Asset (and Data) Managers

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Abstract

This paper studies the direct impact of new technologies on the asset management industry. I show that technological innovations substantially improve fund managers' ability to target product demand and attract capital inflows, with implications for the industry's structure. Exploiting information from their websites' codes, I track when fund managers start collecting and analyzing customers' data using tools like Google Analytics or A/B testing. Funds adopting such technologies attract 1.5% higher annual flows and charge higher fees, with no improvement in performance. Results are concentrated in retail share classes and do not hold on placebo technologies. Additionally, funds expand product offerings and the effects decrease with competition, as more funds within the same fund-category adopt similar technologies. Overall, these results show that fund managers extract more value from financial markets after adopting data technologies –without sharing it with their own investors. This evidence high-lights that technological innovation in asset management extends beyond portfolio allocation decisions to impact how funds attract and retain capital.

Keywords: Asset Management, Data Economy, Information, FinTech

JEL Classification: G14, G23, L10

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1 Introduction

Asset managers are in the business of making predictions. It is not surprising then, that increasing availability of data and technological innovations are impacting the industry. For example, artificial intelligence or increasing computational power can affect the way managers select their assets. A growing literature studies how data abundancy and new technologies impact the asset allocation decisions of fund managers. In this paper, I take a different perspective. Asset managers focus on more than just predicting returns. The majority of their compensation is tied to the total assets under management (AUM) and the inflows they can attract¹. Therefore, a significant portion of their incentives is aligned toward increasing the total assets they manage. These observations raise several important questions: Do asset managers use new technologies to improve their ability to attract capital flows? How does this impact the structure of the industry and the distribution of rents between fund managers and investors?

These are important questions. Recent advances in digital technologies have substantially increased the ability of corporations to observe detailed information from interaction with customers. Understanding how such shifts in the information structure affect an industry's equilibrium is of first-order importance for practitioners and policymakers concerned with competitive and welfare consequences of a "data economy". The asset management industry offers an ideal setting to study these economic forces. Mutual funds operate in a regulatory environment that ensures high-frequency reporting of fund flows, fees, holdings, and performance. Investors in this market span from unsophisticated retail clients to large institutions, making it possible to observe heterogeneous responses to a shift in managers' data availability. Moreover, the industry's well-defined contractual structure allows to study the distribution of value added between fund managers and investors.

Most studies on the role of new technologies in asset management focus on their impli-

¹See Cen, Dou, Kogan and Wu (2024) for details on US mutual funds' contract structure. Ibert, Kaniel, Van Nieuwerburgh and Vestman (2017) find similar compensation structure in Swedish mutual funds.

cations for the portfolio management side of the industry. Yet, fund managers have strong incentives to predict investors' demand, and such innovations may improve their ability to do so. Little is known about this direct impact of technologies on the asset management industry. While it is widely recognized that investors learn managers' skills over time, the implicit common assumption in the literature has been that no economic forces work in the opposite direction –i.e., there is no learning channel from fund managers to investors. This paper helps bridge that gap by showing that asset managers learn from investors' data and recent technological innovations have direct implications for the asset management industry.

Answering whether asset managers use new technologies to attract more flows requires observing which (if any) fund managers adopt such technologies. A key challenge is that neither regulatory filings nor standard surveys record whether managers employ technologies to extract information from customers interaction. To address this issue, I exploit information from asset managers' websites to quantify their willingness to collect and analyze investors' data. Every website is made by different building blocks, called *technologies*. For example, e-commerce often install technologies that allow safe payments, like Apple Pay or PayPal. My strategy is to identify technologies designed to collect and analyze customers' data (e.g., Google Analytics) and the exact installation date on asset managers' websites. These data technologies allow storing digitized information about user interactions over websites' pages. For instance, they let run A/B testing (tools similar to Randomized Control Trials), learn about which channels are bringing more potential customers, audience overlap with competitors, detailed demographics, and search history. I obtain data from BuiltWith, an alternative data provider specialized in website profiling. BuiltWith scans website codes in search for clues that identify the usage of technologies, such as HTML tags. They continuously crawl several websites and keep track of the installation date (and eventual removal) of a website's technologies. Thus, observing the adoption date of data technologies by asset managers, I can proxy for when a given manager starts collecting investors' information.

I use a difference-in-differences framework to study how asset managers change after in-

stalling technologies that process customers' data. I compare changes in monthly inflows (pre- and post-adoption) within the same fund and month-category, controlling for commonly used covariates. This approach allows me to reduce concerns that time-invariant fund characteristics or common shocks are driving the results. First, I find that asset managers receive more flows after adopting a data technology on their website. Funds using technologies that collect and analyze investors' information receive 1.5% more flows each year. This effect is not negligible. The magnitude is comparable to inflows from flow-performance sensitivity associated with a 1.30% annual net alpha². The effect is driven by an increase in *inflows* with no significant impact on outflows, suggesting the results might be primarily attributable to change along the extensive margin –rather than the intensive margin.

Second, I find that funds charge higher expense ratios after installing data technologies. The effect is not driven by an increase in marketing and distribution fees. This result is important since it highlights that technological innovation does not always reduce search costs frictions³. Development in technologies such as smartphone apps might reduce investors' search costs, as they allow easier access to information at their fingertips. However, my results show that the impact of new technologies on the asset management industry is more complex than this. When *managers* learn about customer preferences and data, digital innovations allow funds to charge higher fees in equilibrium. Importantly, after adoption, there is no change in funds' net performance to investors, suggesting that managers appropriate all the monetary surplus, as measured by value added (Berk and van Binsbergen, 2015).

Third, I conduct a number of placebo and robustness tests to examine the empirical validity of results being driven by a learning channel. For example, I exploit the granularity of mutual funds data at the share class level to study heterogeneity of the effect. The data technologies I use in this paper generate signals from web traffic activity, which is arguably mostly informative about retail investors. Therefore, I compare the effect of data technology

 $^{^{2}}$ Results are robust to concerns over staggered difference-in-differences (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021).

³See, among many others, Thakor (2020); Basten and Ongena (2020); Hong et al. (2024); Argyle et al. (2022) for examples in which development in financial technologies reduce search costs.

adoption on retail share classes against institutional share classes, within fund. Consistent with this hypothesis, I find no effect on institutional share classes and a strong positive effect on retail share classes. Further placebo tests on adoption of website technologies *not* aimed to collect and analyze customers' data (e.g., JavaScript plugins) give insignificant results, suggesting the effect is unique to technologies designed to process customer data. Moreover, if the above results are driven by a learning channel, when many funds observe similar information, the marginal benefit of it should decline. Accordingly, I show that the positive effect of data technologies decreases as more funds within the same category adopt those technologies. Finally, if managers are learning about investor preferences through web traffic data, this should enable fund managers to better predict demand and fill gaps in their product offerings. Consistent with this conjecture, I find that at the fund family level, data technology adopters open more new funds than non-adopters in the period following adoption.

The above results do not warrant a causal interpretation, since the adoption of data technology is a choice made by asset managers. For example, even though I find no evidence of pre-treatment trends, managers might still install those technologies when they expect higher demand for their products. Similarly, assuming time-varying managerial skills, managers' adoption might be correlated with an increase in their skills (e.g., training in general data analytics). In this setting, asset managers' endogenous choice makes it challenging to identify a causal link. To alleviate endogeneity concerns, I use variation in the information that funds can extract from web traffic data, which is plausibly unrelated to fund flows. Specifically, I exploit the public release of TensorFlow, a widely used open-source machine learning (ML) library that significantly increased the availability of ML worldwide⁴. Google's release of TensorFlow in November 2015 dramatically increased predictions' precision where large amounts of data are available. For example, Uber and Airbnb directly integrated TensorFlow to develop their ML algorithms for rider-driver matching and pricing models,

⁴See, for example: wired.com/[...]/google-open-sources-its-artificial-intelligence-engine.

among other things. Intuitively, if the widespread availability of ML allow to extract more informative signals from data, the effect of data technology adoption, should increase post TensorFlow release. I confirm this conjecture by estimating the additional effect of data technologies after the shock, removing from the analysis fund managers who adopt after TensorFlow's release. The impact of data is 30% larger after the release of TensorFlow, which plausibly allows extracting more precise signals from customers' data. Furthermore, I exploit cross-sectional heterogeneity *before* TensorFlow's release to confirm the intuition behind this result. I construct two proxies for funds' availability of data when TensorFlow is released: (i) the number of months between the fund's adoption of a technology and November 2015, and (ii) the number of different data technologies installed. These two measures serve as proxy for the amount of data available, when TensorFlow is released (i.e., (i) proxy for the time series of customer data collected up to TensorFlow's release, and (ii) proxy for the cross-sectional size of the dataset). Using a difference-in-differences specification with (i) and (ii) as continuous treatment intensity, I show that funds with larger datasets benefit more from TensorFlow's release. Importantly, these results do not assume that all funds must use ML algorithms to analyze their customers' data, as this setting is similar in spirit to an intent-to-treat (ITT) specification.

I entertain several alternative explanations for my findings. One rationale behind the results might be that funds adoption of new technologies correlates with a superior ability to generate performance. Although I control for past performance across all specifications and the results on retail share classes (with no effect on institutional share classes within same fund) is inconsistent with this hypothesis, I formally test and reject this conjecture using different measures of risk-adjusted performance. Another plausible explanation is that fund managers may not be learning about investor preferences, but they are *persuading* them. For example, it might be that fund managers' adoption of data technologies is correlated with a re-branding of the fund. This mechanism would align with results being purely driven by obfuscation and marketing (Mullainathan et al., 2008; Ellison and Ellison, 2009). If this

were true, one key prediction would be that fund flows should be less responsive to a change in fees after adopting data technologies. Nevertheless, I reject this hypothesis, as fund flows are not less responsive to fee changes after technology adoption but rather more elastic.

Overall, my findings suggest that the impact of new technologies on the asset management industry is not limited to asset allocation. These results have important implications. For example, larger asset managers might disproportionately benefit from the bigger amount of data they can collect relative to competitors. On a similar note, this trend can affect managers' incentives. The efficiency of the asset management industry hinges on investors' ability to identify good funds and allocate capital to them. Using data, managers may reach their AUM capacity without fully aligning their incentives with investors'.

Related Literature. This paper contributes mainly to three strands of literature. First, it contributes to the growing literature on the role of new technologies in financial markets. Existing research studies the effect of these technologies in financial forecasting (e.g., Chi, Hwang and Zheng, 2024; Coleman et al., 2022; Dessaint, Foucault and Frésard (2024); van Binsbergen, Han and Lopez-Lira, 2022), stock market quality (e.g., Martin and Nagel, 2022; Farboodi and Veldkamp, 2020; Dugast and Foucault, 2024), households (e.g., Mihet, 2022; Rossi and Utkus, 2024; D'Acunto and Rossi, 2023) and capital allocation (Abis, 2022; Bonelli, 2024; Birru et al., 2024; Bonelli and Foucault, 2024). I study the effects of new technologies on asset managers' capital collection and their consequences on the industry structure. My results show that fund managers can use data technologies to gather and analyze investors' information and increase their inflows. In that sense, this work also relates to studies on the impact of technologies on the financial industry more broadly (Abis and Veldkamp, 2023).

Second, this paper contributes to the literature on the industrial organization of the asset management industry.⁵ Hortaçsu and Syverson (2004) show that investors' search costs are crucial to explain why homogeneous S&P500 index funds charge different fees. Intuitively,

 $^{{}^{5}}$ Gârleanu and Pedersen (2018) link the efficiency of asset prices to the efficiency of the market for asset management services. These findings bridge the (in)efficiencies in both markets and emphasize the importance of the asset management industry for asset prices.

if investors face costs when searching for managers' products, their choice will not necessarily be to buy the best option available. They will pick the option within a subset of all available products, limiting competition and generating price dispersion even in homogeneous product markets. Roussanov, Ruan and Wei (2020) explore the role of mutual funds' marketing and distribution expenditures in a market with search costs. Their results highlight the importance of mutual funds' marketing for attracting investors' capital⁶ (Sirri and Tufano, 1998; Reuter and Zitzewitz, 2006). According to this strand of literature, technological improvement will reduce search costs frictions and increase the industry's competition. More recently, Obizhaeva (2024) finds that ETFs attract more flows when advertising on online search engines. Within this literature, a few papers consider the strategic product market choices by asset managers (e.g., Massa, 2003; Betermier et al., 2023; Cvitanić and Hugonnier, 2022; Kostovetsky and Warner, 2020; Bonelli, Buyalskaya and Yao, 2024; Loseto and Mainardi, 2023). In these works, fund families change their product menus to reduce investors' switching costs or to differentiate themselves from others. To the best of my knowledge, this paper is the first to investigate whether asset managers collect and analyze customers' data to improve their ability to attract flows. These findings provide a framework for thinking about managers learning from investors' demand to optimize their product menu (offering vertical differentiation, expanding the product space or changing fee structure).

Third, this paper contributes to the literature on the role of data in the economy (e.g., Jones and Tonetti, 2020; Cong et al., 2020; Brynjolfsson and McElheran, 2016; Goldfarb and Tucker, 2019). Chung and Veldkamp (2024) review this growing literature in detail. The main insight is that the increasing amount of digitized information is valuable for economic agents, and a no-data equilibrium is different from a data economy (Farboodi and Veldkamp, 2023). Although digitized information itself might not be different from simple information, what is different is the enormous amount of data points available and the sources from which

⁶This literature intersects with research studying what drives investors' flows to asset managers and their effect on asset prices (e.g., Dou, Kogan and Wu, 2024). See Christoffersen, Musto and Wermers (2014) for a survey.

agents extract those information. I show that investors' data are part of an asset manager's stock of knowledge and help funds cater to investors' demand. Fund managers can collect and analyze useful information about prospect investors from web traffic on their own websites. Therefore, valuable data for asset managers are not only datasets for identifying investment opportunities (Farboodi et al., 2021, 2024; Bonelli and Foucault, 2024), but customers' data also represent a crucial part of managers' information set.

2 Hypotheses Development

Traditional models of competitive markets for asset management services (e.g., Berk and Green, 2004) assume investors learn fund managers' skills observing their risk-adjusted performance over time. However, the other side of the learning channel is silent. In other words, whether managers do or do not have information about investors' behavior and preferences is of second- or third-order importance in determining the industry equilibrium. Appendix A describes a simple economic framework in which customers' information are relevant to determine the equilibrium of the industry. In this section, I summarize the main intuition and define the main hypothesis.

Consider an industry with two identical funds, A and B. Suppose investors have heterogeneous preferences about which type of product they want to buy, or their preferred distribution channel. For example, investors based in Boston may be more open to buy a fund their financial advisor advice them, whereas investors in Seattle might prefer funds they lookup online or their friends' advice. If funds A and B have the same information about investors' tastes, they will offer the same product and compete. However, if fund A observes a signal about investors' behavior, it might benefit from such information, offering a product more aligned with their preferences. Thus, it is natural to expect that funds with more information about investors would attract more flows, all else equal. Formally, the first empirical question that I address is whether adoption of technologies aimed to collect and analyze customer data has explanatory power for fund flows. Intuitively, as funds with data technologies in place may offer products closer to a larger mass of customer preferences, they will collect more capital. Therefore, my first hypothesis posits that funds receive higher flows after adopting a data technology (i.e., after collecting signals on investor preferences).

Hypothesis 1. (Flows and Data Technologies)

Asset managers with more information about investor preferences receive a larger share of the total flows to the asset management industry.

The second hypothesis concerns product prices, i.e., fund fees. When a fund's product offering is closer to a larger mass of (heterogeneous) investor preferences, those consumers are willing to pay more for the product (e.g., Salop, 1979; Lancaster, 1966; Pellegrino, 2024 among many others). Thus, my second hypothesis is that fund managers that know more about customer preferences can charge higher fees in equilibrium.

Hypothesis 2. (Expense Ratio and Data Technologies)

Funds with more information about investor preferences charge higher fees compared to competitors.

