation with SMB and HML, they can serve as flexible instruments for investors to obtain desired exposures to non-market risks.

2.3. Measuring mutual fund performance—alpha construction

For the purpose of our paper, we apply standard risk factor models to estimate the fund alphas. Specifically, we obtain the CAPM alpha, the three-factor alpha (3F), the four-factor alpha (4F), and the seven-factor alpha (7F). For each mutual fund *p* in month *t*, we estimate alphas for different models using an estimation window of five years. Using the 7F-model as an example, we calculate alphas with the following two steps.

First, we use Eq. (2) to calculate coefficients for different factors:

$$(R_{pi} - R_{fi}) = \alpha_{pi} + \beta_{pi}\left(R_{mi} - R_{fi}\right) + s_{pi}SMB_i + h_{pi}HML_i + m_{pi}UMD_i + \sum_{k=1}^{3} \delta_{pi}^{k}\, IND_i^k + \varepsilon_{pi} \qquad (2)$$

where i proxies for an estimation window of the past 60 months (*t-1, t-60*), R_{pi} is the mutual fund return in month i, R_{fi} is the risk-free rate, R_{mi} is the market return, SMB_i is the return on the size factor (small minus big), HML_i is the return on the value factor (high-minus-low book to market stocks), UMD_i is the return on the momentum factor (up-minus-down stocks), and IND_i^k

[15] Specifically, for each ETF we calculate the correlation between ETF returns and a risk factor, and subtract the correlation between contemporaneous market returns and the same risk factor, over the same period of that ETF covered in our sample.

is the return on the *kth* industry portfolios. Details on the industry portfolio constructions are reported in Appendix 2.

Based on the factor coefficients estimated above, we then use Eq. (3) to calculate the alphas. We repeat the two steps for funds in different months to obtain their time-series alphas and repeat the procedure for other models.

$$\hat{a}_{pi} = (R_{pi} - R_{fi}) - [\beta_{pi}(R_{mi} - R_{fi}) + s_{pi}SMB_i + h_{pi}HML_i + m_{pi}UMD_i + \sum_{k=1}^{3} \delta_{pi}^{k}\, IND_i^k] \qquad (3)$$

However, as pointed by Barber et al. (2016), it is unclear how investors weigh past returns when assessing managers' skills. Following their method, we calculate the decay rate λ and construct a comprehensive alpha to incorporate past performance information.

First, we estimate Eq. (4) to obtain the flow-return relation:

$$Flow_{pt} = a + \sum_{s=1}^{18} b_s\, CAPM_{\ p,t-s} + cX_{pt} + u_t + \varepsilon_{pt} \qquad (4)$$

where $Flow_{pt}$ is the fund flow for fund p in month *t*, $CAPM_{p,t-s}$ is the lagged CAPM alpha for fund p at lag *s (s=1 to 18)*, and X_{pt} includes a set of control variables. The control variables include lagged month fund flows from month *t-19* to moth *t-1*, the fund's lagged expense ratio, a dummy variable indicating whether a fund charges load fees, the fund's return standard deviation over the last 12 months, the fund's lagged size, and the log of fund age in month *t-1*. We also include time fixed effects (u_t).

Figure 2 shows the relationship between the estimated coefficients b_s at different lags. The graph shows that recent returns are more important than distant returns. To capture the decaying effect, we use an exponential function to estimate the decay rate λ:

$$b_{ps} = e^{-\lambda(s-1)} + \varepsilon_{pt} \qquad (5)$$

We then use the decaying rate to calculate a comprehensive alpha as the weighted average alphas in the past 18 months. We repeat Eq. (6) for different models to obtain monthly time-series alphas for every fund:

$$alpha_{pt} = \frac{\sum_{s=1}^{18} e^{-\hat{\lambda}(s-1)}\hat{\alpha}_{t-s}}{\sum_{s=1}^{18} e^{-\hat{\lambda}(s-1)}} \qquad (6)$$

[Insert Figure 2 about here]

Table 1 Panel E presents the correlation matrix of alphas estimated based on the four models: CAPM, 3F, 4F, and 7F. As indicated by the table, the correlations among different alphas are high. The lowest correlation is 0.67, which is between the alpha from the CAPM and the alpha from the 7F. The highest correlation is as high as 0.92, which is between the alpha from the 3F and the alpha from the 4F.

3. Empirical Methods and Results

3.1. Baseline results

To directly test the impact of smart beta ETFs trading on investors' fund flow responses to alphas, we run Eq. (7). After splitting our sample period into high- and low-non-market-tracking ETF trading periods, we interact the time dummy with fund performance measured by alphas from different models. If such ETFs indeed change the way that investors evaluate the performance of mutual fund managers, we should observe a significantly positive coefficient of the interaction term. Importantly, the significance should only appear when the alphas from the three-factor or the more complicated multi-factor models are interacted, as shown:

$$Flow_{pt} = a + \beta alpha_{pt} + \gamma alpha_{pt} * MVOL + \delta Volume + cX_{pt} + u_t + \varepsilon_{pt} \quad (7)$$

where $alpha_{pt}$ is the alpha for fund p in month t based on one of the four competing models (CAPM, 3F, 4F, and 7F). MVOL is a dummy variable equal to 1 when the monthly average trading volume of non-market-tracking ETFs is above its median value across all periods, and zero otherwise. X_{pt} represents for the control variables. The control variables include lagged month fund flows from month *t-19* to moth *t-1*, the fund's lagged expense ratio, a dummy variable indicating whether a fund charges load fees, the fund's return standard deviation over the last 12 months, the fund's lagged size, and the log of fund age in month *t-1*. We also include time fixed effects (u_t). Standard errors are clustered at both fund and month levels.

[Insert Table 2 about here]

Table 2 presents the empirical results under both Categorization I and Categorization II. Panel A shows the results when we split the sample using the monthly average trading volume (MVOL) of non-market-tracking ETFs. Each column reports the panel regression results using the alpha from a different asset-pricing model. Consistent with our argument, we find significant and positive coefficients for the interaction terms when the alphas are constructed with more complicated multi-factor asset pricing models, that is, the 3F, 4F, and 7F. The magnitude is also economically significant. The results hold under both Categorization I and II. For example, under Categorization II, the fund flow sensitivity to 3F alpha is 0.196 (Categorization II) when non-market-tracking ETFs trading volume is low, and it increases by 0.051 (Categorization II) when non-market-tracking ETFs are actively traded. More importantly, we find that the dominance of the CAPM alpha over other alphas disappears when non-market-tracking ETFs' trading volume is high. In the low trading volume period, fund flow sensitivity to the CAPM alpha is the highest, namely 0.210. The flow sensitivity to the 7F alpha is the lowest, namely 0.156. The evidence is consistent with the findings of previous literature. In the high trading volume period, fund flow sensitivity to the CAPM alpha does not change significantly. The sensitivity to multi-factor alphas, in contrast, increases and reduces the gap. For example, using the 3F alpha, the flow sensitivity is (0.196+0.051=0.247, Categorization II), which is higher than that to CAPM alpha.

In Panel B, we split the sample according to the total trading volume of non-market-tracking ETFs. Compared with the average trading volume, which captures the usage of an individual ETF, the total trading volume captures the activeness of all ETFs in the same category. TVOL is a dummy equal to 1 when the monthly total trading volume of non-market ETFs is above the median across all periods, and zero otherwise. The results show a similar pattern to Panel A, and confirms our conjecture that the trading of non-market-tracking ETFs changes investors' behavior and increases their flow sensitivity to the multi-factor model alphas.

In Panel C, we split the sample according to the monthly average dollar trading volume rather than the share volume. Dollar volume is important to institutional investors because they tend to make large trades. Dollar volume is also important for small ETFs because they might not have the same liquidity as large ETFs. DMVOL is a dummy equal to 1 when the monthly average dollar trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise. Consistent with Panel A and B, the results in Panel C indicate that fund flow sensitivity to multi-factor model alphas increases when the liquidity of non-market-tracking ETFs is high. In Panel D, we further use a quasi-continuous variable (SMVOL) to define the activeness of individual ETF trading for a given month.[16] Although this method allows for more variation over time than the corresponding dummy variable MVOL, all results are consistent.

To ensure that our non-market-tracking ETFs sample is not contaminated, in subsequent analyses, we rely on Categorization II as our main method to differentiate market-tracking and non-market-tracking ETFs.

3.2. Robustness—alternative empirical methods

Our baseline results indicate that investors tend to use multi-factor models to assess mutual fund managers' skills, when the trading of non-market-tracking ETFs is high. We also point out that the dominance of the CAPM model alpha is diminishing. In this section, we directly test the significance of the CAPM alpha's dominance over the other alphas, conditional on the trading of non-market-tracking ETFs. We apply two methods to test the horserace competition, namely simultaneous panel regression and the performance ranking method used by Barber et al. (2016). Both empirical methods confirm that the dominance of the CAPM alpha weakens during the high non-market-tracking ETFs trading period. The dominance of the CAPM alpha over the 3F alpha completely disappears, as a large portion of non-market-tracking ETFs use size- and value-related strategies.

3.2.1. Simultaneous panel regression

We test fund flow sensitivity to different alphas directly using the following equation. The regression settings are the same as Eq. (7) except for the interaction terms. We then directly compare magnitude differences between β s from regressions with different alphas as independent variables. The equation is as follows:

$$Flow_{pt} = a + \beta ALPHA_{pt} + cX_{pt} + u_t + \varepsilon_{pt} \quad (8)$$

We tabulate the results in Table 3. Panel A shows the regression coefficients, βs. In the first two columns, we split the sample period according to the monthly average trading volume

[16] Specifically, we rank all 192 months in our sample based on the monthly average trading volume of non-market-tracking ETFs. SMVOL for a given month is then defined as its rank scaled by 192, and ranges between 0 and 1.

of non-market ETFs. In Columns (3) and (4), we split the sample period according to the monthly total trading volume of the non-market ETFs. As shown in Table 3, the magnitudes of βs are quite close when the trading volume of such ETFs is high. The gap between the CAPM and other models seems to only be significant when the trading volume of such ETFs is low. The gap becomes wider for more complicated multi-factor models.

[Insert Table 3 about here]

In Panel B, we test the significance of the gaps between βs.[17] Panel B1 presents the dominance of the CAPM alpha over other multi-factor model alphas in periods when the average trading volume of the non-market-tracking ETFs is high. The dominance of the CAPM alpha over the 3F alpha and 4F alpha is insignificant. The CAPM alpha is only dominating the 7F alpha. In Panel B2, we test the dominance of the CAPM alpha over the other alphas when the average trading volume of such ETFs is low. As investors could not buy or sell the ETFs easily in the "low" period, they have limited capability to replicate the return exposures to non-market risks. Therefore, in these periods, the dominance of CAPM over other alphas remains. Panel B3 and Panel B4 lend further support to our argument using the total monthly trading volume of non-market-tracking ETFs.[18]

3.2.2. Pairwise horserace competition (Barber et al. (2016))

As shown in previous literature, the relation between fund flow and fund return is nonlinear. In order to address the concern and further test the robustness of our findings, we follow Barber et al. (2016) and run a pairwise horserace competition between different models. Specifically, in each month, we rank the mutual funds into deciles according to each of the alphas from the four competing models. Funds with better performance rank higher. We then run the regression below to test the dominance of the CAPM alpha over the alpha from a multi-factor model:

$$Flow_{pt} = a + \sum_i \sum_j b_{ij} D_{ijpt} + cX_{pt} + u_t + \varepsilon_{pt} \quad (9)$$

[17] Panel B1 and B2 correspond to Column (1) and Column (2) in Panel A, respectively. Panel B3 and B4 correspond to Columns (3) and (4) in Panel A.

[18] Our results hold when using Categorization I to differentiate market-tracking and non-market-tracking ETFs. Refer to Appendix 6 for details.

