

# Advising the Advisors: Evidence from ETFs\*

Jonathan Brogaard<sup>†</sup>      Nataliya Gerasimova<sup>‡</sup>      Ying Liu<sup>§</sup>

June 1, 2025

## Abstract

Model providers play a dual role by simultaneously managing funds and increasingly providing investment recommendations to third-party financial advisors. Using a novel data set on model portfolio recommendations, we show that the \$4.8 trillion recommendation market has a substantial impact on ETF flows. Investors following the recommendations exhibit weaker sensitivity to funds' returns. Model providers recommend their affiliated ETFs more frequently. These ETFs tend to have higher fees and lower liquidity than recommended unaffiliated ETFs. We fail to find evidence that model providers with affiliated ETFs generate significantly higher alphas at a model level.

*JEL classification:* G11, G23

*Keywords:* Exchange-Traded Funds, Model Portfolios, Recommendations, Institutional Asset Management, Financial Advisors

---

\*We are grateful to Darwin Choi (discussant), Maxime Couvert (discussant), Thomas Ernst (discussant), Bing Han (discussant), Qiping Huang (discussant), Egle Karmaziene (discussant), Matthijs Lof (discussant), Haoyi Luo (discussant), Mancy Luo (discussant), Ananth Madhavan, Vesa Pursiainen (discussant), Vincent Tena (discussant), Tobias Sichert (discussant), Tushar Yadava, and participants of the 10th Conference on Professional Asset Management, 14th Annual Hedge Fund Research Conference, Summer Workshop at Shanghai University of Finance and Economics, Dolomites Summer Finance Conference, FMA 2022, DGF 2022, CICF 2022, 4th Future of Financial Information Conference, AFFI 2022, FMCG 2022, NFN Young Scholars Finance Webinar Series, NHH Brownbag Series, and SHUFE Brownbag Series for helpful comments.

<sup>†</sup>David Eccles School of Business, University of Utah, Email: BrogaardJ@eccles.utah.edu

<sup>‡</sup>Department of Finance, BI Business School, Email: Nataliya.Gerasimova@bi.no

<sup>§</sup>The World Federation of Exchanges, Email: YLiu@world-exchanges.org. The views expressed here are entirely the authors' and do not necessarily reflect those of the World Federation of Exchanges.

Model portfolios are ready-made recommendation baskets delivered by asset managers and strategists to financial advisors. These recommendations offer a wide range of stocks, bonds, and funds that are usually updated monthly or quarterly. According to estimates by data provider Broadridge Financial Solutions, \$4.8 trillion of US fund assets in March 2021 were invested using model portfolios, up from \$3 trillion in March 2020.<sup>1</sup> They also forecast that the market of model portfolios is expected to double over the next five years, to \$10 trillion.<sup>2</sup>

Despite their broad adoption, these model recommendations have received scant attention in the academic literature.<sup>3</sup> Using a novel data set on the recommendations offered to financial advisors, this paper aims to fill this gap by investigating how model portfolios influence fund flows and examine potential conflicts of interest. First, we find that model providers recommend exchange-traded funds (ETFs) that, on average, are less expensive and more liquid than the rest of ETFs. Second, we find that these model recommendations drive flows to ETFs. Investors who follow recommendations also behave differently, as they pay less attention to the performance of the ETFs.

Finally, we show a conflict of interest among model providers who are also asset managers. In particular, we find that recommended affiliated ETFs, which are ETFs that belong to the same company or fund family as the model provider, exhibit higher fees and lower liquidity than unaffiliated ETFs. Moreover, the probability of an ETF being added to a model portfolio is higher for affiliated ETFs, and affiliated ETFs with high fees are even more likely to be added. Finally, we show that asset manager model providers do not yield economically higher alphas than strategist model providers – model providers without their own ETFs.

Unlike mutual funds and ETFs, model portfolios are not directly investable and are not managed from a central location. The models are distributed to financial advisors as an asset-allocation

---

<sup>1</sup><https://www.wsj.com/articles/blackrock-tweaked-some-models-it-triggered-a-wave-of-buying-and-selling-11625857596>.

<sup>2</sup><https://www.wsj.com/articles/model-portfolios-surgings-as-advisers-look-for-quick-ways-to-invest-client-money-11607091645>.

<sup>3</sup>In this paper, we use two terms “model portfolios” and “model recommendations” interchangeably.

and fund-selection recommendation. 85% of financial advisors employ a combination of custom and model portfolios. More than half (54%) of advised assets are in model portfolios.<sup>4</sup> More than 500 model portfolios were initiated between 2018 and 2021.<sup>5</sup> One of the largest asset managers, BlackRock, forecasts that in five years, half of new inflows to its ETFs, iShares, will be directed by model portfolios of its own and those of other firms, up from around a third in 2020.<sup>6</sup>

This paper is the first to analyze asset managers' and strategists' model recommendations to financial advisors and their potential conflicts of interest. We focus on ETFs since in December 2020 five out of the 10 largest models in terms of assets under advisement in the Morningstar Direct database recommended solely ETFs.<sup>7</sup> Only one model among these 10 models recommended solely mutual funds. Moreover, according to Envestnet Analytics 56% of inflows to model portfolios on their platform went to ETF-only portfolios and only 26% to model portfolios solely recommending mutual funds between June 2021 and June 2023.<sup>8</sup>

The analysis includes three main parts. First, we compare the recommended ETFs with non-recommended funds, model and non-model ETFs, respectively. Second, we examine the impact that model recommendations have on ETF flows. Finally, we investigate the quality of the model ETFs and potential bias in recommendations.

First we compare the different types of ETFs (recommended versus non-recommended; model versus non-model). The expense ratio of model ETFs is 34 basis points (bps), lower than that of non-model ETFs, at 49 bps. The Amihud ratio of model ETFs is 0.02 while the ratio of non-model ETFs is 0.10, and the quoted spread of model ETFs is 0.10 while the spread of non-model ETFs is 0.26, suggesting that model ETFs are more liquid. The monthly category-adjusted

---

<sup>4</sup>[https://www.broadridge.com/\\_assets/pdf/broadridge-fa-model-portfolio-may-2019.pdf](https://www.broadridge.com/_assets/pdf/broadridge-fa-model-portfolio-may-2019.pdf).

<sup>5</sup><https://www.morningstar.com/articles/1028488/our-favorite-model-portfolios-for-advisors>.

<sup>6</sup><https://www.ft.com/content/fc35e189-4f0a-4d22-8444-25ad2e82c6c1>.

<sup>7</sup>As of September 2021, the Morningstar Direct database provided information on 2,316 active and inactive unique models between January 2010 and December 2020.

<sup>8</sup><https://www.investpmc.com/insights/commentaries/etf-model-portfolios-gaining-traction-and-market-share>.

return of model ETFs is 0.02%, which is essentially the same as the  $-0.02\%$  for non-model ETFs. Model ETFs' prior return ranks are also nearly the same as the prior return ranks of non-model ETFs.<sup>9</sup> In addition, we evaluate the overall performance of the model portfolios. Due to a lack of return data of model portfolios, we derive the return (alpha) of model portfolios by computing the weighted return (alpha) of ETFs within the portfolio. On average, the models do not meaningfully outperform CRSP value-weighted stock index or a 60/40 portfolio.<sup>10</sup>

Second, we examine the impact that model recommendations have on ETF flows. We find that model ETFs experience flows between 5 and 6 bps higher per month per model. The model ETF flows display a lower sensitivity to past performance of 4 bps per model. The lower sensitivity suggests that some investors reduce their performance chasing behavior, follow the recommendations of model providers and pay less attention to the returns of model ETFs.<sup>11</sup>

It is possible that the model providers select ETFs based on their expectations of future fund flows. They may choose to add ETFs to their model portfolios in anticipation of increasing future inflows. While such an endogeneity issue seems remote, it is important to not misinterpret the empirical results. To address this concern, we exploit the collapse of F-Squared Investments. F-Squared Investments operated one of the largest model portfolio operations in the US, managing 19 model portfolios. The models were discontinued in 2015 because the company filed for bankruptcy after the US Securities and Exchange Commission (SEC) charged it with defrauding investors.<sup>12</sup> We use the closure of the F-Squared Investments models as a shock to the recommendation of ETFs in their models, therefore, we can test the impact on the fund flows in a clean setting. The closure allows us to shut down the potential reverse causality explanation. We find that in the nine months following the F-Squared model discontinuation, the formerly

---

<sup>9</sup>To get the category-adjusted returns, we deduct the median monthly return of ETFs of the same Morningstar category from the monthly ETF return. To define these categories and also to rank ETFs within them, we use "Morningstar Category" field in the Morningstar Direct database.

<sup>10</sup>60/40 portfolio is composed of 60% of S&P 500 index and 40% of Bloomberg Barclays US Aggregate Bond Index.

<sup>11</sup>Prior studies show that investors increase their demand for ETFs that performed well in the past or for ETFs that are less expensive (Dannhauser and Pontiff, 2021; Ben-David et al., 2023).

<sup>12</sup><https://www.sec.gov/litigation/admin/2014/ia-3988.pdf>.

recommended ETFs received 4.57 percentage points lower flows than other ETFs of the same investment category that other models recommended.

Finally, we turn to investigating the quality of the model ETFs and potential bias in recommendations. Specifically, we test whether model providers favor their own affiliated ETFs. We compare the affiliated ETFs against their unaffiliated peers. A simple univariate test shows that affiliated ETFs are generally more expensive and less liquid than unaffiliated ETFs. On average, affiliated ETFs charge 4 bps higher expense ratios. The Amihud ratio of affiliated ETFs is 0.03 while the ratio of unaffiliated ETFs is 0.01, and the quoted spread of affiliated ETFs is 0.12 while the spread of unaffiliated ETFs is 0.06.

We model the probability of an ETF being added to a model. We find the probability of addition is significantly higher for affiliated funds. The addition odds of affiliated ETFs is as high as 7 times the addition odds of unaffiliated ETFs, conditional on having the same performance and expense ratio.<sup>13</sup> An examination of the average marginal effect suggests that being affiliated increases the probability of addition to model portfolio by 0.62 percentage points.<sup>14</sup> The odds ratio of the best-performing affiliated ETFs is insignificantly different from the odds ratio of the worst-performing affiliated ETFs. Moreover, even though higher fees decrease the probability of addition to the recommendations, when we interact expense ratio with the affiliation, we find that affiliated funds with higher fees have a higher probability of addition. When the expense ratio of affiliated ETFs increases by 1 bp, the probability of addition increases at least by 0.25 percentage points. It suggests that more expensive affiliated ETFs have a higher chance of being recommended than cheaper affiliated funds. However, the result is the opposite for unaffiliated ETFs. The favoritism toward affiliated funds is consistent with Pool et al. (2016), who find that mutual fund families favor affiliated funds in the 401(k) plans they provide.

We explore the performance of models provided conditional on their type – asset managers and

---

<sup>13</sup>The addition odds are defined as  $p/(1-p)$ , where  $p$  is the probability of addition.

<sup>14</sup>The average model-implied monthly addition probability for affiliated funds is 0.71%, and only 0.09% for unaffiliated funds.

strategists. We first compare the return of model recommendations with the return of CRSP value-weighted stock index, as well as the 60/40 portfolio, respectively. We observe that both types of model providers do not outperform the benchmarks. Next, we compare the alpha of the model portfolios that are calculated using the ETFs' net returns. The monthly alpha of models provided by strategists is 0.02%, it statistically significantly surpasses the monthly alpha of models provided by asset managers. Nevertheless, both alphas are economically small.

We add to two strands of literature. First, we add to the nascent literature on what drives ETF fund flows. Clifford et al. (2014) and Dannhauser and Pontiff (2021) document that investor flows are sensitive to a fund's past performance. Most ETFs are passively managed and track an index. Kostovetsky and Warner (2022) find that the choice of benchmark index affects the flows to ETFs, as brand-name indices attract more capital flows from investors. Pu and Xie (2022) document that investors of index ETFs are sensitive to short-term fund returns, but not to long-term returns and index-tracking error. Other studies focus on the rapid growth of specialized ETFs – for example, Brown et al. (2020) and Huang et al. (2023) study the rise of “smart-beta” ETFs; Ben-David et al. (2023) investigate the growth of thematic ETFs. We contribute to this literature by identifying model recommendations by asset managers and strategists as a novel factor that drives ETF flows.

Second, we contribute to the growing literature studying the recommendations of financial advisors. Bergstresser et al. (2009) find that broker-sold funds underperform funds sold through direct channels. Pool et al. (2016) find that mutual fund families acting as trustees of 401(k) plans display a bias toward affiliated funds. Doellman and Sardarli (2016) document that the higher fees and lower returns are related to the existence of affiliated funds in these plans. Jenkinson et al. (2016) focus on external consulting firm fund recommendations. They find that these recommendations impact asset allocation but fail to add value. Boyson (2019) finds that investment advisors dually registered as broker-dealers fail to fulfill their fiduciary duties to clients. Cookson et al. (2021) find that platforms favor “own-brand” funds and those paying them a higher commission share. We add to this literature by looking at the recommendations

made to financial advisors.

The results raise questions about the opacity of model portfolios. Currently, model providers face less severe regulations around reporting performance to potential clients than do ETFs or mutual funds. In June 2022, the SEC requested public opinion on whether certain information providers, including model portfolio providers, should be regarded as “investment advisors” and be regulated under the Investment Company Act. The SEC is concerned that these information providers may be involved in front-running when they provide information to financial advisors, or may have conflicts of interest in that they are holding investments they recommend in their models. Moreover, the SEC questioned whether investors understand the fees they pay to financial advisors and model providers and conflicts of interest related to these fees.<sup>15</sup>

## **1 Background and Data**

### **1.1 Institutional Details**

Financial advisors mainly use model recommendations to outsource investment management and to have more time for other financial-planning services. To extend the analogy of Gennaioli et al. (2015) and Jenkinson et al. (2016), financial advisors can be thought of as “money doctors” who save time better spent identifying their patients’ illnesses by providing pre-mixed formulas instead of creating custom medications.

These recommendations are designed by strategists such as 3D/L Capital Management and asset managers such as BlackRock. Then they transfer their recommendations to financial advisors. Model providers also adjust their recommendations over time. When changes are made, they send them to financial advisors. Financial advisors invest their clients’ investments into the recommended securities. Advisors can adapt the recommendations to their portfolios or override them. They are responsible for implementing the recommended portfolio.

---

<sup>15</sup><https://www.sec.gov/rules/other/2022/ia-6050.pdf>.

The main difference between strategists and asset managers is that strategists usually do not have affiliated ETFs. Moreover, the fee varies between these two types of model providers. According to Kephart et al. (2020), strategists typically charge a “strategist” fee, which varies from 0.10% to 0.25%. However, asset managers usually do not charge additional fees for asset-allocation advice when they recommend their own products.