Interestingly, in a setting where the fee set by funds without data technologies is equal to investor search costs (e.g., as in Gârleanu and Pedersen, 2018), adoption of data technologies increase fund fees dispersion in a given product market. Thus, the dispersion in fees charged by funds in equilibrium can remain large even though search cost frictions decline. This is also consistent with what we have observed empirically in the past years. Even though search cost frictions have arguably been declining (e.g., because of cheaper internet access), the dispersion in fund fees within a given category did not decrease at all. Figure C.2 in the Appendix shows the fee dispersion within fund categories from 1995 to 2022. In this modern sample period, the dispersion in fund fees has been remarkably stable, which is at odds with theories purely based on search cost frictions. This mechanism is consistent with results in Bonelli et al. (2024) and reminiscent of Menzio (2023).

While this examples abstract from some important considerations, it illustrates how data

technology can help funds to attract capital. Asset managers with more information about investors' tastes can collect more flows and charge higher fees at the same time.

Fees, Redemptions, and Number of Funds. The availability of data technologies to inform managers on investor preferences have a few additional testable implications on asset managers. First, if a data technology informs managers about their investors' preferences, it may enable to maintain a lower cash buffer during bad times (when expected returns are higher but redemption volatility is large). Intuitively, funds with better knowledge of their customers have lower uncertainty about fund liquidation. Thus, when more investment opportunities are available (in states of the world with higher expected returns) managers may face less redemption uncertainty and maintain a lower cash buffer in their portfolios. On a similar note, funds should hold more illiquid assets when they face less redemption risk, consistent with more "committed" capital (Gómez, Prado and Zambrana, 2024).

Second, the information advantage gained through investors' data may influence product development strategies. For instance, suppose funds predict a surge in demand for thematic products. In that case, they might be better positioned to timely offer those funds to investors and increase their product offerings accordingly⁷.

3 Data and Measurement

In this section, I describe the data and report a series of new facts on asset managers' adoption of data technologies.

3.1 Data

I focus on US mutual funds and ETFs from March 1993 to December 2022. My main data sources are the CRSP Survivorship Bias-Free Mutual Funds dataset and Factset, to identify

⁷Ben-David et al. (2022) rationalize the increase in offerings of thematic products as "competition for attention". In their paper, ETFs compete on either price (fees) or attention (specializing in the product space). While their findings align with this paper's results, I provide another perspective on the proliferation of thematic funds.

share classes of the same fund. I also use Thomson Reuters⁸ (s12) holdings, and information from N-SAR filings reported at the SEC. I merge CRSP/Factset by *cusip*, which identifies unique financial securities and is not re-assigned over time. I follow Berk and van Binsbergen (2015) as closely as possible in cleaning CRSP funds' data. I summarize here the main steps and provide thorough details in Appendix B. I select all US equity mutual funds and ETFs. I adjust all AUM numbers by inflation (in January 2000 dollars). I remove observations dated before the fund's first offer date to reduce incubation bias concerns (Evans, 2010). I also drop funds with less than two years in the sample and before their total (inflation-adjusted) AUM reaches \$5 million for the first time (Berk and van Binsbergen, 2015). CRSP data are available at the share class level; that is, different share classes belonging to the same fund are reported separately. Therefore, for each month I aggregate share classes at the fund level, summing up the AUM of all subclasses and weighting all other variables (e.g., fees, returns) by lagged AUM. The sample start date (March 1993) is dictated by the limited availability of AUM before that date (see Pástor, Stambaugh and Taylor, 2015). The final sample includes 7,900 funds (7,649 equity mutual funds and 251 ETFs) and 987,242 fund-month observations. My sample is somewhat larger than comparable samples using CRSP mutual funds data. The reason is that I do not remove index funds, institutional share classes, sector funds, or funds that allocate less than 80% of their portfolio to stocks. I estimate funds' alphas using rolling-window regressions from monthly returns in the past 24 months. The holdings' sample starts in 2004:Q2, because the SEC began requiring quarterly holdings disclosure in May 2004, following the adoption of Rule 30b1-5.

Following prior literature (e.g., Lou, 2012), I compute the investment flow to fund i in month t as

$$Flow_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1} \cdot (1 + r_{i,t}) - MRG_{i,t}}{AUM_{i,t-1}} \times 100,$$
(1)

⁸Previous research (e.g., Shive and Yun, 2013) reports a discontinuity in Thomson Reuters (s12) mutual funds holdings coverage after 2008, when compared to CRSP holdings. A common solution in the literature has been to use s12 holdings before June 2008 and CRSP thereafter. However, Thomson Reuters seems to have solved this issue in later vintages (Appendix Figure C.3). Thus, I prefer not to append different data sources and use the updated s12 holdings throughout the sample.

where $AUM_{i,t}$ is assets under management (Total Net Assets) of fund *i* in month *t*, $r_{i,t}$ is the monthly (gross) return, and $MRG_{i,t}$ is the increase in AUM due to fund's mergers happening in month *t*. Accounting for $MRG_{i,t}$, I avoid to misattribute funds' mergers as inflows. Finally, I winsorize all variables at the 1% and 99% level.

Table 1 about here

Table 1 presents summary statistics for all fund-months observations in my sample. The distribution of AUM is rightly skewed, as is common in the institutional investors' literature. The average expense ratio is 1.13%, with 0.28% attributable to marketing and distribution expenses (12b-1 fees). On average, funds in my sample have statistically insignificant 0.12% outflows each month and net abnormal returns (after expenses) are zero or negative on average, consistent with evidence for the US.

3.2 Data Technologies

To identify asset managers' willingness to collect data, I exploit information contained on their websites. Specifically, I use the website's code to detect whether asset managers adopt technologies for storing and analyzing investors' web traffic data. Web traffic data are widely used in several industries to understand customers' behaviors and preferences. Therefore, this is a good laboratory for studying the role of customer data in asset management.

Every website is made by different tools that work as building blocks. These building blocks are typically called *technologies*. For example, installing Google Maps technology allows a website to display an interactive map on its pages (e.g., to show store locations). Other technologies, like Adobe Analytics, are aimed to collect and analyze web visitors' data. I obtain technologies' adoption data from BuiltWith, an alternative data provider, and use the adoption date of analytics technologies as a proxy for managers' willingness to collect customers' data. BuiltWith analyzes websites' source code and searches for specific patterns, such as HTML tags, that identify the presence of technologies. They continuously crawl websites to capture installed technologies, starting January 2000. Therefore, I observe the exact month a website installs (and eventually removes) a technology. Henceforth, I define *data technologies* as those aimed to collect and analyze visitors' data, such as Google Analytics or Adobe Analytics. These tools are specifically designed to gather or generate signals from users' data. My goal is to study whether the ability to collect capital differs between asset managers adopting data technologies and non-adopters.

A legitimate concern about using website technologies as a proxy for the willingness to collect and analyze customer data might be that the hosting provider pre-determines the adoption choice. For example, the same set of technologies could be installed by default on all funds' websites registered using AWS Web Hosting. In this case, the adoption would not be a fund's choice but rather a hosting provider's choice, undermining the idea that data technologies proxy for a fund's willingness to collect data. To ensure this is not the case, I collect the hosting service used by all websites in my sample. Then, for each hosting-month group, I compute the average cosine similarity in website technology adoption within a group. The cosine similarity measures the overlap between two vectors. Intuitively, if two websites using the same hosting provider in a given month share the same set of technologies, the cosine similarity equals one. When the cosine similarity within hosting-month group is lower than one, the websites installed different technologies. In Appendix Figure C.1, I show the histogram of cosine similarities within hosting-month groups in my sample⁹. The technology overlap for websites using the same hosting service in a given month is almost always below one (mean 0.29). Thus, website technology adoption is unlikely to be a choice entirely made by hosting services.

I merge BuiltWith data with all funds' websites from CRSP. Moreover, since CRSP reports funds' websites starting January 2008, I hand-collected information on the website registration date from whois.com, and back-fill a fund's website until its registration date¹⁰.

 $^{^{9}}$ For comparison, Appendix Figure C.1 also reports the distribution of cosine similarity for a simulation in which the adoption of technology within hosting-group is randomly assigned.

¹⁰This procedure marginally increases the number of technologies' adoptions in my sample (see Figure 1). However, it ensures I don't misclassify funds as non-adopters before January 2008.

Figure 1 and Table 2 about here

Figure 1 shows the adoption of data technologies in my sample of funds. The blue area represents the total number of funds with at least one data technology on their website each month. The red line shows the percentage of funds adopting data technologies. A few early adopters started employing these technologies since 2006-2007. However, the big shift in data technology adoption occurred in 2012, when the percentage of funds with such technologies grew from 15% to 30% in the cross-section. This increase is concurrent with a major release of Google Analytics by Google, which is still the leading data technology provider nowadays. Data technologies' adoption in asset management surged significantly after 2012 and gradually stabilized after 2017. As of December 2022, as many as 75% of asset managers in my sample (more than 2,000 unique funds) have adopted technologies to collect visitors' web traffic data.

In Table 2 I report the leading data technologies by adoption, as of end-of-sample. Google Analytics accounts for the lion's share of adoption, with around 60% of funds installing it¹¹. Among other leading technologies, I find Omniture Test & Target, used for A/B testing¹², and LiveRamp, which helps the storage of big data. Overall, all technologies in Table 2 are used to collect or generate informative signals about web visitors' preferences. This features are not limited to the most common data technologies used by asset managers in my sample. Appendix Figure C.4 shows the word cloud built from descriptions of all data technologies installed by asset managers.

Technology Diffusion in the Asset Management Industry. The diffusion of technological innovation is critical for understanding growth and improvements in several industries (Barro and Sala-I-Martin, 1997). The dynamic of technology adoption in the asset management industry is particularly important, as it might inform us about the dynamics of information diffusion. For example, technology diffusion (and information) may spread

¹¹Appendix C.2 ensures the results are not entirely driven by Google Analytics (see Tables C.7 and C.8).

 $^{^{12}}A/B$ tests are tools similar to RCTs, which are increasingly used in several industries. They allow to randomly split web traffic audience and study several alternatives of products' bundles, pricing, etc.

among peers within a particular fund style (e.g., among competitors) or geographically (e.g., within a given state or city through social interactions). Given that precise data on technology adoption are typically not readily available (Stokey, 2020), I briefly examine how data technology diffuses among asset managers. I explore whether adoption is driven primarily by geographic location or fund category by regressing the probability of installing a data technology, on the (lagged) adoption rate within a given geographic cluster or fund category. In particular, I define the adoption rate in a fund category for month t as the percentage of funds within that category with data technology in place as of month t. Similarly, I define adoption rate within US states, cities, and zip codes. Then, I regress the probability to adopt data technology on the lagged adoption rate within fund category and geographic location, using a probit/logit specification¹³. The results are in Appendix Table C.9. Interestingly, the adoption rate within fund style is never significant in predicting the probability of adopting data technology in the subsequent month. On the other hand, adoption rates at the state, city, and zip code levels consistently show a positive relationship with the probability of installing data technology. This result is in line with previous research on the information diffusion among asset managers (Christoffersen and Sarkissian, 2009; Cujean, 2020). While it is important to emphasize that technological adoption differs fundamentally from the diffusion of *ideas* and information, these results suggest a potential relationship between technology and information diffusion in asset management. Clearly, this evidence is only suggestive and by far not conclusive. Exploring how technology adoption spread in the asset management industry remains a relevant area for future research.

4 Empirical Findings

In this section, I use information on asset managers' adoption of data technologies to explore the impact of new technologies on the industry. Guided by the hypothesis in Section

¹³To avoid double counting, I exclude all observations after the first adoption month from the logit/probit regression. Given the persistence in technology use after initial adoption, this correction is important.

2, I first examine the effect of data technology adoption on fund flows and fees. Then, I examine ancillary results consistent with fund managers extracting useful information from customers' data.

4.1 Funds Flows and Data Technologies

The first main hypothesis (Hypothesis 1, Section 2), argues that if data technology allows an asset manager to collect signals on investors' preferences, it will ultimately be reflected in the fund's flows. Therefore, I first study whether funds receive more capital after adopting a technology analyzing web traffic data. For each fund i and month t, I define a dummy variable DATA_{*i*,*t*} equal to one if the fund has at least one data technology in place in that month. Then, I estimate the following baseline specification:

$$Flow_{i,t+1} = \alpha_i + \eta_t + \theta \text{ DATA}_{i,t} + \beta' \boldsymbol{X}_{i,t} + \varepsilon_{i,t+1},$$
(2)

where $Flow_{i,t+1}$ is the fund *i*'s flow in month t+1, defined in equation (1). α_i and η_t are fund and time fixed effects, respectively, and $X_{i,t}$ is a set of control variables. The control variable vector contains fund size (logAUM), performance, (log) age, expense ratio, turnover, and monthly flows. I proxy for fund performance with the annual CAPM alpha, as it is the closest model to the one investors use to make capital allocation decisions (Berk and van Binsbergen, 2016). Results are similar using other measures such as Fama-French 3- or 5-factors alpha (see Appendix C.2). The main coefficient of interest is θ . Importantly, including fund and time fixed effects implies that identification of θ comes from variation in flows before versus after data-adoption, relative to the same change for other funds without data technology. Standard errors are clustered at fund and month-levels¹⁴.

Table 3 about here

 $^{^{14}}$ As funds might share the same website within the fund family (on average, a fund family has 1.30 websites), for some funds the "treatment" is at the fund family level. To ensure the results are not driven by within-family cross-sectional dependence, I verify the results hold two-way clustering at fund family-month levels.

Table 3 reports the main results from regression (2). I omit coefficients on control variables for brevity¹⁵. The first row shows the coefficient on the dummy variable DATA_i. The baseline result of 0.14 (t-stat 3.39) in column (1) suggests that funds adopting technologies aimed to store and analyze web traffic data are associated with larger fund flows. The coefficient implies a 0.14% (1.68%) larger monthly (yearly) inflows for data-driven funds after adoption. In columns (2) and (4), I include category×time fixed effects to account for any category-specific shift in a given month. The coefficients are consistent with the baseline specification in equation (2) (t-stat 3.14), suggesting that results are not driven by one category. I further address the concern that results might be driven by funds marketing and sales expenditures. If adoption of data technologies is associated with a fund's re-branding or increasing marketing efforts, my findings might reflect the effect of marketing in attracting fund flows (Sirri and Tufano, 1998; Roussanov, Ruan and Wei, 2020). To reduce concerns that these results are purely driven by marketing, in columns (3) and (4), I include 12b-1 $\text{Fees}_{i,t}$ in the set of covariates, which represent marketing and distribution expenses incurred by the fund. As expected, marketing and distribution fees are positively related to fund flows (second row). However, the effect of marketing on flows does not explain the coefficient on data technologies (t-stat 3.47). Therefore, funds adopting data technologies experience larger fund flows above and beyond the role played by marketing efforts¹⁶.

Moreover, as the adoption of data technologies is staggered over time, in Table C.1 I verify these results are robust to recent critiques on staggered difference-in-differences (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). The results are qualitatively and quantitatively unchanged. Notably, the magnitude of the estimated coefficient for θ and its t-stat remains nearly identical across all specifications. Indeed, in my setting, the total weight attached to "forbidden comparisons" in staggered

¹⁵All controls enter with the expected sign across all specifications, e.g., positive flow performance sensitivity (Sirri and Tufano, 1998; Pástor et al., 2015; Franzoni and Schmalz, 2017). For comparison with effects on flow-performance sensitivity, Appendix Table C.2 shows detailed results.

¹⁶In Section 5.2, I provide further evidence that my results are unlikely to be explained by re-branding or marketing.

difference-in-differences (Goodman-Bacon, 2021) is only 8%. This is because my sample starts several years before the first adoption of data technology (treatment), which allows precise estimates of group effects (Gardner et al., 2024). A similar argument applies for period (time) effects.

The fund flows described in equation (1) represent *net* flows, which capture the difference between inflows and outflows for fund *i* during month *t*. To further investigate the impact of data technology on fund flows, I exploit information from SEC regulatory filings (NSAR), which require funds to report their monthly inflows and outflows separately. The NSAR sample runs from January 2006 to June 2018, at which point NCEN filings replaced NSAR. For additional details on these SEC regulatory filings, see Evans et al. (2024). Appendix Table C.3 shows the results for fund inflows and outflows, separately. In line with my Hypothesis 1, funds experience larger (new) inflows following the adoption of data technologies (columns (1) to (3)), while there is no significant difference in the funds' outflows post-adoption. This result suggests the effect may primarily be product of a change in the extensive margin (e.g., funds attracting new investors).