The dependent variable ($Flow_{pt}$) is the fund flow for mutual fund p in month t. D_{ijpt} is a dummy variable that equals to 1 if the fund performance is ranked as *ith* decile in the CAPM model and ranked as jth in a competing model—for example, 3F, and 0 otherwise. Considering the collinearity, we exclude the dummy variable with j = 5 and i=5. The matrix X_{pt} represents the control variables. The coefficients b_{ij} can be interpreted as the percentage flows received by the fund ranking as *ith* decile in CAPM model and *jth* decile in 3F. To make the idea more intuitive, we extract Figure 3 from Barber et al. (2016) to give a visual expression. We empirically compare coefficients in the 45 lower off-angle cells with coefficients in the 45 upper off-diagonal cells. The lower off-angle cells represent funds with better performances based on the CAPM, and the upper off-angle cells represent funds with better performances based on the three-factor model. If investors show no preference between the two competing models, we then expect $b_{ij} = b_{ji}$ for all $i \neq j$. However, if investors prefer using the CAPM to the 3F, then we expect $b_{ij} > b_{ji}$ $(i > j)$. Our method is slightly different from Barber et al. (2016). In their setting, the null hypothesis tests the idea that all summed differences across 45 comparisons is equal to zero, and calculate a binomial test statistic to test the null hypothesis that the proportion of differences is equal to 50%. However, we test whether the mean of the summed different 45 comparisons is equal to zero. We then calculate the proportion of comparisons larger than zero, the proportion of comparisons lower than zero, and further test whether the difference is equal to zero.

[Insert Figure 3 about here]

To make a comparison with Barber et al. (2016), we report both full sample and subsample results in Table 4. Panel A confirms the findings in previous literature that the CAPM alpha dominates all other alphas in explaining the fund flows. We then split the sample according to the trading volume of non-market-tracking ETFs and run the horserace competition again. Consistent with our previous finding, the dominance of the CAPM alpha over the 3F and 4F alpha is absent when non-market-tracking ETFs are more actively traded (Panel B and Panel D).

Only when such ETFs are less actively traded does the dominance of the CAPM alpha against the 3F and 4F alphas remain significant.[19]

[Insert Table 4 about here]

3.3. Placebo tests

Though our results are robust to different measures and different empirical methods, one may argue that our results could be contaminated by some unobservable trends in the financial market. We therefore conduct two placebo tests.

3.3.1. Placebo test I: market-tracking ETFs

Intuitively, only non-market-tracking ETFs should have the impact on flow sensitivity to multi-factor alphas. If we observe a similar impact from market-tracking ETFs, then our previously documented results might have been contaminated by some general trends in the domestic equity ETF market. To ensure that our results truly come from the effect of non-market-tracking ETFs, we split our sample according to the trading of *market-tracking* ETFs. We first check the overlap of the periods with high trading volume of market-tracking and non-market-tracking ETFs. The overlap is 59% under Categorization I and 51% under Categorization II. The low overlap partially alleviates our concerns, as it is less likely that the way we split the sample is associated with the financial market trend. We then replace the dummy variable in Eq. (7) by a dummy variable (MVOLM), which equals to 1 when the monthly average trading volume of market ETFs is above the median value across all periods. We expect the coefficient γ of the interaction term $alpha_{pt} *$ MVOLM to be insignificant for alphas of all models. The results are tabulated in Table 5.[20]

[Insert Table 5 about here]

[19] Our results here still hold when using Categorization I to differentiate market-tracking and non-market-tracking ETFs. Refer to Appendix 7 for details.
[20] We use an average trading volume of market-tracking ETFs, which are identified both in Categorization I and Categorization II to split our samples. We do not use the total trading volume here because the total trading volumes of market-tracking and non-market ETFs both are almost monotonically increasing, which make it difficult for us to disentangle the trading activities of market-tracking and non-market ETFs.

Panel A of Table 5 splits the sample according to the average trading volume of market-tracking ETFs identified under Categorization I. Panel B splits the sample according to the average trading volume of market-tracking ETFs identified under Categorization II. The interaction terms, consistent with our expectations, are never significant.[21] Taken together, the fund flows are more sensitive to the multi-factor model alphas only when non-market-tracking ETFs are more actively traded. It is less likely that the results we observe are driven by certain general trends in the entire domestic equity ETF industry.

3.3.2. Placebo test II: index mutual funds

Previous studies have discussed the competition between ETFs and index mutual funds (See e.g., Elton et al. (2004); Poterba and Shoven (2002); Guedj and Huang (2010)). We also explore this popular question from a different perspective: whether ETFs or index mutual funds better help investors gain exposure to non-market risks and increase their responses to multi-factor model alphas. In this section, we examine in more detail whether non-market index mutual funds have the same impact on the active mutual fund flow sensitivity to multi-factor alphas.

The total net assets of non-market index mutual funds have indeed increased substantially over the last 15 years. Nevertheless, the pace is still relatively behind the growth of smart beta ETFs. In December 2015, the assets of 603 non-market equity index mutual funds totaled 272,279.62 million, approximately 41% of the total net assets of the 520 non-market-tracking ETFs (667,586.50 million, Categorization II), and 34% of the 705 non-market-tracking ETFs (805,735.5 million, Categorization I). To gain exposure to non-market risks, investors might prefer using ETFs for lower management fees and better flexibility when compared with index mutual funds. Another advantage of ETFs over index mutual funds is short selling: investors can short ETFs to hedge risk exposures and manage risks.[22] The potential disadvantage of trading ETFs is the cost of transactions including commission fees, bid-ask spreads, and liquidity.

[21] Our placebo tests based on trading volume of market-tracking ETFs hold in both Categorization I and Categorization II, mainly because the 187 (227 minus 42) ETFs are significantly smaller compared with the 42 purely identified ones. In December 2015, the total net assets of the 42 purely market-tracking ETFs (398.465 million) are three times as large as those of the 180 ETFs (138.149 million), the total trading volumes (34,817,689, number of shares, in hundreds) are two times as large as those of the 180 ETFs (16,604,976, number of shares, in hundreds), and average trading volumes (916,254, number of shares, in hundreds) are 10 times as large as those of the 180 ETFs (91,236, number of shares, in hundreds).

[22] For example, Li and Zhu (2016) find that during 2002–2013, 3.90% of equity ETFs have average short-interest ratios above 20% and 10.64% have average short-interest ratios above 10% of shares outstanding. For stocks, the corresponding figures are 0.92% and 5.46%, respectively.

Therefore, institutional investors that face low transaction costs are more likely to prefer using ETFs, particularly in periods with more active ETF trading. In contrast, retail investors might prefer using index mutual funds, particularly in periods when ETF trading volume is low and transaction costs are high.

We identify non-market equity index mutual funds from the CRSP mutual fund database. Specifically, we use the CRSP style code to focus on index funds starting with "ED" and the forth character not being "L" or "M." "L" represents large-cap funds that track indexes such as the S&P 500 Index. "M" represents mid-cap funds. After June of 2008, we further exclude index funds with a flag "D" (Pure Index fund).[23] We use Eq. (1) to measure the monthly flow of each index mutual fund and then replace the dummy variable in Eq. (7) by MVOL_Index (or TVOL_Index), which is equal to 1 when the monthly average (or total) flow of such index mutual funds is above the median value across all periods. We expect the coefficient γ of the interaction term to be insignificant for the alphas of all models. The results are reported in Table 6.

[Insert Table 6 about here]

Panel A of Table 6 splits the sample according to the monthly average flow of non-market index mutual funds. Panel B splits the sample according to the monthly total flow of such index mutual funds. It is clear that the interaction terms are always insignificant. The results indicate that the growth of index mutual funds does not generate a similar impact as smart beta ETFs. That is, mutual fund flows are more sensitive to multi-factor model alphas only when non-market-tracking ETFs are more actively traded. It is plausible that even retail investors, compared with institutional investors, prefer using index mutual funds because they are less likely to understand the complicated multi-factor models. (We further discuss the investor sophistication of mutual fund investors in Section 4.2). Therefore, it is unlikely that our key results are driven by the concurrent development of the index mutual funds industry.

[23] Starting in June of 2008, the CRSP mutual fund database provides the following descriptions of index fund flags: B = index-based fund, which utilizes indices as its primary filter for the purchase and sale of securities. D = pure index fund, in which the objective is to match the total investment performance of a publicly recognized securities market index. E = index fund enhanced, in which the objective is to exceed the total investment performance of a publicly recognized securities market.

4. Channels

4.1. Exposures to non-market risks and fund flow response to alphas

Our primary results indicate that investors are shifting from the CAPM to the three-factor model, and even the four-factor model to evaluate fund performance in periods with a high trading volume of non-market-tracking ETFs. The main reason is that with more investment vehicles available, investors can simply trade non-market-tracking ETFs to acquire returns related to SMB and HML, and therefore no longer reward the mutual fund managers for bearing such risk exposures. Thus, SMB- or HML-related returns are removed from managers' skillset when the substitute products are easily acquired. Naturally, such an impact would be more pronounced for funds with higher exposure to the non-market risk factors. Such mutual funds' CAPM alphas are more likely to be contaminated by returns related to SMB and HML. Consequently, we expect the increased sensitivity to the multi-factor model alphas to be more pronounced in funds with higher exposure to SMB or HML.

To measure funds' exposures to market and non-market risk factor, we run the Fama-French three-factor model regression for each mutual fund over the full sample period. We take the *absolute value* of factor loadings to measure the risk exposure. We then rank all funds into terciles based on their exposures to SMB and HML, respectively. The top tercile represents funds with the highest exposure to SMB or HML. We take those funds ranking both in the top SMB and HML terciles as funds with high exposures to non-market risks and those ranking in the bottom terciles as funds with low exposures to non-market risks. We then run Eq. (7) again to examine the impact of non-market-tracking ETFs on flow-alpha sensitivity.

Table 7 presents the results. For funds with high exposure to SMB and HML, responses of fund flows to the alphas of 3F, 4F, and 7F significantly increase in periods with high trading volume of non-market-tracking ETFs. However, in funds with low exposure to SMB and HML, there are no such increases. For example, in Column (2), the response to the 3F alpha increases from 0.145 to 0.221, while there is no such increase in Column (3). Therefore, our results are driven by funds with high exposure to SMB and HML whose CAPM alphas are more contaminated by returns related to SMB and HML. This evidence lends further support to our argument that the insufficiency of non-market-tracking ETFs may have contributed to the dominance of the CAPM alpha over alphas from multi-factor models.

[Insert Table 7 about here]

4.2. Investor sophistication and fund flow response to alphas

Our results thus far treat investors as homogeneous. Nevertheless, investor heterogeneity might play a big role in the model selection process. Barber et al. (2016) find evidence showing that more sophisticated investors use more sophisticated models. Our null hypothesis proposes the usage of Smart Beta ETFs as an explanation for investors' shift toward more sophisticated models. But who are the pioneers of using these instruments? Anecdotal evidence shows that Smart Beta ETFs are particularly attractive to institutional investors. Smart Beta ETFs allow institutions to take very specific perspective in constructing portfolios with lower cost and better transparency. (ETF.com, 2015) The development in the retail market is relatively slow (Ricketts, 2016). As the usage of Smart Beta ETFs also requires investors' understanding of factor models, we expect the change to be driven by sophisticated investors.

4.2.1. Sentiment measure

We rely on two measures to define investor sophistication. We first use sentiment trading as a proxy for overall investor sophistication. Specifically, for each month we create a sentiment measure ($SENT_t$) that captures variations in aggregate trading in mutual funds:

$$SENT_t = \frac{\sum_{i=1}^{n} |F_{it}|}{\sum_{i=1}^{n} TNA_{i,t-1}} \quad , \tag{10}$$

where $|F_{it}|$ is the absolute value of flow for fund *i* in month *t*, and $TNA_{i,t-1}$ is the lagged net assets for fund *i* in month *t-1*. Brown, Goetaman, Hiraki, Shiraishi, and Watanabe (2003) and Ben-Rephael, Kandel, and Wohl (2012) show that aggregate fund flows can proxy for overall investor sentiment. Investor sentiment will be larger when aggregate fund flows (whether inflows or outflows) are larger. Thus we define high sentiment periods as those with $SENT_t$ above the median value across our sample periods. As normally there would be an increase in unsophisticated investors in the market in high sentiment periods, low $SENT_t$ represents more sophisticated investors while high $SENT_t$ represents less-sophisticated investors.

[Insert Table 8 about here]

The results are presented in Table 8. We split our full sample into two sub-periods based on the sentiment measure. The interaction terms between the alphas and the average trading volume dummy (MVOL) are only significant for sophisticated investors regarding the alphas of 3F, 4F, and 7F. This suggests that only sophisticated investors respond to the active trading of non-market-tracking ETFs. For sophisticated investors, the response to the 3F alpha increases by 0.136, resulting a change from 0.194 to 0.330 in high ETF trading periods. For unsophisticated investors, the response to the 3F alpha is still 0.202. The response increases for sophisticated investors regarding the alphas of 4F and 7F are even larger. The results in Table 8 indicate that sophisticated investors are more likely to understand sophisticated models as well as non-market risk. With the active trading of smart beta ETFs that track various non-market risks, sophisticated investors will switch to more complicated models to evaluate mutual fund performance, while unsophisticated investors are less likely to understand sophisticated models or be aware of non-market risk factors. Therefore, the development and trading of non-market-tracking ETFs have a weak impact on their way of evaluating a mutual fund performance.

