Advising the Advisors: Evidence from ETFs*

Jonathan Brogaard† Nataliya Gerasimova‡ Ying Liu§

May 30, 2026

Abstract

This paper is among the first to study the $7.96 trillion model portfolio marketplace. Using novel Morningstar data, we show that these recommendations heavily influence ETF flows and alter investor behavior by weakening flow-performance sensitivity. We document a self-recommendation bias: providers disproportionately recommend affiliated ETFs, which carry higher fees and lower liquidity than unaffiliated alternatives. This favoritism is unjustified, as models with affiliated funds fail to generate superior returns or alphas. Our findings suggest that providers exploit their dual role as managers and advisors to steer assets into proprietary products, highlighting significant agency conflicts in the wealth management industry.

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), Daniel Garrett, Bing Han (discussant), Qiping Huang (discussant), Egle Karmaziene (discussant), Matthijs Lof (discussant), Haoyi Luo (discussant), Mancy Luo (discussant), Ananth Madhavan, Vesa Pursiainen (discussant), Nick Roussanov, Pari Sastry, Tobias Sichert (discussant), Vincent Tena (discussant), Tushar Yadava, and participants of the Frontiers of Factor Investing Conference 2026, 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, SHUFE Brownbag Series, Wharton Micro Finance Seminars and University of Delaware Seminar Series in Finance for helpful comments.

†David Eccles School of Business, University of Utah, Email: `BrogaardJ@eccles.utah.edu`

‡Department of Finance, BI Business School, Email: `Nataliya.Gerasimova@bi.no`

§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 or of its member institutions.

Model portfolios function as pre-constructed asset allocation frameworks delivered by asset managers and strategists to financial advisors. These recommendations provide diversified portfolios of stocks, bonds, and funds that are typically updated on a monthly or quarterly basis. The scale of this market has expanded at an extraordinary rate in recent years. According to Broadridge Financial Solutions, US fund assets invested via model portfolios reached $7.96 trillion by April 2025, representing a considerable increase from the $3 trillion recorded in March 2020.[1]

Despite governing nearly $8 trillion in assets, model portfolios represent an under-examined segment of the investment landscape.[2] We utilize a novel dataset from Morningstar Direct to provide the first systematic analysis of how these recommendations influence capital flows and can lead to conflicts of interest. Unlike the prevailing literature that focuses on retail investors, our study examines advice directed toward sophisticated financial advisors. This perspective allows us to study the agency costs and biases that influence institutional intermediaries.

We investigate the allocative efficiency of the model portfolio marketplace by examining three core questions. First, do model portfolio recommendations materially affect the capital allocation to ETFs, or are they largely "paper advice" that advisors ignore? Second, if recommendations matter, do they change how investors allocate? Specifically, do they weaken the usual tendency to reallocate toward recent winners and away from laggards? Third, when model providers are also asset managers, do conflicts of interest distort fund selection toward proprietary products, and if so, are those distortions justified by better performance for end investors?

Our results yield several key insights. First, we find that model providers generally recommend

[1] For the April 2025 data, see Jack Pitcher, "More Financial Advisers Are Outsourcing Investment Decisions," Wall Street Journal, June 12, 2025, https://www.wsj.com/finance/investing/more-financial-advisers-are-outsourcing-investment-decisions-a27ebc1f?reflink=desktopwebshare_permalink. For the historical March 2020 comparison, see Dawn Lim,"BlackRock Tweaked Some Models. It Triggered a Wave of Buying and Selling," Wall Street Journal, July 9, 2021, https://www.wsj.com/articles/blackrock-tweaked-some-models-it-triggered-a-wave-of-buying-and-selling-11625857596.

[2] In this paper, we use the terms "model portfolios" and "model recommendations" interchangeably.

ETFs that are significantly more cost-efficient and liquid than the broader universe of available funds. Second, these recommendations exert a powerful influence on capital allocation, driving substantial flows into the selected ETFs. Third, we document a fundamental shift in investor behavior: those who follow model recommendations exhibit significantly lower sensitivity to past fund performance. This suggests that the inclusion of an ETF in a model portfolio partially decouples its capital flows from its historical returns.

Finally, we document significant agency conflicts among model providers who also operate as asset managers. We find that recommended affiliated ETFs, defined as proprietary funds within the provider's own fund family, exhibit significantly higher fees and lower liquidity than unaffiliated funds. The probability of inclusion in a model portfolio is markedly higher for affiliated ETFs, and this bias is further intensified for proprietary funds with high expense ratios. Despite this preferential selection, model portfolios managed by asset managers do not yield economically superior alphas relative to those offered by independent strategists who lack proprietary fund offerings. In sum, model portfolios induce large ETF demand flows and distort fund selection via conflicts of interest, without delivering offsetting performance value.

Unlike traditional investment vehicles such as mutual funds and ETFs, model portfolios are not directly investable and are not managed from a central location. They instead function as asset-allocation and fund-selection recommendations distributed to financial advisors. Importantly, advisors retain discretion to deviate from the recommendation, so whether and how models affect ETF demand is an empirical question. The adoption of these frameworks is now pervasive: 85% of financial advisors utilize a combination of custom and model portfolios, and more than half (54%) of total advised assets are governed by these models.[3] The impact on capital allocation is substantial. In 2020, approximately one third of new inflows into BlackRock's iShares ETFs were directed by model portfolios managed by BlackRock and other firms.[4] The speed and magnitude of this effect are illustrated by the iShares AI Innovation and Tech Active ETF.

[3] https://www.broadridge.com/_assets/pdf/broadridge-fa-model-portfolio-may-2019.pdf.
[4] https://www.ft.com/content/fc35e189-4f0a-4d22-8444-25ad2e82c6c1.

On May 20, 2025, the fund held $144 million in assets; following its inclusion in model recommendations, its assets under management grew more than ten-fold to $1.5 billion by May 23, 2025.[5]

The incentive to steer flows is structural. Independent strategists typically charge an explicit strategist fee, whereas asset managers often market model portfolios as "no-additional-fee" advice while earning revenue through the underlying funds included in the model. This business model can create a wedge between the advisor's objective (low-cost, implementable building blocks) and the provider's objective (capturing assets and fee revenues inside its own product suite), making the model-portfolio channel a natural place to study self-recommendation.

Conceptually, model portfolios can also reduce flow–performance sensitivity because they act as a delegated default. Once an ETF is embedded in a widely distributed model, the marginal allocator is less likely to re-optimize based on the ETF's idiosyncratic track record and more likely to implement (or remain close to) the provider's recommended weights. In this sense, models can substitute for performance-chasing by shifting attention from realized returns to the perceived credibility of the model provider and the convenience of outsourced portfolio construction.

Our study focuses on ETFs because they dominate the model portfolio landscape. As of December 2020, five of the ten largest models by assets under advisement in the Morningstar Direct database recommended ETFs exclusively.[6] In contrast, only one of these top ten models focused solely on mutual funds. This preference is reflected in broader market dynamics. Data from Envestnet Analytics show that between June 2021 and June 2023, 56% of inflows to their model platform were directed to ETF-only portfolios, while just 26% went to models recommending mutual funds exclusively.[7] These trends are corroborated by a 2024 Cerulli Associates

[5] `https://www.wsj.com/finance/investing/more-financial-advisers-are-outsourcing-investment-decisions-a27ebc1f`.

[6] As of September 2021, the Morningstar Direct database provided information on 2,316 active and inactive unique models between January 2010 and December 2020.

[7] `https://www.envestnet.com/active-passive`.

report, which finds that model providers maintain an approximate 54% asset-weighted average allocation to ETFs.[8]

Our analysis proceeds in three primary stages. First, we contrast recommended (model) ETFs with their non-recommended counterparts. We find that model ETFs are substantially more cost-efficient and liquid, with expense ratios roughly 31% lower and liquidity levels at least twice as high as non-model funds. The monthly category-adjusted and prospectus-adjusted returns for model ETFs are 0.02%, outperforming the respective returns of -0.02% and -0.06% observed for non-model ETFs.[9] Second, we assess the aggregate performance of the model portfolios.[10] On average, the portfolios underperform both the CRSP value-weighted stock index and a 60/40 benchmark.[11] Crucially, we find that these models fail to deliver economically significant alphas.

