Advising the Advisors: Evidence from ETFs*

Preliminary and Subject to Change

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Abstract

Asset managers play a dual role by simultaneously managing funds and increasingly providing investment model recommendations to third-party financial advisors. Using a novel data set focusing on recommendations by ETF issuers and strategists, we discover that these recommendations have a substantial impact on ETF flows. Model providers recommend their affiliated ETFs more frequently, and these funds tend to have higher fees and lower performance than recommended unaffiliated ETFs. In addition, investors who follow the recommendations exhibit weaker sensitivity to funds' prices and returns. We fail to find evidence that recommendations are driven by private information about the future outperformance of affiliated funds.

JEL classification: G11, G23

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

Unlike traditional asset management solutions, model portfolios are not subject to direct investment in which funds flow “in” and are managed from a central location. Instead, the models are distributed “out” to financial advisors as an asset allocation and fund selection recommendation. 85% of financial advisors employ a combination of custom and model portfolios. More than half, 54%, of advised assets are in model portfolios.[3] Exchange-traded funds (ETFs) issuers and strategists have responded to that demand, launching more than 500 model portfolios over the past three years, as reported by Morningstar.[4] The recommendations also play an essential role in the underlying assets.[5] One of the largest ETF issuers, BlackRock, forecasts that in five years, half of new investor inflows to its ETFs, iShares, will be directed by model portfolios of its own and other firms, up from around a third in 2020.[6]

Nevertheless, the broad adoption of these model recommendations has received little attention in the literature. Using a novel data set on the recommendations offered to financial advisors, this paper aims to fill this gap by investigating how these recommendations shape investments in ETFs. First, we find that these model recommendations drive the future flows to ETFs. Investors who chase the recommendations also behave differently, as they pay less attention to both the

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

[2] https://www.wsj.com/articles/model-portfolios-surging-as-advisers-seek-quick-ways-to-invest-client-money-11607091645

[3] https://www.broadridge.com/_assets/pdf/broadridge-fa-model-portfolio-may-2019.pdf

[4] https://www.morningstar.com/articles/1028488/our-favorite-model-portfolios-for-advisors

[5] A study by Broadridge documents that of the assets recommended by model portfolios, ETFs account for 42% (see https://www.broadridge.com/_assets/pdf/broadridge-des-etf-outlook-2020-portrait.pdf).

[6] https://ir.blackrock.com/news-and-events/2021-investor-day/

price and the performance of the ETFs. Then, we show that recommended affiliated ETFs, which are ETFs that belong to the same management company or fund family as the model providers do, exhibit worse performance and higher fees than unaffiliated ETFs. Moreover, the probability of addition to these recommendations is higher for affiliated funds. High fee funds among them are even more likely to be added. Finally, we investigate the future performance of recommended ETFs, and we fail to find evidence supporting the superior performance of affiliated funds relative to unaffiliated funds. To the best of our knowledge, our paper is the first to analyze asset managers' and strategists' model recommendations to financial advisors and relate them to the conflicts they face.

Our analysis includes two main parts. For model providers to benefit from their recommendations, at least some financial advisors must rely upon them. Therefore, first, we examine the impact that model recommendations have on ETF flows. A financial advisor may interpret a model provider's fund recommendation as the provider conveying new insights and thus follow their guidance. Practitioners claim that models become a more prominent force, that they challenge the idea that flows across funds reflect the hive mind of millions of people making decisions on their own. Instead, the moves may reflect the views of an individual firm. "When you see these massive flows, it's more than likely because a manager like me has decided to make a change within their portfolios," says Phil Blancato, chief executive of Ladenburg Thalmann Asset Management.[7]

On the other hand, the recommendations may be neglected by financial advisors because they are unverifiable products. Unlike traditional turnkey asset-management solutions, such as funds of funds and separate management accounts, model portfolios are not directly investable. Instead, models are offered as a blueprint for asset allocation and fund selection. Financial advisors are not forced to follow them fully, that is, they may deviate from the allocations recommended for a model portfolio at their discretion.

[7] https://www.wsj.com/articles/the-growing-clout-of-etf-strategists-1506306203

First, we find that being part of a model recommendation substantially increases future flows to these ETFs. The estimates indicate that an ETF experiences 1.10 percentage points higher flows per month following its addition to a model recommendation. Investor flows to funds are sensitive to the fee and quality of the funds. Prior studies show that investors increase their demand for ETFs that performed well in the past or ETFs that are cheaper (Ben-David et al., 2021; Dannhauser and Pontiff, 2021). Our second result suggests that the sensitivities of investor demand to funds recommended by models are different from other funds in both aspects. Specifically, flows to model-recommended ETFs display a lower sensitivity to fees of 2 percentage points and and lower sensitivity to past performance of 1 percentage point. It implies that some investors may completely follow the recommendations of model providers and pay less attention to the price and quality of recommended ETFs.

Our results support industry concerns. “The concern is that somebody would look at an ETF today and think there is a broader following than it has,” says Todd Rosenbluth, head of exchange-traded-fund and mutual-fund research at CFRA.[8]

Endogeneity issues may arise if the model providers select ETFs based on their expectations of the fund flows. They may choose to add these ETFs into their model portfolios in anticipation of increasing future inflows. To address this concern, we test the impact of model recommendations on funding flows using a natural experiment – the collapse of F-Squared Investments. F-Squared Investments ran one of the largest ETF strategies in the US, and it managed 19 model portfolios that recommended ETFs. However, all the models were closed gradually in 2015 because the company filed for bankruptcy after the US Securities and Exchange Commission (SEC) charged it with defrauding investors.[9] The closure of all models from F-Squared Investments is a shock to the recommendation of ETFs in the models; therefore, we can test the impact on the fund flows in a clean setting.

[8]https://www.wsj.com/articles/blackrock-tweaked-some-models-it-triggered-a-wave-of-buying-and-selling-11625857596

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

Our results support the argument that recommendations by model providers increase the ETF flows. In the six months following deletion, the ETFs deleted from models recommended by F-Squared received flows 6.25 percentage points lower than other ETFs of the same investment category that models hold.

Having identified that model recommendations indeed drive investor flows into ETFs, we investigate the quality of the recommended ETFs, as well as the determinants of recommendation from model providers. Specifically, we would like to know whether model providers favor their own ETFs over others. We define an ETF as affiliated if it is issued by the same management company that supplies the models. We compare the affiliated ETFs against their unaffiliated peers. Our univariate tests show that affiliated ETFs are generally more expensive and have worse performance than unaffiliated ETFs. On average, affiliated ETFs charge 6 basis points (bps) higher expense ratios and generate 67 bps lower net year-to-date (YTD) returns than unaffiliated funds. Their past performance, measured by the performance-rank percentiles over the previous one and three years, is also five and six ranks lower, respectively.