4.2.2. Distribution channels

In this part, we use fund distribution channels as another proxy for investor sophistication. The underlying intuition is that investors in direct-sold funds are on average more sophisticated than investors in broker-sold funds. Such sophistication means better education, older age, more experience, or more wealth. Chalmers and Reuter (2013) document that investors in broker-sold funds are normally younger, less well educated, and possess less wealth than investors in direct-sold channels. In addition, investors in direct-sold funds perform better on average. Del Guercio and Reuter (2013) find that flows for direct-sold funds are more sensitive to alphas. Christoffersen, Evans, and Musto (2013) find that payments by fund companies to brokers will impose a large influence on flows for broker-sold funds. Thus we hypothesize that the impact of Smart Beta ETFs on direct-sold funds is stronger than that on broker-sold funds. More specifically, we define a fund as broker-sold if any share class takes 75% or more of its total assets and meets any of the following criteria: the fund charges a front-end load, a back-end load, or a 12b-1 fee greater than 25bps (see Barber et al. (2016); Bergstresser, Chalmers, and Tufano (2009)).

[Insert Table 9 about here]

We present results of this analysis in Table 9. Consistent with our findings in Table 8, the results indicate that direct-sold funds are more respondent to the active trading of non-market-tracking ETFs, consistent with the view that sophisticated investors use Smart Beta ETFs more. Sophisticated investors tend to use complicated multi-factor models to evaluate fund performance in periods with high trading volume of non-market-tracking ETFs. To sum up, our results, based on two measures of sophistication, support the conjecture that sophisticated investors are more respondent to the availability and liquidity of non-market-tracking ETFs and then shift from CAPM to multi-factor models to assess mutual fund managers.

5. Return Decomposition: Response of Fund Flow to Components of Fund Returns

Barber et al. (2016) document that investors respond most to the market risk of a fund when assessing its performance. However, investors in aggregate do account for size, value, and industry tilts of a fund, and their response of flows to these return components is much stronger than to the market return component. Agarwal et al. (2017) classify systematic risk factors into traditional and exotic categories based on effort cost involved in gaining exposure to the risk factor.[24] They find that the sensitivity of exotic return components is greater than that of traditional return components, and interpret their finding as investors' preference for returns from exotic risks over returns from traditional risks. Moreover, they document that investors' update their capital allocation decisions by tilting more towards exotic return components with increased knowledge over time.[25]

[24] For example, in the Carhart-4 model, Agarwal et al. (2017) take return components related with market, SMB, and HML as traditional categories, and the return component related with momentum as an exotic category. They argue that both size and value premium can be easily and inexpensively achieved through mutual funds. However, we find that size and value premium are still not easy to obtain simply using mutual funds.

[25] Agarwal et al. (2017) argue investors' tilting towards returns-related exotic risks over time by documenting investors' increasing response to exotic return components over traditional components. Our paper provides another explanation: the preference of exotic return components over traditional components could mainly be driven by investors' decreasing response to traditional components, as investors have more substitutive tools (ETFs) to acquire returns related to market, size, and value, than returns related to more exotic risks like momentum.

In this paper, we argue that the availability and liquidity of ETFs could help investors gain return components related with risk factors which were previously obtained through mutual fund managers. Nevertheless, the ETF development is uneven regarding different risk factors. Within our ETF sample, most are size or industry related,[26] with value ETFs in third place. Very few ETFs capture the momentum effect. Few momentum ETFs means that investors still have difficulty in obtaining this component without mutual funds. Therefore, the uneven development of ETFs gives investors different incentives to acquire return components through mutual funds. In principle, investors should respond less to return components that are easily obtained and mainly related with market, SMB, and HML risk factors. Components related to momentum and industry factors are relatively harder to get through ETFs and accordingly will attract more investor response.

To test this hypothesis, we use a 7F model to decompose a fund's return and classify it into three components: alpha and two systematic components. The details of fund return decomposition are reported in Appendix 3. The first systematic component consists of returns related with market, SMB, and HML risk factors. The second systematic component consists of returns related with momentum and three industry risk factors. As we have discussed, investors have easily replicated the first systematic component through ETFs in recent years, while the second one remains hard to replicate.

[Insert Table 10 about here]

Table 10 presents return decompositions and the response of fund flows to different components. We use Categorization II to differentiate ETFs and split the sample into high and low trading periods of non-market-tracking ETFs. Panel A reports results using average trading volume. Panel B reports results using total trading volume. Our results first show that the sensitivity of fund flows to the first systematic return component is the smallest in all periods. For example, in Panel A, the coefficient of the first systematic component is only 0.130 in high trading periods and 0.121 in low trading periods, both are significantly smaller than that of the other two components. This is consistent with our expectation and previous studies that have

[26] Even though the development of industry ETFs provides investors with a lot of investment instruments, it is still very difficult for investors to fully replicate industry portfolios using ETFs.

shown that the availability of substitutive investment tools will give investors less incentive to acquire relevant return components through mutual funds.

More importantly, our results document investors' changing response to the three return components of mutual funds. As shown in Panel A, in low-ETF trading periods investors respond most aggressively to the second systematic component. The coefficient for the second systematic component is even 0.037 higher than that of the alpha component. However, in high-ETF trading periods, the largest responding coefficient comes from the 7F alpha, which is 0.259 and even 0.043 higher than the coefficient for the second systematic component. We also observe investors' increasing response to the 7F alpha over the first systematic components. The difference is 0.095 in the low trading period but increases to 0.129 in the high trading period, which increases by 35.76%. The same findings are confirmed in Panel B. Even though sensitivity to the second component is 0.036 higher than that of the 7F alpha in low-ETF trading periods, it is 0.039 lower than that of alpha in high-ETF trading periods. Moreover, the difference between the coefficients for alpha and the first component increases by 18.18% in high-ETF trading periods. Taken together, our results show that investors respond less to return components that can be readily achieved by substitutive investment tools. In summary, the development of ETFs gives investors less incentive to acquire factor-related return components through actively managed mutual funds that charge much higher fees.

6. Conclusion

In this paper, we examine the impact of ETFs on financial markets. Specifically, we investigate how the trading of non-market-tracking equity ETFs change the way investors assess active mutual fund managers' performance. Superior mutual fund returns can be decomposed into two components: exposure to factor returns and superior abnormal performance (i.e., alpha) after controlling for factor exposures. In theory, investors should only reward fund managers for alphas. However, in contrast to theoretical predictions, mutual fund investors reward mutual fund managers for the returns related to non-market risk factors. Although factor models such as the Fama-French three- or Carhart four-factor models have been well recognized over the past 20 years, their application is much more limited than CAPM in reality. We propose and show that observed investors' behavior is due to the lack of products tracking the non-market risk exposure.

Relying on the trading volume of non-market-tracking (smart beta) ETFs, which shows the availability and liquidity of these investment tools, we find that the fund flow sensitivity to the three-factor, four-factor, and seven-factor alphas significantly increase when such ETFs are actively traded. Such findings are robust across different measures and different empirical methods. Our empirical tests further show that the dominance of the CAPM alpha over the multi-factor model alphas in explaining fund flows diminishes when non-market-tracking ETFs' trading volume is high. Such results are absent in periods when the market-tracking ETFs or non-market-tracking index mutual funds are actively traded; hence, our findings are not due to some unobservable changes or time trend in the financial market. The impact of non-market-tracking ETFs are more pronounced in funds with higher exposure to non-market risk factors and for funds with a higher portion of sophisticated investors.

Our paper documents a new and important impact of ETFs. ETFs continue to draw a growing share of the investment product market. This phenomenon has drawn attention from both academia and practitioners. While the literature shows that ETFs might have an adverse effect on the financial market, we show that smart beta ETFs have changed the asset management industry in a constructive way. With increased availability of lower-cost investment options to gain exposure to non-market risks, investors no longer need to rely on mutual fund managers and could remove the non-market risk exposure aspect from fund managers' skillsets. With intensified competition from Smart Beta ETFs, mutual fund managers now must provide an outperformance after adjusting for the influence of easily replicable risk factors. Moreover, the story in the mutual fund industry can be replicated in the hedge fund world as well. Even in the case of hedge funds relying on exposure to exotic risk factors, such funds also might face challenges when new ETFs are created to track such exotic risks. Therefore, active fund managers with the capability to provide pure alpha will receive more flow and keep charging high fees. In contrast, other fund managers might switch to manage smart beta products and charge lower fees.

Our paper also highlights that the application of asset pricing models in the assets management industry could be limited due to the lack of investment vehicles. Even though investors may be aware of factor models or styles, their revealed behaviors could still deviate from theoretical predictions. With more opportunities provided by financial innovation, investors' behavior shifts gradually toward theoretical predictions and the dominance of the CAPM alpha over the multi-factor model alphas in explaining fund flows diminishes.

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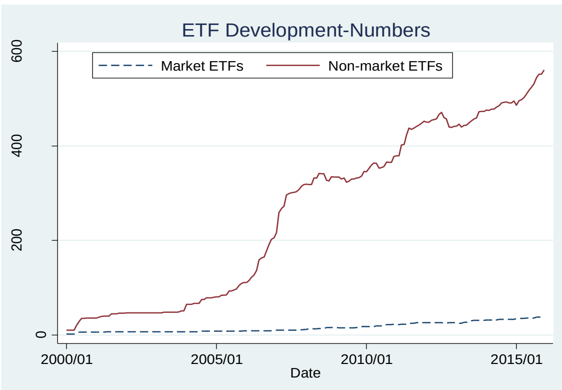
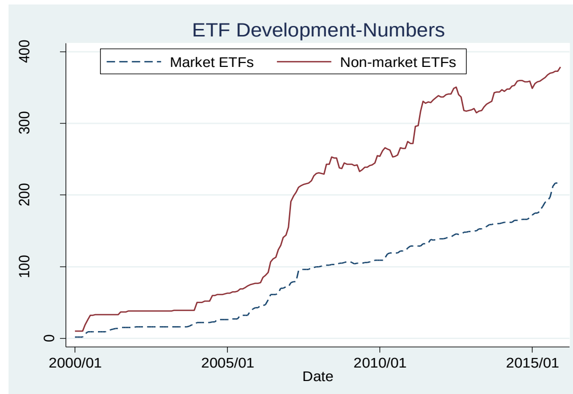
Figure 1 ETF Development

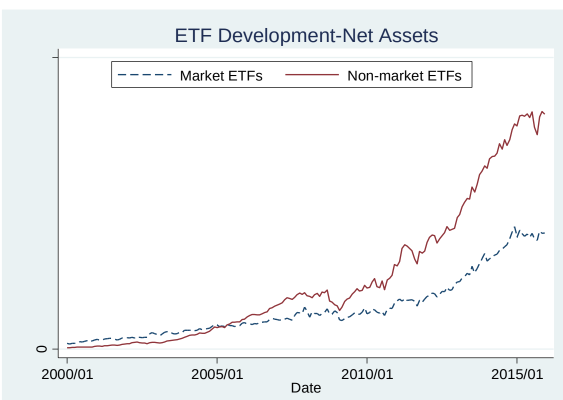
Figure 1 shows the development of U.S. domestic equity ETFs across the 192 months from January 2000 to December 2015. Graph 1, 2 and 3 represents ETF development under Categorization I. Graph 4, 5 and 6 represents ETF developments under Categorization II. Graph 1 and 2 show the number. Graph 3 and 4 show the monthly total net assets (MNAV) under managed.



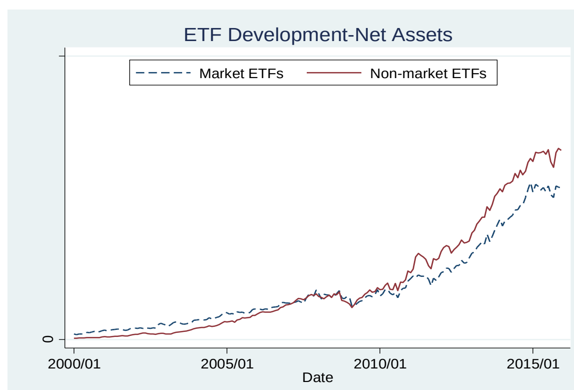
Graph 1 Categorization I: ETF Numbers



Graph 2 Categorization II: ETF Numbers



Graph 3 Categorization I: ETF Net Assets



Graph 4 Categorization II: ETF Net Assets

Figure 2 Decay in Fund Flow Relation

This figure shows the relation of fund flows with the lagged fund returns. Numbers in Y axis represent the coefficients for the 18 lags by regressing F_{pt} (flow for fund p in month t) on the past adjusted fund returns (i=t-1 to t-18). Numbers in X axis represent lags.