Second, we investigate how model recommendations influence capital allocation. Our results show that model inclusion has a substantial impact on fund flows, with ETFs receiving an additional four to six basis points in monthly flows for each model recommendation. Moreover, being part of a model portfolio significantly attenuates the flow-performance relationship, reducing sensitivity to past returns by four basis points per model. This lower sensitivity indicates that model recommendations act as a substitute for traditional performance chasing, as investors delegate fund selection to providers and pay less attention to idiosyncratic returns.[12]

To address the concern that model providers may select ETFs in anticipation of future capital inflows, we exploit the 2015 collapse of F-Squared Investments as a natural experiment. F-Squared operated a leading model portfolio business with 19 portfolios until its discontinuation

[8] `https://www.cerulli.com/press-releases/retail-financial-advisors-and-their-model-portfolios-propel-etf-assets`.

[9] Category-adjusted (prospectus-adjusted) return measures an ETF's excess return relative to the median ETF return within the same Morningstar category (Prospectus objective).

[10] Due to a lack of return data for the model portfolios, we derive the returns and alphas of model portfolios by computing the weighted average returns and alphas of ETFs within the portfolio.

[11] The 60/40 portfolio is composed of 60% of the S&P 500 index and 40% of the Bloomberg Barclays US Aggregate Bond Index.

[12] Existing studies show that investors increase their demand for ETFs that performed well in the past or for ETFs that are less expensive (Ben-David et al., 2023; Dannhauser and Pontiff, 2025).

following SEC fraud charges and a subsequent bankruptcy filing.[13] The sudden closure of these models provides a clean, exogenous shock to the recommendation status of the underlying ETFs, allowing us to isolate the causal impact of recommendations on fund flows. Our results show that in the nine months following the closure, formerly recommended ETFs experienced a significant decline in capital, receiving 7.77 percentage points lower flows relative to ETFs in the same investment category recommended by other models. This natural experiment supports a causal interpretation of the relationship between model portfolios and fund flows.

Finally, we evaluate the quality of recommended ETFs and test for systematic bias in the selection process. Specifically, we investigate whether model providers exhibit favoritism toward affiliated funds. Our comparison between affiliated and unaffiliated ETFs reveals that proprietary offerings are significantly more expensive and less liquid than their unaffiliated peers. Affiliated ETFs carry expense ratios that are seven basis points higher on average, and their Amihud ratio is four times larger than that of unaffiliated alternatives.

Next, we estimate the probability of an ETF being added to a model portfolio. We restrict this analysis to asset managers because strategists lack proprietary funds by construction. We find that the probability of inclusion is significantly higher for affiliated funds. Specifically, the average marginal effect of affiliation corresponds to a 0.25 percentage point increase in the probability of addition.[14] While higher fees generally reduce the likelihood of selection, the interaction between expense ratios and affiliation reveals a striking reversal for proprietary products. For affiliated ETFs, a one basis point increase in the expense ratio is associated with a 0.34 percentage point increase in the probability of addition. This suggests that asset managers prioritize higher-revenue proprietary funds over cheaper internal alternatives, whereas the selection of unaffiliated ETFs follows a cost-minimization logic. This evidence of favoritism is consistent with Pool et al. (2016), who document similar preferences for affiliated funds within 401(k) plans.

[13] `https://www.sec.gov/litigation/admin/2014/ia-3988.pdf`.

[14] The average model-implied monthly addition probability for affiliated funds is 0.30%, compared to only 0.05% for unaffiliated funds.

In the final section of the paper, we investigate whether model performance varies systematically by provider type. We compare the performance of portfolios constructed by asset managers against those managed by independent strategists. We find that neither group outperforms the CRSP value-weighted stock index or a 60/40 benchmark. However, models provided by asset managers generate significantly lower returns than those offered by strategists. This performance gap persists when examining category-adjusted and prospectus-adjusted returns, although these differences are not statistically significant. The divergence is most evident in risk-adjusted performance: while models from strategists deliver a monthly alpha of 0.03%, models from asset managers fail to generate any significant alpha.

Our study contributes to two primary strands of literature. First, we expand the nascent research on the determinants of ETF flows. While prior work by Clifford et al. (2014) and Dannhauser and Pontiff (2025) establishes that ETF flows are sensitive to past performance, we identify model recommendations as a significant and previously unstudied driver of these flows. This adds to findings by Kostovetsky and Warner (2025), who show that benchmark choice and brand-name indices attract capital, and Pu and Xie (2022), who document investor sensitivity to short-term returns and tracking error. Our results also complement research on specialized investment vehicles, including smart-beta ETFs (Brown et al., 2024; Huang et al., 2024) and thematic ETFs (Ben-David et al., 2023). By identifying model recommendations from both asset managers and strategists as a novel factor in capital allocation, we provide a more complete characterization of the forces shaping the ETF market.

Second, we contribute to the literature on financial advisor recommendations and institutional agency conflicts. While prior studies by Bergstresser et al. (2009) and Boyson (2019) document underperformance and fiduciary failures in advisor-mediated channels, we demonstrate that these issues persist in the rapidly expanding model portfolio market. Our evidence of self-recommendation bias extends the work of Pool et al. (2016), Doellman and Sardarli (2016), and Cookson et al. (2021), who find that intermediaries often prioritize affiliated or "own-brand" products despite higher costs. Furthermore, our results align with Jenkinson et al. (2016) in finding that although recommendations significantly shift asset allocation, they often fail to add objective economic value. We distinguish our study by focusing on recommendations delivered to financial advisors. As professional and sophisticated market participants, these advisors represent a high-stakes environment where one might expect agency costs to be mitigated by expertise, yet we find that these professionalized channels remain highly susceptible to systematic biases.

Our results raise critical questions regarding the opacity of the model portfolio market. Currently, model providers are subject to significantly less stringent performance reporting regulations than the managers of ETFs or mutual funds. This regulatory disparity prompted the SEC to request public comment in June 2022 on whether model portfolio providers should be classified as "investment advisors" and regulated under the Investment Company Act. The Commission expressed specific concerns that these providers might engage in front-running or harbor undisclosed conflicts of interest by holding the very securities they recommend. Furthermore, the SEC questioned whether end-investors fully comprehend the layered fee structures and associated agency conflicts that characterize these professionalized recommendation channels.[15]

1 Background and Data

1.1 Institutional Details

Financial advisors mainly use model recommendations to outsource investment management and 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 premixed formulas instead of creating custom medications.

[15] `https://www.sec.gov/rules/other/2022/ia-6050.pdf`.

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 distribute 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.

The main difference between strategists and asset managers is that strategists usually do not have affiliated ETFs. In addition, 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 on 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 financial planning.[16]

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 provide a certain level of risk. Tax-managed portfolios aim to maximize the after-tax return for investors, and thus these portfolios usually include funds of municipal bonds. Income-oriented portfolios seek to generate high

[16]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 Mattus, 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).

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 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. In addition to these four types of portfolios, there are also a small number of models that focus on stand-alone equity or fixed-income assets.

Although model providers offer 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, 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."[17]

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.[18] AllianceBernstein L.P. ("AB") 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

[17] https://adviserinfo.sec.gov/firm/summary/146932.

[18] 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.

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."[19]

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 active and inactive model recommendations.[20]

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 the models report holdings monthly and 69% report them quarterly. We perform the analysis on a monthly basis, so we adjust the holdings to monthly frequency by assuming that 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 model 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 ETFs whose base currency is the US dollar. We exclude ETFs classified as leveraged ETFs.[21] For the ETF data,

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

[20] 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."

[21] Leveraged ETFs conventionally use leverage or debt to amplify the return of underlying index, consequently

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). In addition, we exclude ETFs that report negative expense ratios. We also exclude models that start to report their holdings earlier than one quarter before their official inception date.[22] The final sample contains 2,596 (474 of them are active) unique US ETFs. 1,101 (129 of them are active) of these ETFs are recommended by 1,215 unique US models constructed by 106 unique model providers. The remaining 1,495 ETFs are not recommended by any model providers.

Table 1 provides the number of models, model providers, and model ETFs by year.[23]

[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.[24] 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. In 2010, there were only 53 models provided by 11 companies. The number of models and companies increases overtime; there are 1,055 models from 92 companies in 2020. The average number of ETFs per model recommendation decreases from 12.32 to 8.80 during the sample period, while the average percentage of ETFs per model remains quite constant. We observe the opposite trend for affiliated ETFs. The average number increases from 0.79 in 2014 to 3.17 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,

engendering higher risk and volatility than other non-leveraged ETFs.