To study the dynamic of the effect of data technologies on flows, I interact the coefficient of interest in Table 3, with event-time dummies for each month before and after adoption. Figure 2 shows the estimated coefficients with 95% confidence intervals. Importantly, there is no evidence of significant pre-trend before installing a technology. Moreover, the effect of data technology on fund flows is persistently significant after 8 months from adoption.

Figure 2 about here

In Appendix C.2, I run tests for the parallel trends assumption, implicitly behind the identification in equation (2), and balance covariates. I find no evidence of statistically different pre-trends (Table C.4) or imbalanced covariates before adoption (Table C.5).

Taken together, these results support the view that data technologies help asset managers attract more capital. Funds adopting data technology are associated with larger inflows after adoption, and this result goes beyond the role of marketing expenditures.

4.2 Increase in Expense Ratio

My second hypothesis in Section 2, is that fund managers with more data about customer preferences should charge higher expense ratio, all else equal. For example, if these technologies allow managers to offer funds closer to investors' personal preferences, they might elicit a higher willingness-to-pay and increase fees.

Interestignly, theory of the industrial organization of asset management predicts that equilibrium fees are determined by investors' search costs (see Hortaçsu and Syverson (2004); Gârleanu and Pedersen (2018); Roussanov et al. (2020), among others). A key prediction in these models is that when investors' search costs decrease, fees should decrease too. Intuitively, with lower search costs, investors can contact more managers, identify good ones, and the economy approaches the first-best with no price dispersion and equilibrium fees equal to the fund's marginal cost. According to these models, new technologies should reduce fees for financial services (e.g., FinTech lending). However, the data technology I study in this paper differs from traditional financial technology. Data technologies do not facilitate information acquisition for customers but for asset managers. Thus, the prediction on funds' fees might be the opposite of traditional financial innovation studied in the literature. When fund managers better align their product offerings with investors' demand, they can elicit a greater willingness-to-pay for products closer to personal preferences.

Table 4 about here

I study this hypothesis with a similar specification to equation (2), where the expense ratio (in %) is on the LHS. Table 4 shows the results. The first row reports coefficients on the dummy variable DATA_{*i*,*t*}. As predicted, funds installing data technologies are associated with higher fees after adoption. The estimates in column (1) imply that funds using a data technology increase their fees by 1.5 basis points after adoption. Results are similar, including category×time fixed effects and controlling for marketing fees. Therefore, the increase in expense ratio is independent of changes in marketing and distribution expenditures. Overall, these results are consistent with fund managers charging higher fees for funds closer to customers' preferences. Below, I explore other predictions consistent with the hypothesis that managers learn from customers' information.

4.3 Ancillary Results: Cash Buffer, and Number of Funds

In this section, I study further how new technologies can impact the asset management industry. First, managers better informed about customers' demand may face less redemption uncertainty. Therefore, I explore whether data technologies allow maintaining a smaller cash buffer when investment opportunities are available, and more illiquid assets. Second, I study whether the product menu offered by the fund family expands to cater to specific preferences and diversify with respect to peers.

Cash Buffer. If data technologies allow for extracting informative signals on customers' demand, installing such technologies should help funds better predict future demand shocks. Therefore, adopting funds should face lower redemption uncertainty. To test this hypothesis, I study whether (after adoption) funds maintain a smaller cash buffer in their portfolio when expected returns are high. The intuition is that when good investment opportunities are available, an asset manager with no uncertainty about investors' redemption will try to take advantage of those opportunities and keep only a small part of her AUM to accommodate unexpected liquidations. On the other hand, if the manager has no information on investors' redemption, she might decide to maintain a larger cash buffer –forgoing investment opportunities. I study this prediction using the dividend-price ratio (D/P) to proxy for investment opportunities. Specifically, I run the following regression:

$$w_{i,t}(cash) = \alpha_i + \lambda_1 \cdot D/P_t + \lambda_2 \cdot (D/P_t \times \text{DATA}_{i,t}) + \beta' \boldsymbol{X}_{i,t} + \varepsilon_{i,t},$$
(3)

where $w_{i,t}(cash)$ is fund *i*'s portfolio weight in cash (in %), at month *t*, and $X_{i,t}$ is the same fund-month controls' vector as in my main results. Intuitively, when D/P_t is high,

equity prices are (relatively) low and expected returns are high. Therefore, I expect λ_1 to be negative as asset managers might reduce their cash holdings when good investment opportunities are available. The main coefficient of interest is on the interaction term (λ_2). Importantly, identification of λ_2 comes from variation over time within a fund, not from variation across funds.

Table 5 about here

Table 5 shows the results. The coefficient estimates for λ_1 and λ_2 are in the first and second rows, respectively. Column (1) confirms that when the dividend-price ratio is high (higher expected returns), fund managers tend to reduce their cash holdings –although with only 10% statistical significance. Columns (2) and (3) include the main coefficient of interest: the interaction term with DATA_{*i*,*t*}. As predicted, funds with data technology in place maintain a lower cash buffer ($\lambda_2 < 0$). These results support the view that data technologies allow to extract useful signals about investor preferences. Asset managers with better precision about customers' demand face lower redemption uncertainty. Consequently, they can maintain a smaller cash buffer and deploy capital in investment opportunities.

On a similar note, data technology adoption is associated with funds tilting their holdings towards illiquid stocks, as measured by the Amihud illiquidity ratio (Appendix Table C.11). This result is in line with existing research showing that funds with more "committed" capital hold more illiquid stocks (Gómez, Prado and Zambrana, 2024).

Number of Products. Next, I test whether fund families increase their product offerings when funds within the family adopt a data technology. To test this prediction, I aggregate observations within the same fund family and test whether the number of funds within the family increases after adopting a data technology. I estimate the following specification¹⁷:

$$log(N. of Funds_{f,t+1}) = \alpha_f + \eta_t + \delta DATA_{f,t} + log(Age_{f,t}) + \varepsilon_{f,t+1},$$
(4)

 $^{^{17}}$ Importantly, as the argument of the *log* in my specification is never zero, it does not suffer for well known identification challenges when the argument can equal zero (see Chen and Roth, 2023).

where N. of Funds_{*f*,*t*+1} denoted the number of funds offered by fund family *f* in month *t* + 1. Similarly to previous specifications, I define a dummy variable DATA_{*f*,*t*} which takes value one if at least one fund within family *f* has a data technology in place in month *t*. I control for the fund family's age as it is plausible that families develop organizational skills over time, which reduces the cost of setting up a new fund. As for the results above, including family and time fixed effects ensures that identification comes from variation in the number of funds offered before versus after data-adoption, relative to the same change for fund families not adopting data technologies. I report results in Table 6, column (1).

Table 6 about here

Table 6 confirms that fund families with at least one data technology installed increase their product menu after adoption. More precisely, the semi-elasticity coefficient suggests that fund families offer 8% more funds after adoption. In column (2), I estimate a similar specification with a Poisson regression where the LHS is N. of Funds_{f,t+1} (not in *log*). Results are similar, although statistical significance is reduced to 10%.

This result is consistent with the effect of other new technologies, such as AI, on firms' product portfolio. Babina et al. (2024) finds that more AI-intensive firms expand their product varieties, as AI facilitates the accumulation of knowledge and reduces uncertainty in product innovation.

Overall, these findings support the view that the role of new technologies in asset management extends beyond portfolio allocation decisions. The results in this section are consistent with fund managers adopting technologies to learn useful signals from investors' web traffic behavior, which in turn helps their capital collection efforts. Moreover, asset managers adopting technologies charge higher fees, keep smaller cash buffer when investment opportunities are available, and increase the number of funds offered within fund family.

4.4 Identification: Open Source Machine Learning

The above results suggest a positive relationship between data technologies and fund inflows, but do not establish causality. Adoption is an endogenous choice made by fund managers, so it might be correlated with other fund characteristics that cause fund flows. In this section, I exploit variation in the information that funds can extract from web traffic data, which is plausibly exogenous to investors' flows. Specifically, I use the public release of TensorFlow in November 2015, a major open-source machine learning (ML) library. The release of TensorFlow drastically decreased the cost of training and using ML algorithms in settings with large amounts of data available. Intuitively, ML allows fund managers to extract more informative signals from a given dataset. Accordingly, the effect of data technology on fund flows should increase after TensorFlow's release in November 2015.

The goal of my identification strategy is to isolate plausibly exogenous shock in the precision of information that managers can leverage to learn about their investors' preferences. Therefore, I compare the effect of data technology before and after TensorFlow's release, within fund. To alleviate endogeneity concerns about the adoption of data technologies after the shock, I remove from this analysis: (i) all funds installing data technology after November 2015, and (ii) funds installing technologies in the six-months window before TensorFlow's release¹⁸. This filters ensure that results are not driven by asset managers choosing to adopt a data technology, anticipating the release of TensorFlow.

As a first step, I compare the effect of data technologies on flows before and after TensorFlow's release. Specifically, I interact the dummy variable $DATA_{i,t}$ with a dummy equal to one post-November 2015 and zero otherwise (denoted $Post_t$):

$$Flow_{i,t+1} = \alpha_i + \eta_t + \theta_1 \text{ DATA}_{i,t} + \theta_2 \left(\text{DATA}_{i,t} \times \text{Post}_t \right) + \beta' \boldsymbol{X}_{i,t} + \varepsilon_{i,t+1},$$
(5)

where the coefficient θ_2 captures the additional impact of installing a data technology, after

¹⁸Results are unchanged extending this window to 12 months.

TensorFlow's release.

Next, I exploit cross-sectional heterogeneity in funds to define a continuous treatment. Ideally, I would construct a continuous treatment based on the amount of investors' data available to each fund (just before TensorFlow's release). The intuition is that asset managers with larger datasets can benefit more from ML algorithms, and therefore, one should observe a more significant incremental effect for those funds. Since I cannot directly observe the amount of data available as of TensorFow's release date, I construct two fund-specific measures to proxy for it. The first proxy is the tenure of data technology adoption for each fund i as of November 2015. I construct a continuous variable equal to the (log) number of months between fund i's first adoption of data technology and TensorFlow's release date. Intuitively, this proxy captures the length of the time series data that asset manager i can use to train ML algorithms. The second proxy is the number of different technologies installed as of November 2015. The idea behind this proxy is that funds with more data technologies can collect more customers' characteristics and, thus, have larger datasets. Then, I study the impact of TensorFlow's release on data technologies using the following specification:

$$Flow_{i,t+1} = \alpha_i + \eta_t + \theta_1 \text{ DATA}_{i,t} + \theta_3 \left(\text{DATA}_{i,t} \times \text{Post}_t \times z_i \right) + \theta_4 z_i + \beta' \boldsymbol{X}_{i,t} + \varepsilon_{i,t+1}, \quad (6)$$

where z_i is either the tenure of data technology adoption as of November 2015, or the number of technologies installed (i.e., the continuous treatments introduced above). The coefficient of interest is the interaction with the continuous treatment: θ_3 . Table 7 reports the results.

The second row shows results for θ_2 in specification (5). Coefficients estimates on this interaction term in columns (1) and (2) show that the effect of data technologies on fund inflows is 30% higher after TensorFlow's release. The third row reports estimates for θ_3 . Columns (3)-(4) and (5)-(6) show the results using as continuous treatment the tenure of technology adoption, and the number of technologies installed, respectively. Results using both continuous treatment confirm the intuition that the additional effect post-November 2015 is higher for funds with larger datasets.

A limitation in my identification is that by design, it relies on plausibly exogenous variation in prediction precision, not variation in data availability. With this caveat in mind, I think it is plausible in this context that more precise predictions are economically akin to more data/signals (i.e., ML increases the signal-to-noise ratio in customers' data).

Taken together, these results mitigate endogeneity concerns linked to the adoption choice, and they are consistent with a causal interpretation of data technology on asset managers' ability to attract capital.

5 Learning Mechanism: Validation and Robustness

The results above corroborate the hypothesis that asset managers use data technologies to learn investors' preferences and better attract flows. To further support that these results stem from a learning mechanism, I investigate other robustness tests to validate my hypothesis. First, I study the connection between technology adoption for retail and institutional share classes separately. Since my hypothesis hinges on asset managers observing signals from web traffic data, they should generate more information about retail investors. Second, I run placebo tests on different technologies that are not aimed at collecting and analyzing data. Third, I explore whether the returns to data technology are concave. Fourth, I study whether managers' competition in data collection impacts their ability to attract more flows.

Retail and Institutional Share Classes. The type of data technologies I study in this paper are designed to collect and analyze information from web traffic data. Accordingly, if fund managers improve capital collection by observing signals on customers' demand from these technologies, one would expect a more significant effect on retail investors. Intuitively, web traffic data should reveal more information about retail investors than institutional investors. Mutual funds data offer a good laboratory to test this prediction, as I can compare the effect of data technology on retail and institutional share classes *within fund*. Specifically, I run a specification similar to equation (2), but at the share class level:

$$Flow_{j,i,t+1} = \alpha_i + \eta_t + \theta \text{ DATA}_{j,i,t} + \theta_R (\text{DATA}_{j,i,t} \times \text{Retail}_{j,i,t}) + \beta' \boldsymbol{X}_{j,i,t} + \varepsilon_{j,i,t+1},$$
(7)

where $Flow_{j,i,t+1}$ is the flow of share class j, in fund i at month t. I separate retail and institutional share classes and denote by Retail_{j,i,t} a dummy equal to one if the share class j of fund i is sold to retail investors. Importantly, including fund fixed effects allows me to compare the effect on different share classes within the same fund. The coefficient of interest is θ_R , which captures the coefficient of data technology on retail share classes. If managers extract valuable signals from web traffic data, I expect θ_R to be positive. Table 8 shows the results.

Table 8 about here

The first row in Table 8 confirms that the effect of data technologies I study in this paper is concentrated on retail investors. The coefficient θ^R is positive and significant across all specifications. Moreover, data technologies have no effect on institutional share classes (second row). This result is consistent with websites' technologies being useful to generate signals about retail investors, but not enough to cater to institutional investors' preferences¹⁹. These results support the view that asset managers can learn customers' preferences to attract capital inflows.

Placebo tests. Next, to strengthen the interpretation of the results, I run a falsification test on my main result using technologies *not* aimed to collect and analyze data. That is, I estimate regression (2) substituting $DATA_{i,t}$ with placebo technologies installed on funds websites²⁰. These technologies include, for example, Feeds (e.g., used to publish blog pages),

¹⁹Results in Table 8 are unchanged when aggregating retail (institutional) share classes separately, and running the regression at the fund level. See Appendix Table C.14.

 $^{^{20}}$ To select place bo technologies, I select technologies with adoption rate comparable to the adoption of data technologies.

JavaScript (e.g., to show interactive plugins), and Advertising technologies. In Figure 3, I display the 90% confidence interval on the coefficient associated with the effect of each placebo technology. All placebo technologies yield statistically insignificant results. This evidence corroborates the idea that managers use data technology to extract information from web traffic activity.

Figure 3 about here

Decreasing Returns to Data. A natural prediction of managers learning investors' preferences from web traffic data is that giving fund managers additional (new) information should increase the beneficial effect of data. Assuming different data technologies allow to generate different signals, I can test this prediction using the number of data technologies installed by the fund manager. For example, one technology might allow to observe the average time visitors spend on each website's page. In contrast, other technologies might allow to observe information about age, geolocation, and other demographics. Those technologies provide different signals to the fund managers. In columns (1) to (3) of Table 9, I test this prediction.

Table 9 about here

As expected, the effect of data technologies on the ability to attract flows increases with the number of technologies installed. When the squared number of technologies is included in the specification, its coefficient enters negatively (although not significantly) in the regression (column (2)), suggesting concave returns to data.