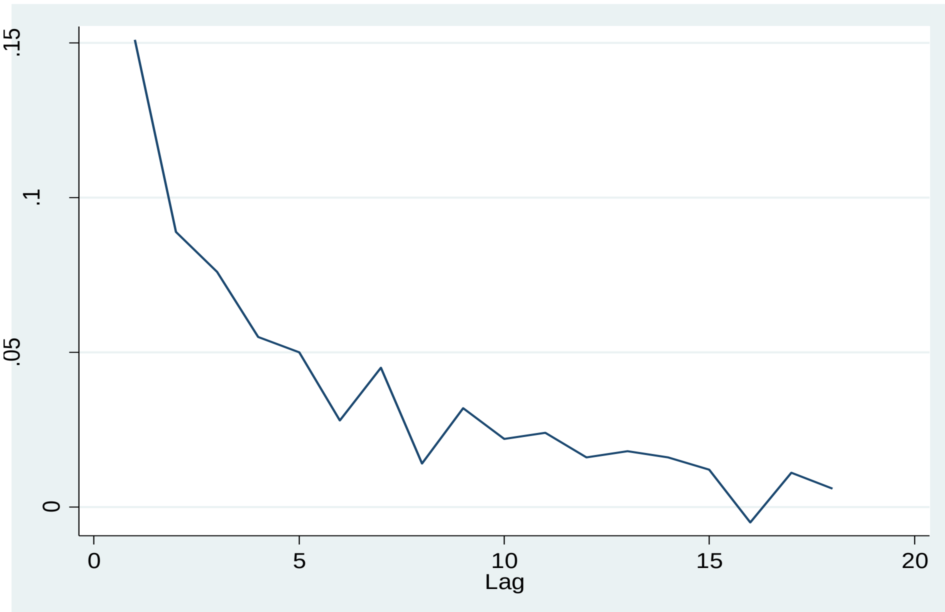


Figure 3 Horse Race Dummy Variables

The figure shows the 100 possible dummy variables for the flow regression that compares relative fund performances based on a fund's CAPM alpha versus three-factor alpha, where decile 10 represents funds with better performances. In the regression, the omitted dummy variables (regression constant) are funds with a decile rank of 5 based on both models (black square). The grey and black cells represent funds with similar ranks based on both models. The empirical tests compare the coefficients corresponding to the 45 lower off-diagonal cells (where funds have better performance based on the CAPM Alpha) to the 45 upper off-diagonal cells (where funds have better performance based on the 3F Alpha). For example, we compare the coefficient estimate on the dummy variable for funds with a CAPM alpha in the 9th decile and 3F alpha in the 3rd decile (red cell) to funds with a CAPM alpha in the 3rd decile and 3F alpha in the 9th decile (green cell).

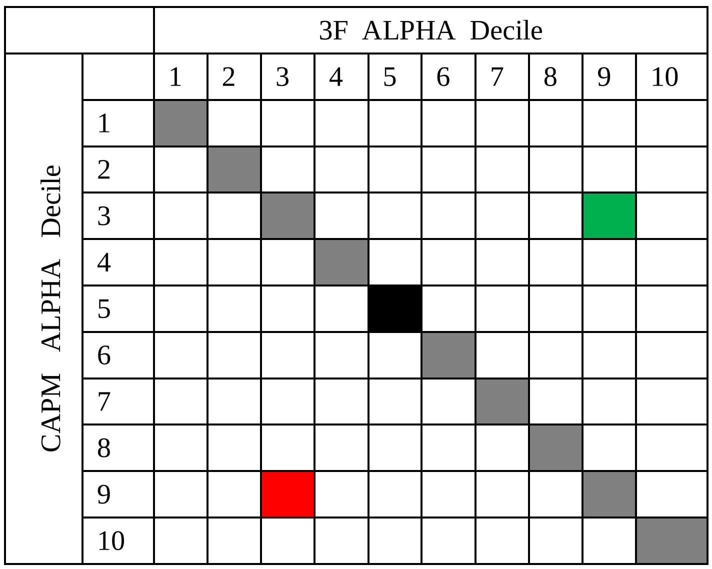


Table 1 Summary Statistics

Panel A presents summary statistics for mutual fund characteristics. Our sample contains 397,352 fund-month observations from 4,587 unique mutual funds over January 2000 to December 2015. Flow is the fund flow change from month t-1 to month t adjusted for fund return in month t. Age is the log of fund age in month t-1. Volatility is the fund's return standard deviation estimated over the last 12 months. Expense is the fund's total expense ratio (TNA-weighted across all share classes) at month t-1. The load dummy equals to one if any share class of the fund charges load fees, whether front-end load or back-end load.

Panel B presents summary statistics for mutual fund return exposures to different factors. We use the full sample to estimate a fund's exposures to three common risk factors: market risk factor (MKTRF), SMB, and HML.

Panel C presents the summary statistics for ETFs from January 2000 to December 2015. Our sample contains 52,944 ETF-month observations, covering 747 ETFs. We divide ETFs into market tracking and non-market tracking ones under Categorization I and Categorization II. In Categorization I, we have 42 purely market tracking ETFs and 705 non-market ETFs. In Categorization II, we have 227 market-tracking ETFs and 520 non-market-tracking ETFs. Return is ETFs' monthly return. Mnav is ETFs' monthly net assets under managed ($, in millions). Volume is the monthly trading volume (number of shares, in hundreds).

Panel D presents the correlations between ETF returns and factors (MKTRF, SMB, and HML). We divide ETFs into market-tracking and non-market-tracking ones under Categorization I and Categorization II, receptively. In Categorization I, we have 42 purely market-tracking ETFs and 705 non-market-tracking ETFs. In Categorization II, we have 227 market-tracking ETFs and 520 non-market-tracking ETFs. Specifically, for each individual ETF covered in our sample we use all the available periods to calculate its return correlations with three risk factors. To benchmark against market returns, for each ETF we also calculate the correlations between contemporaneous market returns and three risk factors during the exact same period for that ETF covered in our sample. Column (1) shows the average correlations between ETF returns and risk factors. Column (2) shows the average correlations between contemporaneous market returns and risk factors during the same period for each ETF. Column (3)–(4) show the differences between these two correlations on average and significances. In Column (5), (6), and (7), we report the cross-ETF distributions of the differences between these two correlations.

Panel E presents the correlation matrix among abnormal return (performance) measures of mutual funds. The monthly abnormal returns are calculated from four competing models: the Capital Asset Pricing Model (CAPM), the Three-factor Model (3F), the Four-factor model (4F), and the Seven-factor Model (7F).

Panel A. Mutual Fund Characteristics (Fund-Month Observations)

	N	Mean	Std	p25	p50	p75
Flow (%)	397,352	0.34	13.28	-1.56	-0.42	1.07
Size ($million)	397,352	1,434.02	5,736.05	87.20	281.90	948.65
Age (log, month)	397,352	4.81	0.71	4.32	4.81	5.27
Expense (%)	397,352	1.25	0.45	1.00	1.25	1.49
Load	397,352	0.74	0.44	0.00	1.00	1.00
Volatility (t-12 to t-1, %)	397,352	4.53	2.46	2.82	4.05	5.71

Panel B. Mutual Fund Exposures to FF-3 Factors (Fund Level)

	N	Mean	Std	p25	p50	p75
Exposure to MKTRF	4,587	0.89	0.28	0.78	0.95	1.05
Exposure to SMB	4,587	0.11	0.29	-0.09	0.03	0.27
Exposure to HML	4,587	0.05	0.30	-0.10	0.04	0.22

Panel C. ETF Characteristics (Fund Level)

Categorization I

ETF	Variables	N	Mean	Std	P25	P50	P75
Market ETFs	Return (%)	3,128	0.66	4.32	-1.75	1.08	3.39
	Mnav	3,162	8,645.17	23,232.80	111.10	676.40	5,012.40
	Volume	3,162	1,727,525.00	7,815,150.00	3,270.00	20,918.00	193,590.00
Non-market ETFs	Return (%)	49,152	0.47	9.57	-2.91	0.96	4.15
	Mnav	49,782	927.10	2,742.33	23.90	119.40	542.20
	Volume	49,782	279,018.10	1,645,412.00	1,811.00	8,699.00	46,481.00

Categorization II

ETF	Variables	N	Mean	Std	P25	P50	P75
Market ETFs	Return (%)	16,356	0.60	6.85	-2.57	1.10	4.18
	Mnav	16,560	2,106.89	10,745.88	34.55	150.50	650.50
	Volume	16,560	428,105.40	3,498,869.00	2,370.50	10,752.50	55,002.50
Non-market ETFs	Return (%)	35,924	0.43	10.27	-2.94	0.91	4.04
	Mnav	36,384	1,060.87	3025.72	21.70	120.50	586.15
	Volume	36,384	337,046.20	1,899,448.00	1,682.00	8,308.50	47,790.00

Panel D. Correlations between ETF Returns and FF-3 Factors (Fund Level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ETF_RET	Contemporaneous MKT_RET	Difference	t-stat	Difference_p25	Difference_P50	Difference_P75
Categorization I	**Market-tracking ETFs**						
ETFRET	1.00						
MKTRF	0.93	1.00	-0.07	-1.53	-0.03	-0.01	0.00
SMB	0.24	0.28	-0.04	-1.60	-0.09	-0.05	-0.01
HML	0.09	0.08	0.01	0.66	-0.01	0.01	0.03
Categorization I	**Non-Market-tracking ETFs**						
ETFRET	1.00						
MKTRF	0.68	1.00	-0.32***	-16.10	-0.28	-0.11	-0.05
SMB	0.26	0.31	-0.05***	-3.85	-0.13	0.00	0.12
HML	0.10	0.14	-0.04***	-3.56	-0.13	-0.01	0.11
Categorization II	**Market-tracking ETFs**						
ETFRET	1.00						
MKTRF	0.72	1.00	-0.28***	-9.45	-0.30	-0.14	-0.04
SMB	0.25	0.26	-0.01	-0.81	-0.09	0.00	0.09
HML	0.14	0.17	-0.03	-1.67	-0.13	-0.01	0.05
Categorization II	**Non-Market-tracking ETFs**						
ETFRET	1.00						
MKTRF	0.68	1.00	-0.32***	-13.15	-0.24	-0.09	-0.04
SMB	0.27	0.33	-0.06***	-4.18	-0.14	-0.01	0.12
HML	0.08	0.12	-0.04***	-3.08	-0.12	0.00	0.11

Panel E. Correlations between Mutual Fund Alphas (Fund-Month Observations)

	CAPM Alpha	3F Alpha	4F Alpha	7F Alpha
CAPM Alpha	1.00			
3F Alpha	0.79	1.00		
4F Alpha	0.74	0.92	1.00	
7F Alpha	0.67	0.82	0.89	1.00

Table 2 Non-Market-tracking ETF Trading Volume and Mutual Fund Flow Response to Alphas

This table reports how mutual fund flows respond to alphas from different models when the trading volumes of non-market-tracking ETFs are different. We use panel regressions. The four competing models to generate alphas include the Capital Asset Pricing Model (CAPM), the Three-factor Model (3F), the Four-factor model (4F), and the Seven-factor Model (7F). We use both categorization I and categorization II to differentiate market ETFs and non-market ETFs. In Categorization I, we have 42 purely market-tracking ETFs and 705 non-market-tracking ETFs. In Categorization II, we have 227 market-tracking ETFs and 520 non-market-tracking ETFs. Column (1) - (4) report results under Categorization I. Column (5) - (8) report results under Categorization II. MVOL is a dummy equal to 1 when the monthly average trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise. TVOL is a dummy equal to 1 when the monthly total trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise. DMVOL is a dummy equal to 1 when the monthly average dollar trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise. SMVOL is a quasi-continuous variable which standardizes the rank of monthly average trading volume between 0 to 1. Panel A reports the results using MVOL dummy. Panel B reports the results using TVOL dummy. Panel C reports the results using DMVOL dummy. Panel D reports the results using SMVOL measure. Controls include lagged fund flows from month t-19, lagged values of log of fund size, log of fund age (months), expense ratio, load fund dummy (equals to one if any share class of the fund charges the front-end load or the back-end load), return volatility and month fixed effects. Standard errors are clustered at the fund and month levels and reported in parentheses. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