Both types of model providers give recommendations regarding the purchase or sale of specific ETFs, at specific weights for each individual ETF, in a model portfolio. However, the decision regarding the acted timing and magnitude of purchases or sales is at the financial advisor’s sole discretion. Financial advisors claim that they employ model recommendations to spend more time on client-facing activities and for financial planning.<sup>16</sup>

Model portfolios are constructed to meet various objectives such as target-risk, tax-managed, income-oriented, or environmental, social, and governance (ESG). The target-risk portfolios are composed of different equity and fixed-income funds to deliver a certain level of risk. Tax-managed portfolios aim to maximize the after-tax return for investors, thus these portfolios usually include funds of municipal bonds. Income-oriented portfolios seek to generate high income levels by including funds of investment-grade bonds, high-yield bonds, high-dividend equities, preferred stocks, and REITs. ESG portfolios usually contain a large portion of funds that invest in companies with high ESG scores. According to Kephart and Millson (2021), in July 2021, 1,097 out of the 2,068 models portfolios were target-risk portfolios. Tax-oriented portfolios were the second most popular with 285, followed by ESG and income portfolios. Aside from these four types of portfolios, there are also a small number of models that focus on stand-alone equity or fixed-income assets.

---

<sup>16</sup>For example, Tom O’Shea, research director at Cerulli Associates, claimed that “Packaged products are becoming incredibly popular, as more wealth management firms are encouraging advisors to shift their focus away from investment management to financial planning,” (PIMCO, 2021). “These models give our financial advisors an opportunity to allocate day-to-day investment management responsibilities to an outside strategist, and that frees up financial advisors’ time to focus on deepening the relationships that they have with clients,” says Steve Matus, head of advisory and planning at UBS Global Wealth Management (PIMCO, 2021). John Murphy, a former financial advisor with Addison Avenue Investment Services, says, “We’re able to help the smaller client and we’re also able to take on more clients.” He added that model recommendations “[free] me up from micro-managing and [allow] me to do macromanagement for my clients” (State Street Global Advisors, 2016).

While model providers provide a description of how they conduct their fund choices, there is a large element of judgment involved. The model providers may have interests that conflict with those of investors who use model recommendations. For example, the asset managers may face a financial incentive to recommend their affiliated funds that have high fees and those unaffiliated funds that share the most solicitation fees. Most ETF managers address their potential conflicts of interest in their ADV forms. For example, Global X, discloses the following conflict of interest in its ADV form: “[we] may receive compensation from Third-Party Providers for use of the Model Portfolios and will be indirectly compensated by investments in the Global X ETFs based on the Model Portfolios.”<sup>17</sup>

Second, the advisor might implement the recommendations made in the model at some point after they have been implemented by the model provider’s discretionary accounts. The result of financial advisors delaying model implementation may be the model provider’s discretionary and non-discretionary accounts obtaining better trade executions than financial advisors’ accounts.<sup>18</sup> AllianceBernstein L.P. describes this type of conflicts as follows: “Certain strategies are made available through delivery of investment models to clients and/or institutional advisors (“Model Clients”) who may offer substantially similar services to their clients. These investment recommendations may be provided to multiple Model Clients at a similar time, but the client’s implementation of the recommendations made in the model will generally be made at some point after they have been implemented by AB’s discretionary accounts. The delay in model implementation for Model Clients may result in AB discretionary and other non-discretionary accounts obtaining better execution for their transactions than the accounts of Model Clients.”<sup>19</sup>

---

<sup>17</sup><https://adviserinfo.sec.gov/firm/summary/146932>.

<sup>18</sup>A discretionary account is an investment account where the model provider can determine if a trade is valuable or not at their own discretion and exercise it. A non-discretionary account is an account in which the investor decides on what trades to execute.

<sup>19</sup><https://www.alliancebernstein.com/content/dam/corporate/corporate-pdfs/bernstein-pc-form-adv-part-2a.pdf>.

## 1.2 Data

We combine data from multiple sources. The main data source is a unique database for model recommendations created by Morningstar Direct. The models are self-reported by asset managers and third-party strategists. The sample covers a period from January 2010, when there is a sufficient coverage of models, to December 2020. The data set includes both active and inactive model recommendations.<sup>20</sup>

The data set allows us to identify, for each model, when an investment product was first recommended and the period during which it is recommended. Model providers may report their portfolios in different frequencies. In the sample, 28% of models report holdings monthly, and 69% report them quarterly. We conduct the analysis on a monthly basis, so we adjust the holdings to monthly frequency by assuming the holdings of a missing month are equal to the available holdings of the closest previous month.

Model portfolios recommendations cover a range of asset classes, investment styles, and regions. Since we focus on models portfolios that recommend ETFs, we restrict the sample to model providers that have at least one ETF in their recommendations during a given month and whose base currency is US dollars. More specifically, we focus on US passive ETFs whose base currency is the US dollar. We exclude ETFs that are classified as leveraged or active ETFs.<sup>21</sup> For the ETF data, we also require at least one observation in assets under management (AUM) between 2010 and 2020 to filter out funds with excessive missing values. Moreover, we exclude fund-date observations for funds that are younger than six months and whose AUM are lower than \$5 million, to avoid incubation bias as reported by Evans (2010). We also exclude the models that start to report their holdings earlier than one quarter before their official inception

---

<sup>20</sup>According to Kephart and Millson (2021), this data set “doesn’t include models that large wealth management firms, such as Merrill Lynch, offer exclusively through their advisors and turnkey asset-management programs because they typically are not public. It also excludes roboadvisors that mostly target retail investors, not financial advisors.”

<sup>21</sup>These two types of ETFs exhibit different characteristics from passive ETFs. Leveraged ETFs conventionally use leverage or debt to amplify the return of underlying index, consequently engendering higher risk and volatility than other non-leveraged ETFs. Active ETFs apply an active strategy, and their objectives are to generate higher return than benchmark indices.

date.<sup>22</sup> The final sample contains 2,122 unique US ETFs. 972 of these ETFs are recommended by 1,210 unique US models constructed by 106 unique model providers. The remaining 1,150 ETFs are not recommended by any model providers.

Table 1 provides the number of models, model providers, and model ETFs by year.<sup>23</sup>

[Insert Table 1 about here]

There are two groups of ETFs recommended by the model providers in the sample: those affiliated with the model providers and those unaffiliated with them. We use a Morningstar Direct data field – “Branding Name” – to track affiliation. A fund is considered affiliated with a model if it shares a branding name with the model provider.<sup>24</sup> Detailed variable definitions are given in Table A1 in the Appendix.

Table 1 shows that the number of models is much lower during the earlier part of the sample. There were only 53 models provided by 11 companies in 2010. The number of models and companies increase overtime; there are 1,046 models from 90 companies in 2020. The average number of ETFs per model recommendation decreases from 12.13 to 8.33 during the sample period, while the average percentage of ETFs per model stays quite constant. We observe the opposite trend for affiliated ETFs. The average number increases from 0.79 in 2014 to 2.91 in 2020. The first affiliated ETFs in the sample appear in 2014. According to industry experts, a bankruptcy filing by one of the largest ETF strategists at that time, F-Squared Investments, and further penalties to several other firms opened the model space for large asset-management companies that used this opportunity to recommend their own funds.<sup>25</sup>

Panel B of Table 1 focuses only on the model recommendations that include affiliated ETFs.<sup>26</sup>

---

<sup>22</sup>The first reporting date earlier than one quarter before the inception date might result from a data reporting error.

<sup>23</sup>For each model we use its last available holding in each year that contains at least one ETF.

<sup>24</sup>To identify branding names, we use a snapshot dated September 2021. Several asset-management companies, like BlackRock and iShares, State Street and State Street Global Advisors, have different names for subsidiaries. In this analysis, such entities are considered as one company.

<sup>25</sup><https://www.investmentnews.com/etf-strategists-getting-crowded-out-by-big-asset-managers-80590>.

<sup>26</sup>To compute this statistic, for each model we use its last available holding in each year that contains at least

By definition, only one type of model providers, asset managers, hold affiliated ETFs. Thus, panel B demonstrates the summary statistics only for model recommendations coming from asset managers. Compared with panel A, we can find that although the number of asset managers who recommend their affiliated ETFs accounts for less than 20% of the sample, the total number of models provided by these asset managers are more than one-third of the sample. For these model recommendations, the average number of ETFs oscillates around nine during the sample period.

Each model usually recommends multiple ETFs at the same time. The styles of ETFs are equity, fixed income, commodities, allocation, alternative, convertibles, and miscellaneous ETFs.<sup>27</sup> Table 2 reports further information on ETFs that are recommended by models, panel A reports the average number of each style of ETF per model by year, and panel B reports the average weight of each style of ETF.

[Insert Table 2 about here]

The largest style is equity ETFs, followed by fixed-income ETFs. The average number of equity ETFs per model is 6.14, and the average number of fixed-income ETFs 3.01. This composition is similar to the distribution of domestic ETFs in the US market.<sup>28</sup> Note that commodity ETFs experience a sharp reduction in model recommendations starting in 2013, consistent with the observed strong outflows from commodity ETFs in that year.<sup>29</sup>

Panel B shows similar patterns. Equity and fixed income are the most pronounced categories of ETFs. In addition, there was an increase in average weight among equity ETFs between 2011 and 2014. Hence, the model recommendations of equity ETFs were more concentrated during this period. The rest of the categories have weights below 1.00% for most of the period.

---

one affiliated ETF.

<sup>27</sup>To identify styles, we use “Global Broad Category Group” field in the Morningstar Direct database.

<sup>28</sup>See Table 12 in the ICI 2021 Factbook; [https://www.ici.org/system/files/2021-05/2021\\_factbook.pdf](https://www.ici.org/system/files/2021-05/2021_factbook.pdf).

<sup>29</sup><https://www.reuters.com/article/etps-annual/record-outflows-from-commodity-etps-in-2013-as-investors-dump-gold-idUKL6N0KI2H620140109>.

Using Morningstar, we obtain the assets under management (fund size), the monthly returns,<sup>30</sup> the expense ratios, and the turnover of the ETFs. We use CRSP to get ETFs' daily trading price, volume, and share outstanding. We merge Morningstar with CRSP by ETF ticker and inception date. If there is a missing ETF ticker or unsuccessful match, we conduct a fuzzy name match and manually verify the matches. We calculate the Amihud (2002) illiquidity ratio and quoted bid-ask spread by using CRSP daily trading data. The sample contains 145,614 ETF-month observations. Table 3 shows the summary statistics of all ETFs.

To analyze performance we use category-adjusted returns, as well as return percentile rank during the previous one year and previous three years (see Cookson et al. (2021)). To get the category-adjusted returns, we deduct the median monthly return of ETFs of the same Morningstar category from the monthly ETF return.<sup>31</sup> We measure the performance over the previous one year and three years by the percentile rank of cumulative returns among funds of the same Morningstar category. We normalize the rank by dividing it by 100. A percentile rank of 0.01 means that 1% of the values in the sample are at or below that specific point, indicating the poorest performance. Conversely, a percentile rank of 1 denotes the highest performance. The return volatility is measured by monthly returns over a year.

[Insert Table 3 about here]

On average, the ETF is recommended by 2.6 models. The median ETF is not recommended by any model. The monthly return and category-adjusted return of the average fund are 0.7% and -0.01%, respectively. On average, the expense ratio is 0.44%. The average fund is slightly younger than 7 years and its size is approximately \$2 billion.

---

<sup>30</sup>If it is not explicitly specified, we use net return data.

<sup>31</sup>According to the Morningstar Methodology Paper, Morningstar categorizes funds based on their holdings into 122 categories.

## 2 Evaluation of Model Portfolios

In this section, we first investigate the fund selection skills of model providers by comparing the model ETFs with non-model ETFs. Then we look at the overall performance of the model portfolios to address the incentives of the financial advisors that use these recommendations.

### 2.1 Difference between Model and Non-model ETFs

Model providers recommend a limited ETFs' set in each model portfolio. To shed light on the fund selection skills of model providers, the initial analysis focus on the disparity between the ETFs that are recommended by models and those that are not recommended.

Table 4 presents summary statistics of model and non-model ETFs' characteristics. 30% of these observations are ETFs recommended by at least one model provider.

[Insert Table 4 about here]

Table 4 shows that model ETFs are significantly older than non-model ETFs, on average, by 2.6 years. They also tend to be more than 10 times larger. The Fund Size of model ETFs and non-model ETFs are \$5.99 billion and \$0.43 billion, respectively.

The table shows that the expense ratio of model ETFs is 34 bps, lower than that of non-model ETFs, at 49 bps. The difference of 15 bps is both economically and statistically significant. The model ETFs' monthly category-adjusted return is 0.02%, which is statistically significantly higher than  $-0.02\%$  of non-model ETFs. Their prior return ranks are also significantly higher than the ranks of non-model ETFs. Nevertheless, these differences are not economically significant. The return of model ETFs is significantly less volatile than the return of non-model ETFs. Model ETFs tend to replace their holdings less frequently than non-model ETFs; the turnover ratio of model ETFs is 20 percentage points lower than the turnover ratio of non-model ETFs. The Amihud ratio of model ETFs is 0.02 while the ratio of non-model ETFs is 0.10, and the quoted spread of model ETFs is 0.10 while the spread of non-model ETFs is 0.26, suggesting

that model ETFs are more liquid.

The ETF sample covers a broad array of ETF categories, ranging from allocation to options-based categories. We have addressed the impact of fund category on fund performance measures, nevertheless, other fund characteristics may also exhibit associations with their respective categories. Table A2 in the Appendix provides other category-adjusted variables. Expense Ratio, Return Std. Dev., Turnover, Amihud Ratio, and Quoted Spread are category-adjusted by deducting the median value of funds of the same Morningstar Category. The results stay qualitatively the same.

## 2.2 Performance of Model Portfolios

In this subsection, we provide an evaluation of models from a portfolio perspective. Model portfolios are not registered investment vehicles with the SEC, therefore their reported performance often reflect hypothetical and back-filled returns, as reported by Kephart and Millson (2021). In the sample, only 41 out of 1,210 models reported their returns. Therefore, we conduct analysis of the performance of models using their reported portfolio holdings. Specifically, following Elton et al. (2011) we use the bottom-up approach to calculate the weighted average return of each model using the model reported holdings and their weights.