[22]The first reporting date earlier than one quarter before the inception date might result from a data reporting error.

[23]For each model we use its last available holding in each year that contains at least one ETF.

[24]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.

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.[25]

Panel B of Table 1 focuses only on the model recommendations that include affiliated ETFs.[26] By definition, only one type of model providers, asset managers, holds 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 represents less than 25% of the sample, the total number of models provided by these asset managers is more than a third of the sample in 2020. 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.[27] Table 2 reports further information on the ETFs recommended by the 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 6.15, and the average number of fixed-income ETFs 3.18. This composition is similar to the distribution of domestic ETFs in the US market.[28] Note that commodity ETFs experience a sharp reduction in model recommendations starting in 2013, consistent with the strong outflows observed from commodity ETFs in that year.[29]

[25] `https://www.investmentnews.com/etf-strategists-getting-crowded-out-by-big-asset-managers-80590`.

[26] To compute this statistic, for each model we use its last available holding in each year that contains at least one affiliated ETF.

[27] To identify styles, we use "Global Broad Category Group" field in the Morningstar Direct database.

[28] See Table 12 in the ICI 2021 Factbook; `https://www.ici.org/system/files/2021-05/2021_factbook.pdf`.

[29] `https://www.reuters.com/article/etps-annual/record-outflows-from-commodity-etps-in-2013-as-investors-dump-gold-idUKL6N0KI2H620140109`.

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.

Using Morningstar, we obtain the assets under management (fund size), the monthly returns,[30] 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 an unsuccessful match, we perform a fuzzy name match and manually verify the matches. We calculate the Amihud (2002) illiquidity ratio and the quoted bid-ask spread using CRSP daily trading data. The sample contains 162,019 ETF-month observations. Table 3 shows the summary statistics of all ETFs.

[Insert Table 3 about here]

To analyze performance, we use category-adjusted returns, prospectus-adjusted returns, and return percentile rank during the previous year and the previous three years (see Cookson et al. (2021)). To get the category-adjusted returns and prospectus-adjusted returns, we deduct the median monthly return of ETFs of the same Morningstar category[31] and the median monthly return of ETFs that have the same investment objective indicated in their prospectus from the monthly ETF return, respectively.[32] We measure performance over the previous 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. In contrast, a percentile rank of one denotes the highest performance. Return volatility is calculated as the standard deviation of monthly returns over a one-year period.

[30] If it is not explicitly specified, we use net return data.

[31] According to the Morningstar Methodology Paper, Morningstar categorizes funds based on their holdings into 122 categories.

[32] Prospectus objective specifies investment goals of a fund, based on the description in a fund's prospectus. The data set covers 34 different prospectus objectives.

On average, the ETF is recommended by 2.42 models. The median ETF is not recommended by any model. The monthly return, category-adjusted return and prospectus-adjusted return of the average fund are 0.68%, -0.01% and -0.04%, respectively.[33] On average, the expense ratio is 0.46%. The average fund is slightly younger than seven years and its size is approximately $2 billion.

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 focuses on the disparity between the ETFs that are recommended by the models and those that are not recommended.

Table 4 presents summary statistics of model and non-model ETFs' characteristics. 28% 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 2.7 years.[34] They also tend to be more than 10 times larger. The Fund Size of model ETFs and non-model ETFs are $5.68 billion and $0.39 billion, respectively.

The table shows that the expense ratio of model ETFs is 35 bps, lower than that of non-model

[33] In additional tests, throughout the paper we also compute adjusted returns taking into account whether funds are active or not, the results stay qualitatively the same.

[34] This evidence is consistent with an industry view that ETFs should have a three year-track record to be included in a model. `https://www.cerulli.com/press-releases/retail-financial-advisors-and-their-model-portfolios-propel-etf-assets`.

ETFs, at 51 bps. The difference of 16 bps is both economically and statistically significant. The monthly category-adjusted and prospectus-adjusted returns for model ETFs are 0.02%, significantly outperforming the respective returns of -0.02% and -0.06% observed for non-model ETFs. Their prior return ranks are also significantly higher than the ranks of non-model ETFs. Nevertheless, the differences in ranks are not economically significant. The return of model ETFs is 25% less volatile than the return of non-model ETFs. Model ETFs tend to replace their holdings 36% less frequently than non-model ETFs; the turnover ratio of model ETFs is 25 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 0.11, and the quoted spread of model ETFs is 0.11 while the spread of non-model ETFs is 0.27, suggesting that model ETFs are more liquid.[35]

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

2.2 Performance of Model Portfolios

In this subsection, we provide an evaluation of the models from a portfolio perspective. Model portfolios are not registered investment vehicles with the SEC; therefore, their reported performance often reflects hypothetical and back-filled returns, as reported by Kephart and Millson (2021). In the sample, only 41 of 1,215 models reported their net returns. Therefore, we conduct an analysis of the performance of models using their reported portfolio holdings. Specifically,

[35]In untabulated results, we compare model ETFs that are recommended only by models advising to invest at least 80% assets into ETFs with non-model ETFs. We get very similar results.

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.[36]

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 the 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.[37]

Second, we compute the model portfolio returns using category-adjusted and prospectus-adjusted ETF returns, respectively. Specifically, for each model portfolio, we calculate the weighted average of the adjusted returns of constituent ETFs, where the weights correspond to the portfolio allocation reported by the model. The adjusted returns capture the performance of ETFs relative to peers with a similar category classification or investment objective.

Third, we derive the alpha of each model as the weighted average alpha of ETFs within the model portfolio. We calculate the alpha α_i of ETF i from 24-month rolling regressions using the following equation:[38]

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

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 the 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

[36] Approximately 91% of models in our sample report gross returns in the Morningstar Direct database. We compute the correlation between reported gross returns and bottom-up gross returns constructed from holdings, and find a correlation of 0.98, indicating a high degree of consistency between the two measures.

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

[38] We require at least 12 observations for each regression.

different styles of ETFs. For domestic equity ETFs,[39] we use the Carhart (1997) four-factor model.[40] 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.[41] 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 the 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 factors. All indices are in excess return form.[42]

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 the return or alpha of an ETF is missing, we remove the ETF from the calculation and rescale the weight so that the total weight of the ETFs of one model is 100%. Using these criteria, we get a subsample of 730 unique models and 25,134 model-month observations.[43]

Table 5 presents the excess returns, adjusted returns, and alphas. Row 1 shows the performance calculated using gross returns of ETFs, and Row 3 shows the performance calculated using net returns of ETFs. Gross return of ETFs is provided by the Morningstar Direct database, they are

[39] We use "US Category Group" field in the Morningstar Direct database to distinguish between domestic and international equity ETFs.

[40] 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`.

[41] We are able to obtain returns for FTSE World Government Bond Index only until February 2019. Therefore, we exclude this index from the regressions after this date.

[42] 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. In addition, these funds are a limited fraction in the model portfolios, as shown in Table 2.

[43] Panel A of Table A3 in the Appendix provides the results for the models with at least 60% of total weight in ETFs. The results are qualitatively the same.

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]

Column 1 shows that the difference between the return of models and the 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 gross excess return is small and insignificant, while the net excess return is modestly negative and significant at the 5% level. Columns 3 and 4 report portfolio returns constructed using category-adjusted and prospectus-adjusted ETF returns, respectively. Both measures are positive and significant at 1% level. These results indicate that model portfolios outperform peers within the same category or investment objective. Column 5 considers the alpha of the models. Although the results show a statistically significant difference from zero, their economic magnitude is negligible.

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?

Although 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 example, not allocating capital to poorly performing funds. The potential deviation of financial advisors from these recommendations introduces uncertainty about their impact on the flows of the underlying ETFs. We investigate whether model recommendations have an impact on the overall allocation of investors to 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:

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

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:

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

where $No.Models_{i,t}$ is the number of models that recommend ETF i in month t; $Return\ Rank_{i,t-1}$ is the percentile rank of ETF i's return among ETFs of the same Morningstar category in month $t-1$, and we multiply the rank by $1/100$; $Expense\ Ratio_{i,t-1}$ denotes the expense ratio of ETF

i in month $t-1$, 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, $No.Models_{i,t} \times Return\,Rank_{i,t-1}$, and number of models with expense ratio, $No.Models_{i,t} \times Expense\,Ratio_{i,t-1}$ to examine whether investors exhibit different demand sensitivity to model-recommended ETFs. We follow 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) η_t to account for time-varying aggregate shocks, as well as fund fixed effects γ_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 five bps higher per month per model than non-model ETFs. This difference suggests that financial advisors respond to a model recommendation by reallocating capital 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, among others, by Ben-David et al. (2023) and Dannhauser and Pontiff (2025). The interaction of return rank with the number of models documents a fundamental shift in investor behavior: those who follow model recommendations exhibit significantly lower sensitivity to past fund performance. This suggests that the inclusion of an ETF in a model portfolio partially decouples its capital flows from its historical returns.