Panel A. Baseline Results - Average Trading Volume of Non-Market Tracking ETFs

	Categorization I				Categorization II			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CAPM	3F	4F	7F	CAPM	3F	4F	7F
Alpha	0.214***	0.190***	0.184***	0.160***	0.210***	0.196***	0.180***	0.156***
	(0.019)	(0.017)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.018)
ALPHA*MVOL	0.034	0.040**	0.057**	0.066***	0.043	0.051**	0.068***	0.077***
	(0.026)	(0.020)	(0.026)	(0.022)	(0.026)	(0.025)	(0.026)	(0.027)
Constant	0.606***	0.630***	0.663***	0.737***	0.607***	0.727***	0.663***	0.734***
	(0.095)	(0.088)	(0.100)	(0.101)	(0.095)	(0.100)	(0.100)	(0.101)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Month fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	397,352	397,352	397,352	397,352	397,352	397,352	397,352	397,352
R-squared	0.191	0.186	0.188	0.187	0.191	0.189	0.188	0.187

Panel B. Alternative Measure - Total Trading Volume of Non-Market Tracking ETFs

	CAPM	3F	4F	7F	CAPM	3F	4F	7F
Alpha	0.191***	0.175***	0.173***	0.169***	0.191***	0.173***	0.157***	0.137***
	(0.019)	(0.018)	(0.017)	(0.019)	(0.018)	(0.019)	(0.019)	(0.018)
ALPHA*TVOL	0.040	0.045**	0.041*	0.047**	0.039	0.050**	0.069***	0.079***
	(0.025)	(0.022)	(0.024)	(0.023)	(0.025)	(0.024)	(0.025)	(0.026)
Constant	0.576***	0.538***	0.739***	0.7508**	0.576***	0.707***	0.646***	0.744***
	(0.096)	(0.101)	(0.101)	(0.102)	(0.096)	(0.100)	(0.101)	(0.101)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Month fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	397,352	397,352	397,352	397,352	397,352	397,352	397,352	397,352
R-squared	0.190	0.188	0.187	0.187	0.190	0.188	0.188	0.187

Panel C. Alternative Measure - Average Dollar Trading Volume of Non-Market Tracking ETFs

	Categorization I				Categorization II			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CAPM	3F	4F	7F	CAPM	3F	4F	7F
Alpha	0.212***	0.190***	0.183***	0.161***	0.209***	0.195***	0.179***	0.158***
	(0.019)	(0.017)	(0.019)	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)
ALPHA*DMVOL	0.039	0.047**	0.062**	0.062**	0.046*	0.055**	0.070***	0.072***
	(0.026)	(0.024)	(0.026)	(0.027)	(0.026)	(0.025)	(0.026)	(0.027)
Constant	0.606***	0.681***	0.663***	0.738***	0.606***	0.726***	0.661***	0.736***
	(0.096)	(0.093)	(0.100)	(0.101)	(0.095)	(0.100)	(0.100)	(0.101)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Month fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	397,352	397,352	397,352	397,352	397,352	397,352	397,352	397,352
R-squared	0.191	0.192	0.188	0.187	0.191	0.189	0.188	0.187

Panel D. Quasi-Continuous Measure - Average Trading Volume of Non-Market Tracking ETFs

	CAPM	3F	4F	7F	CAPM	3F	4F	7F
Alpha	0.201***	0.186***	0.164***	0.136***	0.200***	0.184***	0.162***	0.134***
	(0.025)	(0.025)	(0.025)	(0.024)	(0.025)	(0.025)	(0.025)	(0.024)
ALPHA*SMVOL	0.062	0.073*	0.104**	0.121***	0.065	0.077*	0.0108**	0.126***
	(0.042)	(0.041)	(0.045)	(0.046)	(0.043)	(0.042)	(0.044)	(0.046)
Constant	0.607***	0.732***	0.664***	0.746***	0.607***	0.731***	0.664***	0.744**
	(0.096)	(0.100)	(0.100)	(0.101)	(0.095)	(0.100)	(0.100)	(0.101)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Month fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	397,352	397,352	397,352	397,352	397,352	397,352	397,352	397,352
R-squared	0.191	0.189	0.188	0.187	0.191	0.189	0.188	0.187

Table 3 Simultaneous Panel Regressions on Competing Measures of Fund Performances

This table reports the comparisons of Capital Asset Pricing Model (CAPM) and the other three competing models in high and low non-market-tracking ETF trading periods. We use simultaneous panel regressions to calculate coefficients of alphas in Panel A and then compare their dominances. The four competing models to generate alphas include the Capital Asset Pricing Model (CAPM), the Three-factor Model (3F), the Four-factor model (4F), and the Seven-factor Model (7F). We use categorization II to differentiate market-tracking ETFs (227) and non-market-tracking ETFs (520). In Panel A column (1) and (2), we divide our sample into high and low trading periods based on MVOL. MVOL is a dummy equal to 1 when the monthly total trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise. In Panel A column (3) and (4), we divide our sample into high and low trading periods based on TVOL. TVOL is a dummy equal to 1 when the monthly average trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise. Controls include lagged fund flows from month t-19, lagged values of log of fund size, log of fund age (months), expense ratio, load fund dummy (equals to one if any share class of the fund charges the front-end load or the back-end load), return volatility and month fixed effects. Panel A reports coefficient estimates from simultaneous panel regressions of fund flow on alphas based on the four competing models and other control variables. Panel B presents the horserace comparisons between CAPM and the remaining three competing models. For each panel in Table B, we take CAPM as the initial model and compete it against other models to see whether it can dominate. Standard errors are clustered at the fund level and reported in parentheses. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

Panel A	(1)	(2)	(3)	(4)
Sample	Monthly *Average* Trading Volume of Non-Market-tracking ETFs		Monthly *Total* Trading Volume of Non-Market-tracking ETFs	
	HIGH Periods	LOW Periods	HIGH Periods	LOW Periods
CAPM Alpha	0.243***	0.216***	0.229***	0.228***
	(0.009)	(0.007)	(0.009)	(0.007)
3F Alpha	0.240***	0.200***	0.226***	0.213***
	(0.009)	(0.008)	(0.009)	(0.009)
4F Alpha	0.238***	0.185***	0.225***	0.197***
	(0.009)	(0.008)	(0.009)	(0.008)
7F Alpha	0.223***	0.160***	0.211***	0.170***
	(0.009)	(0.008)	(0.009)	(0.008)
Controls	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES
Observations	199,436	197,916	199,848	197,504

Panel B

Panel B.1. Average Trading Volume of Non-Market-tracking ETFs: High Periods (Column (1) Continued)			
Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Coefficients Mean Difference (+/-)	0.03	0.005	0.020^{***}
$\chi^2(1)$	1.04	1.95	20.56

Panel B.2. Average Trading Volume of Non-Market-tracking ETFs: LOW Periods (Column (2) Continued)			
Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Coefficients Mean Difference (+/-)	0.016^{***}	0.031^{***}	0.056^{***}
$\chi^2(1)$	10.90	35.84	106.68

Panel B.3. Total Trading Volume of Non-Market-tracking ETFs: High Periods (Column (3) Continued)			
Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Coefficients Mean Difference (+/-)	0.003	0.004	0.018^{***}
$\chi^2(1)$	0.74	0.84	16.11

Panel B.4. Total Trading Volume of Non-Market-tracking ETFs: Low Periods (Column (4) Continued)			
Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Coefficients Mean Difference (+/-)	0.015^{***}	0.031^{***}	0.058^{***}
$\chi^2(1)$	9.94	36.83	111.33

Table 4 Results of Pairwise Model Horserace

This table reports the pairwise horserace results of CAPM and other three competing models in high and low non-market-tracking ETF trading periods. We run cross-sectional regressions of fund flows on the ranking dummy variables. The four competing models to generate alphas include the Capital Asset Pricing Model (CAPM), the Three-factor Model (3F), the Four-factor model (4F), and the Seven-factor Model (7F).

$$\mathrm{Flow}_{\mathrm{pt}} = \mathrm{a} + \sum_{\mathrm{i}} \sum_{\mathrm{j}} \mathrm{b}_{\mathrm{ij}} \mathrm{D}_{\mathrm{ijpt}} + \mathrm{cX}_{\mathrm{pt}} + \varepsilon_{\mathrm{pt}}$$

The dependent variable ($\mathrm{Flow}_{\mathrm{pt}}$) is the fund flow for mutual fund *p* in month *t*. We get the dummy $\mathrm{D}_{\mathrm{ijpt}}$ by raking fund performance based on $\mathrm{alpha}_{\mathrm{pt}}$ into 10 deciles separately. Decile 10 presents funds with better performances. $\mathrm{D}_{\mathrm{ijpt}}$ is a dummy variable that equals to 1 if the fund performance is ranked as the ith decile in CAPM model and ranked as jth decile in the other four models. Considering collinearity, we exclude the dummy variable for j=5 and i=5. The matrix X_{pt} represents the control variables. We use categorization II to differentiate market-tracking ETFs (227) and non-market-tracking ETFs (520). Panel A presents the full sample test. Panel B, Panel C, Panel D, and Panel E present subsample tests. In panel B and Panel C, we divide our sample into high and low trading periods based on MVOL. MVOL is a dummy equal to 1 when the monthly average trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise. In panel D and Panel E, we divide our sample into high and low trading periods based on TVOL. TVOL is a dummy equal to 1 when the monthly total trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise. Controls include lagged fund flows from month t-19, lagged values of log of fund size, log of fund age (months), expense ratio, load fund dummy (equals to one if any share class of the fund charges the front-end load or the back-end load), return volatility.

We compare the coefficients where the decile ranks are the same magnitude but the orderings are reversed. We both test the magnitude differences and proportion differences. The null hypotheses are: (1) The mean of coefficient differences is zero and (2) The mean of the differences of coefficient proportions is zero. Standard errors are clustered at the fund level and reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

Panel A. Full Sample

Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Magnitude Difference	0.26**	0.28**	0.54***
t-stat	2.56	2.36	4.93
Proportion Difference (%)	5.71***	6.68***	10.37***
t-stat	3.77	4.08	6.23

Panel B. Average Trading Volume of Non-Market-tracking ETFs: HIGH Periods

Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Magnitude Difference	0.25	0.19	0.52***
t-stat	1.63	1.10	3.09
Proportion Difference (%)	4.06**	3.10	9.81***
t-stat	2.34	1.39	4.19

Panel C. Average Trading Volume of Non-Market-tracking ETFs: LOW Periods

Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Magnitude Difference	0.27**	0.38**	0.57***
t-stat	2.02	2.30	4.01
Proportion Difference (%)	7.46***	10.49***	10.97***
t-stat	2.96	4.46	4.61

Panel D. Total Trading Volume of Non-Market-tracking ETFs: HIGH Periods

Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Magnitude Difference	0.20	0.13	0.43**
t-stat	1.26	0.76	2.43
Proportion Difference (%)	2.76	2.29	8.56***
t-stat	1.59	1.06	3.69

Panel E. Total Trading Volume of Non-Market-tracking ETFs: LOW Periods

Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Magnitude Difference	0.32***	0.44***	0.67***
t-stat	2.76	2.84	5.35
Proportion Difference (%)	8.99***	11.55***	12.38***
t-stat	3.57	4.79	5.20

Table 5 Placebo Test I:

Market-tracking ETF Trading Volume and Fund Flow Response to Alphas

This table reports how mutual fund flows respond to alphas from different models when the trading volumes of market-tracking ETFs are different. We use panel regressions. The four competing models to generate alphas include the Capital Asset Pricing Model (CAPM), the Three-factor Model (3F), the Four-factor model (4F), and the Seven-factor Model (7F). Panel A reports the results using MVOLM dummy Under Categorization I, which consist of 42 purely market-tracking ETFs and 705 non-market-tracking ETFs. Panel B reports the results using MVOLM dummy under Categorization II, which consists of 227 market-tracking ETFs and 520 non-market-tracking ETFs. MVOLM is a dummy equal to 1 when the monthly average trading volume of market-tracking ETFs is above the median across all periods, and zero otherwise. Controls include lagged fund flows from month t-19, lagged values of log of fund size, log of fund age (months), expense ratio, load fund dummy (equals to one if any share class of the fund charges the front-end load or the back-end load), return volatility and month fixed effects. Standard errors are clustered at the fund and month levels and reported in parentheses. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