We first calculate the return of the model in excess of two benchmarks. The return of each model portfolio is calculated as the weighted average return of ETFs in the portfolio. Then, we subtract from these returns the CRSP value-weighted stock index, as well as a portfolio of 60% of S&P 500 Index and 40% of Bloomberg Barclays US Aggregate Bond Index.<sup>32</sup>

Second, we derive the alpha of each model as the weighted average alpha of ETFs within the model portfolio.<sup>33</sup> We calculate the alpha  $\alpha_i$  of ETF  $i$  from 24-month rolling regressions using

---

<sup>32</sup>This portfolio is the 60/40 portfolio – a classic asset allocation strategy recommended by financial advisors. For an overview of the benchmark, please see <https://www.cnbc.com/2022/07/01/sp-500-had-worst-half-in-50-years-but-the-60/40-portfolio-isnt-dead.html>.

<sup>33</sup>In case alpha of an ETF is missing, we remove the ETF from calculation and rescale the weight such that the total weight of ETFs is 100%.

the following equation:<sup>34</sup>

$$R_{i,t} - R_{f,t} = \alpha_i + \sum_j \beta_{i,j} F_{j,t} + \varepsilon_{i,t}, \quad (1)$$

where  $R_{i,t}$  is the return of ETF  $i$  in month  $t$ ,  $R_{f,t}$  is the risk-free interest rate in month  $t$ ,  $F_{j,t}$  is factor  $j$  in month  $t$ ,  $\beta_{i,j}$  is the sensitivity of ETF  $i$  to factor  $j$ ,  $\varepsilon_{i,t}$  is the residual for ETF  $i$  in month  $t$ .

There are usually multiple styles of ETFs in one model portfolio, we thus adapt the factors to different styles of ETFs. For domestic equity ETFs,<sup>35</sup> we use the Carhart (1997) four-factor model.<sup>36</sup> Following Elton et al. (2015), we use Bloomberg Barclays US Aggregate Bond Index, Bloomberg Barclays US Mortgage Backed Securities (MBS) Index, ICE BofA US High Yield Index and Bloomberg Global Aggregate ex-USD Index for fixed-income ETFs. For international equity ETFs, we use Fama-French market factors, MSCI Europe Index, MSCI Pacific Index, MSCI Emerging Market Index, FTSE World Government Bond Index.<sup>37</sup> For commodity ETFs, we use S&P GSCI Commodity Index. Allocation funds are similar to target date funds in the sense that they usually include multiple styles of funds ranging from equity to commodity in their portfolios, we thus follow Balduzzi and Reuter (2018) and use Fama-French market factor, MSCI AC World ex USA Index, Bloomberg Barclays US Aggregate Bond Index, Bloomberg Global Aggregate ex-USD Index, S&P GSCI Commodity Index as the factors. All indices are in excess return form.<sup>38</sup>

To further examine the fund selection ability of model providers, we follow Elton et al. (2007)

---

<sup>34</sup>We require at least 12 observations for each regression.

<sup>35</sup>We use “US Category Group” field in the Morningstar Direct database to distinguish between domestic and international equity ETFs.

<sup>36</sup>We thank Kenneth French for providing data on the Fama-French factors, Momentum factor, and the risk-free rate via his website [https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

<sup>37</sup>We are able to obtain returns for FTSE World Government Bond Index only until February 2019. Hence, we exclude this index from the regressions after this date.

<sup>38</sup>We use the Refinitiv Data Library to retrieve the indices’ returns. Alternative, Convertibles, and Miscellaneous ETFs are not considered in this section, since the factors for these styles of funds are not well-defined. Besides, these funds is a limited fraction in the model portfolios, as shown in Table 2.

by constructing a “differential alpha,” which is the difference between the alpha of an existing model and the alpha of a model that we construct using a random sample of similar ETFs. For each ETF in a model portfolio, we search for ETFs of the same Morningstar category and then rank the ETFs by their size, we keep the funds in the same size quintile of the ETF recommended by model. According to Elton et al. (2007), adjusting for the category controls for year-to-year variation in the performance of any category not captured by performance model, and adjusting for size controls for any difference in fund performance due to the size of funds. In case multiple ETFs are matched with the model ETF, we take the average alpha of all matched ETFs. The alpha of matched model is calculated as the weighted average alpha of matched ETFs. The matched model stands as an alternative portfolio that the model provider could potentially have constructed. By examining differential alphas, we can determine whether model providers select ETFs that are better than a set of randomly chosen ETFs of the same category and size. Therefore, the differential alpha measures the fund selection proficiency of the model providers.

Since we focus on models that recommend ETFs, we require the total weight of recommended ETFs in a model to be at least 80%. Then, if alpha of an ETF is missing, we remove the ETF from calculation and rescale the weight such that the total weight of ETFs of one model is 100%. Using these criteria, we get a subsample of 659 unique models and 22,572 model-month observations.<sup>39</sup>

Table 5 presents the excess returns, alphas and differential alphas of all models. Row 1 shows the performance calculated using gross returns of ETFs, Row 3 shows the performance calculated using net returns of ETFs. Gross return of ETFs are provided by the Morningstar Direct database, they are defined as  $GR = ((1 + TR)/(1 - E/12) - 1) \times 100$ , where  $TR$  is the net return,  $E$  is the annual expense ratio of ETF.

[Insert Table 5 about here]

---

<sup>39</sup>Panel A of Table A12 in the Appendix provides the results for the models with at least 60% ETFs. The results are qualitatively the same.

Column 1 shows that the difference between return of models and CRSP value-weighted stock index, the difference is significantly negative. Column 2 presents the return of models in excess of a 60/40 portfolio. The difference is negligible and statistically insignificant. Column 3 considers the alpha of the models. While the results show a statistically significant difference from zero, they are economically zero, and so we conclude the model portfolios do not outperform the benchmarks. Column 4 presents the differential alpha. Both differential alphas are not significantly different from zero.

To sum up, model providers tend to include ETFs in their models that exhibit lower expenses and higher liquidity than non-model ETFs. Model portfolios do not outperform the benchmarks in an economically meaningful way.

### **3 Do Model Portfolios Impact Fund Flows**

While the investment opportunity set of the model is determined by the model provider (asset manager or strategist), they exercise no discretion. Financial advisors are not obliged to follow these recommendations. They could adjust their own portfolios by, for instance, not allocating capital to poorly performing funds. The potential deviation of financial advisors from these recommendations introduces uncertainty of their impact on the flows of the underlying ETFs. We investigate whether model recommendations have an impact on the overall allocation of investors into ETFs and examine the sensitivity of these flows. We start the analysis by examining the impact of model recommendation from a conventional fund flow-performance regression. Next, we address the endogeneity issue by exploiting a natural experiment.

#### **3.1 OLS Evidence**

To explore how fund flows respond to model recommendations, we expand a flow-performance regression from Ben-David et al. (2023) by including a variable that enumerates the number of models that recommend an ETF as a regressor. We expect that fund flows increase in the

number of models that recommend them.

Following Ben-David et al. (2023), our flow measure is the percentage flow relative to the AUM in the ETF as of the end of the previous month:

$$\text{Flow}_{i,t} = \frac{\text{AUM}_{i,t} - \text{AUM}_{i,t-1} \times (1 + R_{i,t})}{\text{AUM}_{i,t-1}} \times 100, \quad (2)$$

where  $R_{i,t}$  is the monthly return of ETF  $i$ . Flow is winsorized at the 1st and 99th percentiles in each month.

To capture how fund flows respond to model recommendations, we estimate the response of Flow to recommendations using the following regression on monthly data:

$$\begin{aligned} \text{Flow}_{i,t} = & \alpha + \beta_1 \text{No. Models}_{i,t} + \beta_2 \text{Return Rank}_{i,t-1} + \beta_3 \text{No. Models}_{i,t} \times \text{Return Rank}_{i,t-1} \\ & + \beta_4 \text{Expense Ratio}_{i,t-1} + \beta_5 \text{No. Models}_{i,t} \times \text{Expense Ratio}_{i,t-1} \\ & + \text{Controls}_{i,t-1} + \gamma_i + \eta_t + \varepsilon_{i,t}, \end{aligned} \quad (3)$$

where  $\text{No. Models}_{i,t}$  is the number of models that recommend ETF  $i$  in month  $t$ ;  $\text{Return Rank}_{i,t-1}$  is the percentile rank of ETF  $i$ 's return among ETFs of the same Morningstar category in month  $t - 1$ ;  $\text{Expense Ratio}_{i,t-1}$  denotes the expense ratio of ETF  $i$ , measured in percentage points.

Chevalier and Ellison (1997) and Sirri and Tufano (1998) document that investor demand is sensitive to a fund's past performance, Ben-David et al. (2023) show that it is also sensitive to fund's fees. Hence, we interact number of models with past performance,  $\text{No. Models}_{i,t} \times \text{Return Rank}_{i,t-1}$ , and number of models with expense ratio,  $\text{No. Models}_{i,t} \times \text{Expense Ratio}_{i,t-1}$

to examine whether investors exhibit different demand sensitivity to model-recommended ETFs. We follow the studies on fund flows by including the size of the fund in the previous period  $\log(Size_{i,t-1})$ , and the age of the fund in the previous period  $\log(Age_{i,t-1})$  as controls. Since ETFs are traded in the exchanges like stocks, we include ETF turnover in a previous month (see Clifford et al. (2014) ) and the Amihud ratio in the previous month (see Broman and Shum (2018)) as additional controls. Standard errors are clustered at the fund and month-year levels.

Table 6 reports the results from estimating Equation 3. Each column in the table represents a separate regression. In columns 1 and 2, the control variables include lagged fund size and lagged fund age. We add lagged turnover and lagged Amihud ratio in columns 3 and 4 as additional control variables. In columns 2 and 4, we also include time fixed effects (FE)  $\eta_t$  to account for time-varying aggregate shocks, as well as fund fixed effects  $\gamma_i$  to account for any time-invariant fund characteristics. The results show that ETF model recommendations have a significant positive effect on an ETF's flow. The estimates indicate that model ETFs experience flows 5 bps higher per month per model than non-model ETFs. This difference suggests that financial advisors respond to a model recommendation by moving money in the direction implied by the recommendation. In the regressions, we successively include additional controls and fixed effects that only affect magnitudes marginally. Statistical significance of the  $No.Models_{i,t}$  is at the 1% level for all specifications.

[Insert Table 6 about here]

We also explore whether investors show different sensitivity to the past performance and fees of ETFs that are in recommendations than to these characteristics of ETFs that are not recommended. Investors are usually sensitive to the past performance of passive ETFs, as documented by, among others, Dannhauser and Pontiff (2021) and Ben-David et al. (2023). The interaction of return rank with the number of models indicates that flows are significantly less sensitive to the performance of model ETFs than non-model ETFs. Lower sensitivity implies that investors

may completely follow the recommendation of model providers and pay less attention to the performance of model ETFs. The flow is also influenced by the expense ratio of ETFs; funds that charge higher fees tend to receive lower flows.

The coefficients before the control variables  $\log(Size_{i,t-1})$  and  $\log(Age_{i,t-1})$  are both negative and significant, reflecting the fact that an equal dollar flow will have a larger percentage impact on smaller or younger funds. In column 4, the coefficient before  $Turnover_{i,t-1}$  is negative and significant. The result is consistent with the study by Clifford et al. (2014) that ETF flow decreases with an increase in fund turnover. Finally, the negative and significant coefficients before Amihud ratio in columns 3 and 4 imply that more liquid ETFs tend to have higher investor demand, similar to the findings by Broman and Shum (2018).

In the Appendix, we provide two robustness checks: 1) using quarterly data and 2) using also only non-equity ETFs. Some model providers update their recommendations only quarterly. To address this less-frequent rebalancing, we also estimate the response of flows to recommendations using the quarterly data. The results are in line with the results using monthly data. The ETFs experience, on average, 18 bps more flows per quarter (6 bps per month) after they are recommended by one more model (see Table A3 in the Appendix).

We also check that the results are not driven only by non-equity ETFs, which tend to be more opaque and less liquid than equity ETFs. Table A4 in the Appendix shows that the impact of model recommendation on ETF flows is significant for both subsamples: equity and non-equity ETFs.

Since model recommendations are provided by both asset managers and strategists, we examine whether the impacts on ETF flows would vary between these two types. Table A5 shows that both asset managers' and strategists' recommendations play an important role in ETF flows.

To sum up, model providers' recommendations attract additional investor flows to the ETFs. Investors who chase these recommendations also behave differently, as they are less sensitive

to the ETF past performance.

### **3.2 Natural Experiment: The closure of F-Squared Investments**

An unlikely, but possible endogeneity issue is that model providers select ETFs based on their expectation of fund flows. They may favor the ETFs that are already popular among investors. Hence, they may choose to add these ETFs into their model recommendations in anticipation of increasing future inflows. To address this issue, we exploit the closure of F-Squared Investments.

The collapse of one of the largest ETF strategists in the US, F-Squared Investments, is plausibly exogenous to the concern of flow induced model fund selection. It provides a unique setting in which to test the causal relation between model recommendations and ETF flows. F-Squared Investments, as an investment advisor, started to offer ETF strategies in 2008. By 2014, F-Squared's ETF strategy was one of the largest in the market, with approximately \$28.5 billion in assets following the strategy. In December 2014, the SEC charged F-Squared with defrauding investors through false performance advertising about its flagship product "AlphaSector".<sup>40</sup> In July 2015, F-Squared filed for bankruptcy.

We can observe 19 model recommendations offered by F-Squared in the sample. On average, each model recommendation covers 7.6 US ETFs. The last available holdings of each model portfolio ranges from December 2014 to June 2015. F-Squared's model portfolios were gradually closed because of the firm's financial distress. The closure of the portfolios and thus the passive deletion of ETFs from models serves as an exogenous shock with respect to future fund flows. It allows us to test the impact of model recommendations on flows of ETFs.

We construct the treatment group to be ETFs that were recommended by F-Squared models for the last time post November 2014. We define the first month when an ETF is omitted from the recommendation due to model closure as the deletion date. Given the data frequencies, this

---

<sup>40</sup><https://www.sec.gov/files/litigation/admin/2014/ia-3988.pdf>.

will either be January, April, or July 2015. Following Gormley and Matsa (2011), we construct a cohort of treated and control ETFs for each deletion date using fund-date observations for the nine months before and the nine months after the deletion date. The control group is constructed by matching each treated ETF from each cohort with other ETFs recommended by other model providers in the same Morningstar category in the month preceding deletion. In the control group, we eliminate the ETFs that were deleted by any models in the following three months.