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 greater 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) splitting the sample into equity and non-equity ETFs and conducting the analysis separately for each subsample. 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, 15 bps more flows per quarter (5 bps per month) after they are recommended by one more model (see Table A4 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 A5 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 recommendations of both types impact ETF flows. Table A6 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 ETFs that are already popular among investors. Hence, they may choose to add these ETFs to 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 relationship 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".[44] 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 range 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

[44] `https://www.sec.gov/files/litigation/admin/2014/ia-3988.pdf`.

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 after December 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 will either be January, April, or July 2015. In our empirical analysis, we focus on the first event, which occurs in January 2015. Focusing on the first event allows us to isolate the cleanest and most exogenous variation in model recommendations, minimizing concerns that later deletions are driven by investors' anticipation or information already incorporated by investors. We construct treated and control ETFs around the January 2015 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 with other ETFs recommended by other model providers in the same Morningstar category and sharing the same active management style 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 to isolate 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:

$$\text{Flow}_{i,t} = \alpha + \beta_1 \text{Treatment}_i \times \text{Post}_t + \text{Controls}_{i,t-1} + \gamma_i + \eta_t + \varepsilon_{i,t}, \tag{4}$$

where $Flow_{i,t}$ is the percent flow for ETF i in month t, and $Treatment_i$ is set to one for ETFs that were deleted by F-Squared, and zero for the matched ETFs. $Post_t$ is set to one for the months following the closure of F-Squared's models. We also include the fund fixed effects, γ_i, to ensure that we estimate the impact of exposure after controlling for any fixed differences between ETFs, and we include time fixed effects, η_t, as a nonparametric control for any secular time trends. 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 β_1 in an opposite way as we do in Equation (3). The ETFs that are deleted from model portfolios receive 7.77 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.[45]

[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 an interaction term between $Treatment_i$ and Pre_t to Equation (4), where Pre_t is an indicator that is equal to one for three months before the closure of F-Squared's models.

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. While the estimated coefficients are economically sizable, they are not statistically distinguishable from zero in either specification. 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.

There is a concern that the documented outflows from ETFs recommended by F-Squared models

[45]The lower number of observations is because of missing values for Amihud Ratio.

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.[46] To address this concern, we adjust ETF 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

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

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 7.60 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 7.77 in Table 7, we can see that part of the outflows from ETFs in the treated group come from Virtus mutual funds. However, the influence of mutual funds on the ETF flows is negligible.

[46] `https://www.sec.gov/litigation/admin/2015/ia-4266.pdf`.

It is worth noting that the average impact of model recommendations on ETF flows that we observe in this experiment is 7.77 percentage points. This estimate notably exceeds the 0.04-0.06 percentage points that we document in the whole sample regression outlined in Table 6. The first potential reason for this variation might stem from the disparity in the 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 $1556.20 million (exp(7.35)), which is smaller compared to the average fund size of $1887.18 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 0.08. These findings imply that the ETFs within the natural experiment are relatively smaller and more liquid compared to the average ETF. In particular, smaller and more liquid funds tend to attract more investor flows than larger and less liquid ETFs (Broman and Shum (2018)). Second, Table 6 reports the effect of model recommendations on ETF flows over a 10-year period, while the natural experiment test only covers an 18-month period. The impact of model portfolio rebalancing on ETF flows is likely to be 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.[47]

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 influence capital allocation. 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

[47] `https://www.ft.com/content/cb57eb93-d8ef-41e9-b238-fd802aa13f1e`.

ETFs, even when other ETFs may dominate, that is, whether model providers exhibit favoritism toward proprietary funds within their own fund family. 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*.[48] 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 can potentially affect the performance of the entire model portfolio. Therefore, we conclude this section by 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. Thus, we 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 92,417 company-ETF-month observations. 10,723 company-ETF-month observations correspond to affiliated ETFs and 81,694 to unaffiliated ETFs. The expense ratio of affiliated ETFs is 36 bps, higher than that of unaffiliated ETFs, at 29 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 $8.846 billion and is significantly lower than that of unaffiliated ETFs at the 1% level. The category-adjusted and prospectus-adjusted return differences are four bps and six bps, statistically significant at the 1% and 5% levels, respectively, but economically negligible.

[48]By definition, only asset managers have affiliated ETFs since strategists do not have proprietary funds.

Note that one type of model providers, strategists, do not have affiliated ETFs. As a result, all affiliated ETFs are 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 adjusted characteristics. Expense Ratio, Return Std. Dev., Turnover, Amihud Ratio, and Quoted Spread are category-adjusted (prospectus-adjusted) by deducting the median value of funds of the same Morningstar category (Prospectus objective). The results remain qualitatively unchanged.

Overall, affiliated ETFs are more expensive and less liquid than unaffiliated ETFs. These results might imply potential favoritism toward proprietary 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. Similarly to Pool et al. (2016) and Cookson et al. (2021), we use the following logit model to estimate ETF addition probability:

$$\begin{aligned} prob(Add_{c,i,t}=1) \;=\; & \Lambda(\beta_1 \text{Affiliated}_{c,i} + \beta_2 \text{Return Rank}_{i,t-1} + \beta_3 \text{Affiliated}_{c,i} \times \text{Return Rank}_{i,t-1} \\ & + \beta_4 \text{Expense Ratio}_{i,t-1} + \beta_5 \text{Affiliated}_{c,i} \times \text{Expense Ratio}_{i,t-1} + \text{Controls}_{c,i,t-1}), \end{aligned} \tag{6}$$

where $Add_{c,i,t}$ 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 $\Lambda(z) = exp(z)/(1+exp(z))$; $Affiliated_{c,i}$ is an indicator variable that takes the value one if ETF i is affiliated to company c; $Return\ Rank_{i,t-1}$ is the percentile rank of returns of ETF i among ETFs of the same Morningstar category in the previous year or three years, and we multiply the rank by $1/100$; $Expense\ Ratio_{i,t-1}$ denotes the expense ratio of ETF i in month $t-1$, 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. Since one type of model providers, strategists, lack affiliated ETFs by construction, we restrict this analysis to asset managers. 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 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 0.25 percentage points. The average model-implied monthly addition probabilities for affiliated funds are 0.30%, and only 0.05% for unaffiliated funds.[49] By contrast, the probability of addition is not influenced by prior performance: the coefficients on both the prior 1-year and prior 3-year performance ranks are statistically insignificant.

[49]The average model implied addition probability for affiliated ETFs is computed as the average across the sample of $\Lambda(\beta_1 + (\beta_2+\beta_3)\text{Return Rank}_{i,t-1} + (\beta_4+\beta_5)\text{Expense Ratio}_{i,t-1} + \text{Controls}_{c,i,t-1})$, whereas the average model implied addition probability for unaffiliated ETFs is computed as the average across the sample of $\Lambda(\beta_2\text{Return Rank}_{i,t-1} + \beta_4\text{Expense Ratio}_{i,t-1} + \text{Controls}_{c,i,t-1})$.

Second, while higher fees reduce the likelihood of addition for unaffiliated ETFs, the interaction between expense ratios and affiliation reveals a reversal for proprietary products. Among unaffiliated ETFs, more expensive funds are less likely to be added than cheaper alternatives. In contrast, among affiliated ETFs, higher expense ratios are associated with a greater probability of addition. Specifically, if the expense ratio of affiliated ETFs increases by one bp, the probability of addition increases by 0.34 percentage points.[50] This difference implies that model providers prioritize higher-fee proprietary funds over cheaper internal alternatives, whereas the selection of unaffiliated ETFs follows a cost-minimization logic. 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 affiliated ETFs to model recommendations, we do not observe many deletions of affiliated funds from the models. Of the 92,417 company-ETF-month observations, we only discover 163 deletions of affiliated ETFs from models, and 2,761 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, in untabulated results, we confirm that the evidence is not driven only by equity ETFs.