Competing for Data. Finally, if results are indeed driven by managers extracting information from web traffic activity, the effect of data technologies should decline as more funds adopt such tools. Intuitively, as more agents observe a signal, the marginal benefit of that signal should decline (Grossman and Stiglitz, 1980). Therefore, I test whether there is a competition effect in the data space. To test this prediction, I define a coefficient that

captures "data competition" within a fund category as:

$$\gamma_{c,t} = \frac{\sum_{i=1}^{N_{c,t}} \text{DATA}_{i,c,t}}{N_{c,t}},\tag{8}$$

where $N_{c,t}$ denotes the total number of funds in category c, in month t; and the sum in the numerator is the number of funds with data technology in place, in category c at time t. A larger $\gamma_{c,t}$ means that a larger fraction of funds within a fund-category collect signals using data technologies. I test whether funds adopting in less competitive markets have stronger benefits from data. Figure 4 shows the coefficient on DATA_{i,t} (θ in equation 2), by different values of $\gamma_{c,t}$ at the adoption date. For example, the leftmost bar in Figure 4 represents funds adopting a data technology when competition for data is relatively low $\gamma_{c,t} < 25\%$. According to the assertion that the marginal benefit of data should decline as many acquire similar signals, the coefficient is decreasing in competition (from left to right), with last adopters having insignificant effect on their net flows. Furthermore, the effect of competition marginally affects even funds that already installed data technologies. I include an interaction term with $\gamma_{c,t}$ in regression (2), to capture the additional effect of competition within fund-category after adoption. Results are in Table 9, column (4). The coefficient on the interaction term is negative, suggesting again that competition within fund category reduces the marginal benefit of data.

Overall, these findings are consistent with the hypothesis that fund managers observe signals to predict customers' demand. Data technologies allow managers to collect and analyze data from web traffic activity, which helps attract (retail) capital.

5.1 How do Funds Attract More Flows?

The findings above indicate that data technology adoption is associated with funds attracting more (in)flows. A natural further question for understanding the role of data in the asset management industry is: *what* do managers learn from these technologies? In other words, what type of data are useful for fund managers to attract capital? Unfortunately, a key limitation common to much of the literature using proxies for learning, is that I do not observe the fund managers' actual information sets. As such, providing a definitive answer to this question is virtually impossible²¹.

However, I can explore how do funds attract flows after adoption of data technology. Categorizing data technologies by what they allow to do, might yield intuition on *how* fund managers use customer data and the type of information they process. To this end, I use BuiltWith's classification of data technologies to define six different categories, based on a technology's capabilities (i.e., based on what each technology allow to do). BuiltWith provide a short classification for the majority of data technology in my sample. I group those classification to identify six separate categories: Customer Tracking, A/B Testing, Lead Generation, Analytics Automation, and Search Engine Optimization (SEO). Furthermore, I group the remaining data technologies (unclassified by BuiltWith) as "Others"²². Customer Tracking technologies include those plugins that allow to measure audience visits (e.g., collect basic demographics or bounce rate), A/B Testing tools allow running RCT on web traffic audience, Lead Generation technologies help identify target or prospect customers, Analytics Automation include technologies aimed to personalize content and forecast customer conversion, SEO improves a website's search engine positioning tailoring to specific keywords.

After assigning a unique category to each data technology, I run a specification similar to (2), in order to tentatively understand which types of technologies are driving the results. Before discussing the results, it is important to note a caveat in their interpretation.

²¹Moreover, the type and usage of data by different funds can be fundamentally different. For example, 1st Source Monogram Diversified Equity mentions on its cookies policy that "The types of personal information we collect and share depend on the product or service you have with us. This information can include: Social Security number and income, Account balances and transaction history, Credit history and credit scores". While American Beacon Large Cap Value fund mentions using "demographic information to better understand your investment and service needs. To know your online preferences and viewing behaviors [...]".

²²Most of these technologies provide supplementary services to other technologies. For example, Makazi and Spotler Activate integrate data collected from several analytics technologies in a unique database, and help comply with privacy regulation.

When classifying data technology, I assign one unique category for each technology. However, several technologies might integrate more than one specific features. For instance, the technology Dynamic Yield is classified as an A/B Testing tool but also supports segmentation and personalization, features typically associated with Analytics Automation. Thus, the analysis is suggestive at best, offering tentative intuition into the precise mechanisms through which data technologies influence fund flows.

Table 10 shows the results for each of the six categories I identified from BuiltWith's classification. The coefficients for two out of six technology categories are statistically insignificant at conventional confidence level. In particular, adoption of Customer Tracking and SEO technologies are not associated with more flows. This suggests that merely collecting data on customer demographics or improving search engine rankings may not, by themselves, enhance a fund's ability to attract capital.

In contrast, the adoption of A/B Testing tools and Analytics Automation technologies is associated with significantly higher post-adoption flows. These results suggest that fund managers who actively experiment to learn customer preferences (e.g., via A/B Testing) or optimize their targeting (Analytics Automation) are those that benefit from data technologies. Interestingly, many technologies categorized as Analytics Automation include features at the intersection between AI and marketing (e.g., Autoketing, Black Crow AI, Blueshift). Although these results are far from conclusive, they suggest that one channel through which customer data help fund managers attracting flows is by improving customer conversion via personalization and targeting strategies.

5.2 Alternative Channels

The main findings above are consistent with fund managers using new technologies to learn about (potential) customers. According to a learning channel, funds observe signals about investor tastes and deviate from their peers (e.g., specialize) to cater more to customers' demand. However, the results of funds attracting more capital after installing data technologies and charging higher fees are arguably consistent with alternative explanations. Here, I rule out two main alternative stories. First, one possible explanation might be that adoption of data technologies correlates with managers' ability to generate alpha. If funds earn high risk-adjusted performance after installing a data technology, investors should notice it and increase their inflows to those funds. In Appendix Tables C.13, I test this alternative explanation with different measures of risk-adjusted performance, as well as using the recursive demeaning approach in Pástor, Stambaugh and Taylor (2015). Across all specifications, I cannot reject the hypothesis that managers' skills are unchanged after adoption of a data technology. Therefore, since investors should *observe* funds' superior ability to generate performance if this were the main driver of larger inflows, this alternative explanation seems implausible.

Another interpretation of my main findings could be that data technologies adoption is correlated with re-branding, *persuading* rather than learning about customer preferences (Mullainathan et al., 2008). According to this channel, a mechanism similar to obfuscation would drive the results on flows and fees. One key implication of this interpretation is that customers would react less to price changes after being subject to persuasion (Varian, 1980; Ellison and Ellison, 2009). To test this hypothesis, I compare the elasticity of fund flows to changes in fees after adopting data technology. If an obfuscation mechanism is at play, the "flows-fee elasticity" should be significantly lower, in absolute terms, after adoption (i.e., flows react less to change in expense ratio while investors are obfuscated). I show that this is not the case in Appendix Table C.15. On the contrary, if anything flows became more elastic to fees change after funds adopt new technology. This result squares with the framework in Appendix A: the share of investors who perceive both funds A and Battractive is proportional to the area between x = 0 and x_A (shaded blue area in Figure A.1). This result is also inconsistent with a "competing for attention" interpretation (Ben-David et al., 2022), where funds would not compete on fees. Overall, my results are in line with a channel based on fund managers using new technologies to learn about investors and improving the match with customers accordingly. Notwithstanding the evidence presented, it is important to recognize that I cannot completely rule out that other mechanisms explain my results. However, any other interpretation requires to be consistent with all the results above. For example, it should explain why funds adopting data technologies hold more illiquid assets after adoption, why the effect is concentrated in retail share classes and specific to technologies designed to collect and analyze customer data.

6 Concluding Remarks

The development of new technologies is changing how asset managers operate. While existing research focuses on their impact on portfolio allocation decisions, this paper shows that technological innovation also affects how managers attract and retain capital. Using novel data on website technologies, I show that asset managers actively collect and analyze customers' data, leading to 1.5% higher annual flows for adopting funds.

The effects are concentrated in retail share classes, decline with competition in data collection, and allow funds to maintain a smaller cash buffer when investment opportunities are available, consistent with managers extracting valuable signals about investors' preferences. Moreover, fund managers expand their product offerings after adoption and increase fees, suggesting that customers' data helps optimize both product placement and pricing strategies. To alleviate endogeneity concerns, I exploit the release of TensorFlow, an opensource machine learning library, as positive shock in signals' precision that asset managers can extract from investors' data.

These findings underline the economic importance of asset managers learning customers' preferences to attract capital. This mechanism raises important questions about market efficiency and fund manager incentives. While better knowledge of investor tastes could help match funds to customers, whether investors' product preferences are rational becomes even more critical to understanding the welfare implications of new technologies. Product prolif-

eration might harm investors, as households show well-known systematic biases and make mistakes in their economic decisions. Moreover, tools informing about detailed customer information may disproportionately benefit larger fund families as they are able to collect more extensive datasets.

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FIGURE 1: Funds and Data Technology adoption. This figure shows the adoption of data technologies aimed to capture visitors data, on funds' websites. The data are from BuiltWith, which detects the installation and removal of various technologies by analyzing webpage code. See Section 3.2 for details on data technologies. The blue line (left axis) represents the number of funds with at least one data technology in place for each month of the sample period. The red line (right axis) shows the percentage of funds adopting data technologies relative to the total number of funds in a given month.



FIGURE 2: The Dynamic Effect of Data Technologies on Fund Flows. This figure shows results for the difference-in-differences regression where the dependent variable is the one-month-ahead fund flow. Each point represents the estimated coefficient on the treatment group interaction with each month before/after data technology adoption. The treatment is a dummy equal to one if a fund *i* has a data technology in place at month *t* (DATA_{*i*,*t*}). The fund-month control variables include a fund's size (*logAUM*), expense ratio, (*log*) age, flows, turnover, CAPM alpha, 12b-1 fees, and the coefficient of data competition (equation (8)) in month *t*. Regression include fund and category×month fixed effects, and the gray area represent the 95% confidence interval for the coefficient estimates. The month just before data technology adoption (-1) is the excluded category in the regression, and is reported as zero in the figure. The rightmost (leftmost) estimates include all observations after (before) 12 months from the adoption month. The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022.



FIGURE 3: **Placebo tests**. This figure shows results from placebo tests on technologies different from data technologies. Each horizontal line represents the 95% confidence interval for tests replacing data technologies with one of the following (placebo) technologies: Network (Content Delivery Network), Server, JavaScript, Copyright, Feeds, and Ads. The specification is the same as the main results in Table 3, column (1). The dependent variable is the one-month-ahead fund flow. The confidence interval refers to the coefficient on a dummy equal to one if fund *i* has a technology of the respective type in place at month *t*; i.e., analogous to θ in Equation (2). All regressions include fund and time fixed effects, and controls: fund's size (logTNA), (log) age, flows, turnover, and CAPM alpha in month *t*.



FIGURE 4: Effect of Competition within Fund-Category. This figure shows results for differencein-differences coefficients across different values of competition ($\gamma_{c,t}$) as of data technology adoption. The competition coefficient $\gamma_{c,t}$ is built following equation (8), and it captures the fraction of funds with data technologies in place within fund category-month. Each bar represents a level of competition as of adoption date (e.g., the first bar represents all fund managers installing their first data technology when less then 25% of funds within its own fund-category have a data technology already installed). Each vertical line represents the 95% confidence interval. The specification is the same as the main specification in equation (2). All regressions include fund and time fixed effects, and controls: fund's size (logTNA), (log) age, flows, turnover, 12b-1 fees, and CAPM alpha in month t.

	obs.	mean	sd	p5	p25	p50	p75	p95
AUM (\$M)	987,242	1,529.46	8,250.46	8.73	54.06	215.77	820.84	5,551.85
Expense Ratio (%)	987,242	1.13	0.53	0.18	0.83	1.12	1.45	2.05
12b-1 Fees $(\%)$	987,242	0.28	0.24	0.00	0.06	0.25	0.41	0.75
Flows $(\%)$	987,242	-0.12	5.71	-6.04	-1.80	-0.63	0.82	7.16
Turnover Ratio	987,242	0.80	1.02	0.06	0.25	0.51	0.95	2.34
Age (Years)	987,242	12.87	8.59	2.50	5.92	11.00	18.25	30.00
Raw Returns	987,242	0.01	0.05	-0.08	-0.02	0.01	0.03	0.08
CAPM Alpha	987,242	0.00	0.10	-0.17	-0.05	-0.00	0.05	0.17
FF5 Alpha	987,242	-0.00	0.26	-0.45	-0.11	0.01	0.11	0.38
N. of Data Tech.	987,242	1.09	2.25	0.00	0.00	0.00	1.00	6.00
Data	987,242	0.35	0.48	0.00	0.00	0.00	1.00	1.00

TABLE 1: Summary Statistics: This table reports summary statistics for the full sample. For each variable, the table shows the number of available observations (obs,), the mean (mean), the standard deviation (sd), the 5th (p5), 25th (p25), 50th (p50), 75th (p75), and the 95th (p95) percentiles. AUM is inflation adjusted in January 2000 \$ million. Expense Ratio, 12b-1 Fees, and Flows are in %; e.g., the average fund flow in the sample is -0.12% monthly. The variable N. of Data Tech. represents the total number of data technologies installed on the fund's website in a given month, the variable DATA is a dummy equal to 1 if the fund-month observation has at least one data technology installed. The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022.

Data Technology Name	Installation % (in 2022)	Description
Google Analytics	63.50	Users Tracking and Analytics
LinkedIn Insights	37.51	Social Media Tracking and Analytics
Adobe Analytics	29.68	Users Tracking and Analytics
Omniture Test & Target	17.74	A/B Testing
Facebook Pixel	16.98	Social Media Tracking and Analytics
Google Analytics 4	15.04	Users Tracking and Analytics
RapLeaf	13.80	Users Tracking
Twitter Analytics	12.02	Social Media Tracking and Analytics
Bing Universal Event Tracking	11.76	Users Tracking and Analytics
LiveRamp	8.64	Data Connectivity Platform
Yahoo Web Analytics	7.10	Users Tracking and Analytics
Crazy Egg	6.94	Track and Visualize User Interaction
mPulse	6.60	Real Time Customer Experience
Google Optimize 360	6.41	A/B Testing
iPerceptions	6.31	Analyze Customer Feedback
Hotjar	6.05	Users Tracking and Analytics

TABLE 2: Main Data Technologies: This table reports the main data technologies installed on funds' websites, as of December 2022. This technologies are aimed to collect and analyze website visitors' data. The second column shows the percentage of funds having the technology installed on its website with respect to the total number of funds, as of December 2022. The third column reports a short description of the technology's features.