Panel A. Average Trading Volume of Market-tracking ETFs (Categorization I)

	CAPM	3F	4F	7F
Alpha	0.218***	0.204***	0.191***	0.169***
	(0.019)	(0.017)	(0.018)	(0.018)
ALPHA*MVOLM	0.021	0.032	0.041	0.044
	(0.027)	(0.026)	(0.027)	(0.028)
Constant	0.604***	0.730***	0.661***	0.738***
	(0.095)	(0.100)	(0.101)	(0.102)
Controls	YES	YES	YES	YES
Month fixed Effects	YES	YES	YES	YES
Observations	397,352	397,352	397,352	397,352
R-squared	0.191	0.189	0.188	0.187

Panel B. Average Trading Volume of Market-tracking ETFs (Categorizations II)

	CAPM	3F	4F	7F
Alpha	0.243***	0.230***	0.221***	0.195***
	(0.019)	(0.020)	(0.022)	(0.022)
ALPHA*MVOLM	-0.031	-0.024	-0.026	-0.014
	(0.027)	(0.025)	(0.028)	(0.028)
Constant	0.596***	0.731***	0.661***	0.746***
	(0.095)	(0.099)	(0.100)	(0.101)
Controls	YES	YES	YES	YES
Month fixed Effects	YES	YES	YES	YES
Observations	397,352	397,352	397,352	397,352
R-squared	0.191	0.189	0.188	0.187

Table 6 Placebo Test II:

Index Mutual Funds Flow and Fund Flow Response to Alphas

This table reports how mutual fund flows respond to alphas from different models when the flows of index mutual funds are different. We use panel regressions. The four competing models to generate alphas include the Capital Asset Pricing Model (CAPM), the Three-factor Model (3F), the Four-factor model (4F), and the Seven-factor Model (7F). MVOL_Index is a dummy equal to 1 when the monthly average flow of non-market index mutual funds is above the median across all periods, and zero otherwise. TVOL_Index is a dummy equal to 1 when the monthly total flow of non-market index mutual funds is above the median across all periods, and zero otherwise. Panel A reports the results using MVOL_Index dummy. Panel B reports the results using TVOL_Index dummy. Controls include lagged fund flows from month t-19, lagged values of log of fund size, log of fund age (months), expense ratio, load fund dummy (equals to one if any share class of the fund charges the front-end load or the back-end load), return volatility and month fixed effects. Standard errors are clustered at the fund and month levels and reported in parentheses. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

Panel A. Average Flow of Non-Market Index Mutual Funds

	CAPM	3F	4F	7F
Alpha	0.241***	0.220***	0.226***	0.211***
	(0.019)	(0.019)	(0.019)	(0.020)
Alpha* MVOL_Index	-0.024	-0.004	-0.031	-0.040
	(0.026)	(0.025)	(0.026)	(0.027)
Constant	0.602***	0.739***	0.664***	0.759***
	(0.095)	(0.099)	(0.100)	(0.101)
Observations	397,352	397,352	397,352	397,352
R-squared	0.191	0.189	0.188	0.187

Panel B. Total Flow of Non-Market Index Mutual Funds

	CAPM	3F	4F	7F
Alpha	0.231***	0.222***	0.215***	0.188***
	(0.020)	(0.020)	(0.019)	(0.018)
Alpha* TVOL_Index	-0.009	-0.009	-0.013	-0.001
	(0.027)	(0.025)	(0.027)	(0.028)
Constant	0.604***	0.741***	0.665***	0.749***
	(0.095)	(0.097)	(0.100)	(0.100)
Observations	397,352	397,352	397,352	397,352
R-squared	0.191	0.189	0.188	0.187

Table 7 Exposures to Non-Market Risks and Fund Flow Response to Alphas

This table reports how mutual fund return exposures to non-market risks could affect flows responding to multi-factor model alphas when the average trading volumes of non-market-tracking ETFs are different. To measure funds' return exposures to market risk and non-market risks, we run the Fama-French three-factor model regression for each mutual fund over the full sample period. We take the absolute value of factor loadings to measure the risk exposure and divide all mutual funds into two categories: high exposures to SMB and HML (HIGH), and low exposures to SMB and HML (LOW). "FULL" in column (1), (4), and (7) represents full sample analysis. "HIGH" in column (2), (5), and (8) represents high-exposure mutual funds. "LOW" in column (3), (6), and (9) represents low-exposure mutual funds. We use panel regressions and three multi-factor models to generate alphas including the Three-factor Model (3F), the Four-factor model (4F), and the Seven-factor Model (7F). We use categorization II to differentiate market-tracking ETFs (227) and non-market-tracking ETFs (520). MVOL is a dummy equal to 1 when the monthly average trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise. Controls include lagged fund flows from month t-19, lagged values of log of fund size, log of fund age (months), expense ratio, load fund dummy (equals to one if any share class of the fund charges the front-end load or the back-end load), return volatility and month fixed effects. Standard errors are clustered at the fund and month levels and reported in parentheses. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	3F	3F	3F	4F	4F	4F	7F	7F	7F
	FULL	HIGH-Exposure Funds	LOW-Exposure Funds	FULL	HIGH-Exposure Funds	LOW-Exposure Funds	FULL	HIGH-Exposure Funds	LOW-Exposure Funds
Alpha	0.196***	0.145***	0.231***	0.180***	0.135***	0.218***	0.156***	0.115***	0.183***
	(0.019)	(0.025)	(0.040)	(0.019)	(0.023)	(0.039)	(0.018)	(0.019)	(0.039)
Alpha*MVOL	0.051**	0.076**	0.051	0.068***	0.091***	0.057	0.077***	0.109***	0.074
	(0.025)	(0.037)	(0.047)	(0.026)	(0.037)	(0.048)	(0.027)	(0.032)	(0.051)
Constant	0.727***	1.180***	0.655***	0.663***	1.041***	0.770***	0.734***	1.089***	0.853***
	(0.100)	(0.255)	(0.177)	(0.100)	(0.249)	(0.175)	(0.101)	(0.248)	(0.173)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Moth Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	397,352	59,576	59,134	397,352	59,576	59,134	397,352	59,576	59,134
R-squared	0.189	0.177	0.259	0.188	0.176	0.259	0.187	0.176	0.258

Table 8 Investor Sophistication and Fund Flow Response to Alphas (Sentiment Measure)

This table reports how investor sophistication could affect fund flows responding to multi-factor model alphas when the average trading volumes of non-market-tracking ETFs are different. We use investor sentiment as a proxy for investor sophistication (more sentiment-motivated and unsophisticated investors are present in periods of high sentiment as measured by above median trading of mutual funds). "FULL" in column (1), (4), and (7) represents full sample analysis. "S" in column (2), (5), and (8) represents sophisticated investors. "U" in column (3), (6), and (9) represents unsophisticated investors. We use panel regressions and three multi-factor models to generate alphas including the Three-factor Model (3F), the Four-factor model (4F), and the Seven-factor Model (7F). We use categorization II to differentiate market-tracking ETFs (227) and non-market-tracking ETFs (520). MVOL is a dummy equal to 1 when the monthly average trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise. Controls include lagged fund flows from month t-19, lagged values of log of fund size, log of fund age (months), expense ratio, load fund dummy (equals to one if any share class of the fund charges the front-end load or the back-end load), return volatility and month fixed effects. Standard errors are clustered at the fund and month levels and reported in parentheses. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	3F	3F	3F	4F	4F	4F	7F	7F	7F
	FULL	S	U	FULL	S	U	FULL	S	U
Alpha	0.196***	0.194***	0.202***	0.180***	0.172***	0.192***	0.156***	0.145***	0.173***
	(0.019)	(0.026)	(0.026)	(0.019)	(0.027)	(0.025)	(0.018)	(0.027)	(0.024)
Alpha*MVOL	0.051**	0.136***	0.011	0.068***	0.140***	0.026	0.077***	0.141**	0.035
	(0.025)	(0.045)	(0.031)	(0.026)	(0.054)	(0.031)	(0.027)	(0.058)	(0.030)
Constant	0.727***	0.856***	0.289**	0.663***	0.813***	0.178	0.734***	0.852***	0.126
	(0.100)	(0.168)	(0.130)	(0.100)	(0.171)	(0.129)	(0.101)	(0.173)	(0.128)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Moth Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	397,352	168,913	228,439	397,352	168,913	228,439	397,352	168,913	228,439
R-squared	0.189	0.192	0.173	0.188	0.191	0.173	0.187	0.190	0.172

Table 9 Investor Sophistication and Fund Flow Response to Alphas (Distribution Channel)

This table reports how investor sophistication could affect fund flows responding to multi-factor model alphas when the average trading volumes of non-market-tracking ETFs are different. We use mutual fund distribution channel as a proxy for investor sophistication (investors in the direct-sold funds are more sophisticated than those in the broker-sold channel). "FULL" in column (1), (4), and (7) represents full sample analysis. "S" in column (2), (5), and (8) represents sophisticated investors. "U" in column (3), (6), and (9) represents unsophisticated investors. We use panel regressions and three multi-factor models to generate alphas including the Three-factor Model (3F), the Four-factor model (4F), and the Seven-factor Model (7F). We use categorization II to differentiate market-tracking ETFs (227) and non-market-tracking ETFs (520). MVOL is a dummy equal to 1 when the monthly average trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise. Controls include lagged fund flows from month t-19, lagged values of log of fund size, log of fund age (months), expense ratio, load fund dummy (equals to one if any share class of the fund charges the front-end load or the back-end load), return volatility and month fixed effects. Standard errors are clustered at the fund and month levels and reported in parentheses. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	3F	3F	3F	4F	4F	4F	7F	7F	7F
	FULL	S	U	FULL	S	U	FULL	S	U
Alpha	0.196***	0.156***	0.226***	0.180***	0.141***	0.208***	0.156***	0.117***	0.186***
	(0.019)	(0.017)	(0.023)	(0.019)	(0.018)	(0.023)	(0.018)	(0.017)	(0.022)
Alpha*MVOL	0.051**	0.072***	0.034	0.068***	0.091***	0.049	0.077***	0.097***	0.059*
	(0.025)	(0.025)	(0.029)	(0.026)	(0.026)	(0.031)	(0.027)	(0.027)	(0.031)
Constant	0.727***	0.757***	0.729***	0.663***	0.710***	0.640***	0.734***	0.732***	0.769***
	(0.100)	(0.109)	(0.147)	(0.100)	(0.109)	(0.148)	(0.101)	(0.108)	(0.149)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Moth Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	397,352	207,658	189,694	397,352	207,658	189,694	397,352	207,658	189,694
R-squared	0.189	0.197	0.183	0.188	0.197	0.182	0.187	0.196	0.181

Table 10 Response of Fund Flow to Components of Fund Returns

This table reports how mutual fund flows respond to the components of a fund's return. We use seven-factor model (7F) to split a fund's return into three components-alpha and two systematic components. Alpha is the abnormal return form seven-factor (7F) model. SYS_Comp1 represents return component related with market, SMB and HML risk factors. SYS_Comp2 represents return component related with momentum and three industry risk factors. We use categorization II to differentiate market ETFs and non-market ETFs, which results in 227 market-tracking ETFs and 520 non-market ETFs. MVOL is a dummy equal to 1 when the monthly average trading volume of non-market ETFs is above the median across all periods, and zero otherwise. TVOL is a dummy equal to 1 when the monthly total trading volume of non-market ETFs is above the median across all periods, and zero otherwise. Panel A reports the results using MVOL dummy. Panel B reports the results using TVOL dummy. Controls include volume dummy, lagged fund flows from month t-19, lagged values of log of fund size, log of fund age (months), expense ratio, load fund dummy (equals to one if any share class of the fund charges the front-end load or the back-end load), return volatility and month fixed effects. Standard errors are clustered at the fund and month levels and reported in parentheses. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

Panel A. Monthly Average Trading Volume

	HIGH				LOW			
	N	R^2	Coefficient	Difference	N	R^2	Coefficient	Difference
	199,436				197,916			
		0.198				0.182		
b_1(Alpha)			0.259***				0.216***	
t-stat			(46.56)				(38.48)	
b_2(SYS_Comp1)			0.130***				0.121***	
t-stat			(18.76)				(20.86)	
b_3(SYS_Comp2)			0.216***				0.253***	
t-stat			(21.79)				(25.11)	
$b_1 - b_2$				0.129***				0.095***
$\chi^2(1)$				(123.45)				(97.80)
$b_1 - b_3$				0.043***				-0.037***
$\chi^2(1)$				(12.35)				(9.73)