[50] If the expense ratio increases by one bp, the average marginal impact on the probability of addition is $0.0053 - 0.0012 = 0.0041$ when performance is measured by prior one-year performance rank, and the average marginal impact on the probability of addition is $0.0060 - 0.0009 = 0.0051$ when performance is measured by prior three-year performance rank.

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 entire model. To get an answer, we evaluate the models based on the type of providers.

We classify models according to whether they are offered by asset managers or strategists and compare performance between the two types of providers. Since asset managers only start to provide model portfolios in 2014, we 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. In addition, the models provided by asset managers significantly underpeform the models provided by strategists.

[Insert Table 10 about here]

We further examine category-adjusted (column 3) and prospectus-adjusted (column 4) returns. The differences in adjusted returns between two provider types are not statistically significant. Finally, the models provided by asset managers generate 3 basis points lower alphas (column 5) per month than the models provided by strategists. However, the difference is not economically significant.[51]

To conclude, the findings reveal a significant difference between affiliated and unaffiliated ETFs. Specifically, affiliated ETFs are significantly more expensive and less liquid compared to their unaffiliated peers. Model providers also display a self-recommendation bias, by prioritizing higher-revenue proprietary funds over cheaper unaffiliated alternatives, whereas the choice of unaffiliated ETFs follows a cost-minimization logic. Finally, we note that the models provided by asset managers fail to generate superior returns or alphas relative to the models provided by

[51] Panel B of Table A3 in the Appendix provides the results for the models with at least 60% recommendations weights in ETFs. The results are qualitatively the same.

independent strategists.

5 Conclusion

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

We analyze the 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 significantly more cost-efficient and liquid than the rest of ETFs. We also find that the model recommendations strongly influence the ETF flows. Nevertheless, self-recommendation bias among asset managers seems to affect the quality of these recommendations when comparing between model provider types. Asset managers disproportionately include affiliated ETFs. These affiliated ETFs, on average, carry higher fees and lower liquidity than unaffiliated funds. In addition, the models recommended by asset managers do not generate superior returns or alphas relative to the models recommended by strategists.

An unanswered question is why financial advisors follow these recommendations. Although answering this question is beyond the scope of this paper, we have several possible 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 not using any (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 (2024). Dominated ETFs. Critical Finance Review, forthcoming.

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 (2025). 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 (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.

Huang, S., Y. Song, and H. Xiang (2024). The smart beta mirage. *Journal of Financial and Quantitative Analysis 59*(6), 2515–2546.

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 (2025). Investor heterogeneity and the market for fund benchmarks: Evidence from passive ETFS. *Journal of Banking & Finance 173*.

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	12.32	0	65.70	0
2011	100	21	9.31	0	59.66	0
2012	144	26	9.89	0	67.29	0
2013	187	29	9.76	0	69.08	0
2014	242	34	9.48	0.79	75.14	10.12
2015	275	39	8.89	1.44	76.92	17.62
2016	322	45	9.99	2.45	76.65	24.31
2017	453	49	9.86	3.22	76.52	28.00
2018	579	58	8.72	3.03	70.29	25.92
2019	833	71	8.85	3.12	68.25	28.60
2020	1,055	92	8.80	3.17	67.88	28.72
			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	83	7	9.46	9.51	93.31	94.31
2017	165	10	9.96	8.84	88.36	76.87
2018	224	9	9.54	7.82	84.37	67.00
2019	331	14	9.44	7.91	86.56	72.59
2020	408	21	9.49	8.24	86.28	74.36

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	8.40	3.38	0.55	0.00	0.00	0.00	0.00
2011	6.21	2.63	0.38	0.02	0.02	0.01	0.04
2012	6.35	2.94	0.53	0.01	0.02	0.00	0.05
2013	6.51	3.13	0.07	0.04	0.01	0.01	0.00
2014	6.46	2.90	0.05	0.03	0.01	0.02	0.01
2015	5.58	3.18	0.05	0.03	0.03	0.00	0.01
2016	6.16	3.57	0.11	0.03	0.08	0.03	0.01
2017	6.10	3.53	0.12	0.03	0.06	0.02	0.01
2018	5.28	3.26	0.12	0.01	0.03	0.01	0.01
2019	5.34	3.29	0.14	0.01	0.05	0.01	0.00
2020	5.28	3.22	0.20	0.02	0.06	0.00	0.02
Overall	6.15	3.18	0.21	0.02	0.03	0.01	0.01

Panel B: Average Weight of ETFs							
Year	Equity	Fixed Income	Commodities	Allocation	Alternative	Convertibles	Miscellaneous
2010	34.74	27.65	3.31	0.00	0.00	0.00	0.00
2011	34.22	22.40	2.07	0.55	0.25	0.05	0.12
2012	38.05	26.15	2.82	0.02	0.10	0.00	0.14
2013	42.25	25.30	0.40	1.00	0.03	0.11	0.00
2014	47.45	26.57	0.33	0.68	0.07	0.04	0.01
2015	44.28	30.93	0.59	0.89	0.18	0.01	0.04
2016	43.10	31.75	0.74	0.55	0.37	0.13	0.01
2017	44.14	30.68	0.85	0.44	0.32	0.08	0.01
2018	38.27	30.69	0.79	0.28	0.20	0.04	0.02
2019	38.14	28.86	0.57	0.38	0.26	0.04	0.00
2020	37.66	28.42	0.78	0.66	0.33	0.02	0.03
Overall	40.21	28.13	1.20	0.50	0.19	0.05	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. Models* is the number of models that recommend the ETF. *Monthly Return* is the monthly net 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. *Prospectus-adjusted Return* is the monthly return of a fund deducting the median return of funds that have the same investment objective indicated in their prospectus. *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 multiply 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 multiply it by 100.

Variable	Mean	Median	SD	Observations
No. Models	2.42	0.00	7.35	162,019
Monthly Return (%)	0.68	0.63	5.26	161,007
Category-adjusted Return (%)	-0.01	0.00	2.47	161,007
Prospectus-adjusted Return (%)	-0.04	0.00	3.32	161,007
Prior 1-Yr. Perf.	0.50	0.50	0.27	150,091
Prior 3-Yr. Perf.	0.50	0.50	0.26	114,696
Expense Ratio (%)	0.46	0.45	0.33	158,928
Fund Age (years)	6.45	5.35	4.65	162,019
Fund Size ($ mn)	1,887.18	155.97	8,861.53	162,019
Return Std. Dev. (%)	4.25	3.83	2.85	150,091
Turnover (%)	62.96	27.00	708.76	151,271
Amihud Ratio	0.08	0.00	0.28	111,031
Quoted Spread	0.21	0.11	0.56	113,165

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. *Prospectus-adjusted Return* is the monthly return of a fund deducting the median return of funds that have the same investment objective indicated in their prospectus. *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 multiply 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 multiply 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***	3.04
Prospectus-adjusted Return (%)	0.02	−0.06	0.08***	4.51
Prior 1-Yr. Perf.	0.52	0.49	0.04***	7.28
Prior 3-Yr. Perf.	0.53	0.48	0.05***	6.24
Expense Ratio (%)	0.35	0.51	−0.16***	−13.73
Fund Age (years)	8.38	5.68	2.70***	14.84
Fund Size ($ mn)	5,679.71	390.49	5,289.25***	7.35
Return Std. Dev. (%)	3.61	4.52	−0.91***	−10.80
Turnover (%)	44.90	70.48	−25.58***	−2.65
Amihud Ratio	0.02	0.11	−0.09***	−18.66
Quoted Spread	0.11	0.27	−0.16***	−15.84
Observations	45,847	116,172		

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 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 weighted average monthly return in excess of CRSP value-weighted stock index. Column 2 refers to the weighted average monthly return in excess of a portfolio of 60% of S&P 500 index and 40% of Bloomberg Barclays US Aggregate Bond Index. Category-adjusted Return and Prospectus-adjusted Return is the weighted average of category-adjusted and prospectus-adjusted ETF returns, respectively. Alpha is calculated as the weighted average alpha of ETFs within the model. 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 (60/40)	Category-adjusted Return	Prospectus-adjusted Return	Alpha
Gross Return	-0.46^{***}	-0.03	0.01^{***}	0.05^{***}	0.03^{***}
	(-14.48)	(-1.33)	(2.72)	(3.23)	(4.37)
Net Return	-0.48^{***}	-0.05^{**}	0.02^{***}	0.06^{***}	0.01^{**}
	(-14.84)	(-2.10)	(3.86)	(3.65)	(2.14)