	Fund Flows _{<i>i</i>,<i>t</i>+1} (%)					
	(1)	(2)	(3)	(4)		
DATA _{i,t}	$\begin{array}{c} 0.141^{***} \\ (0.042) \end{array}$	$\begin{array}{c} 0.127^{***} \\ (0.041) \end{array}$	$\begin{array}{c} 0.144^{***} \\ (0.042) \end{array}$	$\begin{array}{c} 0.130^{***} \\ (0.041) \end{array}$		
12b-1 $\operatorname{Fees}_{i,t}$			$\begin{array}{c} 0.251^{**} \\ (0.112) \end{array}$	$\begin{array}{c} 0.251^{**} \\ (0.109) \end{array}$		
Controls	\checkmark	\checkmark	\checkmark	\checkmark		
Fund FE	\checkmark	\checkmark	\checkmark	\checkmark		
Time FE	\checkmark	×	\checkmark	×		
Category×Time FE	×	\checkmark	×	\checkmark		
Outcome mean	0.221	0.221	0.221	0.221		
Outcome SE	6.293	6.293	6.293	6.293		
Obs. Adj. R^2	$971,730 \\ 0.112$	$970,832 \\ 0.141$	$971,730 \\ 0.112$	$970,832 \\ 0.141$		

TABLE 3: Fund Flows and Data Technologies: This table shows results of OLS panel regression in which the dependent variable is the one-month-ahead fund flow. The regressors are a dummy equal to one if a fund *i* has a data technology in place at month t (DATA_{*i*,t}), 12b-1 fees, and controls for fund-month characteristics (omitted for brevity). See Section 3.2 for details on data technologies. The control variables include a fund's size (*logAUM*), expense ratio, (*log*) age, flows, turnover, and CAPM alpha in month t. The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022. All standard errors are two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	Expense Ratio _{<i>i</i>,<i>t</i>+1} (%)					
	(1)	(2)	(3)	(4)		
$\mathrm{DATA}_{i,t}$	$\begin{array}{c} 0.015^{***} \\ (0.004) \end{array}$	$\begin{array}{c} 0.015^{***} \\ (0.004) \end{array}$	$\begin{array}{c} 0.018^{***} \\ (0.004) \end{array}$	$\begin{array}{c} 0.017^{***} \\ (0.004) \end{array}$		
12b-1 $\operatorname{Fees}_{i,t}$			$\begin{array}{c} 0.255^{***} \\ (0.017) \end{array}$	$\begin{array}{c} 0.237^{***} \\ (0.016) \end{array}$		
Controls	\checkmark	\checkmark	\checkmark	\checkmark		
Fund FE	\checkmark	\checkmark	\checkmark	\checkmark		
Time FE	\checkmark	×	\checkmark	×		
Category×Time FE	×	\checkmark	×	\checkmark		
Outcome mean	1.141	1.141	1.141	1.141		
Outcome SE	0.538	0.538	0.538	0.538		
Obs. Adj. R^2	$971,918 \\ 0.918$	$971,013 \\ 0.922$	$971,918 \\ 0.921$	$971,013 \\ 0.925$		

TABLE 4: Expense Ratio and Data Technologies: This table shows results of OLS panel regression in which the dependent variable is the one-month-ahead fund expense ratio. The regressors are a dummy equal to one if a fund *i* has a data technology in place at month t (DATA_{*i*,*t*}), 12b-1 fees, and controls for fund-month characteristics (omitted for brevity). See Section 3.2 for details on data technologies. The control variables include a fund's size (*logAUM*), (*log*) age, flows, turnover, and CAPM alpha in month *t*. The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022. All standard errors are two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

		$w_{i,t}(\operatorname{cash})$ (%	~)
	(1)	(2)	(3)
D/P_t	-29.905^{*} (15.704)		-26.035^{*} (15.533)
$DATA_{i,t} \times D/P_t$		-21.969^{***} (4.825)	-20.837^{***} (4.878)
Controls Fund FE	\checkmark	\checkmark	\checkmark
Outcome mean Outcome SE	$4.367 \\ 12.085$	$4.367 \\ 12.085$	$4.367 \\ 12.085$
Obs. Adj. R^2	$837,070\ 0.569$	$837,070 \\ 0.569$	$837,070 \\ 0.569$

TABLE 5: Portfolio Cash Holdings and Technologies: This table shows results of OLS panel regression in which the dependent variable is the one-month-ahead portfolio weight in cash. The regressors are the dividend-price ratio (DP_t) , an interaction term with a dummy equal to one if a fund *i* has a data technology in place at month *t* (DATA_{*i*,*t*}), and controls for fund-month characteristics (omitted for brevity). See Section 3.2 for details on data technologies. The control variables include a fund's size (*logAUM*), expense ratio, flows, turnover, and CAPM alpha in month *t*. The monthly sample is from March 1993 to December 2022. All standard errors are two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	$log(N. of Funds)_{f,t+1}$	N. of Funds $_{f,t+1}$
	(1)	(2)
$\mathrm{DATA}_{f,t}$	0.079**	0.058^{*}
	(0.031)	(0.032)
$log(Age)_{f,t}$	0.3323***	0.479***
	(0.023)	(0.040)
Estimator	OLS	Poisson
Fund Family FE	\checkmark	\checkmark
Time FE	\checkmark	\checkmark
Outcome mean	1.495	13.375
Outcome SE	1.358	30.652
Obs.	159,566	159,566
Adj. R^2	0.906	-
Pseudo R^2	_	0.852

TABLE 6: Number of Funds in Fund Family and Data Technologies: This table shows results of OLS panel regression in which the dependent variable is the number of funds offered by fund family f in month t+1. The regressors are a dummy equal to one if at least one fund within family f has a data technology in place at month t (DATA_{f,t}), and the (*log*) fund family age. See Section 3.2 for details on data technologies. The monthly sample is from March 1993 to December 2022. All standard errors are two-way clustered by fund family and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	Fund Flows _{<i>i</i>,<i>t</i>+1} (%)						
			z_i :	Tenure of	Adoption	N. of Data Tech	
	(1)	(2)		(3)	(4)	(5)	(6)
$DATA_{i,t}$	0.590^{***} (0.126)	0.606^{***} (0.126)	$\begin{array}{c} 0.654^{***} \\ (0.146) \end{array}$	0.686^{***} (0.148)	$\begin{array}{c} 0.654^{***} \\ (0.135) \end{array}$	$\begin{array}{c} 0.647^{***} \\ (0.133) \end{array}$	
$DATA_{i,t} \times Post_t$	0.260^{**} (0.109)	$\begin{array}{c} 0.313^{***} \\ (0.109) \end{array}$					
$DATA_{i,t} \times Post_t \times z_i$				0.071^{**} (0.031)	$\begin{array}{c} 0.091^{***} \\ (0.031) \end{array}$	$\begin{array}{c} 0.130^{***} \\ (0.035) \end{array}$	$\begin{array}{c} 0.140^{***} \\ (0.034) \end{array}$
Controls	\checkmark	\checkmark		\checkmark	\checkmark	\checkmark	\checkmark
Fund FE	\checkmark	\checkmark		\checkmark	\checkmark	\checkmark	\checkmark
Time FE	\checkmark	×		\checkmark	×	\checkmark	×
Category×Time FE	Х	\checkmark		х	\checkmark	х	\checkmark
Outcome mean	0.170	0.170		0.170	0.170	0.170	0.170
Outcome SE	6.322	6.322		6.322	6.322	6.322	6.322
Obs. Adj. R^2	$770,276 \\ 0.107$	$769,423 \\ 0.139$	$555,493 \\ 0.096$	$554,\!639 \\ 0.136$	$\begin{array}{c} 662,336 \\ 0.104 \end{array}$	$\begin{array}{c} 661,\!458 \\ 0.137 \end{array}$	

TABLE 7: Fund Flows and Data Technologies after TensorFlow Release: This table shows results of OLS panel regression in which the dependent variable is the one-month-ahead flow for share class j of fund i. Columns (1) and (2) follow specification in equation (5), while columns (3) to (6) follow (6). In columns (3) and (4) the continuous treatment z_i is the (log) number of months between the first data technology adoption and TensorFlow's release. Columns (5) and (6) use the number of data technologies installed as of TensorFlow's release, as continuous treatment z_i . DATA_{i,t} is a dummy equal to one if fund i has a data technology in place at month t. See Section 3.2 for details on data technologies. The fund-month control variables (omitted for brevity) include a fund's size (logAUM), expense ratio, (log) age, flows, turnover, CAPM alpha, 12b-1 fees, and the coefficient of data competition (equation (8)) in month t. The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022, which did not adopt a data technology after June 2015 (i.e., six-months before TensorFlow's release). All standard errors are two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	Share Class Flows _{$j,i,t+1$} (%)					
	(1)	(2)	(3)	(4)		
$DATA_{i,t} \times Retail$	$\begin{array}{c} 0.467^{***} \\ (0.088) \end{array}$	$\begin{array}{c} 0.446^{***} \\ (0.092) \end{array}$	$\begin{array}{c} 0.377^{***} \\ (0.089) \end{array}$	$\begin{array}{c} 0.358^{***} \\ (0.092) \end{array}$		
$\mathrm{Data}_{i,t}$	-0.153 (0.100)	-0.165 (0.104)	0.019 (0.102)	$0.003 \\ (0.106)$		
12b-1 $\mathrm{Fees}_{j,i,t}$			$\begin{array}{c} 0.825^{***} \\ (0.094) \end{array}$	$\begin{array}{c} 0.804^{***} \\ (0.093) \end{array}$		
Controls	\checkmark	\checkmark	\checkmark	\checkmark		
Fund FE	\checkmark	\checkmark	\checkmark	\checkmark		
Time FE	\checkmark	×	\checkmark	×		
Category×Time FE	×	\checkmark	×	\checkmark		
Outcome mean	0.691	0.691	0.691	0.691		
Outcome SE	10.541	10.541	10.541	10.541		
Obs. Adj. R^2	$799,220 \\ 0.104$	$\begin{array}{c} 798,719 \\ 0.114 \end{array}$	$799,220 \\ 0.104$	$798,719 \\ 0.115$		

TABLE 8: Retail and Institutional Share Classes: This table shows results of OLS panel regression in which the dependent variable is the one-month-ahead flow for share class j of fund i. The regressors are a dummy equal to one if fund i has a data technology in place at month t (DATA_{*i*,*t*}) interacted with the share class' j type (retail or institutional), 12b-1 fees, and controls for share class-month characteristics (omitted for brevity). See Section 3.2 for details on data technologies. All funds in this sample have both retail and institutional share classes, to compare different share classes within the same fund. The control variables include a share class' (*log*) AUM, expense ratio, (*log*) age, flows, turnover, and CAPM alpha in month t. The monthly sample is from March 1993 to December 2022. All standard errors are two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	Number of Technologies			Competition Effect		
	Fune	d Flows _{$i,t+1$}	(%)		Fund Flows _{<i>i</i>,<i>t</i>+1} (%)	
	(1)	(2)	(3)		(4)	
N. $Tech_{i,t}$	0.030^{***} (0.007)	$\begin{array}{c} 0.047^{***} \\ (0.018) \end{array}$		$\mathrm{Data}_{i,t}$	$\begin{array}{c} 0.377^{***} \\ (0.114) \end{array}$	
N. $Tech_{i,t}^2$		-0.002 (0.001)		$DATA_{i,t} \times \gamma_{c,t}$	-0.471^{**} (0.186)	
$log(1 + N. Tech_{i,t})$			$\begin{array}{c} 0.130^{***} \\ (0.031) \end{array}$			
Controls Fund FE Category×Time FE	\checkmark \checkmark \checkmark	\checkmark \checkmark \checkmark	\checkmark \checkmark \checkmark		\checkmark \checkmark \checkmark	
Outcome mean Outcome SE	$0.221 \\ 6.294$	$0.221 \\ 6.294$	$0.221 \\ 6.294$		$0.221 \\ 6.294$	
Obs. Adj. R^2	$850,544 \\ 0.139$	$850,544 \\ 0.139$	$850,\!544$ 0.141		$971,070 \\ 0.141$	

TABLE 9: Fund Flows, Technology Adoption, and Competition: This table shows results of OLS panel regression in which the dependent variable is the one-month-ahead fund flow. The regressors are the number of data technologies in place for fund *i* at month *t* (N. $Tech_{i,t}$) in column (1), column (2) adds its square (N. $Tech_{i,t}^2$), and the log of (1+N. $Tech_{i,t}$) in column (3). In column (4), the regressors are a dummy equal to one if a fund *i* has a data technology in place at month *t* (DATA_{*i*,*t*}), and an interaction term with the competition coefficient $\gamma_{c,t}$ for fund category *c* in month *t*. The competition coefficient is built following equation (8), and it captures the fraction of funds with data technologies in place within fund category-month. See Section 3.2 for details on data technologies. All columns include controls for fund-month characteristics (omitted for brevity). The control variables are a fund's size (logAUM), expense ratio, (log) age, flows, turnover, and CAPM alpha in month *t*. The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022. All standard errors are two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	Fund Flows _{<i>i</i>,<i>t</i>+1} (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Customer $\operatorname{Tracking}_{i,t}$	0.001 (0.022)					
A/B TESTING _{i,t}		$\begin{array}{c} 0.294^{***} \\ (0.090) \end{array}$				
LEAD GENERATION _{i,t}			0.087^{*} (0.049)			
$\mathrm{SEO}_{i,t}$				-0.035 (0.079)		
Analytics $Automation_{i,t}$					$\begin{array}{c} 0.274^{***} \\ (0.059) \end{array}$	
$OTHERS_{i,t}$						0.196^{**} (0.097)
Controls	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Fund FE	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Category×Time FE	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Outcome mean	0.221	0.221	0.221	0.221	0.221	0.221
Outcome SE	6.294	6.294	6.294	6.294	6.294	6.294
Obs. Second-stage Adj. R^2	878,022 0.000	949,947 0.000	950,727 0.000	941,077 0.000	$948,523 \\ 0.001$	948,910 0.000

TABLE 10: Fund Flows and Technology Categories: This table shows results of OLS panel regression in which the dependent variable is the one-month-ahead fund flow. The regressors are a dummy equal to one if a fund *i* has at least one data technology belonging to each category in place at month *t*, and controls for fund-month characteristics (omitted for brevity). The six data technology categories are Customer Targeting, A/B Testing, Lead Generation, Search Engine Optimization (SEO), Analytics Automation, and Others (which included unclassified technology by BuiltWith). See Section 5.1. The control variables include a fund's size (*logAUM*), expense ratio, (*log*) age, flows, turnover, and CAPM alpha in month *t*. The difference-in-differences estimator robust to identification concerns in staggered difference-in-differences settings following Gardner (2021); Gardner et al. (2024). The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022.

Appendix

A Economic Framework

To illustrate the main mechanism, I provide a simple and tractable framework of fund flows and fees in a market with heterogeneous investor preferences. The setup builds on a Hotelling-type of model, where investor preferences are described by a continuous variable. Without information on the distribution of customer preferences, two funds will equally share the flows to the asset management industry. However, when one fund uses data technologies to learn more about the distribution of preferences, it will offer products that are closer to what investors prefer. This mechanism allows the "DATA" fund to attract more capital and charge higher fees in equilibrium. The goal of this framework is to guide the empirical strategy and discuss additional predictions.

Model setup. There are two dates, $t = \{0, 1\}$. Two risk neutral asset managers, denoted by A and B, offer investment portfolios to a measure-one continuum of investors indexed by i who can only invest through the asset managers, i.e., investors do not invest directly in the asset market²³. Here, the fund manager A will have access to data analytics technologies, while fund B has no access to data technology. Without loss of generality, I assume each investor i picks exactly one asset manager. Importantly, investors have heterogeneous preferences. I summarize those preferences in a continuous variable represented on a line $x \in \mathbb{R}$. For example, x might represent a linear combination of several characteristics and tastes, the outcome of k-means analysis, or PCA, all commonly used methodologies in data and customer analytics (Abdulhafedh, 2021; Savic et al., 2019). In the asset management industry, a large x_i might represent investor i's preference for ESG stocks (Pástor, Stambaugh and Taylor, 2021) or specific themes such as AI- or cannabis-ETFs (Ben-David, Franzoni, Kim and Moussawi, 2022). At the same time, x_i might represent other personal tastes, such as the preferred distribution channel for buying a fund (e.g., through a financial advisor

²³This assumption follows, for example, Basak and Cuoco (1998) and Gârleanu and Pedersen (2018). A similar situation might arise because investors can share information costs or other types of frictions. One can think about the investors in this section as the fraction of investors that decide to invest via an asset manager, e.g., $\alpha = \mu/(\gamma \sigma_r^2)$ in a CARA-normal setup similar to Grossman and Stiglitz (1980).

or brokerage account)²⁴. I assume investors have quadratic costs in deviating from their preference x_i . Formally, the net cost investor *i* faces when buying fund *j* is:

$$c_{i,j} = f_j + t \cdot (x_j - x_i)^2$$
, for $j = \{A, B\}$,

where f_j is the fee (price) charged by fund j, and t is a parameter that governs how costly it is for investors to deviate from their own preferences. A large t implies that investors perceive as expensive to buy a product much different from x_i . The term $(x_j - x_i)^2$ represents how investor i's taste is distant from fund j. Asset managers offer a variety of products to clients with heterogeneous needs, endowments, hedging motives, and preferences. Intuitively, investors will find buying a fund closer to their preference more attractive.

The mass of investors with preference equal to x_i is given by $\phi(\mu; x_i)$, where $\phi(\mu; \cdot)$ is the p.d.f. of a logistic distribution with average μ , and scale parameter one. Similarly, the c.d.f. of the same logistic distribution is denoted by $\Phi(\mu; \cdot)$.

Crucially, the average of the distribution, μ , is randomly drawn from a standard normal distribution: $\mu \sim \mathcal{N}\{0,1\}$. If $\mu > 0$, the distribution of preferences $\phi(\mu; x)$ shifts rightwards, which means that a larger mass of investors prefers products with x > 0. Investors know their preferences, while fund managers only know the distribution (i.e., they don't know the realization of μ). Thus, they don't observe the actual profile of customers' tastes. However, the asset managers using data technologies, A, extract a signal s from collecting and analyzing investors' data in t = 0. The signal is unbiased and noisy²⁵: $s|\mu \sim \mathcal{N}\{\mu, \sigma_s^2\}$; I will denote a signal's precision as $\tau_s = \sigma_s^{-2}$. Collecting data allows a manager to learn investors' tastes better, and the lower σ_s^2 , the more data are informative. The unknown realization of μ determines where most investor preferences are, and having a signal on it makes data technologies relevant in this simple framework. Figure A.1 shows an overview of this simple framework for $\mu > 0$. In what follows, I discuss the case of $\mu > 0$: in this case, a larger mass of investors will lie on x > 0. The same economic intuition will hold for $\mu < 0$, with a slightly different formulation.