Next, we observe that the probability of addition is significantly much higher for the affiliated funds. The odds ratio of the addition of affiliated ETFs is 3.19 times the odds ratio of unaffiliated ETFs. Even though worse prior performance and higher fees decrease the probability of addition to the recommendations, when we interact past performance or expense ratio with the affiliation, we find that the affiliated funds with lower prior one-year performance and higher fees have a higher probability of addition. The odds ratio of the worst-performing affiliated ETFs is 1.01 times that of the best-performing affiliated ETFs. When the expense ratio of affiliated ETFs increase by one bp, the odds ratio of addition increases by 3%. It suggests that more expensive affiliated ETFs have a higher chance to be recommended than cheaper affiliated funds. However, the result is the opposite for unaffiliated ETFs. The odds ratio of addition is reduced by 1% when the expense ratio increases by one bp for unaffiliated ETFs. The favoritism toward affiliated funds and lower sensitivity of fund performance in recommendations is consistent with a study by Pool et al. (2016), who find that mutual fund families usually favor their affiliated funds in the 401(K) plans provided by them.

However, it is possible that model providers can identify their funds that deliver positive risk-adjusted returns in the future and add them to their recommendations. For example, Lee (2010) shows that funds of mutual funds can choose the funds with higher future performance because of information advantage relative to the outsiders.

To address this concern, we compute the future performance of the affiliated and unaffiliated ETFs, and our tests show that this is not the case. We find that both future risk-adjusted returns and future peer-adjusted returns of affiliated funds are either negative or not statistically significantly different from zero.

In summary, the findings on the choice of affiliated ETFs and their future performance resonate with the fee structure of model providers. The fees they get from financial advisors are independent of the performance of the models. Moreover, when model providers include their own funds into recommendations, they get indirectly compensated through asset management fees charged by these affiliated ETFs. Hence, the model providers might have incentives to recommend funds with high expense ratios.

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

We also add to the literature examining the recommendations of financial intermediaries. This literature has primarily focused on the recommendations of financial advisors to their institutional and retail clients. Bergstresser et al. (2009) find that broker-sold funds underperform funds sold through direct channels. Pool et al. (2016) find that mutual fund families acting as trustees of 401(K) plans display a bias toward affiliated funds. Doellman and Sardarli (2016) document that the higher fees and lower returns are related to the existence of affiliated funds in these plans. Jenkinson et al. (2016) focus on external consulting firm fund recommendations. They find that these recommendations impact asset allocation but that they fail to add value. Boyson (2019) finds that investment advisors dually registered as broker-dealers fail to fulfill their fiduciary duties to clients. Cookson et al. (2021) find that platforms favor "own-brand" funds and those paying them a higher commission share. We add to this literature by looking at the recommendations not of but to financial advisors. Moreover, these recommendations are about passive products, that is, about products that require fewer management skills and that are more transparent relative to mutual funds.

By exploring the dual role of model providers – they are simultaneously managing assets and providing recommendations to financial advisors – more broadly, our work relates to the literature discussing side-by-side management and multiple stages of decision-making in fund management. Spatt (2020) provides an overview of the conflicts of interest and studies addressing them. On the theory side, Stoughton et al. (2011) model the widespread use of financial advisors by unsophisticated investors due to costly information production. Dasgupta and Maug (2021) build a model to explain the multiple layers of decision-making in fund management with investors, sponsors, and fund managers; they rationalize that the delegation chain exists because it reduces the sponsor's reputational risk. Several empirical studies explore potential conflicts related to side-by-side management of mutual funds and other types, such as ETFs, separately managed accounts (SMAs), and hedge funds (Cici et al., 2010; Nohel et al., 2010; Romero-Pérez and Rodríguez, 2012; Evans and Fahlenbrach, 2012; Chen et al., 2017; Del Guercio et al., 2018; Beggs et al., 2021; Luo and Schumacher, 2021). The critical difference in the organizational structure between model recommendations and mutual funds, funds of funds, or SMAs is that model recommendations shift responsibility for trading, customization, tax management, custody, investing new funds, withdrawing funds, and reporting from third parties to a financial advisor. Funds and separate accounts may be better aligned with their clients than the model providers because their compensation is a direct function of the performance of the selected portfolio.

Finally, we aim to add to the industry and regulatory debate about the opacity of the model portfolios. The ETF "model portfolio" industry is an emerging concern that needs to be explored and standardized to reduce informational opacity and improve comparisons (Clements, 2020; Kephart and Millson, 2021). Model providers face few regulations when it comes to reporting performance to potential clients. "With the reporting standards being less than regulated vehicles, it is important to do the due diligence," says Morningstar analyst Adam Millson.[10]

Many model delivery programs are opaque wrap fee programs by nature.[11] In July 2021, the SEC published a risk alert covering wrap fee programs, focusing on advisors' fiduciary obligations, disclosure, and policies and procedures.[12]

1 Background and Data

1.1 Institutional Details

Model recommendations are designed for financial advisors, to allow them to outsource investment management to focus on strengthening client relationships through other financial planning services, such as developing estate and tax strategies. To extend the analogy of Gen-

[10] https://www.wsj.com/articles/model-portfolios-surging-as-advisers-seek-quick-ways-to-invest-client-money-11607091645

[11] For example, Columbia Management Investment Advisers describes their model recommendation service in its ADV forms as the following "We also participate in Wrap Fee Programs commonly referred to as 'Model Delivery Programs' in which we provide non-discretionary investment services to the program sponsor and/or another investment adviser, commonly referred to as an "overlay manager,"(https://adviserinfo.sec.gov/firm/summary/108257)

[12] https://www.sec.gov/exams/announcement/risk-alert-wrap-fee-programs

naioli et al. (2015) and Jenkinson et al. (2016), financial advisors can be thought of as "money doctors" who have more time to identify a sickness of their patients by saving some time by providing pre-mixed formulas instead of creating custom medications from scratch.

These recommendations are designed by strategists such as 3D/L Capital Management and fund managers such as BlackRock. Then the recommendations are communicated to the financial advisors. The providers also alter the constituents of their recommendations over time. When adjustments are made, they send trading instructions to financial advisors. Financial advisors then track these model portfolios with their clients' money. Advisors can adapt the instructions to their portfolios or override them. They are responsible for executing securities trades.

Strategists are registered investment advisors who primarily focus on investment management and have made their models available for financial advisors to follow. These firms helped popularize ETF Managed Portfolios, forerunners of model portfolios available as more traditional turnkey solutions. These strategists usually do not have their own underlying ETFs in the models, so they charge a "strategist" fee on top of the underlying fund fees. Strategist fees vary from one advisor to the next, though based on ADV forms and industry reports, they typically range from about 0.10% to 0.50%. This cohort typically uses low-cost underlying ETFs to keep the total competitive fee.

Unlike strategists, asset managers build models that predominately use proprietary underlying ETFs. Since they receive compensation from the underlying fund fees, they usually do not layer on an additional fee for asset-allocation advice when they recommend their own products. Model portfolios represent a way for asset managers to distribute not only their funds but also their takes on portfolio construction and risk management capabilities. Asset managers claim that those integrated features might lead to stronger ties with advisors than marketing the best fund of the month.[13] Both types of model providers give recommendations regarding the purchase or sale of specific ETFs, at specific weights for each individual ETF, in a model

[13]Reuter and Zitzewitz (2006) find that mutual fund recommendations are correlated with past advertising, but the cost of advertising bias to investors is small.

portfolio. The third-party advisor may, in turn, at its sole discretion, use the model portfolios as investment strategies to invest third-party advisor's clients' assets. The ETF asset manager does not receive any personal or investment guideline information pertaining to the third-party advisor's clients and does not manage or have discretion over any third-party advisor's clients' assets. The decision regarding the timing and magnitude of purchases or sales rests solely with the financial advisor. The financial advisor may tailor model recommendations, as necessary, to fit an investor's individual financial situation and objectives.