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 $\frac{\text{AUM}_{i,t}-\text{AUM}_{i,t-1}\times(1+R_{i,t})}{\text{AUM}_{i,t-1}} \times 100$. The independent variable 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 multiplied 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: $\text{Flow}_{i,t}$				
No. $\text{Models}_{i,t}$	0.04***	0.04***	0.06***	0.05***
	(4.42)	(3.16)	(5.62)	(3.37)
Return $\text{Rank}_{i,t-1}$	3.08***	2.99***	3.43***	3.26***
	(16.01)	(14.93)	(14.25)	(13.39)
No. $\text{Models}_{i,t}$ × Return $\text{Rank}_{i,t-1}$	−0.04***	−0.02	−0.06***	−0.04***
	(−2.66)	(−1.43)	(−4.00)	(−2.74)
Expense $\text{Ratio}_{i,t-1}$	−1.11***	−3.30***	−1.99***	−8.38***
	(−3.55)	(−4.44)	(−5.09)	(−5.09)
No. $\text{Models}_{i,t}$ × Expense $\text{Ratio}_{i,t-1}$	0.04	0.07	0.05	0.11**
	(1.29)	(1.60)	(1.41)	(2.16)
$\log(\text{Size}_{i,t-1})$	0.03	−1.91***	−0.25***	−2.13***
	(1.08)	(−13.31)	(−5.69)	(−12.74)
$\log(\text{Age}_{i,t-1})$	−2.14***	−3.23***	−2.29***	−2.86***
	(−22.04)	(−12.76)	(−19.79)	(−9.30)
$\text{Turnover}_{i,t-1}$			−0.00*	−0.00
			(−1.85)	(−0.87)
Amihud Ratio $_{i,t-1}$			−2.46***	−1.99***
			(−6.61)	(−3.97)
Month-Year and Fund FE	No	Yes	No	Yes
Observations	155,808	155,774	105,314	105,288
Adjusted R^2	0.03	0.09	0.05	0.11

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 $\frac{\text{AUM}_{i,t} - \text{AUM}_{i,t-1} \times (1+R_{i,t})}{\text{AUM}_{i,t-1}} \times 100$. $Treatment_i$ 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. $Post_t$ is equal to one for the nine months 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: $\text{Flow}_{i,t}$			
$\text{Treatment}_i \times \text{Post}_t$	-7.77^{***}	-9.72^{**}	-6.03^{**}	-8.13^{**}
	(-3.13)	(-2.42)	(-2.50)	(-2.19)
$\text{Treatment}_i \times \text{Pre}_t$			4.92	4.52
			(1.56)	(0.88)
$\text{Return rank}_{i,t-1}$	3.85^{**}	3.67^{*}	3.73^{**}	3.54^{*}
	(2.77)	(2.04)	(2.37)	(1.75)
$\text{Expense Ratio}_{i,t-1}$	-46.39	-77.91	-45.97	-77.44
	(-0.66)	(-0.84)	(-0.66)	(-0.84)
$\log(\text{Size}_{i,t-1})$	-12.43^{***}	-13.56^{***}	-12.41^{***}	-13.47^{***}
	(-3.17)	(-3.15)	(-3.16)	(-3.16)
$\log(\text{Age}_{i,t-1})$	-8.76^{**}	-7.94	-8.17^{*}	-7.55
	(-2.11)	(-1.50)	(-1.80)	(-1.36)
$\text{Turnover}_{i,t-1}$		0.02^{**}		0.02^{**}
		(2.58)		(2.62)
$\text{Amihud Ratio}_{i,t-1}$		-10.83		-11.59
		(-1.40)		(-1.29)
Time and Fund FE	Yes	Yes	Yes	Yes
Observations	1,152	922	1,152	922
Adjusted R^2	0.16	0.18	0.16	0.18

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 unaffilated 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. *Prosp.-adj. Return* is the monthly return of a fund deducting the median return of funds that have the same investment objective indicated in their prospectus. *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 multiply 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 multiply 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	0.04	0.03	−0.04***	−0.05***	−0.04***
					(−2.80)	(−3.08)	(−2.62)
Prosp.-adj.Return (%)	0.00	0.06	0.08	0.05	−0.06**	−0.08***	−0.05**
					(−2.43)	(−2.89)	(−2.18)
Prior 1-Yr. Perf.	0.51	0.53	0.52	0.53	−0.02**	-0.01	−0.02**
					(−2.26)	(−1.32)	(−2.40)
Prior 3-Yr. Perf.	0.53	0.54	0.53	0.54	−0.01	0.00	−0.01
					(−0.68)	(−0.05)	(−0.80)
Expense Ratio (%)	0.36	0.29	0.22	0.30	0.07***	0.14***	0.06***
					(4.83)	(7.64)	(3.92)
Fund Age (years)	8.2	10.26	11.52	9.99	−2.06***	-3.32***	−1.79***
					(−6.36)	(−7.98)	(−5.49)
Fund Size ($ mn)	8,846	14,654	21,257	13,215	−5,808***	−12,411***	−4,369***
					(−4.43)	(−3.40)	(−3.89)
Return Std. Dev. (%)	3.55	3.32	3.04	3.38	0.23**	0.51***	0.17
					(1.99)	(3.50)	(1.47)
Turnover (%)	53.33	45.36	51.94	43.91	7.97	1.39	9.42*
					(1.33)	(0.11)	(1.93)
Amihud Ratio	0.04	0.01	0.00	0.01	0.03***	0.03***	0.03***
					(5.27)	(5.95)	(5.08)
Quoted Spread	0.14	0.06	0.05	0.07	0.07***	0.09***	0.07***
					(8.84)	(10.47)	(8.30)
Observations	10,723	81,694	14,618	67,076			

Table 9: Logit model of ETF additions to recommendations by asset managers
This table reports coefficient estimates for the logit model. $Add_{c,i,t}$ 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: $\text{Add}_{c,i,t}$		
$\text{Affiliated}_{c,i}$	1.83***	1.80***
	(7.16)	(6.11)
Prior 1-Yr. $\text{Perf.}_{i,t-1}$	−0.00	
	(−0.01)	
$\text{Affiliated}_{c,i}$ × Prior 1-Yr. $\text{Perf.}_{i,t-1}$	0.19	
	(0.71)	
Prior 3-Yr. $\text{Perf.}_{i,t-1}$		0.13
		(0.71)
$\text{Affiliated}_{c,i}$ × Prior 3-Yr. $\text{Perf.}_{i,t-1}$		0.06
		(0.17)
Expense $\text{Ratio}_{i,t-1}$	−0.92***	−0.58*
	(−2.77)	(−1.82)
$\text{Affiliated}_{c,i}$ × Expense $\text{Ratio}_{i,t-1}$	3.90***	3.80***
	(8.03)	(7.33)
$\log(\text{Age}_{i,t-1})$	−0.36***	−0.39***
	(−3.94)	(−2.76)
$\log(\text{Size}_{i,t-1})$	0.62***	0.65***
	(17.35)	(16.58)
Return Std. $\text{Dev.}_{i,t-1}$	−0.60	−0.47
	(−0.22)	(−0.16)
$\text{Turnover}_{i,t-1}$	0.00**	0.00**
	(2.19)	(2.31)
Average Marginal Effect		
$\text{Affiliated}_{c,i}$	0.0025	0.0028
Expense $\text{Ratio}_{i,t-1}$	−0.0012	−0.0009
Affiliated_{i} × Expense $\text{Ratio}_{i,t-1}$	0.0053	0.0060
ETF Category and Month-Year FE	Yes	Yes
Observations	1,189,009	925,028
Pseudo R^2	0.28	0.27