²⁴Industry practitioners in the retail funds segment are particularly interested in understanding the best distribution channel for a given clientele, see for instance: broadridge.com/press-release/2025/.

²⁵This simple example does not include endogenous information choice; its only purpose is to illustrate the idea behind the hypothesis that managers can learn valuable information from customers' data.



FIGURE A.1: Economic Framework Overview. This figure illustrates an overview of the distribution of investor preferences $x \in \mathbb{R}$. The black curve shows $\phi(\mu; x)$ for $\mu = 2$. x_A is the location picked by the "DATA" fund denoted A, and \tilde{x} the threshold below which investors will find fund B (without access to data technologies) more convenient (see Section A.1). The area underneath the p.d.f. $\phi(\mu; x)$, on the right of \tilde{x} , represents the total market share of fund A (filled area). The hatched area shows fund's A captive market share, whereas the shaded lightblue area (vertical section between \tilde{x} and x_A) is the fraction of market share that A gains competing with B on fees.

In t = 0, the two asset managers A and B set up a fund picking one location over the line of preferences denoted x_A and x_B , respectively, to align as much as possible with investor demand. I assume the costs of setting up a fund are independent of x, so both funds have the same marginal cost c, regardless of their location choice on the line. In t = 1, funds compete on fees to maximize profits, and each investor i buys the fund that is most convenient for her.

A.1 Summary of the Equilibrium

The fundamental intuition in this simple example is that funds can differentiate their product offerings to better meet investors' demand. Asset managers located closer to a larger mass of customers will receive more capital. An equilibrium in this framework is a set of fund locations (x_A, x_B) and fees (f_A, f_B) such that both funds pick the closer x to their expected μ in t = 0 since they minimize the distance to the mode of investor tastes, and maximize their respective profits in t = 1. Importantly, I separate the location and pricing problems, as it is well known that Hotelling-type of models have no equilibrium when firms can use both location and prices (contemporaneously) as strategies, see for example (Shy, 1995, Proposition 7.7). For instance, this simplification might imply that once funds commit to delivering a particular investment strategy, they find it costly to deviate from it. Abis and Lines (2024) find consistent evidence in the US mutual funds industry. In what follows, I will first consider a baseline equilibrium in which none of the two funds can observe a signal about the distribution of investor preferences. This benchmark is useful for comparison with the second equilibrium, in which I allow the "DATA" fund denoted A to extract a signal from collecting and analyzing customers' data. The subsection A.2 contains all the proofs.

Baseline. First, consider a benchmark economy where no data technologies are available. In this case, asset managers A and B know only the prior distribution of μ (i.e., as if $\tau_s \to 0$). Thus, in t = 0, when funds set their location on the preferences line, they will choose $x_A = x_B = \mathbb{E}[\mu] = 0$. Intuitively, as fund managers have no information about where the realization of investor preferences is, they will locate on their point where they believe more investors lie –i.e., on the mode (and average) of the logistic distribution with $\mu = 0$. In t = 1, with both funds in the same location x = 0, competition will resemble a Bertrand duopoly equilibrium. The two funds will split the total share of investors' flows equally and price at marginal cost c.

Next, I consider a similar market for asset management products, where fund A observes a signal on the realization of investors' preferences.

Asset and Data Managers. When fund A has access to data technologies, the manager receives a signal s about the realization of investor preferences. Now, while in t = 0 the

naive fund B will pick location $x_B = 0$, the "DATA" fund will set $x_A = \frac{\tau_s}{1+\tau_s}s$. Thus, when observing the unbiased signal, asset manager A deviates from x = 0 to locate closer to the mode of investor preferences. The deviation in x can be interpreted as specialization vis-à-vis a "standard" product. In the asset management industry, funds can differentiate from competitors in many ways; for instance, they can overweight stocks with particular characteristics, change their distribution channel, or differentiate their fund prospectus.

Once A sets $x_A > 0$, the mass of investors on the right-hand side of x_A will find the fund offered by A more attractive, as it is closer to their preferences. This market share is given by $1 - \Phi(\mu; x_A)$, and it represents fund A's captive investors (hatched area in Figure A.1). Similarly, investors on the left-hand side of $x_B = 0$ will prefer fund B. This mass of investors is determined by $\Phi(\mu; 0)$, representing fund captive demand for fund B. However, the mass of investors between x_B and x_A is not captive for either of the two funds. In this area, there will be a threshold \tilde{x} above which investors find A more attractive than B, and below, they will prefer B. This threshold is given by:

$$\tilde{x} = \frac{x_A}{2} + \frac{f_A - c}{2x_A t}.\tag{A.1}$$

Intuitively, $x_A/2$ represents the midpoint between the products offered by funds A and B. Then, the threshold \tilde{x} shifts to the right –resulting in lower market share for fund A– as the "DATA" fund increases its fee over its costs. Investors in this area prefer fund B if f_A is too large, even though their preferences might be closer to x_A .

In choosing fund fees f_A , the "DATA" fund manager maximizes its total profits, $\pi_A = [1 - \Phi(\mu; \tilde{x})] \cdot (f_A - c)$, trading-off a higher market share from setting a lower f_A , with fewer profits. The optimal fee satisfies:

$$f_A = c + 2x_A \cdot t \cdot \exp\{-(x_A - \mu)\}.$$
 (A.2)

A key implication from equation (A.2) is that fund A can set its fee above marginal costs. The second term in the equation determines how much the "DATA" fund charges in excess of fund B (without data technologies), in equilibrium. This term increases with the fund's deviation from x = 0, and it is larger as x_A lies closer to μ (i.e. when the signal from data is more precise and the fund A locates closer to a larger mass of investors).

A.2 Proofs

This subsection contains proofs for the simple framework. In t = 0, both funds will pick the location on $x \in \mathbb{R}$ that maximizes the number of investors allocating capital to their respective products. In this example, investor preferences are distributed as a logistic distribution, and capturing the larger mass of customers is equivalent to locate in the mode of the distribution. Since $\phi(\mu, \cdot)$ is a symmetric distribution the mode coincides with the mean, and both funds will choose

$$x_j = \mathbb{E}[\mu \mid \mathcal{I}_j], \quad j = \{A, B\}, \tag{A.3}$$

where \mathcal{I}_j is the information set of fund j –i.e., only the prior for fund B, and the prior plus the signal s for fund A.

In t = 1, funds compete on fees to maximize their revenues. First, I need to compute the threshold that define the market share of the two funds, i.e., the \tilde{x} such that an investor with preference \tilde{x} will find equivalent buying either of the two funds. This is given by:

$$\tilde{x}$$
 s.t.: $f_B + t \cdot \tilde{x}^2 = f_A + t \cdot (\tilde{x} - x_B)^2$. (A.4)

Simple computations yield $\tilde{x} = x_A/2 + \frac{f_A-c}{2x_A t}$, which is equation (A.1). Now, the optimal fee set by fund D is straightforward:

$$f_A = \operatorname{arg} \max \pi_A = \operatorname{arg} \max \underbrace{\Phi(\mu, \tilde{x})}_{\text{Maket share}} \cdot (f_A - c).$$
(A.5)

The F.O.C. is:

$$1 - \Phi(\mu, \tilde{x}) = \phi(\mu, \tilde{x}) \cdot \frac{f_A - c}{2x_A t}$$

$$1 - \frac{1}{1 + e^{-(\tilde{x} - \mu)}} = \frac{e^{-(\tilde{x} - \mu)}}{(1 + e^{-(\tilde{x} - \mu)})^2} \cdot \frac{f_A - c}{2x_A t},$$
(A.6)

denoting $b \coloneqq e^{-(\tilde{x}-\mu)}$, and $\kappa \coloneqq \frac{f_A-c}{2x_A t}$, I can rewrite:

$$\frac{1}{1+b} = \frac{(1+b)^2 - b\kappa}{(1+b)^2}$$

$$(1+b) = (1+b)^2 - b\kappa$$

$$b^2 + b(1-\kappa) = 0,$$
(A.7)

which gives solution $b_1 = \kappa - 1$, and $b_2 = 0$. As $b \coloneqq e^{-(\tilde{x}-\mu)}$, $b_2 = 0$ does not yield a real solution. Substituting back b, and κ :

$$e^{-(\tilde{x}-\mu)} = \frac{f_A - c}{2x_A t} - 1$$

$$f_A - c = 2 \cdot \left(e^{-(\tilde{x}-\mu)} + 1\right) \cdot x_A t$$

$$f_A = c + 2 \cdot \left(e^{-(\tilde{x}-\mu)} + 1\right),$$

$$f_A = c + 2x_A \cdot t \cdot \exp\{-(x_A - \mu)\}$$
(A.8)

which is equation (A.2). The S.O.C. for a maximum is satisfied, as:

$$-\phi(\mu, \tilde{x}) \cdot \frac{1}{2x_{A}t} - \phi'(\mu, \tilde{x}) \cdot \frac{f_{A} - c}{2x_{A}t} - \phi(\mu, \tilde{x}) \cdot \frac{1}{2x_{A}t} =$$

$$= -2 \cdot \phi(\mu, \tilde{x}) \cdot \frac{1}{2x_{A}t} - \phi'(\mu, \tilde{x}) \cdot \frac{f_{A} - c}{2x_{A}t} =$$

$$= -\phi(\mu, \tilde{x}) \cdot \frac{1}{x_{A}t} - \phi'(\mu, \tilde{x}) \cdot \frac{f_{A} - c}{2x_{A}t} < 0, \quad \text{for } x \in (0, \mu).$$
(A.9)

B Data Appendix

In this Appendix I describe the main dataset's construction procedures. I use four main data sources: (i) CRSP Survivorship-Bias-Free US Mutual Funds data, (ii) Factset Mutual Funds data, (iii) BuiltWith for websites' technology installation/removal dates, and (iv) data from whois.com for details on websites' registration date, hosting service, etc.

B.1 CRSP Mutual Funds

I follow Berk and van Binsbergen (2015) and Pástor, Stambaugh and Taylor (2015) procedures as closely as possible. I start from the raw CRSP Survivorship-Bias-Free US Mutual Funds monthly data. Each observation in this dataset identifies a fund's share class $(crsp_fundno)$ in a given month. CRSP Mutual Funds dataset from January 1980 to December 2022 has 8,803,093 share class-month observations. I start filling missing contact information in CRSP data; i.e., address1, city, state, website, and zip. For 62,266 obs. (0.71% of total), the missing information are between two (or more) non-empty information within the same share class, and the two non-empty coincides. I fill those missing observations using the non-empty contact information within the same share class.

CRSP reports a fund's *website* starting January 2008. I use information from whois.com to backward fill missing websites' observations. Whois.com has information on websites' registration date, hosting service, and others. I hand-collected from whois.com the registration date for each website in CRSP (when available), and I verify the website belongs to the CRSP fund using the Internet Archive Wayback Machine. Then, I backward fill 1,423,338 obs. (16.17% of total) missing websites observations before 2008 for months after the website's registration date.

Following Berk and van Binsbergen (2015), I backfill missing *cusip* with the last available non-empty *cusip* within the same share class. This step replace 836, 636 *cusip* obs. (9.50% of total). I do not forward fill missing observations. I replace missing *exp_ratio* and *actual_12b1* fees with their time series average within the same share class (Roussanov, Ruan and Wei, 2020). This step fill 1,506,773 obs. (17.35% of total) and 708,187 obs. (8.16% of total) respectively. Following Sirri and Tufano (1998) and Roussanov, Ruan and Wei (2020) I compute the "effective" 12b-1 fee summing CRSP's *actual_12b1* to the share class-month front load, and assuming the front load fee is amortized over 7 years.

I adjust AUM (TNA) for inflation to be comparable across time. The seasonally adjusted monthly CPI is from FRED All Consumers: All Items, and I use January 2000 as baseline month (as in Berk and van Binsbergen, 2015).

Finally, since several funds in CRSP report their AUM only at the quarterly (or annual) frequency before March 1993 (Pástor, Stambaugh and Taylor, 2015), I drop all share class-month observations before that date. I also drop observations with missing *cusip*. After this steps, I have 8,237,580 share class-month observations from the CRSP Mutual Funds dataset.

B.2 Factset Mutual Funds

I obtain mutual funds data from Factset at the share class level, and I will merge it with CRSP data at the *cusip-month* level. I use *cusip* rather than *ticker*, because the *cusip* cannot be re-assigned. I use Factset mainly to identify all share classes of the same mutual fund *factset_fund_id* in a given month. From Factset, I obtain the fund id, -fund type (e.g., ETF, Open-end fund, etc.), the fund name, brand, share class, leverage factor, category, minimum initial investment, and cash holdings (deflated in January 2000 dollars as done for AUM –see Appendix Section B.1).

B.3 CRSP-Factset Merged

I merge CRSP and Factset dataset by *cusip-month*. The CRSP dataset resulting from Appendix Section B.1 has 3,506 observations (0.04% of total) in which the same *cusip-month* pair appears twice. Inspecting those observations, they do not appear to be double reporting, but rather mistakes on CRSP's side. For each of those observations, I keep the *cusip-month* with the largest total AUM in the sample.

Then, I merge CRSP and Factset dataset by *cusip-month*. The merge results in 7,646,136/8,237,580

observations merged (92.82%). I drop the remaining 472,797 unmerged observations, since merging them by *ticker-month* might result in incorrect attribution of share classes to fund with re-assigned *ticker*.

I classify index funds following Berk and van Binsbergen (2015) and Pástor, Stambaugh and Taylor (2015) as closely as possible. I flag a share class observation as index fund if contains "INDEX", "ETF", "ISHARES", "IDX", "INDX" in its (uppercase letters) fund name, *et_flag* is either "F" or "N", the lipper class belongs to S&P500 index (*lipper_class* is "SPSP" or "SP"), the *index_fund_flag* is "Y", the Factset's fund type is either "ETF" or "ETN", the (uppercase letters) brand name is "ISHARES", or it is an index levered fund. I classify a share classes to be of an index levered funds if it has Factset's leverage factor larger than 1, or if it contains "INVERSE", "SHORT", "ULTRA", "2X", "3X", "4X", "5X", "6X", "7X", "8X", "9X", "0X", "SHORT TERM", "SHORT TM", "SHORT BOND", "SHORT BND", "LONG SHORT", "LG SHORT" in its (uppercase letters) fund name.

I classify institutional share classes as observations with *inst_fund* equal to "Y", or if it contains "INSTITUTIONAL SHARES", "INSTITUTIONAL CLASS", "CLASS I", or "CLASS Y" in its (uppercase letters) fund name. I classify retail share classes as observations with *retail_fund* equal to "Y", or if it contains "RETAIL SHARES", "RETAIL CLASS", "CLASS A", "CLASS B", "CLASS C", or "INVESTOR CLASS" in its (uppercase letters) fund name.