Financial advisors claim that they employ model recommendations to spend more time on client-facing activities and for financial planning. "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," says Tom O'Shea, research director at Cerulli Associates (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 "frees me up from micro-managing and allows me to do macromanagement for my clients" (State Street Global Advisors, 2016).

Model recommendations are presented to financial advisors as the outcome of in-house research and are designed to guide them. For example, a model provider, Global X, explains its process as follows: "Each Model Portfolio is designed to pursue a particular investment strategy and to have a specified risk tolerance level. Each Model Portfolio is intended to achieve such strategy through investment in ETFs in accordance with the target allocations established for the Model Portfolio. Global X will not be limited to using Global X ETFs in the Model Portfolios;

however, a Model Portfolio may have up to a 100% allocation in Global X ETFs."[14]

BlackRock is an example of how granular model portfolios can get. The firm offered 51 model portfolios as of June 30, 2021, which mostly have one of two objectives: target risk or income. Within those two buckets, they have models that only use passive funds, only use active funds, or blend both. They also have models that aim to maximize after-tax returns or are focused on attributes like environmental, social, and governance factors, or smart beta.

While ETF asset managers provide a description of how they go about conducting their fund choices, there is a large element of judgment involved. The ETF managers may have interests that conflict with those of investors who use model recommendations. Most ETF managers address their potential conflicts of interest in their ADV forms. First, an ETF issuer is subject to conflicts of interest in selecting affiliated ETFs because the profitability with respect to the ETF issuer or its affiliates are higher than its profitability by other ETFs. For example, the ETF issuers may also face a financial incentive to recommend their affiliated funds that have high fees and those unaffiliated funds that share the most solicitation fees. One ETF issuer, Global X, discloses the following conflict of interest in its ADV form: "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."[15]

Second, the advisor's implementation of the recommendations made in the model might be made 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 transaction execution than financial advisors' accounts. Equitable Investment Management Group describes this type of conflicts as follows: "Even though the Registrant [model provider] may provide its recommended changes to a model to Non-Discretionary Accounts and Discretionary Accounts at the same time, the Registrant may have already commenced trading before the manager of a

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

Non-Discretionary Account has received or had the opportunity to fully evaluate or to act on our recommendations. In this circumstance, the manager of a Non-Discretionary account may not be able to buy or sell investments in Non-Discretionary accounts at an advantageous time or price or in sufficient amounts to achieve the desired level of exposure, which could negatively impact performance and could result in Non-Discretionary accounts underperforming the Discretionary Accounts."[16]

In addition, subject to applicable law, an ETF issuer or its affiliates may, from time to time and without notice to the financial advisors, insource or outsource certain processes or functions in connection with services that they provide to the model recommendations. Such insourcing or outsourcing may give rise to additional conflicts of interest.

Models have fewer barriers to entry and cost less to launch than mutual funds and other vehicles. They, for instance, do not have to register with the SEC or pay a bank a fee to hold custody of assets because model providers do not hold the assets. Model providers are not required to disclose their past ETF model recommendations in a way that would allow their accuracy to be measured.

ETFs are pooled investment vehicles that can be bought and sold all day on stock exchanges, just like shares of public firms. Their performance is visible in real time, their strategy is detailed in public filings, their holdings are regularly disclosed, and their fees are publicly available. Nevertheless, different rules are applied for combinations of those ETFs. The rules governing "side-by-side comparisons" for ETF model portfolios are sparse, largely non-compulsory, and generally fall within the SEC's advisor advertising rules governing false or misleading statements. The tools to perform such a comparison may be available, but they generally exist behind expensive paywalls on sites such as Morningstar, and due to costs, they are largely inaccessible to many investors. Even on Morningstar, only 25% of model portfolios also have a representative track record in another vehicle, such as a separate account or a mutual fund; the

[16] https://adviserinfo.sec.gov/firm/summary/156933

rest report hypothetical returns that are not held to the same standards as other vehicles that are regulated by independent agencies like the SEC.[17]

1.2 Data

We combine the data from multiple sources. Our 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. Our sample covers a period from January 2010, when there is a sufficient coverage of models, to December 2020. The data set includes both active and inactive model recommendations.[18]

Our data set allows us to identify, for each model, when an investment product was first recommended, the period during which it remained recommended, and, if applicable, when the product was removed from a recommendation. Model providers may report their portfolios in different frequencies, ranging from monthly and quarterly to semiannually. We thus adjust the holdings to monthly frequency by assuming the holdings of a missing month are equal to the holdings of the closest subsequent quarter end.

The recommendation of model portfolios cover a range of asset classes, investment styles, and regions. We restrict our sample to model providers that have at least one ETF in their recommendations during a given month. More specifically, we focus on passive equity ETFs that hold US domestic stocks in their portfolios. Therefore, we exclude ETFs that are classified as non-equity, international equity, inverse, or leveraged, and active ETFs. The final sample contains 788 unique US domestic equity ETFs.

Table 1 provides the number of models, management companies, and recommended ETFs by year. The number of models is much lower during the early part of the sample.

[17]In the middle of 2021, Morningstar Analyst Ratings covered 43 model series and expect that to more than double by the end of 2021. Several model providers mention their ratings in their ADV forms. Also, Morningstar is launching the Morningstar Rating^{TM} for models, also known as the "star rating" in the fourth quarter of 2021.

[18]This data set does not 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 robo-advisors that mostly target retail investors, not financial advisors.

[Insert Table 1 about here]

There are two groups of ETFs recommended by the model providers in our sample: those affiliated with the model providers and those unaffiliated with them. We use two different Morningstar Direct data fields – "Branding Name" and "Management Company" – to track affiliation. Branding Name reflects the fund distributor, and Management Company is the name of fund management company. A fund is considered affiliated with a model if it shares a branding name or the name of a management company with the model provider.

Table 1 shows that the average number of ETFs per model recommendation has been decreasing from 6.84 to 3.99 during the sample period. We observe the opposite trend for affiliated ETFs. The average number of them has increased from 0.22 in 2014 to 1.40 in 2020.

Using Morningstar, we also obtain the assets under management (AUM), the monthly returns, the expense ratios, and turnover of the ETFs. To get daily trading price, volume, and share outstanding of ETFs, we merge Morningstar with CRSP by the ETF ticker and inception dates. In case of a missing ETF ticker or unsuccessful match, we then conduct fuzzy name matching and manually verify the matches.

Table 2 presents summary statistics of the ETF characteristics recommended by model providers at a given month of the sample relative to non-recommended ETFs. Our sample contains 39,118 ETF-month observations that represents 788 unique ETFs from 1,045 unique models from 94 companies. 417 unique ETFs have been recommended at least once during our sample period.