We aim at isolating the change in flows attributable to the deletion of ETFs from a recommendation. Hence, a difference-in-difference regression framework fits the setup. The quantity of interest is the interaction of treatment (ETF in F-Squared recommendation) and post (after models' closure), which identifies the change in flows. We estimate the following specification:

$$\text{Flow}_{i,c,t} = \alpha + \beta_1 \text{Treatment}_{i,c} \times \text{Post}_{c,t} + \text{Controls}_{i,c,t-1} + \gamma_{i,c} + \eta_{c,t} + \varepsilon_{i,c,t}, \quad (4)$$

where  $\text{Flow}_{i,c,t}$  is the percent flow for ETF  $i$  of cohort  $c$  in month  $t$ , and  $\text{Treatment}_{i,c}$  is set to one for ETFs that were deleted by F-Squared in cohort  $c$ , and zero for the matched ETFs.  $\text{Post}_{c,t}$  is set to one for the months following the closure of F-Squared's models from cohort  $c$ . We also include the fund-cohort fixed effects,  $\gamma_{i,c}$ , to ensure that we estimate the impact of exposure after controlling for any fixed differences between ETFs, and we include cohort-time fixed effects,  $\eta_{c,t}$ , as a nonparametric control for any secular time trends. Compared with the simple fund and time fixed effects, the fund-cohort and cohort-time fixed effects are more conservative. We consider a nine-month window around the event.

Table 7 presents the results from estimating Equation 4. Since the experiment is about ETF deletion, we should interpret  $\beta_1$  in an opposite way as we do in Equation 3. The ETFs that are deleted from model portfolios receive 4.57 percentage points lower flows in the nine months following the deletion than do other ETFs of the same investment category that are recommended

by models. The result is significant with multiple control variables. For example, ETF flows are sensitive to past performance, as measured by lagged monthly return rank among all ETFs. The results also show that larger ETFs receive lower future flows. Column 2 of Table 7 presents the similar results with Amihud Ratio and Turnover included in the regression.<sup>41</sup>

[Insert Table 7 about here]

Next, we test for parallel trends. Inference using the difference-in-difference tests on the parallel trend assumption, stating that treatment and control would have behaved similarly in the absence of treatment. We add  $Pre_{c,t}$ , an indicator which is equal to one for three months before the closure of F-Squared's models, as well as an interaction term between  $Treatment_{i,c}$  and  $Pre_{c,t}$  to Equation 4.

Columns 3 and 4 of Table 7 present the results of a specification that includes the interaction of the treatment indicator with the “pre” indicator variable. If treatment and control units exhibit parallel trends and behave similarly pre-event, the  $Treatment \times Pre$  interaction coefficient should be economically small and statistically insignificant. We observe that this coefficient is not statistically significantly different from zero in both models. Therefore, in line with the parallel trend assumption, the pre-event flows to ETFs recommended by F-Squared's models do not differ from the flows to funds recommended by other model providers.

For robustness, we drop the second and third events that happen in April and July 2015, respectively, and only consider the first event in January 2015. Table A6 in the Appendix provides qualitatively similar results.

There is a concern that the documented outflows from ETFs recommended by F-Squared models may be related to the mutual funds subadvised by F-Squared. Between September 2009 and May 2015, F-Squared Investments was hired by Virtus to subadvise its mutual funds that follow the AlphaSector strategies created by F-Squared.<sup>42</sup> To address this concern, we adjust ETF

---

<sup>41</sup>The lower number of observations is because of missing values for Amihud Ratio.

<sup>42</sup><https://www.sec.gov/litigation/admin/2015/ia-4266.pdf>.

flows in the treated group by taking into account the mutual fund portfolio rebalancing and then conduct the difference-in-difference test using these adjusted flows.

In particular, we first obtain the portfolio holdings of mutual funds from Virtus that follow the AlphaSector strategy. Then we identify the ETFs in the treated group of the test from the holdings of Virtus mutual funds. The flow of treated ETFs due to the rebalancing of mutual fund portfolio is calculated as

$$\text{Flow}_{i,t}^{MF} = \frac{\sum_j (N_{i,j,t} - N_{i,j,t-1}) \times p_{i,t}}{AUM_{i,t-1}} \times 100, \quad (5)$$

where  $N_{i,j,t}$  is the number of shares of ETF  $i$  held by mutual fund  $j$  in period  $t$ ,  $p_{i,t}$  is the share price of ETF  $i$  in period  $t$ .

The numerator defines the flow of ETF  $i$  from all mutual funds that hold this ETF. Dividing the flow of ETF  $i$  by its AUM in the previous period, we get the percentage flow of ETF  $i$  because of the the mutual fund portfolio rebalancing.

In the next step, we deduct the  $\text{Flow}_{i,t}^{MF}$  from the total flow of ETF  $\text{Flow}_{i,t}$  calculated from Equation (2) and conduct the difference-in-difference test (4) using the adjusted flows.

Table A7 in the Appendix presents the results. Excluding the flows from mutual funds of Virtus, the ETFs that are deleted from model portfolios receive 4.53 percentage points lower flows in the nine months following the deletion than do other ETFs of the same investment category that are recommended by models. Comparing this number with 4.57 in Table 7, we can see that part of the outflows from ETFs in the treated group comes from Virtus mutual funds. However, the influence of mutual fund on the ETF flows is negligible.

It is worth noting that the average impact of model recommendations on ETF flows that we observe in this experiment is 4.57 percentage points. This estimate notably exceeds the 0.05-0.06 percentage points that we document in the whole sample regression outlined in Table 6. A

first potential reason for this variation might stem from the disparity in samples. Table A8 in the Appendix presents the summary statistics of fund variables within the natural experiment. We can see that the average fund size is \$1299.85 million ( $\exp(7.17)$ ), which is smaller compared to the average fund size of \$2067.52 million (Table 3). Additionally, the Amihud ratio of ETFs within the natural experiment is 0.01, indicating a higher liquidity level compared to the overall sample ratio of 0.07. These findings imply that the ETFs within the natural experiment are relatively smaller and more liquid compared to the average ETF. Particularly, smaller, more liquid funds tend to attract more investor flows than larger, less liquid ETFs (Broman and Shum (2018)). Second, Table 6 reports the effect of model recommendations on ETF flows across a 10-year period, while the natural experiment test only covers an 18-month period. The impact of model portfolio rebalancing on ETF flows likely is stronger in the short term, potentially diminishing over longer time horizons. Moreover, F-squared was one of the largest model providers. Hence, our finding resonates with the observed short-term outflow of almost \$4 billion from iShares ESG ETF within one day, on March 21, 2023, after another giant model provider, BlackRock, rebalanced its model portfolios.<sup>43</sup>

To conclude, the result of the experiment supports the argument that recommendations by model providers causally affect the flows of ETFs.

## 4 Self-recommendations

In the previous section, we show that model portfolios can induce fund flows. All else being equal, higher fund flows increase an ETF's AUM and hence fees generated. In this section, we test whether model providers use their influence to direct fund flows to their own ETFs, even when other ETFs may dominate. First, we look at the difference between affiliated and unaffiliated ETFs that are recommended by model providers. We define an ETF as *Affiliated* if the ETF shares the model provider's branding name. Otherwise, the ETF is *Unaffiliated*.<sup>44</sup>

---

<sup>43</sup><https://www.ft.com/content/cb57eb93-d8ef-41e9-b238-fd802aa13f1e>.

<sup>44</sup>By definition, only asset managers have affiliated ETFs since strategists do not have proprietary funds.

Second, we look at the probability of an ETF that model providers add to their model portfolios, specifically investigating whether its affiliation status plays a role in its inclusion. Moreover, self-recommendations from asset managers may potentially affect the performance of the whole model portfolio. Therefore, we conclude this section with comparing the performance of model recommendations provided by strategists and asset managers.

#### **4.1 Difference between Affiliated and Unaffiliated ETFs**

Since each model provider takes charge of several model recommendations, one ETF may be recommended by several model portfolios simultaneously. We thus only keep one observation if an ETF is recommended by several models from the same provider. Table 8 describes the characteristics of these ETFs.

[Insert Table 8 about here]

The sample contains 88,274 company-ETF-month observations. 9,209 company-ETF-month observations correspond to affiliated ETFs and 79,065 to unaffiliated ETFs. The expense ratio of affiliated ETFs is 32 bps, higher than that of unaffiliated ETFs, at 28 bps. The difference is significant at the 1% level. Affiliated ETFs are significantly younger than unaffiliated ETFs. Moreover, affiliated ETFs also exhibit higher monthly return volatility, higher Amihud ratio, and higher quoted bid-ask spread. The size of affiliated ETFs, the AUM, is \$10.147 billion and is significantly lower than that of unaffiliated ETFs at the 1% level. The difference in category-adjusted returns between the two groups is 4 bps and it is significant at the 5% level. But this difference is not economically significant.

Note that one type of model providers, strategists, do not have affiliated ETFs. As a result, all affiliated ETFs are thus recommended by asset managers, while unaffiliated ETFs are recommended by both types of providers. Therefore, we divide unaffiliated ETFs into two groups – ETFs recommended by asset managers (column 3) and ETFs recommended by strategists (column 4). We compare each of these two groups separately with affiliated ETFs, as shown

in columns (1)-(3) and (1)-(4), respectively. The results remain qualitatively consistent across these comparative analyses.

In addition, we address differences caused by the types of ETFs in other characteristics than returns. Table A9 in the Appendix provides other category-adjusted variables. Expense Ratio, Return Std. Dev., Turnover, Amihud Ratio, and Quoted Spread are category-adjusted by deducting the median value of funds of the same Morningstar Category. The results remain qualitatively unchanged.

To sum up, the affiliated ETFs tend to be more expensive and less liquid. These results might imply preferential treatment of the affiliated ETFs that we test in the next subsection by looking at the changes in the model recommendations.

## 4.2 Binary Choice Models of ETF Addition

To test whether affiliated ETFs are treated preferentially relative to unaffiliated ETFs, we study changes that model providers make to their recommendations. Similar to Pool et al. (2016) and Cookson et al. (2021), we use the following logit model to model ETF addition probability:

$$\begin{aligned} \text{prob}(\text{Addition}_{c,i,t} = 1) = & \Lambda(\beta_1 \text{Affiliated}_{c,i} + \beta_2 R_{i,t-1} + \beta_3 \text{Affiliated}_{c,i} \times R_{i,t-1} \\ & + \beta_4 \text{Fee}_{i,t-1} + \beta_5 \text{Affiliated}_{c,i} \times \text{Fee}_{i,t-1} + \text{Controls}_{c,i,t-1}), \end{aligned} \quad (6)$$

where  $\text{Addition}_{c,i,t}$  is an indicator variable that takes the value one if ETF  $i$  is added to the models of company  $c$  during month  $t$ ; function  $\Lambda(z)$  is defined as  $\Lambda(z) = \exp(z)/(1 + \exp(z))$ ;  $\text{Affiliated}_{c,i}$  is an indicator variable that takes the value one if ETF  $i$  is affiliated to company  $c$ ;  $R_{i,t-1}$  is the percentile rank of returns of ETF  $i$  in the previous one year or three years, and we scale the rank by 1/100;  $\text{Fee}_{i,t-1}$  is the expense ratio of ETF  $i$  measured in percentage points; the vector of lagged control variables includes logarithm of fund age, logarithm of fund size,

the standard deviation of fund return, the turnover of the fund, as well as ETF category and month-year fixed effects. Table 9 reports the results from estimating Equation 6, as well as the average marginal effect of variables of interest.

[Insert Table 9 about here]

There are several key takeaways from the analysis. First, the chances of being added to a recommendation list are significantly higher for affiliated ETFs than for unaffiliated funds. The coefficient before the affiliation dummy is significantly positive at the 1% level when we use either the performance measures of the previous one year or of the previous three years. This result is consistent with the findings by Pool et al. (2016) and Cookson et al. (2021) who show that affiliated funds are more likely to be added to 401(k) plans and platforms' recommendations, respectively.

Following Cookson et al. (2021), we also analyze the average marginal effect of several variables of interest. First, being affiliated increases the probability of addition by 0.62 percentage points. The average model-implied monthly addition probabilities for affiliated funds are 0.71%, and only 0.09% for unaffiliated funds.<sup>45</sup> The probability of addition is influenced by the prior performance. Funds that had better prior performance are more likely to be recommended by models. The prior one-year performance rank is positively significant at the 5% level, while the prior three-year performance rank is only significant at the 10% level. The sensitivity of addition probability to prior performance for affiliated ETFs is insignificantly different from that of unaffiliated ETFs since the estimated  $\beta_3$  is insignificant.

Second, the addition odds of expensive unaffiliated ETFs are lower than addition odds of cheap unaffiliated ETFs. In contrast, the addition odds of expensive affiliated ETFs are higher than that of cheaper affiliated ETFs.<sup>46</sup> When the expense ratio of affiliated ETFs increases by 1

<sup>45</sup>The average model implied addition probability for affiliated ETFs is computed as the average across the sample of  $\Lambda(\beta_1 + (\beta_2 + \beta_3)R_{i,t-1} + (\beta_4 + \beta_5)Fee_{i,t-1} + Controls_{c,i,t-1})$ , whereas the average model implied addition probability for unaffiliated ETFs is computed as the average across the sample of  $\Lambda(\beta_2 R_{i,t-1} + \beta_4 Fee_{i,t-1} + Controls_{c,i,t-1})$ .

<sup>46</sup>Conditioning on same prior performance and controls, the odds ratio between two unaffiliated ETFs whose expense ratios are  $fee_1$  and  $fee_2$  respectively, equals  $exp(\beta_2 R_{i,t-1} + \beta_4 Fee_1 + Controls_{c,i,t-1}) / exp(\beta_2 R_{i,t-1} +$

bp, the probability of addition increases by 0.25 percentage points.<sup>47</sup> It implies that the model providers prefer cheaper ETFs when they choose among unaffiliated funds, but they are more likely to choose more expensive funds among affiliated ETFs. It is consistent with the finding in section 4.1 that recommended affiliated ETFs generally charge higher fees than unaffiliated ETFs.

In addition, we find that the size of the fund plays an important role in the addition probability. In both specifications, the coefficient before the size variable is significant at the 1% level. Larger funds, regardless of affiliation, have higher chances of being recommended by model providers. That also explains why we observe a substantial difference in size between model ETFs and non-model ETFs in Table 4.

In contrast to the relatively frequent additions of new affiliated ETFs into model recommendations, we do not observe many deletions of affiliated funds from the models. Of the 88,274 company-ETF-month observations, we only discover 150 deletions of affiliated ETFs from models, and 2,730 deletions of unaffiliated ETFs. The small number of deleted affiliated ETFs implicitly shows model providers' favoritism toward affiliated funds.