I then aggregate observations across all share classes of the same fund. I sum the AUM of all share classes, and average all other variables (e.g., expense ratio, returns, turnover, etc.), weighted by lagged AUM. I also keep the first offer date of the oldest share class within fund. Finally, I drop observations before the first time a fund reaches more than \$5 million in AUM (in January 2000 dollars) if the fund ever reach that threshold in the sample. I drop observations dated before the fund's first offer date to account for incubation bias (Evans, 2010) and I remove observations with less than 2 years in the full sample (Berk and van Binsbergen, 2015). After this step, I have 2,861,642 fund-month observations

B.4 Website Technologies

I obtain information on a fund website's technology adoption from BuiltWith. In general, website technologies are defined as tools and services like analytics, payment systems, networking and programming scripts that enhance a website's features. For example, Pay-Pal Credit is a technology that enables customers to make buy-now-pay-later payments on a website. BuiltWith is a company specialized in website profiling, who sells these data to companies and consultants. They analyze websites' page code and search for specific patterns that identify the usage of technologies –similar to how a virus scanner searches for pattern in files to identify viruses. The most common patterns they use to identify such technologies are HTML tags, cookies, and Javascript snippets found in a website's source code. BuiltWith continuously crawls websites and analyzes their underlying technologies. The provide a comprehensive database of technologies with installation and (eventual) removal date for millions of websites. They mark a technology as "removed", if they don't find it for two consecutives crawls on a website's code. Appendix Figure B.1 shows a snapshot of the technology data for arrowfunds.com, as it appears in my sample. For each unique website in my sample (from CRSP Mutual Funds data) I collect all the technologies name, and installation/removal dates. BuiltWith also provide a technology_category (e.g., Analytics, Feeds, etc.) for each technology, that I map to all technologies installed at least once in my sample. Then, I build a panel with website-technology_name-month where the first month is the *first_detected* month, and the last one is the *last_detected* month. I further filter for analytics' technologies that are aimed to collect and analyze customers' data, and I count the number of such technologies installed in the website. Finally, I merge this dataset by website-date to the main CRSP/Factset data at the share class level (before aggregation). I merge 3,091,431/7,646,136 observations (i.e., 40.43% of the $crsp_fundno-month$ observations have at least one data technology in place). Then, I replace missing with zeros, if I have a valid website for the $crsp_fundno-month$ observation and I have data from BuiltWith for the associated *website-month*, but BuiltWith does not detect data technologies for that month.

Domain	Technology_name	First_Detected 🔻	Last_Detected 🔻	Live
arrowfunds.com	Ahrefs Bot Disallow	17/09/20	17/07/24	Yes
arrowfunds.com	AJAX Libraries API	14/05/18	24/07/24	Yes
arrowfunds.com	Amazon	21/02/23	13/07/24	Yes
arrowfunds.com	Anthropic Claude Bot Disallow	06/06/24	17/07/24	Yes
arrowfunds.com	ASP.NET	30/05/13	24/07/24	Yes
arrowfunds.com	Baidu Bot Disallow	17/09/20	17/07/24	Yes
arrowfunds.com	Careers	09/03/19	18/07/20	No
arrowfunds.com	Cart Functionality	20/04/23	20/04/23	No
arrowfunds.com	Cohere AI Disallow	18/06/24	17/07/24	Yes
arrowfunds.com	Common Crawl Bot Disallow	06/06/24	17/07/24	Yes
arrowfunds.com	CrUX Dataset	31/12/22	16/07/24	Yes
arrowfunds.com	DoubleClick.Net	26/02/18	24/07/24	Yes
arrowfunds.com	Financial Industry Regulatory Authority	23/12/19	11/08/21	No
arrowfunds.com	Font Awesome	16/04/24	16/04/24	Yes
arrowfunds.com	Global Site Tag	15/02/18	24/07/24	Yes
arrowfunds.com	GoDaddy	02/07/19	13/07/24	Yes
arrowfunds.com	Google AdWords Conversion	15/02/18	05/07/20	No
arrowfunds.com	Google Analytics	21/10/13	24/07/24	Yes
, , ,	- - - - - - - - - - - - - - - - - - -		-	

FIGURE B.1: **Example of website technology data**. This figure displays a snapshot of the website technology data from BuiltWith for **arrowfunds.com** (in my sample).

B.5 Final Sample

From the sample of 2,861,642 *factset_fund_id-month* observations, I compute fund flows following Lou (2012):

$$Flow_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1} \cdot (1 + r_{i,t}) - MGN_{i,t}}{AUM_{i,t-1}},$$
(B.1)

where $AUM_{i,t}$ represents total net assets for fund *i* in month *t*, $r_{i,t}$ is the (gross) monthly return, and $MGN_{i,t}$ is the increase in AUM due to the fund's mergers (if any) in month *t*. Since CRSP does not reports the exact date in which the merger takes place, I follow Lou (2012) and use information about the latest available NAV of the target funds to build a six-months window where the merger plausibly took place. In particular, from CRSP I observe the last date in which the target fund has non-empty NAV, and the identifier of the acquirer. For the acquiring fund, I build a six months window which starts one month before the latest available date of the dead fund, until five months after. Within this window, I compute the flows without accounting for the possible merger (i.e., $\frac{AUM_{i,t-AUM_{i,t-1}}(1+r_{i,t})}{AUM_{i,t-1}}$) and I flag as merger_month the date with highest flow within the six-months window. Appendix Table B.1 gives an example of this approach for the acquirer fund $crsp_fundno = 662$. In the example, the target fund had latest AUM of \$452.5 million (latest date 1999m4). Around the six-months window, the acquirer has one clear flow outlier (computed without accounting for the merger); i.e., 1995m5. I flag the 1999m5 observation as merger date. Therefore, following equation B.1, the actual fund flow in 1999m5 is -0.6417.

Finally, I keep observations with available variables for my analysis (i.e., *Flow*, AUM, fees). I remove fixed income mutual funds, money market funds, variable products, and others (e.g., 529 Plan, Collective Investment Trust). The monthly sample now contains only ETFs and equity (open-end) mutual funds from March 1993 to December 2022.

$crsp_{-}fundno$	month	TNA	window 6M	$trgt_lastTNA$	flow	flagMerger
662	1999m1	19.94	0		0.0203	0
662	1999m2	18.71	0		-0.0127	0
662	$1999 \mathrm{m}3$	20.14	1	452.5	0.0517	0
662	$1999 \mathrm{m4}$	19.19	1	452.5	-0.0818	0
662	$1999\mathrm{m}5$	459.05	1	452.5	22.9441	1
662	1999m6	450.48	1	452.5	-0.0645	0
662	$1999 \mathrm{m7}$	410.50	1	452.5	-0.0478	0
662	$1999 \mathrm{m8}$	400.31	1	452.5	-0.0182	0
662	1999m9	368.87	0		-0.0510	0
662	1999 m 10	375.46	0		-0.0415	0

TABLE B.1: **Example of Funds Merger**: This table shows an example of funds merger attribution date on CRSP. In this case, the attributed merger month is 1999m5, since it has the largest *flow* within the six months window around the target latest AUM (1999m4).

C Additional Results

This section contains additional results and robustness not contained in the main text.



C.1 Appendix Figures

FIGURE C.1: **Overlap in Technology Adoption within Hosting Platform**. The figure shows the cosine similarity in website technology adoption within website hosting platform. Cosine similarity is higher when there is high overlap among website technology within a given hosting platform. For example, when the cosine similarity equals one all website on that hosting platform share the same set of technologies installed. The blue area shows the histogram of cosine similarity for the sample of US mutual funds in this paper (mean 0.29, median 0.27). The red hatched area shows the histogram for the average cosine similarity from simulations where the adoption of technology within hosting platform is randomly assigned and maintaining the same number of technologies within hosting platform, for comparability (mean 0.43, median 0.44).



FIGURE C.2: Fund Fees Dispersion within Fund Categories. The figure plots the average fund fees dispersion within fund categories from 1995 to 2022. Panel A and Panel B show the fund fees dispersion (coefficient of variation) for Small Cap and Emerging Market US funds, respectively. Panel C depicts the average fee dispersion within fund category. For each month t, I compute the average and standard deviation of fund fees in a given category. Then, I obtain the average coefficient of variation for each month from 1995 to 2022. The solid red line in Panel C shows the equally weighted dispersion in fund fees, while the dashed purple line reports the AUM-weighted dispersion.



FIGURE C.3: Total Assets in Thomson Reuters (s12) and CRSP Holdings. The figure shows the total assets (in trillion of US dollars) in the Thomson Reuters (s12) and CRSP mutual funds holdings databases. CRSP has no holdings data before 2003 (shaded area). The solid blue line reports total equity assets in the Thomson Reuters (s12), while the dotted red line show the CRSP mutual funds holdings data. This figure updates Figure 1 in Shive and Yun (2013) using updated vintages of data.



FIGURE C.4: Word Cloud of Data Technologies' Descriptions. The figure shows the word cloud of data technologies' features in my sample. For each data technology, I collect a short description of what the technology allows to do (e.g., ipstack: "provides IP to geolocation APIs and global IP database services") and plot the word cloud where larger fonts indicate a higher word frequency.



FIGURE C.5: Cumulative Average Monthly Flows. The figure shows the cumulative monthly average flows from January 2006 to December 2022, with 95% confidence intervals. For each month t, I compute an equally weighted average of flows for funds with data technology in place (dashed blue line) and funds without data technology (solid red line). See Section 3.2 for details on data technologies. The vertical dotted black line represents the release of TensorFlow in November 2015, which I use as plausibly exogenous variation in signals' precision in Section 4.4. This plot *only* shows sample averages.
C.2 Appendix Tables

	Fund Flows _{<i>i</i>,<i>t</i>+1} (%)					
	(1)	(2)	(3)	(4)		
$\mathrm{Data}_{i,t}$	$\begin{array}{c} 0.175^{***} \\ (0.039) \end{array}$	$\begin{array}{c} 0.173^{***} \\ (0.046) \end{array}$	0.180^{***} (0.052)	$\begin{array}{c} 0.179^{***} \\ (0.050) \end{array}$		
12b-1 Fees	×	×	\checkmark	\checkmark		
Controls	\checkmark	\checkmark	\checkmark	\checkmark		
Fund FE	\checkmark	\checkmark	\checkmark	\checkmark		
Time FE	\checkmark	×	\checkmark	×		
Category×Time FE	×	\checkmark	×	\checkmark		
Outcome mean	0.221	0.221	0.221	0.221		
Outcome SE	6.293	6.293	6.293	6.293		
Obs. Second-stage Adj. R^2	$844,\!344$ 0.001	$830,721 \\ 0.001$	$844,\!345 \\ 0.001$	$830,721 \\ 0.001$		

TABLE C.1: Fund Flows and Data Technologies, staggered treatment correction: This table shows results of panel regression robust to concerns in staggered difference-in-differences (see Goodman-Bacon, 2021). I estimate equation (2) following the approach in Gardner (2021); Gardner et al. (2024) to correct for identification concerns in staggered difference-in-differences settings. The dependent variable is the one-month-ahead fund flow, and the regressors are a dummy equal to one if a fund *i* has a data technology in place at month *t* (DATA_{*i*,*t*}), and controls for fund-month characteristics (omitted for brevity). See Section 3.2 for details on data technologies. The control variables include a fund's size (*logAUM*), expense ratio, (*log*) age, flows, turnover, and CAPM alpha in month *t*. Columns (3) and (4) include 12b-1 fees as additional controls, following Table 3 in the main text. The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022. All standard errors are bootstrapped and two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	Fund Flows _{<i>i</i>,<i>t</i>+1} (%)				
	(1)	(2)	(3)	(4)	
$DATA_{i,t}$	$\begin{array}{c} 0.141^{***} \\ (0.042) \end{array}$	$\begin{array}{c} 0.127^{***} \\ (0.041) \end{array}$	$\begin{array}{c} 0.144^{***} \\ (0.042) \end{array}$	$\begin{array}{c} 0.130^{***} \\ (0.041) \end{array}$	
12b-1 $\mathrm{Fees}_{i,t}$			$\begin{array}{c} 0.251^{**} \\ (0.112) \end{array}$	$\begin{array}{c} 0.251^{**} \\ (0.109) \end{array}$	
Alpha $\mathrm{CAPM}_{i,t}$	$7.402^{***} \\ (0.285)$	$\begin{array}{c} 10.113^{***} \\ (0.363) \end{array}$	$7.404^{***} \\ (0.285)$	$\begin{array}{c} 10.117^{***} \\ (0.363) \end{array}$	
Fund $\mathrm{Flows}_{i,t}$	$\begin{array}{c} 0.125^{***} \\ (0.010) \end{array}$	$\begin{array}{c} 0.117^{***} \\ (0.010) \end{array}$	$\begin{array}{c} 0.125^{***} \\ (0.010) \end{array}$	$\begin{array}{c} 0.117^{***} \\ (0.010) \end{array}$	
$log \mathrm{AUM}_{i,t}$	-0.548^{***} (0.026)	-0.538^{***} (0.026)	-0.549^{***} (0.026)	-0.539^{***} (0.026)	
$log \mathrm{Age}_{i,t}$	-1.709^{***} (0.064)	-1.701^{***} (0.064)	-1.709^{***} (0.064)	-1.701^{***} (0.064)	
Exp. $\text{Ratio}_{i,t}$	-1.212^{***} (0.098)	-1.100^{***} (0.095)	-1.250^{***} (0.100)	-1.137^{***} (0.096)	
Controls	\checkmark	\checkmark	\checkmark	\checkmark	
Fund FE	\checkmark	\checkmark	\checkmark	\checkmark	
Category×Time FE	√ ×	×	√ ×	×	
Outcome mean Outcome SE	$0.221 \\ 6.293$	$0.221 \\ 6.293$	$0.221 \\ 6.293$	$0.221 \\ 6.293$	
Obs. Adj. R^2	$971,730 \\ 0.112$	$970,832 \\ 0.141$	$971,730 \\ 0.112$	$970,832 \\ 0.141$	

TABLE C.2: Fund Flows and Data Technologies, Detailed Results: This table shows results of OLS panel regression in which the dependent variable is the one-month-ahead fund flow. The regressors are a dummy equal to one if a fund *i* has a data technology in place at month t (DATA_{*i*,*t*}), 12b-1 fees, and controls for fund-month characteristics. See Section 3.2 for details on data technologies. The control variables include a fund's size (*logAUM*), expense ratio, (*log*) age, flows, turnover, and CAPM alpha in month *t*. The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022. All standard errors are two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	Int	Inflows _{<i>i</i>,<i>t</i>+1} (%)			Outflows _{$i,t+1$} (%)		
	(1)	(2)	(3)	(4)	(5)	(6)	
$\mathrm{Data}_{i,t}$	$\begin{array}{c} 0.284^{***} \\ (0.053) \end{array}$	0.220^{**} (0.087)	$\begin{array}{c} 0.218^{***} \\ (0.083) \end{array}$	$\begin{array}{c} 0.110\\ (0.115) \end{array}$	$0.005 \\ (0.097)$	$0.007 \\ (0.113)$	
12b-1 Fees	×	\checkmark	\checkmark	×	\checkmark	\checkmark	
Controls	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	
Fund FE	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	
Time FE	\checkmark	×	×	\checkmark	×	×	
Category×Time FE	×	\checkmark	\checkmark	×	\checkmark	\checkmark	
Outcome mean	5.698	5.698	5.698	5.459	5.459	5.459	
Outcome SE	15.466	15.466	15.466	16.620	16.620	16.620	
Obs. Second-stage Adj. R^2	$198,791 \\ 0.002$	$194,\!903 \\ 0.001$	$194,\!903 \\ 0.001$	$198,790 \\ 0.000$	194,901 -0.000	194,902 -0.000	

TABLE C.3: Fund Inflows, Outflows and Data Technologies: This table shows results of panel regression on fund inflows and outflows separately, robust to concerns in staggered difference-in-differences (see Goodman-Bacon, 2021). I estimate equation (2) substituting the LHS with fund inflows and outflows, following the approach in Gardner (2021); Gardner et al. (2024) to correct for identification concerns in staggered difference-in-differences settings. The dependent variable is the one-month-ahead fund inflows in columns (1) to (3) and fund outflows in columns (4) to (6). The regressors are a dummy equal to one if a fund *i* has a data technology in place at month *t* (DATA_{*i*,*t*}), and controls for fund-month characteristics (omitted for brevity). See Section 3.2 for details on data technologies. The control variables include a fund's size (logAUM), expense ratio, (log) age, past flows, turnover, and CAPM alpha in month *t*. Columns (3) and (6) include 12b-1 fees as additional controls, following Table 3 in the main text. The monthly sample is from January 2006 to June 2018. All standard errors are bootstrapped and two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

Pre-adoption growth rates	Control	Treatment	Difference	p-value
Monthly Fund Flows	-0.190	-0.198	0.008	0.780
Quarterly Fund Flows	-0.241	-0.280	0.039	0.260

TABLE C.4: **Parallel trends**: This table reports the growth rate of fund flows in the 12 months preadoption, for adopting and not-adopting fund. For each fund's adoption of a data technology in month t(treatment), I construct the control group as the sample of funds with no data technologies in place in month t. The table shows monthly and quarterly growth rates of fund flows for the sample of treated and control group in the 12 months pre-adoption. I winsorize growth rates at the 1% and 99% level. The last column reports the p-value of the difference between treated and control groups.