Panel B. Monthly Total Trading Volume

	HIGH				LOW			
	N	R^2	Coefficient	Difference	N	R^2	Coefficient	Difference
	199,848				197,504			
		0.188				0.189		
b_1(Alpha)			0.246***				0.227***	
t-stat			(43.50)				(41.12)	
b_2(SYS_Comp1)			0.119***				0.128***	
t-stat			(17.05)				(22.28)	
b_3(SYS_Comp2)			0.207***				0.263***	
t-stat			(20.84)				(26.22)	
$b_1 - b_2$				0.117***				0.099***
$\chi^2(1)$				(116.27)				(105.86)
$b_1 - b_3$				0.039***				-0.036***
$\chi^2(1)$				(11.09)				(8.97)

Appendix 1 Variable Definitions

Variables	Definitions
Flow	Changes in fund flow from month t-1 to month t, with return adjusted.
Size	Net assets under managed.
Age	Log of fund age in month t-1.
Volatility	A fund's return standard deviation over the last 12 months.
Expense	Lag of a fund's total expense ratio.
Load	A dummy variable taking 1 when a fund charges load fees.
Lagflow_i	The *ith (i=1,2…19)* lagged fund flow.
CAPM Alpha	Alpha calculated from CAPM.
3F Alpha	Alpha calculated from Fama and French (1993) three-factor model (3F).
4F Alpha	Alpha calculated from four-factor model (4F).
7F Alpha	Alpha calculated from seven-factor model (7F).
MKTRF	Market risk factor calculated by subtracting risk-free rate from market return.
SMB	Return on the size factor (small minus big).
HML	Return on the value factor (high minus low book-to-market stocks).
UMD	Return on the momentum factor (up minus down stocks).
IND^k	Return on the kth industry portfolios
MVOL	MVOL is a dummy equal to 1 when the monthly average trading volume of non-market ETFs is above the median across all periods, and zero otherwise (either under Categorization I or Categorization II).
TVOL	TVOL is a dummy equal to 1 when the monthly total trading volume of non-market ETFs is above the median across all periods, and zero otherwise (either under Categorization I or Categorization II).
DMVOL	DMVOL is a dummy equal to 1 when the monthly average dollar trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise.
SMVOL	SMVOL is a quasi-continuous variable which standardizes the rank of monthly average trading volume between 0 to 1.
MVOLM	MVOLM is a dummy equal to 1 when the monthly average trading volume of market ETFs is above the median across all periods, and zero otherwise.
TVOLM	TVOLM is a dummy equal to 1 when the monthly total trading volume of market ETFs is above the median across all periods, and zero otherwise
MVOL_Index	MVOL_Index is a dummy equal to 1 when the monthly average flow of non-market equity index mutual funds is above the median across all periods, and zero otherwise.
TVOL3_Index	TVOL_Index is a dummy equal to 1 when the monthly total flow of non-market equity index mutual funds is above the median across all periods, and zero otherwise.
SYS_Comp1	Traditional_comp represents return components related with market risk, SMB and HML based on seven-factor (7F) model.
SYS_Comp2	Components_comp represents return components related with momentum and industry risks based on seven-factor (7F) model.

Appendix 2 Industry Portfolio Constructions

Following Pastor and Stambaugh (2002a, 2002b), we construct three industry portfolios by extracting the three main principal components of Fama-French 17 industry portfolios. The steps are as following.

Firstly, in month *t*, we obtain the residuals in multiple regressions of the 17 industry returns on factors related to market, size, value and momentum. We use the data in previous 10 years (120 months, *t-120 to t-1*) to estimate the residuals.

$$Indret_\tau = \alpha_t + \beta_{1t}\left(R_{m\tau} - R_{f\tau}\right) + \beta_{2t}SMB_\tau + \beta_{3t}HML_\tau + \beta_{4t}UMD_\tau + \epsilon_\tau \qquad \text{(A2.1)}$$

where $Indret_\tau$ is a (17×1) vector of industry returns, α_t is a (17×1) vector of intercepts estimated from the regression in month *t*, β_{1t} is a (17×1) vector of coefficients on market factor estimated from the regression in month *t*, β_{2t} is a (17×1) vector of coefficients on SMB from the regression in month *t*, β_{3t} is a (17×1) vector of coefficients on HML estimated from the regression in month *t*, β_{4t} is a (17×1) vector of coefficients on momentum estimated from the regression in month *t*, and ϵ_τ is a (17×1) vector of residuals month *t*.

Secondly, we use principal components analysis to extract the first three components from the industry return residuals over the 120 months prior to month *t*, $\epsilon_\tau(\tau = t-120, \dots . t-1)$. $[w_{1t}, w_{2t}, w_{3t}]$ represents the (17×3) matrix of the eigenvectors associated with the three largest eigenvalues of the sample covariance matrix of ϵ_τ $(\tau = t-120, \dots . t-1)$. We also adjust the eigenvectors so that the sum of squared elements of each eigenvector is one.

Then we use (2.2) to get the (17×1) vector of industry return residuals.

$$\epsilon_t = Indret_\tau - \hat{\alpha}_t - \hat{\beta}_{1t}\left(R_{m\tau} - R_{f\tau}\right) - \hat{\beta}_{2t}SMB_\tau - \hat{\beta}_{3t}HML_\tau - \hat{\beta}_{4t}UMD_\tau \qquad \text{(A2.2)}$$

Finally, we multiply the return residuals with the adjusted weights to construct the three industry portfolios in month *t*.

$$IND_t^k = w'_{kt}\epsilon_t \qquad \text{(A2.3)}$$

Appendix 3 Mutual Fund Return Decomposition

Our return decomposition tests are based on the seven-factor (7F) model. Firstly, we rearrange equation (3) into equation (A3.1) and decompose fund returns into alphas and seven factors-related return components.

$$(R_{pi} - R_{fi}) = \hat{a}_{pi} + \beta_{pi}\left(R_{mi} - R_{fi}\right) + s_{pi}SMB_i + h_{pi}HML_i + m_{pi}UMD_i + \sum_{k=1}^{3} \delta_{pi}^{k}\, IND_i^k \quad \text{(A3.1)}$$

So, there will be eight components: the seven-factor (7F) alpha, and return components related to market factor, SMB, HML, momentum, and three industry-tilted factors. Then, like equation (6), we weight every return component over the prior 18 months using the exponential decay function. Taking return component related to market factor for an example, the calculation process is showed in equation (A3.2).

$$MKTRET_{pt} = \frac{\sum_{s=1}^{18} e^{-\hat{\lambda}(s-1)}[\hat{\beta}_{m,t-s}(R_{m,t-s} - R_{f,t-s})}{\sum_{s=1}^{18} e^{-\hat{\lambda}(s-1)}} \quad \text{(A3.2)}$$

Then, we group factor-related returns into two systematic return components. The first systematic component consists of returns related to market, SMB and HML. The second systematic component consists of returns related to momentum and three industry factors.

Finally, we will run the following test to look at how investor's response to different return components.

$$Flow_{pt} = b_0 + b_1 alpha_{pt} + b_2 SYS\_Comp1_{pt} + b_3 SYS\_Comp2_{pt} + \gamma X_{pt} + u_t + \varepsilon_{pt} \quad \text{(A3.3)}$$

where b_0 is the intercept, $alpha_{pt}$ is the weighted seven-factor alpha over the last 18 months, SYS_Comp1_{pt} is weighted first systematic component over the last 18 months, SYS_Comp2_{pt} is weighted second systematic component over the last 18 months. X_{pt} represent the control variables. And u_t is the time fixed effects.

Appendix 4 List of 20 Largest ETFs in December 2015

Ticker	MNAV	Categorization I	Categorization II	Bloomberg Descriptions
SPY	182039	Market	Market	SPDR S&P 500 ETF Trust is an exchange-traded fund incorporated in the USA. The ETF tracks the S&P 500 Index. The Trust consists of a portfolio representing all 500 stocks in the S&P 500 Index. It holds predominantly large-cap U.S. stocks. This ETF is structured as a Unit Investment Trust and pays dividends on a quarterly basis. The holdings are weighted by market capitalizations.
IVV	70352	Market	Market	iShares Core S&P 500 Index ETF is an exchange-traded fund incorporated in Canada. The ETF seeks to provide long-term capital growth by replicating, to the extent possible, the performance of the S&P 500 Index, net of expenses.
VTI	57434	Market	Market	Vanguard Total Stock Market ETF is an exchange-traded fund incorporated in the USA. The ETF tracks the performance of the CRSP US Total Market Index. The ETF holds U.S stocks of all cap sizes. Its investments aim to represent the entire U.S. Equity Market. The ETF holds over 3,500 securities and weights these holdings by market capitalization.
QQQ	43055	Non-market	Non-market	Powershares QQQ Trust Series 1 is an exchange-traded fund incorporated in the USA. The ETF tracks the performance of the Nasdaq 100 Index. The ETF holds large cap U.S. stocks. Its investments exclude the financial sector and therefore, tend to be focused on the technology and consumer sector. The ETF weights the holdings using a market capitalization methodology.
VOO	40440	Market	Market	Vanguard S&P 500 ETF is an exchange-traded fund incorporated in the USA. The ETF tracks the performance of the S&P 500 Index. The ETF primarily holds large-cap U.S. stocks. It invests in all 500 stocks that comprise the index. The ETF weights the holdings using a market capitalization methodology and rebalances quarterly.
IWF	31590	Non-market	Non-market	iShares Russell 1000 Growth ETF is an exchange-traded fund incorporated in the USA. The ETF tracks the performance of the Russell 1000 Growth Index. The ETF holds mostly large-cap U.S. stocks. Its investments are in companies whose earnings are expected to grow at an above-average rate relative to the market. The ETF weights the holdings by market capitalization.
IWM	27693	Non-market	Non-market	iShares Russell 2000 ETF is an exchange-traded fund incorporated in the USA. The ETF tracks the performance of the Russell 2000 Index Fund. The ETF holds mid and small-cap U.S. stocks. Its investments are in the smallest 2000 companies from the Russell 3000 Index. The ETF weights the holdings by market capitalization and rebalances annually.
VNQ	27546	Non-market	Market	Vanguard REIT ETF is an exchange-traded fund in USA. The Fund seeks to track the performance of the MSCI REIT Index. The Fund invests in stocks make up the Index, holding each stock in the same proportion as its weighting in the Index, remaining assets are allocated to cash investments.
IWD	27361	Non-market	Non-market	iShares Russell 1000 Value ETF is (USA) tracks the performance of the Russell 1000 Value Index. The ETF holds mid and large-cap U.S. stocks. Its investments are in companies that are thought to be undervalued by the market. The ETF weights the holdings using a market capitalization methodology and rebalances annually.

IJH	26472	Non-market	Non-market	iShares Core S&P Mid-Cap (USA) tracks the performance of the S&P MidCap 400 Index. The ETF holds mid-cap U.S. stocks. Its investments are chosen using a representative sampling strategy to track the Index. The ETF weights the holdings using a market capitalization methodology and rebalances quarterly.
VUG	20706	Non-market	Non-market	Vanguard Growth ETF is (USA) seeks to track the performance of the CRSP U.S. Large Cap Growth Index. The ETF holds large-cap U.S. stocks. The Fund invests all of its assets in the stocks that make up the Index and follows a full replication strategy. It weights the holdings using a multi factor methodology.
XLF	19464	Non-market	Non-market	Financial Select Sector SPDR Fund's (USA) objective is to provide investment results that, before expenses, correspond to the performance of The Financial Select Sector. The Index includes financial services firms whose business' range from investment management to commercial & business banking.
VIG	19225	Non-market	Non-market	Vanguard Dividend Appreciation ETF is (USA) tracks the NASDAQ US Dividend Achievers Select Index. The ETF holds mid and large-cap U.S. stocks. Its investments are focused on U.S. common stocks that have a history of increasing dividends for ten consecutive years, but exclude REITs. The ETF weights the holdings using by market capitalization.
VTV	18648	Non-market	Non-market	Vanguard Value ETF (USA) tracks the performance of CRSP U.S. Large Cap Value Index. The ETF holds large-cap U.S. stocks. The Fund invests its assets in stocks make up the Index and follows a full replication strategy. It weights holdings using a multi factor methodology.
IJR	17022	Non-market	Non-market	iShares Core S&P Small-Cap ETF is an exchange-traded fund incorporated in the USA. The Fund seeks investment results that correspond to the performance of the S&P SmallCap 600 Index. The Fund uses a Representative sampling strategy to track the Index. The Index measures the performance of publicly traded securities in the small capitalization sector of the US equity market.
MDY	14826	Non-market	Non-market	SPDR S&P MidCap 400 ETF Trust (USA) tracks the performance of the S&P Midcap 400 Index. The ETF holds mid-cap U.S. stocks. This ETF reinvests dividends on a quarterly basis because it is structured as a Unit Investment Trust. The holdings are weighted by market capitalization and rebalanced quarterly.
IVW	14186	Non-market	Non-market	iShares S&P 500 Growth ETF (USA) tracks performance of the S&P 500 Growth Index. The ETF holds large-cap U.S. stocks. Its investments are focused on companies with strong growth characteristics. The ETF weights the holdings using a market capitalization methodology.
XLV	13849	Non-market	Non-market	Health Care Select Sector SPDR Fund is an exchange-traded fund incorporated in the USA. The Fund's objective is to provide investment results that correspond to the performance of The Health Care Select Sector Index. The Index includes companies involved in health care equipment and supplies, health care providers and services, biotechnology & pharmaceuticals.
XLK	13685	Non-market	Non-market	Technology Select Sector SPDR Fund (USA) tracks the performance of The Technology Select Sector Index. The ETF holds large and mid-cap technology stocks. Its largest investment allocation is in the United States. The ETF weights the holdings using a market capitalization methodology.
DVY	13265	Non-market	Market	iShares Select Dividend ETF is (USA) tracks the price and yield performance of the Dow Jones Select Dividend Index. The ETF predominantly holds mid and large-cap U.S. stocks. Its investments are selected based on dividend yield. The ETF weights the holdings based on dividends.