[Insert Table 2 about here]

Table 2 shows that recommended ETFs are significantly older than non-recommended ETFs, on average, by 2.8 years. They also tend to be almost ten times larger. The AUM of recommended ETFs and non-recommended ETFs are \$7.21 billion and \$0.78 billion, respectively. To analyze returns, we use net YTD returns and performance during the previous one year and previous three years. YTD return is the return of a fund since January of a year, we then deduct the average YTD return of funds of the same Morningstar category to get the net YTD return.[19] We measure the performance over the previous one year and three years by the percentile rank of returns among funds of the same Morningstar category. The table shows that recommended ETFs have better performance than non-recommended ETFs. Their net YTD return is 0.77%, which is significantly higher than -0.47% of non-recommended ETFs. Their prior return ranks are also significantly higher than the ranks of non-recommended ETFs. The return of recommended ETFs is significantly less volatile than the non-recommended ETFs. Return volatility is measured by monthly returns over a year.

2 Flows

In this section, we investigate whether model recommendations have an impact on the overall allocation of investors into ETFs and examine the sensitivity of these flows. While the investment opportunity set of the model is determined by the model provider (ETF issuer or strategist), no discretion is exercised by them. Financial advisors are not obliged to follow these recommendations. They could adjust their own portfolios by, for instance, not allocating capital to poorly performing affiliated funds.

2.1 Impact on ETF Flows

To explore how asset flows respond to model recommendations, we expand a flow-performance regression from Ben-David et al. (2021) by including a recommendation variable as a regressor.

Our flow measure is the percentage flow relative to the AUM in the ETF as of the end of the

[19] Morningstar categorizes funds based on their holdings. It includes four broad asset classes (US Stock, International Stock, Taxable Bond, and Municipal Bond), and 64 categories (for example, US Equity Large Growth, Sector Equity-Natural Resources, International Equity-Europe Stock, and Taxable Bond-High-Yield Bond).

previous month:

$$\text{Flow}_{i,t+1} = \frac{\text{AUM}_{i,t+1} - \text{AUM}_{i,t} \times \text{ETF Return}_{i,t+1}}{\text{AUM}_{i,t}} \times 100 \tag{1}$$

We are interested in measuring how flows respond to recommendations, controlling for past performance as well as for other ETF characteristics that are known to affect flows (namely, fees, size, age, and turnover). We therefore estimate the response of flows to recommendations using the following regression on monthly data:

$$\begin{aligned}\text{Flow}_{i,t+1} = {} & \alpha + \beta_1 \times \text{Model}_{i,t} + \beta_2 \times \text{Model}_{i,t} \times \text{Expense Ratio}_{i,t} + \beta_3 \times \text{Model}_{i,t} \times \text{Return Rank}_{i,t} \\ & + \beta_4 \times \text{Expense Ratio}_{i,t} + \beta_5 \times \text{Expense Ratio}_{i,t} \times \text{Sector}_i + \beta_6 \times \text{Return Rank}_{i,t} \\ & + \beta_7 \times \text{Return Rank}_{i,t} \times \text{Sector}_i + \text{Controls}_{i,t} + \gamma_i + \eta_t + \varepsilon_{i,t},\end{aligned} \tag{2}$$

where $Model_{i,t}$ is equal to one if ETF i is recommended by any model in month t; $Expense\ Ratio_{i,t}$ denotes the expense ratio of ETF i, measured in bps; $Return\ Rank_{i,t}$ is the percentile rank of ETF i's return in month t; $Sector_i$ is equal to one if the ETF is a sector ETF, we use the "US Category Group" data field in the Morningstar database to identify sector ETFs, and we consider the rest of ETFs to be broad based; γ_i is the fund fixed effect; η_t is the time fixed effect.

Table 3 reports the results from estimating Equation 2. Each column in the table represents a separate regression. The results show that model recommendation of ETF has significant positive effect on its future flows. This suggests that financial advisors respond to model recommendation by moving money in the direction implied by the recommendation. The estimates indicate that ETF experience flows between 1.10 and 1.26 percentage points higher per month following a fund's addition to a model recommendation, or while a fund is still recommended by at least one model. In the regressions, we successively include additional controls that only affect magnitudes marginally. Statistical significance is at the 5% level for all specifications.

[Insert Table 3 about here]

We also focus on the flow sensitivity to fees, as measured by expense ratio, and past performance, as measured by the percentile rank of ETF's monthly return. We explore whether investors show different sensitivity to fees and past performance to ETFs that are in recommendations than to ETFs that are not recommended. The results suggest that investor pay less attention to the fees of ETFs that are recommended by models, since the sensitivity to fees is less negative. Investors are usually sensitive to the past performance of passive ETFs, as documented by, among others, Ben-David et al. (2021) and Dannhauser and Pontiff (2021). The interaction of return rank with the model dummy indicates that flows are significantly less sensitive to the poor performance of recommended ETFs. It implies that investors may completely follow the recommendation of model providers and pay less attention to the quality of recommended ETFs.

Ben-David et al. (2021) document that investors in specialized ETFs are significantly less sensitive to fees and more sensitive to performance. To proxy for this effect, we also include the interaction terms between fees and sector ETFs and return rank and sector ETFs. Our results are similar to the results in their paper. The additional control variables indicate that the flows are lower for larger and older ETFs. We also include lagged flow, turnover, and flows of the past six months, and the results remain robust.

To sum up, the recommendation of model providers attract additional investor flows to the ETFs. Investors who chase these recommendations also behave differently, as they care less about both the price and quality of the ETFs.

2.2 Natural Experiment

Endogeneity issue arises if model providers select ETFs based on their expectation of the fund flows. They may favor the ETFs that are already popular among investors. Hence, they may choose to add these ETFs into their model recommendations in anticipation of increasing future inflows. To address this issue, we focus on a natural experiment to study the impact of exogenous deletions of ETFs from the recommendations on the flows to these ETFs.

The collapse of one of the largest ETF strategists in the US, F-Squared Investments, provides us a setting to test the causal relation between model recommendations and ETF flows. F-Squared Investment, as an investment advisor, started to offer ETF strategies in 2008. According to the SEC, 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. However, in December 2014, F-Squared was charged by the SEC with defrauding investors through false performance advertising about its flagship product. Later, in July 2015, F-Squared filed for bankruptcy.

Our sample contains 19 model recommendations offered by F-Squared. On average, each model recommendation holds 7.5 US domestic equity ETFs. We observe the holdings of each of them. The last available holdings of each portfolio ranges from December 2014 to June 2015. Therefore, we suspect that the F-Squared's model portfolios were gradually closed because of the firm's financial distress. The closure of the portfolio and thus the passive deletion of ETFs from models serves as an exogenous shock for us to test the impact of model recommendations on flows of ETFs.