Moreover, we also conduct several robustness checks. First, when we estimate the probability of ETF addition to a model recommendation using quarterly data, the results are very similar to the main result, as reported in Table A10 in the Appendix. Second, since one type of model providers – strategists – do not have affiliated ETFs by construction, we estimate the probability of addition to the models provided only by asset managers. Table A11 in the Appendix shows that the results hold. Finally, in untabulated results, we confirm that the evidence is not driven

---

$\beta_4 \text{Fee}_2 + \text{Controls}_{c,i,t-1} = \exp(\beta_4(\text{Fee}_1 - \text{Fee}_2))$ . Since  $\beta_4 < 0$ , the odds ratio of an expensive unaffiliated ETF is higher than a cheaper unaffiliated ETF. Similarly, we find that the odds ratio of an affiliated ETF whose expense ratio is  $\text{fee}_1$  and another affiliated ETF whose expense ratio is  $\text{fee}_2$ , conditioning on same prior performance and controls, is  $\exp((\beta_4 + \beta_5)(\text{fee}_1 - \text{fee}_2))$ . Note that  $\beta_4 + \beta_5 > 0$  when we use the prior one-year performance and the prior three-year performance, indicating that the odds of an expensive ETF being added are higher than for a cheap affiliated ETF.

<sup>47</sup>If the expense ratio increases by 1 bp, the average marginal impact on the probability of addition is  $0.0029 - 0.0004 = 0.0025$  when performance is measured by prior one-year performance rank, and the average marginal impact on the probability of addition is  $0.0034 - 0.0004 = 0.0030$  when performance is measured by prior three-year performance rank.

only by equity ETFs.

### 4.3 Affiliated ETFs and Performance of Model Portfolios

Subsections 4.1 and 4.2 establish the fact that asset managers favor their affiliated ETFs, and those affiliated ETFs tend to perform worse than the unaffiliated ETFs. Nevertheless, the proportion of affiliated ETFs might be small enough and therefore ultimately pose insignificant impact on the performance of the whole model. To get an answer, we evaluate the models based on the type of providers.

[Insert Table 10 about here]

We split the models into two groups by the type of providers and compare the performance of these two groups. Since asset managers only start to provide model portfolios in 2014, we thus exclude the years preceding 2014 from this analysis. The performance is calculated using net return of ETFs. Columns 1 and 2 of Table 10 show that both types of model providers underperform the benchmarks. Moreover, the models provided by asset managers generate 3 basis points lower alphas (column 3) per month than the models provided by strategists. However, the difference is not economically significant. Column 4 reports the differential alpha, that is the difference between the alpha of models and the alpha of a matched model of similar ETFs. The ETFs in the matched model belong to the same Morningstar category and size quintile as those ETFs within the models in the sample. The matched model stands as an alternative portfolio that the model provider could potentially have constructed. Column 4 demonstrates that the differential alphas are not significantly different from zero for both types of model providers.<sup>48</sup>

To conclude, the findings reveal a significant difference between affiliated and unaffiliated ETFs. Specifically, affiliated ETFs exhibit lower liquidity and charge higher fees compared to their unaffiliated peers. Model providers also display a tendency toward self-recommendations, with

---

<sup>48</sup>Panel B of Table A12 in the Appendix provides the results for the models with at least 60% recommendations weights in ETFs. The results are qualitatively the same.

the asset managers tending to recommend their affiliated ETFs over unaffiliated ETFs. Finally, we note that alphas of models provided by asset managers are statistically significantly lower than alphas of models provided by strategists. But both alphas are not economically significant.

## 5 Conclusion

Despite the increasing number of model recommendations, little is known about how they influence the investment choices of financial advisors. This paper takes the first step in investigating this question.

We analyze recommendations of asset managers and strategists to third-party financial advisors over the period 2010 to 2020. We show that model providers recommend ETFs that, on average, are less expensive and more liquid than the rest of ETFs. We also find that the model recommendations have a large and significant effect on ETF flows. Nevertheless, conflicts of interest seem to affect the quality of these recommendations when we analyze the nature of model providers. Asset managers tend to include their own ETFs more frequently. These affiliated ETFs, on average, have higher fees and lower liquidity than unaffiliated funds. Moreover, the overall performance of the models recommended by asset managers does not economically differ from the performance of the models recommended by strategists.

An unanswered question is why do financial advisors follow these recommendations. While answering this question is beyond the scope of this paper, we have several potential explanations in mind. First, financial advisors may not be able to fully judge whether these recommendations add value (Cookson et al., 2021). Second, financial advisors might use these recommendations to reduce their reputation concerns (Dasgupta and Maug, 2023). Third, they might still be better off using these recommendations than using none (Chalmers and Reuter, 2020).

## References

- Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets* 5(1), 31–56.
- Balduzzi, P. and J. Reuter (2018). Heterogeneity in target date funds: Strategic risk-taking or risk matching? *Review of Financial Studies* 32(1), 300–337.
- Ben-David, I., F. Franzoni, B. Kim, and R. Moussawi (2023). Competition for attention in the ETF space. *Review of Financial Studies* 36(3), 987–1042.
- Bergstresser, D., J. M. R. Chalmers, and P. Tufano (2009). Assessing the costs and benefits of brokers in the mutual fund industry. *Review of Financial Studies* 22(10), 4129–4156.
- Boyson, N. M. (2019). The worst of both worlds? Dual-registered investment advisers. Working Paper.
- Broman, M. S. and P. Shum (2018). Relative liquidity, fund flows and short-term demand: Evidence from exchange-traded funds. *Financial Review* 53(1), 87–115.
- Brown, D. C., S. Cederburg, and M. Towner (2020). ETFs: The good, the bad, and the ugly. Working Paper.
- Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance* 52(1), 57–82.
- Chalmers, J. and J. Reuter (2020). Is conflicted investment advice better than no advice? *Journal of Financial Economics* 138(2), 366–387.
- Chevalier, J. and G. Ellison (1997). Risk taking by mutual funds as a response to incentives. *Journal of Political Economy* 105(6), 1167–1200.
- Clifford, C. P., J. A. Fulkerson, and B. D. Jordan (2014). What drives ETF flows? *Financial Review* 49, 619–642.

- Cookson, G., T. Jenkinson, H. Jones, and J. V. Martinez (2021). Best buys and own brands: Investment platforms' recommendations of mutual funds. *Review of Financial Studies* 34(1), 227–263.
- Dannhauser, C. and J. Pontiff (2021). FLOW. Working Paper.
- Dasgupta, A. and E. Maug (2023). Delegation chains. Working Paper.
- Doellman, T. W. and S. Sardarli (2016). Investment fees, net returns, and conflict of interest in 401(K) plans. *Journal of Financial Research* 39(1), 5–33.
- Elton, E. J., M. J. Gruber, and C. R. Blake (2007). Participant reaction and the performance of funds offered by 401(k) plans. *Journal of Financial Intermediation* 16(2), 249–271.
- Elton, E. J., M. J. Gruber, and C. R. Blake (2011). Holdings data, security returns, and the selection of superior mutual funds. *Journal of Financial and Quantitative Analysis* 46(2), 341–367.
- Elton, E. J., M. J. Gruber, A. de Souza, and C. R. Blake (2015). Target Date Funds: Characteristics and Performance. *Review of Asset Pricing Studies* 5(2), 254–272.
- Evans, R. B. (2010). Mutual fund incubation. *Journal of Finance* 65(4), 1581–1611.
- Gennaioli, N., A. Shleifer, and R. Vishny (2015). Money doctor. *Journal of Finance* 70(1), 91–114.
- Gormley, T. A. and D. A. Matsa (2011, 04). Growing out of trouble? Corporate responses to liability risk. *Review of Financial Studies* 24(8), 2781–2821.
- Huang, S., Y. Song, and H. Xiang (2023). The smart beta mirage. Working Paper.
- Jenkinson, T., H. Jones, and J. V. Martinez (2016). Picking winners? Investment consultants' recommendations of fund managers. *Journal of Finance* 71(5), 2333–2369.

- Kephart, J. and A. Millson (2021). 2021 Model portfolio landscape. Morningstar Manager Research Report, 1–29.
- Kephart, J., A. Millson, B. Blue, and M. Pacholok (2020). 2020 Model portfolio landscape. Morningstar Manager Research Report, 1–30.
- Kostovetsky, L. and J. Warner (2022). The market for fund benchmarks: Evidence from ETFs. Working Paper.
- PIMCO (2021). Streamlining your practice with model portfolios. Company Report.
- Pool, V. K., C. Sialm, and I. Stefanescu (2016). It pays to set the menu: Mutual fund investment options in 401(K) plans. *Journal of Finance* 71(4), 1779–1812.
- Pu, D. and Y. Xie (2022). Index ETFs’ tracking error as a predictor of performance. Working Paper.
- Sirri, E. R. and P. Tufano (1998). Costly search and mutual fund flows. *Journal of Finance* 53(5), 1589–1622.
- State Street Global Advisors (2016). Partnering with ETF strategists. Enhance your advisory business. Company Report.

**Table 1:** Model recommendations, providers, and ETFs

This table reports descriptive statistics of the sample of models and their providers, as well as ETFs being recommended by these models. Panel A presents the statistics of the whole sample. Panel B reports the statistics of the subsample that only contains models with at least one affiliated ETF. An ETF and a model are defined as affiliated if they share the same branding name. The numbers are calculated by taking the last available holding of each model per year.

	Number of Models	Number of Model Providers	Average Number of ETFs in Model	Average Number of Affiliated ETFs in Model	Average Percentage of ETFs in Model	Average Percentage of Affiliated ETFs in Model
Panel A: All Models						
2010	53	11	12.13	0	64.49	0
2011	100	21	9.29	0	59.61	0
2012	144	26	9.82	0	66.99	0
2013	187	29	9.66	0	68.59	0
2014	242	34	9.37	0.79	74.34	10.12
2015	274	38	8.74	1.44	75.51	17.68
2016	319	44	9.71	2.26	74.56	23
2017	450	49	9.57	3.04	74.47	26.66
2018	576	58	8.40	2.83	67.21	23.82
2019	832	71	8.49	2.95	64.46	26.35
2020	1,046	90	8.33	2.91	62.56	25.18
Panel B: Models with at Least One Affiliated ETF						
2014	25	1	7.64	7.64	98.00	98.00
2015	51	3	8.18	7.75	97.75	95.00
2016	81	7	9.46	8.90	93.31	90.58
2017	160	9	9.96	8.54	86.30	74.97
2018	216	8	9.54	7.55	79.46	63.52
2019	314	12	9.44	7.86	82.00	69.95
2020	387	17	9.49	7.90	79.08	68.27

**Table 2: Model ETFs by style**

This table reports the descriptive statistics by the style of the ETF that are recommended by model providers. The style of ETFs is defined by “Global Broad Category Group” from the Morningstar Direct database. Panel A reports the average number of ETFs per model by style. Panel B reports the average weight of ETFs per model by style. The numbers are calculated by taking the last available holding of each model per year. The average number (weight) of ETFs is calculated by dividing the total number (weight) of ETFs of each style by the total number of models.

Panel A: Average Number of ETFs							
Year	Equity	Fixed Income	Commodities	Allocation	Alternative	Convertibles	Miscellaneous
2010	8.38	3.21	0.55	0.00	0.00	0.00	0.00
2011	6.21	2.62	0.38	0.02	0.02	0.01	0.03
2012	6.35	2.89	0.53	0.01	0.01	0.00	0.04
2013	6.51	3.03	0.07	0.04	0.01	0.01	0.00
2014	6.44	2.81	0.05	0.03	0.01	0.02	0.01
2015	5.59	3.03	0.05	0.03	0.03	0.00	0.01
2016	6.17	3.32	0.11	0.03	0.06	0.03	0.01
2017	6.10	3.30	0.09	0.02	0.04	0.02	0.01
2018	5.27	2.99	0.08	0.01	0.02	0.01	0.01
2019	5.27	3.06	0.10	0.01	0.05	0.01	0.00
2020	5.25	2.85	0.16	0.01	0.05	0.00	0.00
Overall	6.14	3.01	0.20	0.02	0.03	0.01	0.01

  

Panel B: Average Weight of ETFs							
Year	Equity	Fixed Income	Commodities	Allocation	Alternative	Convertibles	Miscellaneous
2010	34.72	26.47	3.31	0.00	0.00	0.00	0.00
2011	34.22	22.37	2.07	0.55	0.25	0.05	0.10
2012	38.05	25.96	2.82	0.02	0.03	0.00	0.11
2013	42.25	24.81	0.40	1.00	0.03	0.11	0.00
2014	47.37	25.89	0.33	0.68	0.03	0.04	0.01
2015	44.43	29.68	0.59	0.60	0.17	0.01	0.04
2016	43.25	29.57	0.75	0.56	0.31	0.11	0.01
2017	44.27	28.67	0.77	0.42	0.27	0.06	0.01
2018	38.25	27.79	0.68	0.28	0.16	0.03	0.02
2019	37.75	25.84	0.46	0.19	0.19	0.03	0.00
2020	37.23	24.16	0.64	0.28	0.21	0.02	0.02
Overall	40.16	26.47	1.16	0.42	0.15	0.04	0.03

**Table 3:** Summary statistics of all ETFs

This table reports the mean, median, standard deviation and number of observations for each characteristic of all ETFs. *No. Model* is the number of models that recommend the ETF. *Monthly Return* is the monthly return of the ETF. *Category-adjusted Return* is the monthly return of a fund deducting the median return of funds that are in the same Morningstar category. *Prior 1-Yr. Perf.* and *Prior 3-Yr. Perf.* are measured by the performance rank percentiles over the prior one year and three years, respectively. We scale the rank by 1/100. *Expense Ratio* is the net expense ratio measured in percentage points. *Fund Age* is the age of the ETF measured in years. *Fund Size* is the total AUM measured in millions of dollars. *Return Std. Dev.* is the standard deviation of monthly net return over the prior one year. *Turnover* is a measure of the fund's trading activity. *Amihud Ratio* is calculated as the mean average of the daily Amihud ratio over a month. *Quoted Spread* is the ratio of bid-ask spread and midpoint, and we scale it by 100.