Appendix 5 List of 42 Purely Market-tracking ETFs

NUM	Ticker	Name	Inception Date
1	SPY	SPDR S&P 500 ETF TRUST	01/22/1993
2	DIA	SPDR DJIA ETF TRUST	01/13/1998
3	IVV	ISHARES CORE S&P 500 ETF	05/15/2000
4	IWB	ISHARES RUSSELL 1000 ETF	05/15/2000
5	IWV	ISHARES RUSSELL 3000 ETF	05/22/2000
6	VTI	VANGUARD TOTAL STOCK MKT ETF	05/24/2000
7	IYY	ISHARES DOW JONES US ETF	06/12/2000
8	THRK	SPDR RUSSELL 3000 ETF	10/04/2000
9	OEF	ISHARES S&P 100 ETF	10/23/2000
10	ITOT	ISHARES CORE S&P TOT U S MKT	01/20/2004
11	JKD	ISHARES MORNINGSTAR LARGE-CP	06/28/2004
12	PRF	POWERSHARES ETF TR FTSE RAFI	12/19/2005
13	RYJ	GUGGENHEIM RAYMOND JAMES SB1	05/19/2006
14	PYH	POWERSHARES MORNSTAR STKINVS	12/01/2006
15	EQWL	POWERSHARES TP 200 EQ WGT PT	12/01/2006
16	TUSA	FIRST TR TTL US MKT ALPHADEX	12/05/2006
17	SZG	SPA MARKETGRADER LGCP 100 FD	10/12/2007
18	MGC	VANGUARD MEGA CAP ETF	12/17/2007
19	RWL	OPPENHEIMER LRG CAP REV ETF	02/22/2008
20	PQBW	POWERSHARES NASDAQ-100 BUYWT	06/13/2008
21	VONE	VANGUARD RUSS1000 INDEX ETF	09/20/2009
22	IWL	ISHARES RUSSELL TOP 200 ETF	09/22/2009
23	SCHB	SCHWAB US BROAD MARKET ETF	11/03/2009
24	FNDB	SCHWAB FNDMTL US BRD MKT IDX	11/03/2009
25	SCHX	SCHWAB US LARGE-CAP ETF	11/03/2009
26	EUSA	ISHARES MSCI USA EQL WTD ETF	05/05/2010
27	VOO	VANGUARD S&P 500 ETF	09/07/2010
28	VTHR	VANGUARD RUSS3000 INDEX ETF	09/20/2010
29	EWRI	GUGGENHEIM RUSSELL 1000 EQ	12/08/2010
30	FLG	FOCUS MORNINGSTAR LARGE CAP	03/30/2011
31	TOTS	DIREXION DAILY TOTAL MKT BE	06/15/2011
32	FWDD	ADVISORSHARES MADRONA DOMSTC	06/20/2011
33	TILT	FLEXSHARES MS US MKT FACT FD	09/16/2011
34	SIZE	ISHARES EDGE MSCI USA SIZE	04/16/2013
35	IELG	ISHARES ENHANCED US LARGE CP	04/18/2013
36	BFOR	ALPS BARRON'S 400 ETF	06/03/2013
37	VUSE	ETF SERIES VIDENT CORE US EQ	01/22/2014
38	DGRO	ISHARES CORE DIV GROWTH ETF	06/10/2014
39	EQAL	POWERSHARES RUSS 1000 EQ WT	12/22/2014
40	GSLC	GOLDMAN SACHS ACTVBT US LGCP	09/17/2015
41	JHML	JOHN HANCOCK MULTIFCTR LRGCP	09/29/2015
42	ONEK	SPDR RUSSELL 1000 ETF	11/08/2015

Appendix 6 Categorization I:

Simultaneous Panel Regressions on Competing Measures of Fund Performances

This table reports the comparisons of Capital Asset Pricing Model (CAPM) and the other three competing models in high and low non-market-tracking ETF trading periods. We use simultaneous panel regressions to calculate coefficients of alphas in Panel A and then compare their dominances. The four competing models to generate alphas include the Capital Asset Pricing Model (CAPM), the Three-factor Model (3F), the Four-factor model (4F), and the Seven-factor Model (7F). We use categorization II to differentiate market-tracking ETFs and non-market-tracking ETFs, which results in 227 market-tracking ETFs and 520 non-market-tracking ETFs. In Panel A column (1) and (2), we divide our sample into high and low trading periods based on MVOL. MVOL is a dummy equal to 1 when the monthly total trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise. In Panel A column (3) and (4), we divide our sample into high and low trading periods based on TVOL. TVOL is a dummy equal to 1 when the monthly average trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise. Controls include lagged fund flows from month t-19, lagged values of log of fund size, log of fund age (months), expense ratio, load fund dummy (equals to one if any share class of the fund charges the front-end load or the back-end load), return volatility and month fixed effects. Panel A reports coefficient estimates from simultaneous panel regressions of fund flow on alphas based on the four competing models and other control variables. Panel B presents the horserace comparisons between CAPM and the remaining three competing models. For each panel in Table B, we take CAPM as the initial model and compete it against other models to see whether it can dominate. Standard errors are clustered at the fund level and reported in parentheses. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

Panel A	(1)	(2)	(3)	(4)
Sample	Monthly *Average* Trading Volume of Non-Market-tracking ETFs		Monthly *Total* Trading Volume of Non-Market-tracking ETFs	
	HIGH Periods	LOW Periods	HIGH Periods	LOW Periods
CAPM Alpha	0.238***	0.220***	0.226***	0.230***
	(0.009)	(0.007)	(0.009)	(0.007)
3F Alpha	0.235***	0.205***	0.223***	0.215***
	(0.009)	(0.008)	(0.009)	(0.009)
4F Alpha	0.232***	0.190***	0.222***	0.199***
	(0.009)	(0.008)	(0.009)	(0.009)
7F Alpha	0.217***	0.164***	0.208***	0.173***
	(0.009)	(0.008)	(0.009)	(0.008)
Controls	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES
Observations	198,688	198,664	197,609	199,743

Panel B

Panel B.1. Average Trading Volume of Non-Market-tracking ETFs: High Periods (Column (1) Continued)			
Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Coefficients Mean Difference (+/-)	0.003	0.006	0.021***
$\chi^2(1)$	1.47	2.53	22.87

Panel B.2 Average Trading Volume of Non-Market-tracking ETFs: LOW Periods (Column (2) Continued)			
Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Coefficients Mean Difference (+/-)	0.015***	0.030***	0.056***
$\chi^2(1)$	10.01	34.02	102.84

Panel B.3. Total Trading Volume of Non-Market-tracking ETFs: High Periods (Column (3) Continued)			
Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Coefficients Mean Difference (+/-)	0.003	0.004	0.018***
$\chi^2(1)$	0.69	0.82	16.18

Panel B.4. Total Trading Volume of Non-Market-tracking ETFs: Low Periods (Column (4) Continued)			
Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Coefficients Mean Difference (+/-)	0.015***	0.031***	0.057***
$\chi^2(1)$	9.50	36.02	110.25

Appendix 7 Categorization I: Results of Pairwise Model Horserace

This table reports the pairwise horserace results of CAPM and other three competing models in high and low non-market-tracking ETF trading periods. We run cross-sectional regressions of fund flows on the ranking dummy variables. The four competing models to generate alphas include the Capital Asset Pricing Model (CAPM), the Three-factor Model (3F), the Four-factor model (4F), and the Seven-factor Model (7F).

$$\mathrm{Flow_{pt}} = \mathrm{a} + \sum_{\mathrm{i}} \sum_{\mathrm{j}} \mathrm{b_{ij}} \mathrm{D_{ijpt}} + \mathrm{cX_{pt}} + \varepsilon_{\mathrm{pt}}$$

The dependent variable ($\mathrm{Flow_{pt}}$) is the fund flow for mutual fund *p* in month *t*. We get the dummy $\mathrm{D_{ijpt}}$ by raking fund performance based on $\mathrm{alpha_{pt}}$ into 10 deciles separately. Decile 10 presents funds with better performances. $\mathrm{D_{ijpt}}$ is a dummy variable that equals to 1 if the fund performance is ranked as the ith decile in CAPM model and ranked as jth decile in the other four models. Considering collinearity, we exclude the dummy variable for j=5 and i=5. The matrix X_{pt} represents the control variables. We use categorization II to differentiate market ETFs and non-market ETFs, which results in 227 market-tracking ETFs and 520 non-market ETFs. Panel A presents the full sample test. Panel B, Panel C, Panel D, and Panel E present subsample tests. In panel B and Panel C, we divide our sample into high and low trading periods based on MVOL. MVOL is a dummy equal to 1 when the monthly average trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise. In panel D and Panel E, we divide our sample into high and low trading periods based on TVOL. TVOL is a dummy equal to 1 when the monthly total trading volume of non-market-tracking ETFs is above the median across all periods, and zero otherwise. Controls include lagged fund flows from month t-19, lagged values of log of fund size, log of fund age (months), expense ratio, load fund dummy (equals to one if any share class of the fund charges the front-end load or the back-end load), return volatility.

We compare the coefficients where the decile ranks are the same magnitude but the orderings are reversed. We both test the magnitude differences and proportion differences. The null hypotheses are: (1) The mean of coefficient differences is zero and (2) The mean of the differences of coefficient proportions is zero. Standard errors are clustered at the fund level and reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

Panel A. Full Sample

Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Magnitude Difference	0.26**	0.28**	0.54***
t-stat	2.56	2.36	4.93
Proportion Difference (%)	5.71***	6.68***	10.37***
t-stat	3.77	4.08	6.23

Panel B. Average Trading Volume of Non-Market-tracking ETFs: HIGH Periods

Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Magnitude Difference	0.22	0.21	0.54***
t-stat	1.66	1.22	3.12
Proportion Difference (%)	3.79**	2.90	9.56***
t-stat	2.37	1.32	4.05

Panel C. Average Trading Volume of Non-Market-tracking ETFs: LOW Periods

Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Magnitude Difference	0.30**	0.35**	0.54***
t-stat	1.94	2.17	4.09
Proportion Difference (%)	7.74***	10.70***	11.23***
t-stat	2.97	4.48	4.77

Panel D. Total Trading Volume of Non-Market-tracking ETFs: HIGH Periods

Initial Model	CAPM	CAPM	CAPM
Competing Model	0.14	0.07	0.40**
Magnitude Difference	0.94	0.43	2.29
t-stat	2.56	2.22	8.42***
Proportion Difference (%)	1.47	1.02	3.59
t-stat	0.14	0.07	0.40**

Panel E. Total Trading Volume of Non-Market-tracking ETFs: LOW Periods

Initial Model	CAPM	CAPM	CAPM
Competing Model	3F	4F	7F
Magnitude Difference	3F	4F	7F
t-stat	0.38***	0.50***	0.79***
Proportion Difference (%)	2.93	3.03	6.56
t-stat	9.13***	11.52***	14.87***