For the test, we construct the treatment group as ETFs that were held by F-Squared models in December 2014. We define the deletion date as the month following the last holding appearance month. For example, if the last available holding data of Model A is in March 2015, we assume the ETFs in the basket of Model A were deleted in April 2015. We construct the control group by matching each treated ETF with other model ETFs in the same Morningstar category in the month preceding deletion. In the control group, we eliminate the ETFs that were deleted by any models in the following month.

Figure 1 plots the average flow for the treatment and control group around the F-Squared's model closure. The flows of both groups show similar pattern before the closure of the models in month zero. Following the closure of F-Squared models, treated ETFs experienced continued outflows until month three. It suggests that the ETFs experience consistent outflows after they are deleted from models. But this impact seems to be temporary.

[Insert Figure 1 about here]

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

$$\text{Flow}_{i,t+1} = \alpha + \beta_1 \text{Treatment}_i \times \text{Post}_t + \beta_2 \text{Post}_t + \text{Controls}_{i,t} + \gamma_i + \eta_t + \varepsilon_{i,t}, \tag{3}$$

where $Treatment_i$ is set to one for ETFs that were deleted by F-Squared, and zero for the matched ETFs. $Post_t$ is one for the months following the closure of F-Squared models. We consider a six-month window around the event.

Table 4 presents the results from estimating Equation 3. Since the experiment is about ETF deletion, we should interpret β_1 in an opposite way to Equation 2. The ETFs that are passively deleted from model portfolios receive fewer flows, by 6.35 percentage points, in the six months following the deletion than do other ETFs of the same investment category that are held 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 result is not driven by sector ETFs, as the coefficients before Fee $\times$ Sector and Return rank $\times$ Sector are both insignificant. The results also show that larger ETFs receive lower future flows.

[Insert Table 4 about here]

Next we test for parallel trends. Inference using the difference-in-difference rests on the parallel trend assumption, stating that treatment and control would have behaved similarly in the absence of treatment. Although, we provide evidence in support of the parallel trend of treatment group and control group before the treatment in Figure 1, we also test for it in the regression. We add Pre_t, an indicator which is equal to one for three months before the closure of F-Squared models, as well as an interaction term between $Treatment_i$ and Pre_t to Equation 3.

Column 2 of Table 4 presents the results of a specification that includes interactions of an indicator variable equaling one if the ETF was in F-Squared recommendation with time indicator variables. If treatment and control units behave similarly pre-event, we expect the interaction of the treatment indicator variable and the time interval before the event to be economically small and statistically insignificant. In line with the parallel trend assumption, being recommended by F-Squared models does not affect the flows to ETFs pre-event.

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

3 Self-recommendations and Future Performance

Model providers rebalance their holdings periodically by adding new ETFs and deleting others. In this section, we explore what determines the ETF recommendations by model providers. Specifically, we test whether model providers favor ETFs from their own management company. We define an ETF as *affiliated* if the ETF shares the model provider's branding name or has the same management company name. Otherwise, the ETF is *unaffiliated*.

3.1 Difference between Affiliated and Unaffiliated ETFs

We first look at the difference between affiliated and unaffiliated ETFs that are recommended by model providers. Since each model provider takes charge of several model recommendations, one ETF may be recommended by several model portfolios simultaneously. We thus only keep one observation if an ETF is recommended by several recommendations of same provider. Table 5 describes the characteristics of these ETFs.

[Insert Table 5 about here]

Our sample contains 34,024 company-ETF-month observations. 3,241 company-ETF-month observations correspond to affiliated ETFs and 30,783 to unaffiliated ETFs. Affiliated ETFs exhibit significantly worse past performance. The difference in net YTD returns between two groups is 67 bps and it is significant at the 1% level. They also perform worse than the unaffiliated ETFs in the previous one year and three years. The expense ratio of affiliated ETFs is 31.93 bps, higher than that of unaffiliated ETFs, at 26.09 bps. The difference is significant at the 1% level. Affiliated ETFs are significantly younger than unaffiliated ETFs. Moreover, affiliated ETFs also exhibit higher turnover and lower monthly return volatility. The size of affiliated ETFs, the AUM, is $12.02 billion and is significantly lower than that of unaffiliated ETFs at the 10% level.

3.2 Binary Choice Models of ETF Addition

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

$$prob(ADD_{c,i,t} = 1) = \Lambda(\beta_1 \mathrm{AF}_{c,i,t-1} + \beta_2 \mathrm{R}_{i,t-1} + \beta_3 \mathrm{AF}_{c,i,t-1}\mathrm{R}_{i,t-1} + \mathrm{Controls}_{c,i,t-1}), \quad (4)$$

where $ADD_{c,i,t}$ is an indicator variable that takes the value of 1 if ETF i is added to the models of company c during month t; function $\Lambda(z)$ is defined as $\Lambda(z) = exp(z)/(1+exp(z))$; $AF_{c,i,t}$ is an indicator variable that takes the value of one is ETF i is affiliated to company c in month t; $R_{i,t-1}$ is the percentile rank of returns of ETF i in the previous one year or three years, and we scale the rank by $1/100$; 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. Table 6 reports the results from estimating Equation 4.

[Insert Table 6 about here]

First, the chance to be added into recommendation list is significantly larger for affiliated ETFs than unaffiliated funds. The coefficient before the affiliation dummy is significantly positive at the 1% and 5% level when we use the performance measures of the previous one year and of the previous three years, respectively. The probability of addition is influenced by the prior performance and expense ratio of the fund. However, we find that affiliated ETFs experience the opposite impact of past performance and expense ratio to the addition probability that unaffiliated funds experience. For the unaffiliated ETFs, the odds ratio of the ETFs that performed the best is slightly higher than the odds ratio of the funds that performed the worst. But for the affiliated ETFs, if they had the worst performance in the past one year, the odds ratio is 1.01 (exp(0.01)) times higher than the odds ratio of the ETFs that performed the best. The results are similar when we use the performance measure of the past three years. It suggests that model providers have an opposite strategy in choosing affiliated ETFs and unaffiliated ETFs: they tend to recommend worse-performing funds among affiliated ETFs.

The results also show that the addition odds of expensive unaffiliated ETFs are lower than addition odds of cheap unaffiliated ETFs. In contrast, the addition odds of expensive affiliated ETFs are higher than that of cheaper affiliated ETFs. When the expense ratio of affiliated ETF increases by one bp, the addition odds increase by 3%. It implies that the model providers prefer cheaper ETFs when they choose among unaffiliated funds, but they are more likely to choose more expensive affiliated ETFs. It is consistent with our finding in section 3.1 that recommended affiliated ETFs generally charge higher fees but have worse performance than unaffiliated ETFs.

We also find that the size of the fund plays an important role in the addition probability. In either specification, 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 recommended ETFs and non-recommended ETFs in Table 2.

In contrast to the relatively frequent additions of new affiliated ETFs into model recommendations, we do not observe many deletions of affiliated funds from the models. Of the 34,024 company-ETF-month observations, we only discover 17 deletions of affiliated ETFs from models, and 324 deletions of unaffiliated ETFs. Because of the limited number of observations, we are not able to conduct a statistical analysis between affiliated and unaffiliated ETFs. However, the small number of deleted affiliated ETFs implicitly shows the favoritism of model providers toward affiliated funds.