Variable	Mean	Median	SD	Observations
No. Models	2.60	0.00	7.67	145,614
Monthly Return (%)	0.70	0.68	5.36	144,789
Category-adjusted Return (%)	-0.01	0.00	2.49	144,789
Prior 1-Yr. Perf.	0.50	0.50	0.27	136,439
Prior 3-Yr. Perf.	0.50	0.50	0.26	107,776
Expense Ratio (%)	0.44	0.44	0.31	143,026
Fund Age (years)	6.81	5.81	4.71	145,614
Fund Size (\$ mn)	2,067.52	182.56	9,324.27	145,614
Return Std. Dev. (%)	4.38	3.97	2.83	136,439
Turnover (%)	53.66	25.80	734.16	135,850
Amihud Ratio	0.07	0.00	0.25	99,753
Quoted Spread	0.20	0.10	0.57	101,651

**Table 4:** Characteristics of model and non-model ETFs

This table reports the summary statistics of ETFs that are recommended or not recommended by models. *Category-adjusted Return* is the monthly return of a fund deducting the monthly median return of funds that are in the same Morningstar category. *Prior 1-Yr. Perf.* and *Prior 3-Yr. Perf.* are measured by the performance rank percentiles over the prior one year and three years, respectively. We scale the rank by 1/100. *Expense Ratio* is the net expense ratio measured in percentage points. *Fund Age* is the age of the ETF measured in years. *Fund Size* is the total AUM measured in millions of dollars. *Return Std. Dev.* is the standard deviation of monthly return over the prior one year. *Turnover* is a measure of the fund's trading activity. *Amihud Ratio* is calculated as the mean average of daily Amihud ratio over a month. *Quoted Spread* is the ratio of bid-ask spread and midpoint, and we scale it by 100. t-statistics based on standard errors clustered at the fund level are reported in parentheses. Significance levels are denoted by \*, \*\*, and \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

	Model ETFs	Non-model ETFs	Difference	t-stat
Category-adjusted Return (%)	0.02	-0.02	0.04***	2.80
Prior 1-Yr. Perf.	0.52	0.49	0.03***	6.36
Prior 3-Yr. Perf.	0.53	0.48	0.05***	5.41
Expense Ratio (%)	0.34	0.49	-0.15***	-12.91
Fund Age (years)	8.66	6.03	2.63***	-13.90
Fund Size (\$ mn)	5,988.26	425.96	5,562.30***	7.28
Return Std. Dev. (%)	3.71	4.68	-0.97***	-11.03
Turnover (%)	40.30	59.57	-19.27*	-1.84
Amihud Ratio	0.02	0.10	-0.08***	-17.35
Quoted Spread	0.10	0.26	-0.16***	-14.14
Observations	42,974	102,640		

**Table 5:** Performance of model recommendations

This table presents the performance of model recommendations. The return (alpha) of each model is calculated as the weighted average return (alpha) of its portfolio holdings. We require the total weight of recommended ETFs with existing alphas in one model to be at least 80%. Row 1 uses the ETF gross returns. Row 2 uses the ETF net returns. Gross return is the return before expenses. Net return is the return after expenses are included. Column 1 refers to the average monthly return in excess of CRSP value-weighted stock index. Column 2 refers to the average monthly return in excess of a portfolio of 60% of S&P 500 index and 40% of Bloomberg Barclays US Aggregate Bond Index. Alpha is calculated as the weighted average alpha of ETFs within the model. Differential Alpha is the difference between the alpha of an existing model and the alpha of a model that we construct using a random sample of similar ETFs. All the values are in percentage points. t-statistics based on standard errors clustered at the model-provider level are reported in parentheses. Significance levels are denoted by \*, \*\*, \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

	Excess Return (stocks)	Excess Return (mixed)	Alpha	Differential Alpha
Gross Return	-0.42*** (-13.65)	-0.00 (-0.10)	0.03*** (3.75)	-0.00 (-0.30)
Net Return	-0.44*** (-14.35)	-0.02 (-0.79)	0.01* (1.90)	0.00 (0.06)

**Table 6:** The effect of model recommendations on ETF flows

This table reports the impact of model recommendation on an ETF's flow. The dependent variable is  $Flow_{i,t}$  which is defined as  $\frac{AUM_{i,t} - AUM_{i,t-1} \times (1 + R_{i,t})}{AUM_{i,t-1}} \times 100$ . The independent variables are  $No. Models_{i,t}$ , which is the number of models that recommend ETF  $i$  in month  $t$ ;  $Ret. Rank_{i,t-1}$  is the percentile rank of ETF  $i$ 's return scaled by 1/100 in month  $t - 1$ ;  $Expense Ratio_{i,t-1}$  is the expense ratio of ETF  $i$ , measured in percentage points. The control variables include the lagged natural logarithm of the fund's AUM measured in millions of dollars, the lagged natural logarithm of fund age measured in months, the lagged ETF turnover, and the lagged Amihud ratio. Columns 2 and 4 report the results incorporating fund fixed effects and time fixed effects. We report t-statistics based on standard errors clustered at the fund and month-year levels in parentheses. Significance levels are denoted by \*, \*\*, and \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

Dependent Variable: $Flow_{i,t}$				
No. Models $_{i,t}$	0.05*** (5.18)	0.05*** (3.44)	0.06*** (5.46)	0.05*** (3.21)
Return Rank $_{i,t-1}$	3.49*** (15.50)	3.24*** (14.33)	3.75*** (14.02)	3.46*** (13.15)
No. Models $_{i,t} \times$ Return Rank $_{i,t-1}$	-0.05*** (-3.22)	-0.03* (-1.93)	-0.05*** (-3.66)	-0.04** (-2.51)
Expense Ratio $_{i,t-1}$	-0.99*** (-2.86)	-3.11*** (-4.19)	-2.18*** (-4.52)	-10.35*** (-5.33)
No. Models $_{i,t} \times$ Expense Ratio $_{i,t-1}$	0.02 (0.54)	0.04 (0.87)	0.03 (0.84)	0.09 (1.64)
log(Size $_{i,t-1}$ )	0.01 (0.20)	-1.93*** (-13.05)	-0.29*** (-6.34)	-2.18*** (-12.07)
log(Age $_{i,t-1}$ )	-2.12*** (-19.65)	-3.17*** (-11.96)	-2.23*** (-18.25)	-2.79*** (-8.56)
Turnover $_{i,t-1}$			-0.00 (-1.15)	-0.00*** (-3.39)
Amihud Ratio $_{i,t-1}$			-2.88*** (-6.54)	-2.31*** (-3.88)
Month-Year and Fund FE	No	Yes	No	Yes
Observations	140,477	140,454	94,699	94,684
Adjusted R <sup>2</sup>	0.03	0.09	0.05	0.10

**Table 7:** The effect of model closure on fund flows

This table reports the coefficient estimates in the difference-in-difference regression of the natural experiment. The dependent variable is  $Flow_{i,t}$  which is defined as  $\frac{AUM_{i,t} - AUM_{i,t-1} \times (1 + R_{i,t})}{AUM_{i,t-1}} \times 100$ .  $Treatment_{i,c}$  is equal to one for ETFs that are deleted from F-Squared model portfolios after December 2014, and equal to zero for matched model ETFs that have the same investment category as treatment ETFs.  $Post_{c,t}$  is equal to one for the nine months after the deletion of treatment ETFs.  $Pre_{c,t}$  is equal to one for the three months before the closure of treatment ETFs. The control variables include the lagged return rank, the lagged expense ratio, the lagged natural logarithm of the fund's AUM measured in millions of dollars, the lagged natural logarithm of fund age measured in months, the lagged ETF flow, the lagged ETF turnover, and the lagged Amihud ratio. Time-Cohort and Fund-Cohort fixed effects are both included. We report t-statistics with robust standard errors in parentheses. Significance levels are denoted by \*, \*\*, and \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

Dependent Variable: $Flow_{i,c,t}$				
$Treatment_{i,c} \times Post_{c,t}$	-4.57** (-2.71)	-6.55** (-2.68)	-3.77** (-2.32)	-5.52** (-2.45)
$Treatment_{i,c} \times Pre_{c,t}$			2.18 (1.14)	2.92 (0.89)
Return rank $_{i,c,t-1}$	4.85*** (4.23)	4.55*** (3.32)	4.83*** (4.04)	4.51*** (3.20)
Expense Ratio $_{i,c,t-1}$	-55.31 (-0.70)	-77.19 (-0.82)	-51.74 (-0.63)	-71.42 (-0.72)
$\log(Size_{i,c,t-1})$	-11.06*** (-5.38)	-11.64*** (-4.94)	-11.07*** (-5.36)	-11.63*** (-4.92)
$\log(Age_{i,c,t-1})$	-10.27*** (-3.06)	-10.19** (-2.64)	-9.92** (-2.76)	-9.83** (-2.43)
Turnover $_{i,c,t-1}$		0.02** (2.68)		0.02** (2.68)
Amihud Ratio $_{i,c,t-1}$		-12.34 (-1.40)		-12.07 (-1.36)
Time-Cohort and Fund-Cohort FE	Yes	Yes	Yes	Yes
Observations	2,045	1,590	2,045	1,590
Adjusted R <sup>2</sup>	0.185	0.204	0.185	0.204

**Table 8:** Characteristics of affiliated and unaffiliated ETFs

This table reports the summary statistics of ETFs that are affiliated and unaffiliated to a model provider. Unaffiliated ETFs are differentiated by the type of model providers, *All* refers to all unaffiliated ETFs, *AM* refers to unaffiliated ETFs provided by asset managers, *ST* refers to unaffiliated ETFs provided by strategists. *Cat.-adj. Return* is the monthly return of a fund deducting the monthly median return of funds that are in the same Morningstar category. *Prior 1-Yr. Perf.* and *Prior 3-Yr. Perf.* are measured by the performance rank percentiles over the prior one year and three years, respectively. We scale the rank by 1/100. *Expense Ratio* is the net expense ratio measured in percentage points. *Fund Age* is the age of the ETF measured in years. *Fund Size* is the total AUM measured in millions of dollars. *Return Std. Dev.* is the standard deviation of monthly return over the prior one year. *Turnover* is a measure of the fund's trading activity. *Amihud Ratio* is calculated as the mean average of daily Amihud ratio over a month. *Quoted Spread* is the ratio of bid-ask spread and midpoint, and we scale it by 100. t-statistics based on standard errors clustered at the fund level are reported in parentheses. Significance levels are denoted by \*, \*\*, and \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

	Affiliated	Unaffiliated			Difference		
	(1)	All (2)	AM (3)	ST (4)	(1)-(2)	(1)-(3)	(1)-(4)
Cat.-adj. Return (%)	-0.01	0.03	0.03	0.03	-0.04** (-2.17)	-0.04** (-2.02)	-0.04** (-2.13)
Prior 1-Yr. Perf.	0.50	0.53	0.52	0.53	-0.03*** (-2.72)	-0.02* (-1.77)	-0.03*** (-2.76)
Prior 3-Yr. Perf.	0.52	0.54	0.54	0.54	-0.02 (-1.25)	-0.02 (-1.02)	-0.02 (-1.23)
Expense Ratio (%)	0.32	0.28	0.19	0.28	0.04*** (2.93)	0.12*** (7.29)	0.03** (2.33)
Fund Age (years)	8.84	10.44	12.38	10.25	-1.60*** (-4.80)	-3.54*** (-7.94)	-1.40*** (-4.20)
Fund Size (\$ mn)	10,147	15,076	22,675	14,320	-4,928*** (-3.79)	-12,528*** (-3.40)	-4,172** (-3.39)
Return Std. Dev. (%)	3.76	3.37	3.13	3.39	0.39*** (3.34)	0.63*** (3.86)	0.37*** (3.13)
Turnover (%)	46.47	42.47	49.32	41.78	4.00 (0.7)	-2.86 (-0.28)	4.68 (0.88)
Amihud Ratio	0.03	0.01	0.00	0.01	0.02*** (4.36)	0.03*** (5.19)	0.02*** (4.27)
Quoted Spread	0.12	0.06	0.05	0.06	0.06*** (7.57)	0.07*** (8.65)	0.05*** (7.31)
Observations	9,209	79,065	42,158	71,907			

**Table 9:** Logit model of ETF additions to recommendations

This table reports coefficient estimates for the logit model.  $Addition_{c,i,t}$  is an indicator variable that takes the value one if ETF  $i$  is added to the models of company  $c$  during month  $t$ .  $Affiliated_{c,i}$  is an indicator variable that takes the value one if ETF  $i$  is affiliated with a company  $c$ ; past performance is measured by the performance rank percentiles over the prior one year and three years, respectively;  $Expense\ Ratio_{i,t-1}$  denotes the expense ratio of ETF  $i$ , measured in percentage points; a vector of lagged control variables includes logarithm of fund age, logarithm of fund size, the standard deviation of fund return, the expense ratio, the turnover of the fund, as well as ETF category and month-year fixed effects. The second part of the table displays the average marginal effect for the variables of interest:  $Affiliated_{c,i}$ ,  $Expense\ Ratio_{i,t-1}$ ,  $Affiliated_{c,i} \times Expense\ Ratio_{i,t-1}$ . Standard errors are clustered at the fund level and z-values are reported in parentheses. Significance levels are denoted by \*, \*\*, and \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

Dependent Variable: $Addition_{c,i,t}$		
$Affiliated_{c,i}$	2.08*** (9.33)	1.95*** (7.46)
Prior 1-Yr. Perf. $_{i,t-1}$	0.17** (2.20)	
$Affiliated_i \times$ Prior 1-Yr. Perf. $_{i,t-1}$	-0.22 (-0.93)	
Prior 3-Yr. Perf. $_{i,t-1}$		0.15* (1.80)
$Affiliated_i \times$ Prior 3-Yr. Perf. $_{i,t-1}$		-0.18 (-0.57)
Expense Ratio $_{i,t-1}$	-0.43** (-2.34)	-0.35* (-1.85)
$Affiliated_i \times$ Expense Ratio $_{i,t-1}$	2.86*** (7.39)	2.88*** (6.94)
$\log(Age_{i,t-1})$	-0.17*** (-3.07)	-0.07 (-0.82)
$\log(Size_{i,t-1})$	0.66*** (33.78)	0.68*** (31.54)
Return Std. Dev. $_{i,t-1}$	-0.19 (-0.12)	0.08 (0.05)
Turnover $_{i,t-1}$	0.00 (1.27)	0.00 (1.13)
Average Marginal Effect		
$Affiliated_{c,i}$	0.0062	0.0062
Expense Ratio $_{i,t-1}$	-0.0004	-0.0004
$Affiliated_i \times$ Expense Ratio $_{i,t-1}$	0.0029	0.0034
ETF Category and Month-Year FE	Yes	Yes
Observations	4,837,835	3,862,465
Pseudo R <sup>2</sup>	0.20	0.20

**Table 10:** Performance of model recommendations by the type of providers

This table presents the performance of model recommendations for each type of model providers. The return (alpha) of each model is calculated as the weighted average return (alpha) of its portfolio holdings. We require the total weight of recommended ETFs with existing alphas in one model to be at least 80%. Column 1 refers to the average monthly return in excess of CRSP value-weighted stock index. Column 2 refers to the average monthly return in excess of a portfolio of 60% of S&P 500 index and 40% of Bloomberg Barclays US Aggregate Bond Index. Alpha is calculated as the weighted average alpha of each ETF within the model. Differential Alpha is the difference between the alpha of an existing model and the alpha of a model that we construct using a random sample of similar ETFs. All the values are in percentage points. t-statistics based on standard errors clustered at the model-provider level are reported in parentheses. Significance levels are denoted by \*, \*\*, \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

	Excess Return (stocks)	Excess Return (mixed)	Alpha	Differential Alpha
Asset Manager (AM)	-0.53*** (-11.08)	-0.06** (-2.32)	-0.00 (-0.57)	-0.00 (-0.54)
Strategist (ST)	-0.34*** (-8.11)	-0.00 (-0.03)	0.02** (2.19)	0.01 (0.73)
AM minus ST	-0.19*** (-3.16)	-0.06 (-1.27)	-0.03** (-2.29)	-0.01 (-0.91)