Table 10: Performance of model recommendations by the type of providers
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 in one model to be at least 80%. Column 1 refers to the weighted average monthly return in excess of CRSP value-weighted stock index. Column 2 refers to the weighted average monthly return in excess of a portfolio of 60% of S&P 500 index and 40% of Bloomberg Barclays US Aggregate Bond Index. Category-adjusted Return and Prospectus-adjusted Return is the weighted average of category-adjusted and prospectus-adjusted ETF returns, respectively. Alpha is calculated as the weighted average alpha of ETFs within the model. 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 (60/40)	Category-adjusted Return	Prospectus-adjusted Return	Alpha
Asset Manager (AM)	-0.55^{***}	-0.09^{**}	0.02^{**}	0.06^{**}	-0.00
	(-10.68)	(-3.78)	(2.54)	(2.27)	(-1.29)
Strategist (ST)	-0.40^{***}	-0.00	0.03^{***}	0.07^{***}	0.03^{***}
	(-9.41)	(-0.04)	(2.78)	(2.73)	(2.68)
AM minus ST	-0.15^{**}	-0.09^{*}	-0.01	-0.01	-0.03^{***}
	(-2.23)	(-1.93)	(-0.91)	(-0.34)	(-2.96)

Table A1: Variable definitions

Variable	**Definition**	**Source**
Add	An indicator variable that takes the value one if ETF is added to the models of company	Morningstar
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. 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. We 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 for allocation funds. 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

Continued in next page

Table A1: Variable definitions (continued from previous page)

Variable	**Definition**	**Source**
ETF category	Field "Morningstar Category"	Morningstar
ETF style	Field "Global Broad Category Group"	Morningstar
Excess Return (60/40)	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 $100 \times [\text{AUM}_{i,t} - \text{AUM}_{i,t-1} \times (1+R_{i,t})]/\text{AUM}_{i,t-1}$	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
No. Models	Number of models that recommend the 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
Prospectus-adjusted Return	Monthly return of a fund deducting the median return of funds that have the same investment objective indicated in their prospectus	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: 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 multiply it by 100. All variables in Panel A are category-adjusted by deducting the median value of funds of the same Morningstar category. All variables in Panel B are prospectus-adjusted by deducting the median value of funds that have the same investment objective indicated in their prospectus. 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.

Panel A: Category-adjusted characteristics				
	Model ETFs	Non-model ETFs	Difference	t-stat
Expense Ratio (%)	−0.04	0.04	−0.08***	−8.87
Return Std. Dev. (%)	−0.04	0.20	−0.24***	−7.13
Turnover (%)	11.23	28.76	−17.52**	−2.44
Amihud Ratio	0.01	0.09	−0.08***	−17.67
Quoted Spread	−0.02	0.11	−0.13***	−14.65
Panel B: Prospectus-adjusted characteristics				
Expense Ratio (%)	−0.06	0.06	−0.12***	−10.99
Return Std. Dev. (%)	−0.08	0.38	−0.46***	−8.88
Turnover (%)	10.93	39.57	−28.64***	−3.05
Amihud Ratio	0.01	0.10	−0.09***	−18.49
Quoted Spread	−0.02	0.14	−0.15***	−16.31
Observations	45,847	116,172		

Table A3: Performance of model portfolios: at least 60% of total weight in ETFs
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 in one model to be at least 60%. Column 1 refers to the weighted average monthly return in excess of CRSP value-weighted stock index. Column 2 refers to the weighted average monthly return in excess of a portfolio of 60% of S&P 500 index and 40% of Bloomberg Barclays US Aggregate Bond Index. Category-adjusted Return and Prospectus-adjusted Return is the weighted average of category-adjusted and prospectus-adjusted ETF returns, respectively. Alpha is calculated as the weighted average alpha of ETFs within the model. 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 (60/40)	Category-adjusted Return	Prospectus-adjusted Return	Alpha
Gross Return	−0.46***	−0.04	0.02***	0.05***	0.04***
	(−14.15)	(−1.41)	(3.45)	(3.57)	(4.30)
Net Return	−0.48***	−0.05**	0.02***	0.07***	0.02**
	(−14.56)	(−2.11)	(4.60)	(4.01)	(2.28)

Panel B: Model by the type of providers

	Excess Return (Stocks)	Excess Return (60/40)	Category-adjusted Return	Prospectus-adjusted Return	Alpha
Asset Manager (AM)	−0.55***	−0.10**	0.02***	0.08***	−0.00
	(−11.18)	(−3.16)	(2.88)	(3.25)	(−1.02)
Strategist (ST)	−0.40***	−0.01	0.03***	0.06***	0.03***
	(−9.24)	(−0.27)	(3.52)	(2.24)	(2.97)
AM minus ST	−0.15**	−0.09*	−0.01	−0.02	−0.04***
	(−2.37)	(−1.76)	(−1.43)	(−0.61)	(−3.15)

Table A4: 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 $\frac{\text{AUM}_{i,t}-\text{AUM}_{i,t-1}\times(1+R_{i,t})}{\text{AUM}_{i,t-1}}\times 100$. The independent variable 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 multiplied 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$_{i,t}$	0.14***	0.16**	0.15***	0.15**
	(4.15)	(2.66)	(4.71)	(2.56)
Return Rank$_{i,t-1}$	8.86***	7.68***	9.58***	8.24***
	(12.94)	(11.64)	(10.75)	(9.52)
No. Models$_{i,t}$ × Return Rank$_{i,t-1}$	−0.13***	−0.09*	−0.12**	−0.07
	(−3.19)	(−2.00)	(−2.27)	(−1.59)
Expense Ratio$_{i,t-1}$	−3.36***	−8.83**	−6.04***	−24.20***
	(−2.92)	(−2.49)	(−4.13)	(−4.84)
No. Models$_{i,t}$ × Expense Ratio$_{i,t-1}$	0.33**	0.46**	0.36***	0.61***
	(2.64)	(2.49)	(2.70)	(3.02)
log(Size$_{i,t-1}$)	−0.15	−6.14***	−1.00***	−6.86***
	(−1.35)	(−10.36)	(−7.12)	(−9.75)
log(Age$_{i,t-1}$)	−5.94***	−8.53***	−6.33***	−7.33***
	(−17.13)	(−8.96)	(−17.43)	(−6.90)
Turnover$_{i,t-1}$			−0.00**	−0.00
			(−2.09)	(−0.78)
Amihud Ratio $_{i,t-1}$			−7.08***	−6.07***
			(−6.55)	(−3.20)
Month-Year and Fund FE	No	Yes	No	Yes
Observations	49,495	49,384	33,683	33,608
Adjusted R^2	0.06	0.18	0.09	0.20

Table A5: 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 $\frac{\text{AUM}_{i,t} - \text{AUM}_{i,t-1} \times (1+R_{i,t})}{\text{AUM}_{i,t-1}} \times 100$. The independent variable 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 multiplied 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***	0.03*	0.06***	0.05**
	(3.70)	(1.93)	(3.62)	(2.15)
Return Rank$_{i,t-1}$	3.86***	3.57***	2.27***	2.30***
	(13.81)	(13.07)	(6.52)	(6.05)
No. Models$_{i,t}$ × Return Rank$_{i,t-1}$	−0.05***	−0.03*	−0.04*	−0.03
	(−3.26)	(−1.92)	(−1.74)	(−1.36)
Expense Ratio$_{i,t-1}$	−1.92***	−10.47***	−2.55***	−1.57
	(−4.05)	(−5.34)	(−3.57)	(−0.63)
No. Models$_{i,t}$ × Expense Ratio$_{i,t-1}$	0.08	0.15**	0.04	0.08
	(1.63)	(2.23)	(0.60)	(1.21)
log(Size$_{i,t-1}$)	−0.27***	−2.05***	−0.20**	−2.41***
	(−5.35)	(−10.50)	(−2.59)	(−8.43)
log(Age$_{i,t-1}$)	−2.30***	−3.21***	−2.53***	−2.79***
	(−17.24)	(−8.66)	(−12.55)	(−4.83)
Turnover$_{i,t-1}$	−0.00	0.00	−0.00	−0.00***
	(−1.38)	(0.70)	(−0.93)	(−4.59)
Amihud Ratio $_{i,t-1}$	−2.57***	−2.08***	−2.15***	−1.33
	(−6.90)	(−4.13)	(−3.03)	(−1.63)
Month-Year and Fund FE	No	Yes	No	Yes
Observations	79,718	79,698	25,596	25,590
Adjusted R^2	0.05	0.11	0.04	0.09