3.3 Future Performance

The previous results suggest that on average, affiliated ETFs in model recommendations provide worse historical performance than unaffiliated ETFs. One potential explanation of this favoritism toward distressed ETFs is ETF issuers' private information. The model providers may know more about the affiliated ETFs. They may choose the affiliated ETFs because of positive information. In this section, we investigate the future performance of affiliated and unaffiliated ETFs in the model recommendations.

We form equally weighted portfolios of ETFs that are kept in and added to recommendations by model providers in each month based on their affiliation to the providers, which results in four portfolios. We then calculate two different kinds of returns in the portfolios: (1) abnormal return, α, of each portfolio generated by the Fama-French-Carhart four-factor model, the Fama-French three-factor model, and the CAPM model, respectively, using the monthly return of the subsequent 12 months; (2) net return of the following 12 months and 36 months, respectively. The net return is equal to the cumulative return minus the average return of ETFs of the same Morningstar category. The portfolios are rebalanced monthly.

Panel A of Table 7 reports the abnormal return, α, of the portfolios. First, note that the ETFs that are kept in the models exhibit low performance, regardless of their affiliation. They all generate negative alphas. The abnormal returns of ETFs that are added into models are insignificantly different from zero, except the negative CAPM alpha of affiliated ETFs. Therefore, the addition of new ETFs into model portfolios is likely not information driven. Within the group of ETFs that stayed in the models, the affiliated ETFs tend to perform worse than the unaffiliated ETFs. The CAPM alpha of affiliated ETFs of -25 bps per month is lower than that of unaffiliated ETFs at -12 bps. The difference between the Carhart and Fama-French Alpha is smaller, but the alphas of affiliated ETFs are still 3bps lower than that of unaffiliated funds, for both measures. It is consistent with our previous findings that model providers favor their own ETFs over others, even though the affiliated ETFs have worse performance than the unaffiliated funds.

Panel B of Table 7 shows the net returns of the portfolios in the following one year and three years, respectively. To reduce the impact of investing style on fund performance, we deduct the return of each ETF by the average return of ETFs that are in the same Morningstar category. Hence, net return shows the excess return of an ETF over its peers. In general, the unaffiliated ETFs perform better than the affiliated funds. For the following one year, the unaffiliated ETFs that stayed in the model generate 0.60% net return, while the affiliated funds lose 0.47% annually. The return of newly added affiliated ETFs is insignificant, and the return of unaffiliated ETFs is 0.68% and significant at the 1% level. The pattern of returns during the following three years is similar to that of the following one year.

The results in Table 7 imply that the decision to add or keep affiliated ETFs in the model is not information driven. The affiliated ETFs perform worse than the unaffiliated funds in both settings. The absolute returns and risk-adjusted returns of affiliated ETFs are both negative, suggesting that model providers do favor their own ETFs over unaffiliated funds.

4 Conclusion

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

Using data from Morningstar, we analyze recommendations of ETF issuers and strategists to third-party financial advisors over the period 2010 to 2020. We find that these recommendations have a large and significant effect on ETF flows. However, conflicts of interest seem to affect the quality of these recommendations. Asset managers tend to include their own ETFs. These affiliated ETFs, on average, have lower past returns and higher fees than unaffiliated funds. We also do not find evidence that the affiliated ETFs provide superior performance after they are recommended.

We leave it for future research to explore why financial advisors tend to follow these recommendations. We have several potential explanations in mind. First, financial advisors may not be able to fully judge whether these recommendations add value (Cookson et al., 2021). Second, financial advisors might use these recommendations to reduce their reputation concerns (Dasgupta and Maug, 2021). Third, they might still be better off using these recommendations than using none (Chalmers and Reuter, 2020).

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Table 1: Model recommendations, management companies, and ETFs

	Number of Models	Number of Management Companies	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	37	8	6.84	0.00	34.94	0.00
2011	80	18	5.46	0.01	34.60	0.06
2012	124	23	4.91	0.00	33.39	0.00
2013	147	25	5.39	0.00	39.98	0.00
2014	217	31	5.13	0.22	41.97	4.01
2015	246	33	4.32	0.48	36.65	5.89
2016	287	41	4.70	0.90	35.17	9.08
2017	397	45	4.31	1.37	33.39	11.48
2018	490	55	4.09	1.44	30.79	11.05
2019	709	61	4.12	1.34	29.93	11.75
2020	886	79	3.99	1.40	29.44	11.96
Panel B: Models with at least one Affiliated ETF						
2011	1	1	1.00	1.00	5.00	5.00
2014	21	1	2.29	2.29	41.49	41.49
2015	46	2	2.67	2.54	32.20	31.49
2016	74	6	3.58	3.50	35.69	35.23
2017	146	8	3.95	3.73	33.07	31.22
2018	181	9	4.18	3.90	32.43	30.02
2019	270	12	3.81	3.52	33.03	30.86
2020	337	15	4.25	3.67	34.83	31.44

Table 2: Characteristics of ETFs in the model and not in the model

This table reports the summary statistics of ETFs that are held or not held by models. *Fund Age* is the age of the ETF measured in years, *Fund Size* is the total assets under management measured in billions of dollars. *Return Std. Dev.* is measured by monthly return over prior one year. *Net YTD Return* is the year-to-date return (return of a fund since January of a given year) deducting the average year-to-date return of ETFs that share the same investment style. Past performance is measured by the performance rank percentiles over the prior one year and three years, respectively. T-statistics based on standard errors clustered at the ETF level are reported in parentheses. Significance levels are denoted by *, **, and ***, which correspond to the 10%, 5%, and 1% levels, respectively.

	Model ETF	Non-model ETF	Diff.
Net YTD Return(%)	0.77	−0.47	1.30***
			(8.75)
Prior 1-Yr. Perf.	52.76	47.48	5.28***
			(6.44)
Prior 3-Yr. Perf.	53.46	46.63	6.83***
			(5.47)
Expense Ratio (bps)	32.80	41.04	−8.24***
			(−6.23)
Fund Age (years)	10.35	7.52	2.83***
			(10.19)
Fund Size ($ bn)	7.21	0.78	6.42***
			(7.09)
Return Std. Dev. (%)	4.62	4.98	−0.36***
			(−4.16)
Turnover (%)	30.41	43.47	−13.06***
			(−5.66)
Observations	17,054	22,064	

Table 3: The effect of model recommendations on ETF flows

This table reports the impact of model recommendation to an ETF's flows. The dependent variable is $Flow_{i,t+1}$ which is defined as $\frac{\text{AUM}_{i,t+1} - \text{AUM}_{i,t} \times \text{ETF Return}_{i,t+1}}{\text{AUM}_{i,t}} \times 100$. The independent variable are $Model_{i,t}$, which is equal to one if ETF i is recommended by any model in month t; $ExpenseRatio_{i,t}$ denotes the expense ratio of ETF i, measured in basis points; $Ret.Rank_{i,t}$ is the percentile rank of ETF i's return in month t; $Sector_i$ is equal to one if the ETF is a sector ETF. The control variables include the lagged natural logarithm of the fund's AUM measured in billions of dollars, the lagged natural logarithm of fund age measured in months, lagged ETF flow, and lagged ETF turnover. Fund fixed effect and time fixed effect are both included. T-statistics are reported in parentheses. Significance levels are denoted by *, **, and ***, which correspond to the 10%, 5%, and 1% levels, respectively.