**Table A1:** Variable definitions

<b>Variable</b>	<b>Definition</b>	<b>Source</b>
Affiliated	An indicator variable that equals one if ETF shares the same branding name with the model provider	Morningstar
Alpha	ETF alpha is the intercept from a 24-month rolling regression of ETF excess monthly return on corresponding factors, measured in percentage points. For domestic equity ETFs, we use Carhart (1997) four-factors. Following Elton et al. (2015), we use Bloomberg Barclays US Aggregate Bond Index, Bloomberg Barclays US Mortgage Backed Securities (MBS) Index, ICE BofA US High Yield Index and Bloomberg Global Aggregate ex-USD Index for fixed-income ETFs. For international equity ETFs, we use Fama-French market factors, MSCI Europe Index, MSCI Pacific Index, MSCI Emerging Market Index, FTSE World Government Bond Index. For commodity ETFs, we use S&P GSCI Commodity Index. Allocation funds are similar to target date funds in the sense that they usually include multiple styles of funds ranging from equity to commodity in their portfolios, we thus follow Balduzzi and Reuter (2018) and use Fama-French market factor, MSCI AC World ex USA Index, Bloomberg Barclays US Aggregate Bond Index, Bloomberg Global Aggregate ex-USD Index, S&P GSCI Commodity Index as the factors. All indices are in excess return form. Model alpha is the weighted average alpha of all ETFs in the portfolio.	Morningstar
Amihud Ratio	Average daily Amihud ratio over a month; daily Amihud ratio is computed as $10^6 \times  return  / (p \times volume)$	CRSP; Morningstar
Category-adjusted Return	Monthly return of a fund deducting the median return of funds that are in the same category	Morningstar
Differential Alpha	The difference between the alpha of an existing model and the alpha of a model that we construct using a random sample of similar ETFs. The matched model is constructed by selecting ETFs that are in the same Morningstar category and same size quintile of the ETF recommended by the existing model	Morningstar

**Table A1:** Variable definitions (continued from previous page)

<b>Variable</b>	<b>Definition</b>	<b>Source</b>
ETF category	Field “Morningstar Category”	Morningstar
ETF style	Field “Global Broad Category Group”	Morningstar
Excess Return (mixed)	Monthly return of model in excess of a portfolio of 60% of S&P 500 index and 40% of Bloomberg Barclays US Aggregate Bond Index	Morningstar
Excess Return (stocks)	Monthly return of model in excess of CRSP value-weighted stock index	Morningstar
Expense Ratio	Net expense ratio measured in percentage points	Morningstar
Flow	Percentage flow measured as $100 \times [AUM_{i,t} - AUM_{i,t-1} \times (1 + R_{i,t})] / AUM_{i,t-1}$	Morningstar
Fund Age	Time since ETF launch date	Morningstar
Fund Size	Total AUM measured in millions of dollars	Morningstar
Monthly Return	Monthly net return of ETF	Morningstar
Prior 1-year (3-year) Performance	Percentile rank of a fund’s cumulative monthly return over the prior one year (three years) among funds of the same Morningstar category	Morningstar
Quoted Spread	Average daily quoted spread over a month; daily quoted spread is computed as $100 \times (ask - bid) / (ask + bid) / 2$	CRSP
Return Rank	Percentile rank of a fund’s monthly return among funds from the same Morningstar category	Morningstar
Return Std. Dev.	Standard deviation of monthly return over the prior one year	Morningstar
Turnover	The lesser of purchases or sales (excluding all securities with maturities of less than one year) divided by average monthly net assets	Morningstar

**Table A2:** Category-adjusted characteristics of model and non-model ETFs

This table reports the summary statistics of ETFs that are recommended or not recommended by models. *Expense Ratio* is the net expense ratio measured in percentage points. *Return Std. Dev.* is the standard deviation of monthly return over the prior one year. *Turnover* is a measure of the fund's trading activity. *Amihud Ratio* is calculated as the mean average of daily Amihud ratio over a month. *Quoted Spread* is the ratio of bid-ask spread and midpoint, and we scale it by 100. All variables are category-adjusted by deducting the median value of funds of the same Morningstar Category. t-statistics based on standard errors clustered at the fund level are reported in parentheses. Significance levels are denoted by \*, \*\*, and \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

	Model ETFs	Non-model ETFs	Difference	t-stat
Expense Ratio (%)	-0.04	0.03	-0.07***	-7.55
Return Std. Dev. (%)	-0.03	0.20	-0.23***	-6.51
Turnover (%)	10.25	19.45	-9.20***	-2.76
Amihud Ratio	0.01	0.08	-0.07***	-16.28
Quoted Spread	-0.02	0.11	-0.13***	-13.12
Observations	42,974	102,640		

**Table A3:** The effect of model recommendations on ETF flows using quarterly data

This table reports the impact of model recommendation on an ETF's flow. All variables are measured at the quarterly frequency. The dependent variable is  $Flow_{i,t}$  which is defined as  $\frac{AUM_{i,t} - AUM_{i,t-1} \times (1 + R_{i,t})}{AUM_{i,t-1}} \times 100$ . The independent variables are  $No. Models_{i,t}$ , which is the number of models that recommend ETF  $i$  in month  $t$ ;  $Ret. Rank_{i,t-1}$  is the percentile rank of ETF  $i$ 's return scaled by 1/100 in month  $t - 1$ ;  $Expense Ratio_{i,t-1}$  is the expense ratio of ETF  $i$ , measured in percentage points. The control variables include the lagged natural logarithm of the fund's AUM measured in millions of dollars, the lagged natural logarithm of fund age measured in months, the lagged ETF turnover, and the lagged Amihud ratio. Columns 2 and 4 report results incorporating fund fixed effects and time fixed effects. We report t-statistics based on standard errors clustered at the fund and quarter-year levels in parentheses. Significance levels are denoted by \*, \*\*, and \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

Dependent Variable: $Flow_{i,t}$				
No. Models $_{i,t}$	0.18*** (4.88)	0.21*** (3.36)	0.18*** (4.70)	0.18*** (2.90)
Return Rank $_{i,t-1}$	9.63*** (11.82)	8.50*** (10.03)	10.22*** (9.71)	8.96*** (8.10)
No. Models $_{i,t} \times$ Return Rank $_{i,t-1}$	-0.13** (-2.56)	-0.09* (-1.80)	-0.12* (-1.87)	-0.08 (-1.42)
Expense Ratio $_{i,t-1}$	-3.04** (-2.11)	-8.40* (-1.81)	-7.60*** (-3.81)	-36.37*** (-4.90)
No. Models $_{i,t} \times$ Expense Ratio $_{i,t-1}$	0.26* (1.80)	0.45** (2.09)	0.31* (2.01)	0.70*** (2.75)
log(Size $_{i,t-1}$ )	-0.50*** (-3.69)	-7.85*** (-10.02)	-1.49*** (-8.66)	-9.11*** (-9.49)
log(Age $_{i,t-1}$ )	-6.15*** (-14.81)	-8.79*** (-8.26)	-6.50*** (-14.74)	-7.13*** (-5.33)
Turnover $_{i,t-1}$			-0.00** (-2.50)	-0.02*** (-3.56)
Amihud Ratio $_{i,t-1}$			-8.65*** (-8.54)	-6.42*** (-2.79)
Month-Year and Fund FE	No	Yes	No	Yes
Observations	44,825	44,748	30,438	30,396
Adjusted R <sup>2</sup>	0.05	0.15	0.08	0.17

**Table A4:** The effect of model recommendations on equity and non-equity ETF flows

This table reports the impact of model recommendation on an ETF's flow using subsamples: equity ETFs and non-equity ETFs. Columns 1 and 2 report the results for equity ETFs; columns 3 and 4 report the results for non-equity ETFs. The dependent variable is  $Flow_{i,t}$  which is defined as  $\frac{AUM_{i,t} - AUM_{i,t-1} \times (1 + R_{i,t})}{AUM_{i,t-1}} \times 100$ . The independent variables are  $No. Models_{i,t}$ , which is the number of models that recommend ETF  $i$  in month  $t$ ;  $Ret. Rank_{i,t-1}$  is the percentile rank of ETF  $i$ 's return scaled by  $1/100$  in month  $t - 1$ ;  $Expense Ratio_{i,t-1}$  is the expense ratio of ETF  $i$ , measured in percentage points. The control variables include the lagged natural logarithm of the fund's AUM measured in millions of dollars, the lagged natural logarithm of fund age measured in months, the lagged ETF turnover, and the lagged Amihud ratio. Columns 2 and 4 report the results incorporating fund fixed effects and time fixed effects. We report t-statistics based on standard errors clustered at the fund and month-year levels in parentheses. Significance levels are denoted by \*, \*\*, and \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

Dependent Variable: $Flow_{i,t}$				
	Equity ETFs		Non-equity ETFs	
No. Models $_{i,t}$	0.05*** (3.70)	0.03* (1.93)	0.05*** (2.89)	0.03 (1.63)
Return Rank $_{i,t-1}$	3.97*** (13.42)	3.69*** (12.87)	2.47*** (5.98)	2.10*** (5.12)
No. Models $_{i,t} \times$ Return Rank $_{i,t-1}$	-0.05*** (-3.06)	-0.03* (-1.87)	-0.03 (-1.09)	-0.02 (-0.66)
Expense Ratio $_{i,t-1}$	-1.91*** (-3.88)	-10.79*** (-5.09)	-4.19*** (-4.75)	-7.05 (-1.25)
No. Models $_{i,t} \times$ Expense Ratio $_{i,t-1}$	0.07 (1.57)	0.16** (2.22)	0.01 (0.31)	-0.03 (-0.47)
log(Size $_{i,t-1}$ )	-0.29*** (-5.54)	-2.13*** (-10.49)	-0.28*** (-2.97)	-2.50*** (-7.95)
log(Age $_{i,t-1}$ )	-2.28*** (-16.34)	-3.10*** (-8.10)	-2.16*** (-9.58)	-2.37*** (-3.58)
Turnover $_{i,t-1}$	-0.00 (-1.05)	-0.01** (-1.99)	0.00 (0.09)	-0.00** (-2.19)
Amihud Ratio $_{i,t-1}$	-2.94*** (-6.28)	-2.30*** (-3.67)	-2.63*** (-3.28)	-2.18** (-2.45)
Month-Year and Fund FE	No	Yes	No	Yes
Observations	105,708	75,916	34,745	18,768
Adjusted R <sup>2</sup>	0.11	0.13	0.09	0.10

**Table A5:** The effect of model recommendations on ETF flows by type of providers

This table reports the impact of model recommendation to an ETF's flow using subsamples: asset managers and strategists. Columns 1 and 2 report the results for model recommendations from asset managers; columns 3 and 4 report the results for model recommendations from strategists. The dependent variable is  $Flow_{i,t}$  which is defined as  $\frac{AUM_{i,t} - AUM_{i,t-1} \times (1 + R_{i,t})}{AUM_{i,t-1}} \times 100$ . The independent variables are  $No. Models_{i,t}$ , which is the number of models that recommend ETF  $i$  in month  $t$ ;  $Ret. Rank_{i,t-1}$  is the percentile rank of ETF  $i$ 's return scaled by 1/100 in month  $t - 1$ ;  $Expense Ratio_{i,t-1}$  is the expense ratio of ETF  $i$ , measured in percentage points. The control variables include the lagged natural logarithm of the fund's AUM measured in millions of dollars, the lagged natural logarithm of fund age measured in months, the lagged ETF turnover, and the lagged Amihud ratio. Columns 2 and 4 report the results incorporating fund fixed effects and time fixed effects. We report t-statistics based on standard errors clustered at the fund and month-year levels in parentheses. Significance levels are denoted by \*, \*\*, and \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

Dependent Variable: $Flow_{i,t}$				
	Asset Managers		Strategists	
No. Models $_{i,t}$	0.05*** (3.54)	0.06** (2.49)	0.08*** (4.96)	0.05* (1.83)
Return Rank $_{i,t-1}$	3.42*** (12.41)	3.05*** (11.46)	3.46*** (12.26)	3.07*** (11.19)
No. Models $_{i,t} \times$ Return Rank $_{i,t-1}$	-0.06*** (-2.90)	-0.04** (-2.07)	-0.07** (-2.39)	-0.04 (-1.34)
Expense Ratio $_{i,t-1}$	-2.94*** (-5.70)	-8.75*** (-3.80)	-2.94*** (-5.52)	-9.25*** (-3.91)
No. Models $_{i,t} \times$ Expense Ratio $_{i,t-1}$	-0.00 (-0.03)	0.02 (0.21)	0.02 (0.40)	0.17 (1.57)
log(Size $_{i,t-1}$ )	-0.25*** (-5.29)	-2.36*** (-9.62)	-0.31*** (-6.64)	-2.37*** (-9.63)
log(Age $_{i,t-1}$ )	-2.11*** (-15.11)	-2.28*** (-4.69)	-2.10*** (-15.13)	-2.32*** (-4.75)
Turnover $_{i,t-1}$	-0.00 (-0.96)	-0.00** (-2.36)	-0.00 (-1.02)	-0.00** (-2.42)
Amihud Ratio $_{i,t-1}$	-2.51*** (-6.24)	-1.93*** (-3.51)	-2.60*** (-6.36)	-1.93*** (-3.50)
Month-Year and Fund FE	No	Yes	No	Yes
Observations	74,591	74,577	74,591	74,577
Adjusted R <sup>2</sup>	0.05	0.11	0.05	0.11