Table A6: 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 $\frac{\text{AUM}_{i,t}-\text{AUM}_{i,t-1}\times(1+R_{i,t})}{\text{AUM}_{i,t-1}}\times 100$. The independent variable 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 multiplied 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: $\text{Flow}_{i,t}$			
	Asset Managers		Strategists	
No. $\text{Models}_{i,t}$	0.06***	0.08***	0.10***	0.05**
	(3.81)	(2.98)	(5.35)	(2.00)
Return $\text{Rank}_{i,t-1}$	3.28***	2.98***	3.31***	2.92***
	(12.51)	(11.40)	(12.42)	(11.31)
No. $\text{Models}_{i,t}$ × Return $\text{Rank}_{i,t-1}$	−0.07***	−0.05**	−0.08***	−0.05*
	(−3.46)	(−2.55)	(−2.73)	(−1.78)
Expense $\text{Ratio}_{i,t-1}$	−2.33***	−5.95***	−2.30***	−6.26***
	(−5.39)	(−3.27)	(−5.26)	(−3.24)
No. $\text{Models}_{i,t}$ × Expense $\text{Ratio}_{i,t-1}$	0.05	0.06	0.02	0.18*
	(0.84)	(0.72)	(0.40)	(1.86)
$\log(\text{Size}_{i,t-1})$	−0.19***	−2.32***	−0.23***	−2.32***
	(−4.21)	(−10.08)	(−5.20)	(−10.09)
$\log(\text{Age}_{i,t-1})$	−2.24***	−2.35***	−2.24***	−2.40***
	(−17.28)	(−5.37)	(−17.38)	(−5.47)
$\text{Turnover}_{i,t-1}$	−0.00	−0.00	−0.00	−0.00
	(−1.63)	(−0.47)	(−1.62)	(−0.49)
Amihud Ratio $_{i,t-1}$	−2.19***	−1.76***	−2.24***	−1.76***
	(−6.49)	(−3.73)	(−6.58)	(−3.73)
Month-Year and Fund FE	No	Yes	No	Yes
Observations	84,646	84,621	84,646	84,621
Adjusted R^2	0.05	0.11	0.05	0.11

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 $Flow_{i,t}^{Adj}$ which is defined as $(\frac{\text{AUM}_{i,t}-\text{AUM}_{i,t-1}\times(1+R_{i,t})}{\text{AUM}_{i,t-1}} - \frac{\sum_j(N_{i,j,t}-N_{i,j,t-1})\times p_{i,t}}{AUM_{i,t-1}})\times 100$. $Treatment_i$ 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 and active management style as treatment ETFs. $Post_t$ is equal to one for the nine months 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 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: $\text{Flow}_{i,t}^{Adj}$			
$\text{Treatment}_i \times \text{Post}_t$	-7.60^{***}	-9.49^{**}	-5.80^{**}	-7.84^{*}
	(-3.07)	(-2.37)	(-2.36)	(-2.05)
$\text{Treatment}_i \times \text{Pre}_t$			5.09	4.70
			(1.57)	(0.91)
$\text{Return rank}_{i,t-1}$	4.20^{**}	3.89^{*}	4.07^{**}	3.75^{*}
	(2.49)	(2.05)	(2.27)	(1.76)
$\text{Expense Ratio}_{i,t-1}$	-45.76	-77.63	-45.38	-77.17
	(-0.64)	(-0.82)	(-0.64)	(-0.82)
$\log(\text{Size}_{i,t-1})$	-12.72^{***}	-13.89^{***}	-12.69^{***}	-13.80^{***}
	(-3.19)	(-3.17)	(-3.18)	(-3.17)
$\log(\text{Age}_{i,t-1})$	-8.69^{**}	-7.86	-8.11^{*}	-7.47
	(-2.29)	(-1.58)	(-1.93)	(-1.43)
$\text{Turnover}_{i,t-1}$		0.02^{**}		0.02^{**}
		(2.51)		(2.55)
$\text{Amihud Ratio}_{i,t-1}$		-10.93		-11.73
		(-1.25)		(-1.34)
Time and ETF FE	Yes	Yes	Yes	Yes
Observations	1,152	922	1,152	922
Adjusted R^2	0.16	0.18	0.16	0.18

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 $\frac{\text{AUM}_{i,t}-\text{AUM}_{i,t-1}\times(1+R_{i,t})}{\text{AUM}_{i,t-1}} \times 100$. *No. Models* is the number of models that recommend ETF; *Return Rank* is the percentile rank of ETF's return multiplied 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 (%)	2.79	0.56	12.93	1,158
No. Models	7.91	4.00	9.27	1,158
Lag Return rank	0.53	0.53	0.26	1,152
Lag Expense Ratio (%)	0.30	0.20	0.20	1,152
Lag log(Size)	7.35	7.31	2.03	1,152
Lag log(Age)	4.35	4.58	0.83	1,152
Lag Turnover (%)	57.27	8.00	188.76	1,152
Lag Amihud Ratio	0.01	0.00	0.02	923

Table A9: 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 unaffilated 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 multiply it by 100. All variables in Panel A are category-adjusted by deducting the median value of funds of the same Morningstar category. All variables in Panel B are prospectus-adjusted by deducting the median value of funds that have the same investment objective indicated in their prospectus. 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)
Panel A: Category-adjusted characteristics							
Expense Ratio (%)	−0.01	−0.08	−0.11	−0.08	0.08***	0.10***	0.07***
					(5.94)	(6.73)	(5.52)
Return Std. Dev. (%)	−0.02	−0.08	−0.06	−0.08	0.06	0.04	0.07*
					(1.59)	(0.96)	(1.69)
Turnover (%)	15.72	10.70	14.73	9.81	5.02	1.00	5.91
					(0.97)	(0.09)	(1.42)
Amihud Ratio	0.03	0.00	−0.01	0.00	0.03***	0.03***	0.03***
					(4.89)	(5.58)	(4.69)
Quoted Spread	−0.01	−0.06	−0.07	−0.05	0.04***	0.06***	0.04***
					(6.50)	(7.44)	(5.92)
Panel B: Prospectus-adjusted characteristics							
Expense Ratio (%)	−0.04	−0.12	−0.16	−0.11	0.08***	0.12***	0.07***
					(5.06)	(6.39)	(4.47)
Return Std. Dev. (%)	−0.1	−0.18	−0.25	−0.17	0.08	0.15	0.07
					(1.13)	(1.54)	(0.94)
Turnover (%)	12.48	7.49	7.21	7.55	4.99	5.27	4.93
					(1.28)	(0.87)	(1.33)
Amihud Ratio	0.03	0.00	0.00	0.00	0.03***	0.03***	0.03***
					(4.78)	(5.55)	(4.57)
Quoted Spread	−0.01	−0.06	−0.08	−0.05	0.05***	0.07***	0.04***
					(6.27)	(7.91)	(5.68)
Observations	10,723	81,694	14,618	67,076			

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. $Add_{c,i,t}$ 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: $\text{Add}_{c,i,t}$		
$\text{Affiliated}_{c,i}$	1.85^{***}	1.75^{***}
	(6.81)	(5.59)
$\text{Prior 1-Yr. Perf.}_{i,t-1}$	0.11	
	(0.71)	
$\text{Affiliated}_{c,i} \times \text{Prior 1-Yr. Perf.}_{i,t-1}$	0.11	
	(0.40)	
$\text{Prior 3-Yr. Perf.}_{i,t-1}$		0.20
		(1.00)
$\text{Affiliated}_{c,i} \times \text{Prior 3-Yr. Perf.}_{i,t-1}$		0.09
		(0.25)
$\text{Expense Ratio}_{i,t-1}$	-1.21^{***}	-0.85^{**}
	(-3.37)	(-2.53)
$\text{Affiliated}_{c,i} \times \text{Expense Ratio}_{i,t-1}$	4.33^{***}	4.24^{***}
	(8.46)	(7.87)
$\log(\text{Age}_{i,t-1})$	-0.28^{***}	-0.29^{*}
	(-2.76)	(-1.94)
$\log(\text{Size}_{i,t-1})$	0.58^{***}	0.61^{***}
	(16.25)	(15.58)
$\text{Return Std. Dev.}_{i,t-1}$	-1.52	-1.80
	(-0.51)	(-0.56)
$\text{Turnover}_{i,t-1}$	0.00^{*}	0.00^{*}
	(1.95)	(1.78)
Average Marginal Effect		
$\text{Affiliated}_{c,i}$	0.0050	0.0056
$\text{Expense Ratio}_{i,t-1}$	-0.0033	-0.0027
$\text{Affiliated}_{i} \times \text{Expense Ratio}_{i,t-1}$	0.0118	0.0136
ETF Category and Quarter-Year FE	Yes	Yes
Observations	459,608	358,105
Pseudo R^2	0.25	0.25