	Dependent variable: $\text{Flow}_{i,t+1}$			
$\text{Model}_{i,t}$	1.26**	1.21**	1.13**	1.10**
	(2.25)	(2.20)	(2.19)	(2.14)
$\text{Model}_{i,t} \times \text{Return Rank}_{i,t}$	−0.01	−0.01*	−0.01**	−0.01**
	(−1.60)	(−1.91)	(−2.22)	(−2.22)
$\text{Model}_{i,t} \times \text{Expense Ratio}_{i,t}$	0.02*	0.02*	0.02**	0.02**
	(1.81)	(1.93)	(2.06)	(2.11)
$\text{Return Rank}_{i,t}$	0.04***	0.04***	0.04***	0.04***
	(8.88)	(9.13)	(9.05)	(9.04)
$\text{Expense Ratio}_{i,t}$	−0.11***	−0.11***	−0.09***	−0.09***
	(−3.92)	(−3.81)	(−3.52)	(−3.41)
$\text{Return Rank}_{i,t} \times \text{Sector}_i$	0.06***	0.06***	0.06***	0.06***
	(8.89)	(8.89)	(8.87)	(8.89)
$\text{Expense Ratio}_{i,t} \times \text{Sector}_i$	0.08	0.07	0.04	0.04
	(1.16)	(1.08)	(0.78)	(0.77)
$\log(\text{Size}_{i,t})$	−2.00***	−1.91***	−1.84***	−1.85***
	(−8.63)	(−8.40)	(−7.57)	(−7.58)
$\log(\text{Age}_{i,t})$	−3.49***	−3.13***	−1.44***	−1.42***
	(−7.87)	(−7.22)	(−2.93)	(−2.90)
$\text{Flow}_{i,t}$		0.02	−0.00	−0.00
		(0.92)	(−0.23)	(−0.24)
$\text{Turnover}_{i,t}$				−0.01**
				(−2.36)
Past Flows (6 months)	no	no	yes	yes
Month-Year and ETF FE	yes	yes	yes	yes
SE clustered at month-year and ETF	yes	yes	yes	yes
Observations	52,699	52,288	48,458	48,458
Adjusted R^2	0.37	0.38	0.39	0.39

Table 4: 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 regression equation is $\text{Flow}_{i,t+1} = \alpha + \beta_1 \text{Treatment}_i \times \text{Post}_t + \beta_2 \text{Post}_t + \text{Controls}_{i,t} + \gamma_i + \eta_t + \varepsilon_{i,t}$, where $Flow_{t+1}$ is the percentage flow of ETF in month $t+1$, γ_i is the fund fixed effect; η_t is the time fixed effect. $Treatment_i$ 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 style as treatment ETFs. $Post_t$ is equal to one for the month after the deletion of treatment ETFs. T-statistics with robust standard errors are reported in parentheses. Significance levels are denoted by *, **, and ***, which correspond to the 10%, 5%, and 1% levels, respectively.

Dependent variable: $\text{Flow}_{i,t+1}$		
$\text{Treatment}_i \times \text{Post}_t$	-6.35^{***}	-6.70^{***}
	(-3.09)	(-2.76)
Post_t	-1.21	4.36^{***}
	(-0.87)	(2.22)
$\text{Treatment}_i \times \text{Pre}_t$		-0.06
		(-0.02)
Pre_t		5.89^{***}
		(3.72)
$\text{Expense Ratio}_{i,t}$ (bps)	0.61	0.03
	(0.42)	(0.02)
$\text{Expense Ratio}_{i,t}$ (bps) $\times$ Sector_i	-0.15	0.69
	(-0.10)	(0.42)
$\text{Return rank}_{i,t}$	0.04^{**}	0.04^{**}
	(2.07)	(1.97)
$\text{Return rank}_{i,t} \times \text{Sector}_i$	0.03	0.03
	(1.10)	(1.19)
$\log(\text{Size}_{i,t})$	-17.62^{***}	-19.01^{***}
	(-5.71)	(-6.02)
$\log(\text{Age}_{i,t})$	4.91	6.55
	(0.64)	(0.85)
$\text{Flow}_{i,t}$ (%)	-0.05	-0.05
	(-1.04)	(-1.02)
$\text{Turnover}_{i,t}$ (%)	0.01	0.03
	(0.23)	(0.80)
Month-Year and ETF FE	yes	yes
Observations	1,323	1,323
Adjusted R^2	0.29	0.30

Table 5: Characteristics of affiliated and unaffiliated ETFs

This table reports the summary statistics for ETFs that are affiliated and unaffiliated to a model provider. *Net YTD Return* is the year-to-date return deducting the average year-to-date return of ETFs that share the same investment style. Past performance is measured by the performance rank percentiles over the prior one year and three years, respectively. *Fund Age* is the age of the ETF measured in years, *Fund Size* is the total assets under management measured in billions of dollars. Return volatility is measured by monthly returns over a year. T-statistics based on standard errors clustered at the ETF level are reported in parentheses. Significance levels are denoted by *, **, and ***, which correspond to the 10%, 5%, and 1% levels, respectively.

	Affiliated	Unaffiliated	Diff
Net YTD Return (%)	0.35	1.02	−0.67***
			(−2.85)
Prior 1-Yr. Perf.	50.93	56.32	−5.39***
			(−3.76)
Prior 3-Yr. Perf.	51.68	57.82	−6.14***
			(−2.84)
Expense Ratio (bps)	31.93	26.09	5.84***
			(2.86)
Fund Age (years)	9.73	12.37	−2.64***
			(−4.94)
Fund Size ($ bn)	12.02	15.50	−3.48*
			(−1.74)
Return Std. Dev. (%)	4.74	4.45	0.29**
			(2.27)
Turnover (%)	37.97	23.85	14.12***
			(4.31)
Observations	3,241	30,783	