**Table A6:** The effect of model closure on fund flows considering only first event

This table reports the coefficient estimates in the difference-in-difference regression of the natural experiment. The dependent variable is  $Flow_{i,t}$  which is defined as  $\frac{AUM_{i,t} - AUM_{i,t-1} \times (1 + R_{i,t})}{AUM_{i,t-1}} \times 100$ .  $Treatment_i$  is equal to one for ETFs that are deleted from F-Squared model portfolios in January 2015, and equal to zero for matched model ETFs that have the same investment category as treatment ETFs.  $Post_t$  is equal to one for the month after the deletion of treatment ETFs.  $Pre_t$  is equal to one for the three months before the closure of treatment ETFs. The control variables include the lagged return rank, the lagged expense ratio, the lagged natural logarithm of the fund's AUM measured in millions of dollars, the lagged natural logarithm of fund age measured in months, the lagged ETF flow, the lagged ETF turnover, and the lagged Amihud ratio. Time and Fund fixed effects are both included. We report t-statistics with robust standard errors in parentheses. Significance levels are denoted by \*, \*\*, and \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: $Flow_{i,t}$			
$Treatment_i \times Post_t$	-7.68*** (-3.13)	-9.59** (-2.41)	-5.90** (-2.40)	-7.96* (-2.07)
$Treatment_i \times Pre_t$			5.05 (1.52)	4.65 (0.88)
Return rank $_{i,t-1}$	4.19** (2.45)	3.87* (2.01)	4.05** (2.21)	3.73 (1.71)
Expense Ratio $_{i,t-1}$	-46.51 (-0.65)	-78.42 (-0.83)	-46.13 (-0.65)	-77.97 (-0.83)
$\log(Size_{i,t-1})$	-12.73*** (-3.19)	-13.90*** (-3.16)	-12.70*** (-3.18)	-13.81*** (-3.17)
$\log(Age_{i,t-1})$	-8.69** (-2.28)	-7.87 (-1.58)	-8.12* (-1.93)	-7.48 (-1.43)
Turnover $_{i,t-1}$		0.02** (2.51)		0.02** (2.55)
Amihud Ratio $_{i,t-1}$		-10.91 (-1.24)		-11.70 (-1.31)
Time and Fund FE	Yes	Yes	Yes	Yes
Observations	1,152	922	1,152	922
Adjusted R <sup>2</sup>	0.159	0.175	0.161	0.176

**Table A7:** The effect of model closure on fund flows excluding flows of mutual funds

This table reports the coefficient estimates in the difference-in-difference regression of the natural experiment. Specifically, the flows of treated ETFs from mutual funds that are subadvised by F-Squared Investment are deducted from the total flows of each treated ETF. The dependent variable is  $Flow_{i,c,t}^{Adj}$  which is defined as  $(\frac{AUM_{i,c,t} - AUM_{i,c,t-1} \times (1 + R_{i,c,t})}{AUM_{i,c,t-1}} - \frac{\sum_j (N_{i,j,c,t} - N_{i,j,c,t-1}) \times P_{i,c,t}}{AUM_{i,c,t-1}}) \times 100$ .  $Treatment_{i,c}$  is equal to one for ETFs that are deleted from F-Squared model portfolios after December 2014, and equal to zero for matched model ETFs that have the same investment category as treatment ETFs.  $Post_{c,t}$  is equal to one for the nine months after the deletion of treatment ETFs.  $Pre_{c,t}$  is equal to one for the three months before the closure of treatment ETFs. The control variables include the lagged return rank, the lagged expense ratio, the lagged natural logarithm of the fund's AUM measured in millions of dollars, the lagged natural logarithm of fund age measured in months, the lagged ETF turnover, and the lagged Amihud ratio. Time-Cohort and Fund-Cohort fixed effects are both included. We report t-statistics with robust standard errors in parentheses. Significance levels are denoted by \*, \*\*, and \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: $Flow_{i,c,t}^{Adj}$			
$Treatment_{i,c} \times Post_{c,t}$	-4.53** (-2.68)	-6.50** (-2.66)	-3.73** (-2.29)	-5.47** (-2.42)
$Treatment_{i,c} \times Pre_{c,t}$			2.19 (1.15)	2.93 (0.90)
$Return\ rank_{i,c,t-1}$	4.86*** (4.24)	4.56*** (3.33)	4.84*** (4.04)	4.52*** (3.20)
$Expense\ Ratio_{i,c,t-1}$	-55.07 (-0.69)	-76.95 (-0.81)	-51.50 (-0.63)	-71.16 (-0.71)
$\log(Size_{i,c,t-1})$	-11.05*** (-5.38)	-11.64*** (-4.94)	-11.07*** (-5.36)	-11.63*** (-4.92)
$\log(Age_{i,c,t-1})$	-10.27*** (-3.06)	-10.19** (-2.64)	-9.92** (-2.76)	-9.83** (-2.43)
$Turnover_{i,c,t-1}$		0.02** (2.70)		0.02** (2.69)
$Amihud\ Ratio_{i,c,t-1}$		-12.33 (-1.39)		-12.05 (-1.36)
Time-Cohort and ETF-Cohort FE	Yes	Yes	Yes	Yes
Observations	2,045	1,590	2,045	1,590
Adjusted $R^2$	0.185	0.204	0.185	0.204

**Table A8:** Summary Statistics of ETFs in natural experiment

This table reports the mean, median, standard deviation, and the number of observations of all variables in the natural experiment.  $Flow_{i,t}$  which is defined as  $\frac{AUM_{i,t} - AUM_{i,t-1} \times (1 + R_{i,t})}{AUM_{i,t-1}} \times 100$ . *No. Models* is the number of models that recommend ETF; *Return Rank* is the percentile rank of ETF's return scaled by 1/100 in month; *Expense Ratio* denotes the expense ratio of ETF, measured in percentage points; *Size* is the fund's AUM measured in millions of dollars, *Age* is fund age measured in months. *Turnover* is a measure of the fund's trading activity in percentage points. *Amihud Ratio* is calculated as the mean average of daily Amihud ratio over a month.

Variable	Mean	Median	SD	Observations
Flow (%)	2.25	0.34	12.44	2,051
No. Models	6.62	3.00	8.39	2,051
Lag Return rank	0.50	0.51	0.25	2,045
Lag Expense Ratio (%)	0.35	0.35	0.21	2,045
Lag log(Size)	7.17	7.18	1.87	2,045
Lag log(Age)	4.34	4.56	0.79	2,045
Lag Turnover (%)	51.40	12.00	153.63	2,045
Lag Amihud Ratio	0.01	0.00	0.02	1,591

**Table A9:** Category-adjusted characteristics of affiliated and unaffiliated ETFs

This table reports the summary statistics of ETFs that are affiliated and unaffiliated to a model provider. Unaffiliated ETFs are differentiated by the type of model providers, *All* refers to all unaffiliated ETFs, *AM* refers to unaffiliated ETFs provided by asset managers, *ST* refers to unaffiliated ETFs provided by strategists. *Expense Ratio* is the net expense ratio measured in percentage points. *Return Std. Dev.* is the standard deviation of monthly return over the prior one year. *Turnover* is a measure of the fund's trading activity. *Amihud Ratio* is calculated as the mean average of daily Amihud ratio over a month. *Quoted Spread* is the ratio of bid-ask spread and midpoint, and we scale it by 100. All variables are category-adjusted by deducting the median value of funds of the same Morningstar Category. We report t-statistics based on standard errors clustered at the fund level in parentheses. Significance levels are denoted by \*, \*\*, and \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

	Affiliated	Unaffiliated			Difference		
	(1)	All (2)	AM (3)	ST (4)	(1)-(2)	(1)-(3)	(1)-(4)
Expense Ratio (%)	-0.02	-0.08	-0.11	-0.07	0.06*** (4.79)	0.09*** (6.33)	0.06*** (4.49)
Return Std. Dev. (%)	0.03	-0.08	-0.05	-0.08	0.10** (2.50)	0.08 (1.32)	0.10*** (2.59)
Turnover (%)	13.10	10.98	13.91	10.69	2.13 (0.42)	-0.81 (-0.09)	2.42 (0.51)
Amihud Ratio	0.02	-0.00	-0.01	0.00	0.02*** (4.28)	0.03*** (5.06)	0.02*** (4.18)
Quoted Spread	-0.01	-0.05	-0.06	-0.05	0.03*** (5.41)	0.05*** (5.65)	0.04*** (5.19)
Observations	9,209	79,065	7,158	71,907			

**Table A10:** Logit model of ETF addition to recommendations using quarterly data

This table reports coefficient estimates for the logit model. All variables are measured at the quarterly frequency.  $Addition_{c,i,t}$  is an indicator variable that takes the value one if ETF  $i$  is added to the models of company  $c$  during month  $t$ .  $Affiliated_{c,i}$  is an indicator variable that takes the value one if ETF  $i$  is affiliated with a company  $c$ ; past performance is measured by the performance rank percentiles over the prior one year and three years, respectively;  $Expense\ Ratio_{i,t-1}$  denotes the expense ratio of ETF  $i$ , measured in percentage points; a vector of lagged control variables includes logarithm of fund age, logarithm of fund size, the standard deviation of fund return, the expense ratio, the turnover of the fund, as well as ETF category and month-year fixed effects. The second part of the table displays the average marginal effect for the variables of interest:  $Affiliated_{c,i}$ ,  $Expense\ Ratio_{i,t-1}$ ,  $Affiliated_{c,i} \times Expense\ Ratio_{i,t-1}$ . Standard errors are clustered at the fund level and z-values are reported in parentheses. Significance levels are denoted by \*, \*\*, and \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

Dependent Variable: $Addition_{c,i,t}$		
$Affiliated_{c,i}$	2.05*** (8.20)	1.88*** (6.38)
Prior 1-Yr. Perf. $_{i,t-1}$	0.20** (2.42)	
$Affiliated_i \times$ Prior 1-Yr. Perf. $_{i,t-1}$	-0.24 (-0.90)	
Prior 3-Yr. Perf. $_{i,t-1}$		0.13 (1.44)
$Affiliated_i \times$ Prior 3-Yr. Perf. $_{i,t-1}$		-0.10 (-0.30)
Expense Ratio $_{i,t-1}$	-0.56*** (-2.90)	-0.49** (-2.44)
$Affiliated_i \times$ Expense Ratio $_{i,t-1}$	3.11*** (7.48)	3.16*** (6.92)
$\log(Age_{i,t-1})$	-0.14** (-2.47)	-0.06 (-0.66)
$\log(Size_{i,t-1})$	0.64*** (31.91)	0.66*** (29.61)
Return Std. Dev. $_{i,t-1}$	0.13 (0.08)	-0.04 (-0.02)
Turnover $_{i,t-1}$	0.00 (1.24)	0.00 (0.90)
Average Marginal Effect		
$Affiliated_{c,i}$	0.0131	0.0125
Expense Ratio $_{i,t-1}$	-0.0013	-0.0013
$Affiliated_i \times$ Expense Ratio $_{i,t-1}$	0.0071	0.0082
ETF Category and Quarter-Year FE	Yes	Yes
Observations	1,725,043	1,376,707
Pseudo R <sup>2</sup>	55 0.162	0.159

**Table A11:** Logit model of ETF addition to recommendations provided by asset managers

This table reports coefficient estimates for the logit model based on model portfolios that are provided only by asset managers.  $Addition_{c,i,t}$  is an indicator variable that takes the value one if ETF  $i$  is added to the models of company  $c$  during month  $t$ .  $Affiliated_{c,i}$  is an indicator variable that takes the value one if ETF  $i$  is affiliated with a company  $c$ ; past performance is measured by the performance rank percentiles over the prior one year and three years, respectively;  $Expense\ Ratio_{i,t-1}$  denotes the expense ratio of ETF  $i$ , measured in percentage points; a vector of lagged control variables includes logarithm of fund age, logarithm of fund size, the standard deviation of fund return, the expense ratio, the turnover of the fund, as well as ETF category and month-year fixed effects. The second part of the table displays the average marginal effect for the variables of interest:  $Affiliated_{c,i}$ ,  $Expense\ Ratio_{i,t-1}$ ,  $Affiliated_{c,i} \times Expense\ Ratio_{i,t-1}$ . Standard errors are clustered at the fund level and z-values are reported in parentheses. Significance levels are denoted by \*, \*\*, and \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

Dependent Variable: $Addition_{c,i,t}$		
$Affiliated_{c,i}$	2.40*** (8.27)	2.33*** (7.23)
Prior 1-Yr. Perf. $_{i,t-1}$	0.32 (1.38)	
$Affiliated_i \times$ Prior 1-Yr. Perf. $_{i,t-1}$	-0.26 (-0.83)	
Prior 3-Yr. Perf. $_{i,t-1}$		0.39 (1.33)
$Affiliated_i \times$ Prior 3-Yr. Perf. $_{i,t-1}$		-0.13 (-0.32)
Expense Ratio $_{i,t-1}$	-1.14** (-2.34)	-0.43 (-0.97)
$Affiliated_i \times$ Expense Ratio $_{i,t-1}$	3.99*** (6.49)	3.65*** (5.91)
$\log(Age_{i,t-1})$	-0.68*** (-5.63)	-0.84*** (-4.58)
$\log(Size_{i,t-1})$	0.51*** (11.45)	0.54*** (10.83)
Return Std. Dev. $_{i,t-1}$	-2.95 (-0.89)	-2.37 (-0.68)
Turnover $_{i,t-1}$	0.00 (1.52)	0.00* (1.65)
Average Marginal Effect		
$Affiliated_{c,i}$	0.0096	0.0103
Expense Ratio $_{i,t-1}$	-0.0025	-0.0010
$Affiliated_i \times$ Expense Ratio $_{i,t-1}$	0.0086	0.0088
ETF Category and Month-Year FE	Yes	Yes
Observations	397,565	315,847
Pseudo R <sup>2</sup>	56 0.297	0.293

**Table A12:** Performance of model portfolios: at least 60% of total weight in ETFs

This table presents the performance of model portfolios. The return (alpha) of each model is calculated as the weighted average return (alpha) of its portfolio holdings. We require the total weight of recommended ETFs with existing alphas in one model to be at least 60%. Row 1 uses the ETF gross returns. Row 2 uses the ETF net returns. Gross return is the return before expenses. Net return is the return after expenses are included. Column 1 refers to the average monthly return in excess of CRSP value-weighted stock index. Column 2 refers to the average monthly return in excess of a portfolio of 60% of S&P 500 index and 40% of Bloomberg Barclays US Aggregate Bond Index. Alpha is calculated as the weighted average alpha of ETFs within the model. Differential Alpha is the difference between the alpha of an existing model and the alpha of a model that we construct using a random sample of similar ETFs. All the values are in percentage points. t-statistics based on standard errors clustered at the model-provider level are reported in parentheses. Significance levels are denoted by \*, \*\*, \*\*\*, which correspond to the 10%, 5%, and 1% levels, respectively.

Panel A: All models				
	Excess Return(stocks)	Excess Return(mixed)	Alpha	Differential Alpha
Gross Return	-0.42*** (-15.14)	-0.00 (-0.15)	0.04*** (3.92)	0.00 (0.11)
Net Return	-0.43*** (-15.93)	-0.02 (-0.84)	0.02** (2.15)	0.00 (0.58)
Panel B: Model by the type of providers				
	Excess Return(stocks)	Excess Return(mixed)	Alpha	Differential Alpha
Asset Manager (AM)	-0.51*** (-16.35)	-0.05 (-1.63)	-0.00 (-0.37)	-0.00 (-0.33)
Strategist (ST)	-0.34*** (-7.87)	-0.01 (-0.14)	0.03** (2.48)	0.00 (1.12)
AM minus ST	-0.16*** (-3.16)	-0.05 (-0.94)	-0.03** (-2.49)	-0.00 (-0.94)