Table 6: Logit model of ETF additions to recommendations

This table reports coefficient estimates for the logit model $prob(ADD_{c,i,t} = 1) = \Lambda(\beta_1 \mathrm{AF}_{c,i,t-1} + \beta_2 \mathrm{R}_{i,t-1} + \beta_3 \mathrm{AF}_{c,i,t-1}\mathrm{R}_{i,t-1} + \mathrm{Controls}_{c,i,t-1})$, where $ADD_{c,i,t}$ is an indicator variable that takes the value of one if ETF i is added to the models of company c during month t; function $\Lambda(z)$ is defined as $\Lambda(z) = exp(z)/(1+exp(z))$; $AF_{c,i,t}$ is an indicator variable that takes the value of one if ETF i is affiliated to company c in month t; $R_{i,t-1}$ is the percentile rank of returns of ETF i in the previous one year or three years, and we scale the rank by $1/100$; 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. 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: $\text{Addition}_{i,t+1}$				
Affiliated_i	1.08^{***}	0.90^{**}	1.16^{***}	0.99^{**}
	(2.79)	(2.16)	(3.17)	(2.48)
Prior 1-Yr. $\text{Perf.}_{i,t}$	0.01^{***}		0.00^{*}	
	(4.22)		(1.94)	
Affiliated_i × Prior 1-Yr. $\text{Perf.}_{i,t}$	-0.01^{**}		-0.01^{**}	
	(−2.01)		(−2.05)	
Prior 3-Yr. $\text{Perf.}_{i,t}$		0.01^{***}		0.00
		(3.48)		(1.56)
Affiliated_i × Prior 3-Yr. $\text{Perf.}_{i,t}$		−0.00		−0.01
		(−1.14)		(−1.22)
Expense $\text{Ratio}_{i,t}$ (bps)	-0.04^{***}	-0.04^{***}	-0.01^{**}	-0.01^{**}
	(−10.77)	(−9.94)	(−2.56)	(−2.12)
Affiliated_i × Expense $\text{Ratio}_{i,t}$ (bps)	0.05^{***}	0.05^{***}	0.04^{***}	0.04^{***}
	(6.67)	(6.25)	(7.28)	(6.78)
$\log(\text{Age}_{i,t})$			−0.05	0.15
			(−0.55)	(1.26)
$\log(\text{Size}_{i,t})$			0.59^{***}	0.59^{***}
			(20.50)	(19.64)
Return Std. $\text{Dev.}_{i,t}$ (%)			−0.03	-0.04^{*}
			(−1.39)	(−1.90)
$\text{Turnover}_{i,t}$ (%)			0.00	0.00
			(0.70)	(1.17)
ETF Category and Month-Year FE	yes	yes	yes	yes
Observations	1,680,591	1,397,637	1,680,591	1,397,637
Pseudo R^2	0.10	0.10	0.15	0.14

Table 7: Future Performance

This table shows the returns of the ETFs in the future 12 months based on their statue and affiliation to models. Panel A reports the alpha generated by the Fama-French-Carhart four-factor model, the Fama-French three-factor model, and the CAPM model, respectively, using monthly return of the ETFs. Panel B reports the net return, which is defined as the cumulative return deducting the average cumulative return of ETFs of the same Morningstar category. At each month, we form equally weighted portfolios of ETFs based on the their affiliation to the model providers and whether the ETF is added ("Addition") or remained ("No Changes") in the model. Then we calculate the alphas and net returns of each portfolio, respectively. The t-statistics are reported in parentheses. Significance levels are denoted by *, **, ***, which correspond to the 10%, 5%, and 1% levels, respectively.

Panel A: Alphas

	No Changes		Addition	
	Aff.	Unaff.	Aff.	Unaff.
Carhart Alphas	−0.06***	−0.03**	−0.10	0.03
	(−3.01)	(−2.08)	(−1.65)	(0.75)
Fama-French Alphas	−0.07***	−0.04**	−0.05	0.03
	(−3.56)	(−2.25)	(−0.86)	(0.82)
CAPM Alphas	−0.25***	−0.12***	−0.37***	−0.06
	(−5.69)	(−5.48)	(−3.72)	(−1.41)

Panel B: Future Returns

	No Change		Addition	
	Aff.	Unaff.	Aff.	Unaff.
Future 1-Yr. Net Return	−0.47***	0.60***	−1.22	0.68***
	(−3.04)	(3.64)	(−1.65)	(2.66)
Future 3-Yr. Net Return	−0.05	2.74***	−2.02	2.30***
	(−0.24)	(22.46)	(−0.91)	(5.45)

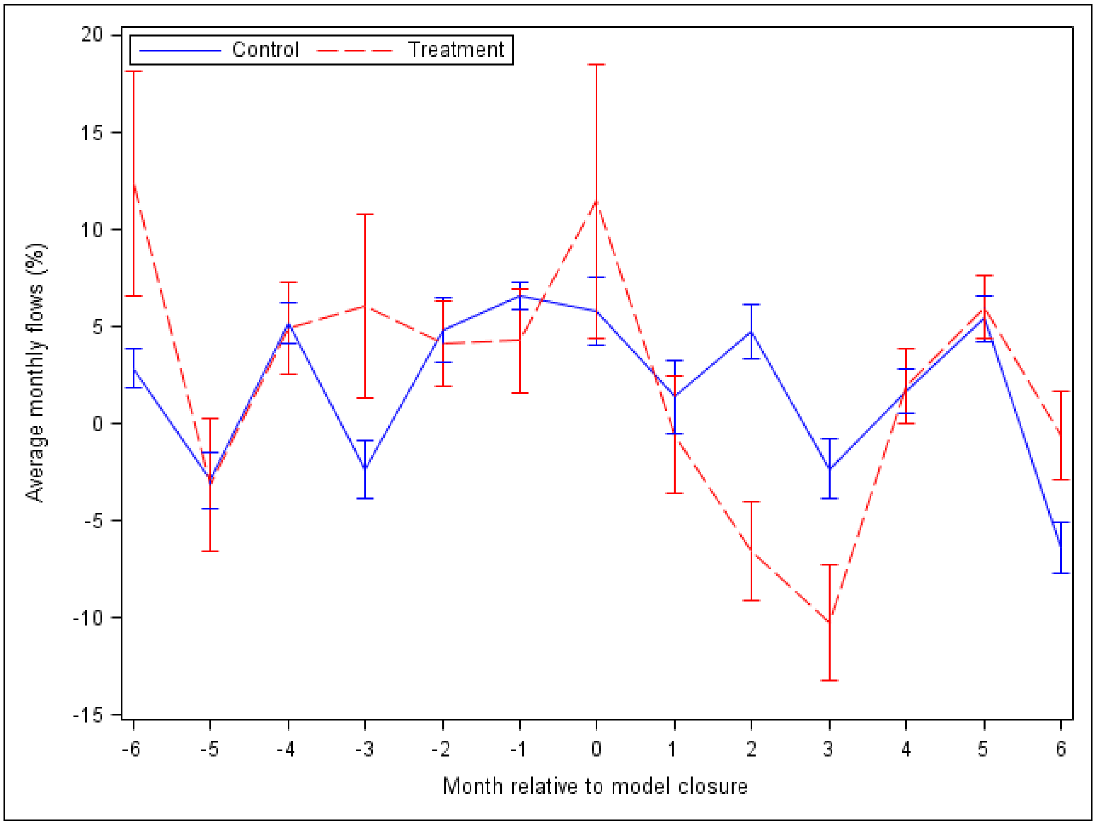

Figure 1: Average flows before and after the model closure
This figure shows the average monthly flows of the treatment and control groups in the natural experiment. The treatment group contains ETFs that were deleted from F-Squared models after December 2014. In case the ETF is held by several models, only the first deletion is considered. The control group contains ETFs that are held by models and are in the same Morningstar category as the treatment ETFs. Time 0 is the month of deletion of the treatment ETF, time -1 is the last month that treatment ETF appears in the holding of model portfolio.