Panel A: Treated (at adoption)							
	mean	sd	p5	p25	p50	p75	p95
AUM (M)	1,509.28	$6,\!934.52$	7.27	45.49	197.33	846.95	5,761.43
Expense Ratio (%)	1.06	0.53	0.13	0.74	1.07	1.39	1.97
12b-1 Fees $(\%)$	0.28	0.21	0.00	0.10	0.25	0.39	0.71
Flows $(\%)$	0.30	6.02	-5.54	-1.55	-0.41	1.12	8.17
Turnover Ratio	0.75	1.08	0.05	0.23	0.46	0.85	2.31
Age (Years)	12.48	8.76	1.42	5.08	11.08	18.00	29.67
		Panel B	: Contre	ol			
	mean	sd	p5	p25	p50	p75	p95
AUM (M)	$1,\!201.05$	$5,\!540.89$	6.85	40.43	171.23	670.08	4,268.67
Expense Ratio (%)	1.12	0.52	0.18	0.81	1.13	1.44	2.01
12b-1 Fees (%)	0.29	0.22	0.00	0.10	0.26	0.43	0.74
Flows $(\%)$	0.20	6.11	-5.76	-1.76	-0.56	1.01	8.76
Turnover Ratio	0.83	1.03	0.07	0.27	0.54	0.99	2.40
Age (Years)	11.58	8.07	1.33	4.83	10.25	16.50	27.42

TABLE C.5: **Balance covariates**: This table reports summary statistics of covariates for funds in the treatment and control group. For each fund's adoption of a data technology in month t (treatment), I construct the control group as the sample of funds with no data technologies in place in month t. For each group, I report the covariates in the 3 months pre-adoption. The table shows covariates included in regressions in the main text. AUM is inflation adjusted in January 2000 \$ million. Expense Ratio, 12b-1 Fees, and Flows are in %; e.g., the average fund flow for the control group is 0.20% monthly.

	Expense Ratio _{<i>i</i>,<i>t</i>+1} (%)						
	(1)	(2)	(3)	(4)			
$DATA_{i,t}$	0.035^{***} (0.006)	0.033^{***} (0.006)	0.038^{***} (0.004)	0.036^{***} (0.006)			
12b-1 Fees	х	×	\checkmark	\checkmark			
Controls	\checkmark	\checkmark	\checkmark	\checkmark			
Fund FE	\checkmark	\checkmark	\checkmark	\checkmark			
Time FE	\checkmark	×	\checkmark	×			
Category×Time FE	×	\checkmark	×	\checkmark			
Outcome mean	1.141	1.141	1.141	1.141			
Outcome SE	0.538	0.538	0.538	0.538			
Obs. Second-stage Adj. R^2	$844,\!345 \\ 0.012$	$830,722 \\ 0.011$	$844,\!344$ 0.015	$830,722 \\ 0.013$			

TABLE C.6: Expense Ratio and Data Technologies, staggered treatment correction: This table shows results of panel regression robust to concerns in staggered difference-in-differences (see Goodman-Bacon, 2021). I estimate a similar specification to results in Table 4, following the approach in Gardner (2021); Gardner et al. (2024) to correct for identification concerns in staggered difference-in-differences settings. The dependent variable is the one-month-ahead expense ratio, and the regressors are a dummy equal to one if a fund *i* has a data technology in place at month *t* (DATA_{*i*,*t*}), and controls for fund-month characteristics (omitted for brevity). See Section 3.2 for details on data technologies. The control variables include a fund's size (logAUM), (log) age, flows, turnover, and CAPM alpha in month *t*. Columns (3) and (4) include 12b-1 fees as additional controls. The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022. All standard errors are bootstrapped and two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	Fund Flows _{<i>i</i>,<i>t</i>+1} (%)					
	(1)	(2)	(3)	(4)		
$\mathrm{DATA}_{i,t}$	$\begin{array}{c} 0.149^{***} \\ (0.041) \end{array}$	$\begin{array}{c} 0.139^{***} \\ (0.041) \end{array}$	$\begin{array}{c} 0.153^{***} \\ (0.042) \end{array}$	$\begin{array}{c} 0.149^{***} \\ (0.042) \end{array}$		
12b-1 $\mathrm{Fees}_{i,t}$			$\begin{array}{c} 0.295^{**} \\ (0.127) \end{array}$	$\begin{array}{c} 0.307^{**} \\ (0.124) \end{array}$		
Controls	\checkmark	\checkmark	\checkmark	\checkmark		
Fund FE	\checkmark	\checkmark	\checkmark	\checkmark		
Time FE	\checkmark	×	\checkmark	×		
Category×Time FE	×	\checkmark	×	\checkmark		
Outcome mean	0.349	0.349	0.349	0.349		
Outcome SE	6.101	6.101	6.101	6.101		
Obs. Adj. R^2	$\begin{array}{c} 683,\!114 \\ 0.145 \end{array}$	$\begin{array}{c} 682,\!065 \\ 0.176 \end{array}$	$\begin{array}{c} 683,\!114 \\ 0.145 \end{array}$			

TABLE C.7: Robustness of Results on Flows, excluding Google Analytics: This table addresses concerns that the results are entirely driven by Google Analytics. The table replicates the main findings on flows (Table 3) excluding Google Analytics from the set of data technologies. Specifically, this table shows results of OLS panel regression in which the dependent variable is the one-month-ahead fund flow. The regressors are a dummy equal to one if a fund *i* has a data technology in place (different from Google Analytics) at month *t* (DATA_{*i*,*t*}), 12b-1 fees, and controls for fund-month characteristics (omitted for brevity). See Section 3.2 for details on data technologies. The control variables include a fund's size (*logAUM*), expense ratio, (*log*) age, flows, turnover, and FF-3 factors alpha (columns (1) and (2)) or FF-5 factors alpha (columns (3) and (4)) in month *t*. For this table, I remove funds with Google Analytics being the only data technology in place. The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022. All standard errors are two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	Expense Ratio _{<i>i</i>,<i>t</i>+1} (%)					
	(1)	(2)	(3)	(4)		
$DATA_{i,t}$	$\begin{array}{c} 0.035^{***} \\ (0.007) \end{array}$	$\begin{array}{c} 0.035^{***} \\ (0.007) \end{array}$	$\begin{array}{c} 0.046^{***} \\ (0.007) \end{array}$	$\begin{array}{c} 0.044^{***} \\ (0.007) \end{array}$		
12b-1 $\operatorname{Fees}_{i,t}$			$\begin{array}{c} 0.273^{***} \\ (0.020) \end{array}$	$\begin{array}{c} 0.252^{***} \\ (0.018) \end{array}$		
Controls	\checkmark	\checkmark	\checkmark	\checkmark		
Fund FE	\checkmark	\checkmark	\checkmark	\checkmark		
Time FE	\checkmark	×	\checkmark	×		
Category×Time FE	×	\checkmark	×	\checkmark		
Outcome mean	1.167	1.167	1.167	1.167		
Outcome SE	0.560	0.560	0.560	0.560		
Obs. Adj. R^2	$\begin{array}{c} 683,\!114 \\ 0.928 \end{array}$	$682,065 \\ 0.932$	$\begin{array}{c} 683,\!114 \\ 0.931 \end{array}$	$682,065 \\ 0.935$		

TABLE C.8: Robustness of Results on Expense Ratio, excluding Google Analytics: This table addresses concerns that the results are entirely driven by Google Analytics. The table replicates the main findings on expense ratio (Table 4) excluding Google Analytics from the set of data technologies. Specifically, this table shows results of OLS panel regression in which the dependent variable is the one-month-ahead fund expense ratio. The regressors are a dummy equal to one if a fund *i* has a data technology in place (different from Google Analytics) at month t (DATA_{*i*,*t*}), 12b-1 fees, and controls for fund-month characteristics (omitted for brevity). See Section 3.2 for details on data technologies. The control variables include a fund's size (*logAUM*), (*log*) age, flows, turnover, and CAPM alpha in month *t*. For this table, I remove funds with Google Analytics being the only data technology in place. The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022. All standard errors are two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

		\mathbb{P} {Adoption} (%)						
	(1)	(2)	(3)	(4)	(5)	(6)		
Category Adoption $\%_{i,t}$	$\begin{array}{c} 0.171 \\ (0.893) \end{array}$	$0.169 \\ (0.291)$	-0.283 (0.731)	$0.140 \\ (0.223)$	$0.272 \\ (0.501)$	0.314^{*} (0.172)		
State Adoption $\mathcal{K}_{i,t}$	3.034^{***} (0.814)	$\begin{array}{c} 1.145^{***} \\ (0.276) \end{array}$						
City Adoption $\%_{i,t}$			$\begin{array}{c} 4.066^{***} \\ (0.692) \end{array}$	$\begin{array}{c} 1.455^{***} \\ (0.227) \end{array}$				
Zip Code Adoption $\mathcal{K}_{i,t}$					$\begin{array}{c} 4.766^{***} \\ (0.463) \end{array}$	$\begin{array}{c} 1.904^{***} \\ (0.183) \end{array}$		
Estimator Controls	$\begin{array}{c} \text{Logit} \\ \checkmark \end{array}$	$\stackrel{\text{Probit}}{\checkmark}$	$\begin{array}{c} \text{Logit} \\ \checkmark \end{array}$	$\stackrel{\text{Probit}}{\checkmark}$	$\begin{array}{c} \text{Logit} \\ \checkmark \end{array}$	$\stackrel{\text{Probit}}{\checkmark}$		
Obs. Pseudo R^2	$720,730 \\ 0.093$	$720,730 \\ 0.096$	$720,730 \\ 0.141$	$720,730 \\ 0.140$	$720,730 \\ 0.233$	$720,730 \\ 0.226$		

TABLE C.9: Technology Diffusion in the Asset Management Industry: This table shows results of logit/probit regression of probability to adopt data technology, on the (lagged) adoption rate at different levels of aggregation. The adoption rate is defined as the percentage of funds with data technology in place, within a given category, state, city, or zip code in month t. Columns (1) and (2) use adoption rate at the state level, columns (3) and (4) at city, and columns (5) and (6) at the zip code level. The regressors are adoption rate within fund category, adoption rate at the geographical level (state, city, or zip code), and controls for fund-month characteristics (omitted for brevity) The control variables include (lagged) fund's size (logAUM), expense ratio, (log) age, and flows. All standard errors are clustered by month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	Fund Flows _{<i>i</i>,<i>t</i>+1} (%)					
	FF-3 f	factors	FF-5 f	factors		
	(1)	(2)	(3)	(4)		
$DATA_{i,t}$	$\begin{array}{c} 0.149^{***} \\ (0.041) \end{array}$	$\begin{array}{c} 0.139^{***} \\ (0.041) \end{array}$	$\begin{array}{c} 0.153^{***} \\ (0.042) \end{array}$	$\begin{array}{c} 0.149^{***} \\ (0.042) \end{array}$		
12b-1 $\operatorname{Fees}_{i,t}$	$\begin{array}{c} 0.247^{**} \\ (0.113) \end{array}$	0.230^{**} (0.110)	$\begin{array}{c} 0.232^{**} \\ (0.114) \end{array}$	0.198^{*} (0.112)		
Controls	\checkmark	\checkmark	\checkmark	\checkmark		
Fund FE	\checkmark	\checkmark	\checkmark	\checkmark		
Time FE	\checkmark	×	\checkmark	×		
Category×Time FE	×	\checkmark	×	\checkmark		
Outcome mean	0.221	0.221	0.221	0.221		
Outcome SE	6.293	6.293	6.293	6.293		
Obs. Adj. R^2	$972,199 \\ 0.106$	$971,294 \\ 0.136$	$972,199 \\ 0.100$	$970,832 \\ 0.129$		

TABLE C.10: Robustness of Main Results with alternative performance measures: This table replicates the main results using different performance measures. This table shows results of OLS panel regression in which the dependent variable is the one-month-ahead fund flow. The regressors are a dummy equal to one if a fund *i* has a data technology in place at month *t* (DATA_{*i*,*t*}), 12b-1 fees, and controls for fund-month characteristics (omitted for brevity). See Section 3.2 for details on data technologies. The control variables include a fund's size (*logAUM*), expense ratio, (*log*) age, flows, turnover, and FF-3 factors alpha (columns (1) and (2)) or FF-5 factors alpha (columns (3) and (4)) in month *t*. The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022. All standard errors are two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	Amihud _{<i>i</i>,<i>q</i>+1} (%)					
	(1)	(2)	(3)	(4)		
$\mathrm{DATA}_{i,q}$	0.496^{***} (0.011)	$\begin{array}{c} 0.426^{***} \\ (0.103) \end{array}$	$\begin{array}{c} 0.492^{***} \\ (0.113) \end{array}$	$\begin{array}{c} 0.433^{***} \\ (0.098) \end{array}$		
12b-1 Fees	×	×	\checkmark	<u> </u>		
Controls	\checkmark	\checkmark	\checkmark	\checkmark		
Fund FE	\checkmark	\checkmark	\checkmark	\checkmark		
Time FE	\checkmark	×	\checkmark	×		
Category×Time FE	×	\checkmark	×	\checkmark		
Outcome mean Outcome SE	$0.525 \\ 4.588$	$0.525 \\ 4.588$	$0.525 \\ 4.588$	$0.525 \\ 4.588$		
Obs. Second-stage Adj. R^2	$149,\!870 \\ 0.010$	$147,328 \\ 0.007$	$149,889 \\ 0.010$	$147,\!346 \\ 0.008$		

TABLE C.11: Illiquid Holdings and Data Technologies: This table shows results of panel regression on the fund portfolio tilt toward illiquid stocks, as measured by Amihud illiquidity. I define portfolio tilts similarly to Pastor et al. (2024). Formally, fund *i* tilt towards illiquid stocks in quarter *q* is the absolute value of deviation in weighted characteristics, as defined in Lettau et al. (2024): $\frac{1}{2} \sum_{n=1}^{N} ||(w_{i,q}(n) - \bar{w}_{i,q}(n)) \cdot$ $Amihud_q(n)||$, where $\bar{w}_{i,q}(n)$ is the weight of a value-weighted portfolio within the stocks held by fund *i* in quarter *q*. In the estimation, I follow the approach in Gardner (2021); Gardner et al. (2024) to correct for identification concerns in staggered difference-in-differences settings, as the sample of fund holdings data begins in 2004:Q2. The dependent variable is the one-month-ahead fund's portfolio tilt towards illiquid (Amihud) stocks, and the regressors are a dummy equal to one if a fund *i* has a data technology in place at month *t* (DATA_{*i*,*t*}), and controls for fund-month characteristics (omitted for brevity). See Section 3.2 for details on data technologies. The control variables include a fund's size (*logAUM*), (*log*) age, flows, turnover, and CAPM alpha in month *t*. The quarterly sample is from 2004:Q2 to 2022:Q4. All standard errors are bootstrapped and two-way clustered by fund and quarter (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	Fund Flows _{<i>i</i>,<i>t</i>+1} (%)							
			z_i :	Tenure of	Adoption	N. of Da	N. of Data Tech.	
	(1)	(2)		(3)	(4)	(5)	(6)	
$\mathrm{DATA}_{i,t}$	$\begin{array}{c} 0.567^{***} \\ (0.139) \end{array}$	$\begin{array}{c} 0.595^{***} \\ (0.140) \end{array}$		$\begin{array}{c} 0.517^{***} \\ (0.146) \end{array}$	$\begin{array}{c} 0.517^{***} \\ (0.146) \end{array}$	$\begin{array}{c} 0.491^{***} \\ (0.136) \end{array}$	$\begin{array}{c} 0.491^{***} \\ (0.136) \end{array}$	
$DATA_{i,t} \times Post_t$	0.253^{**} (0.109)	$\begin{array}{c} 0.313^{***} \\ (0.109) \end{array}$						
$DATA_{i,t} \times Post_t \times z_i$				0.080^{**} (0.033)	0.080^{**} (0.033)	0.023^{**} (0.011)	0.023^{**} (0.011)	
Controls Fund FE Time FE Category×Time FE	√ √ √ ×	√ √ × √		√ √ √ ×	√ √ × √	√ √ √ ×	√ √ × √	
Outcome mean Outcome SE	$\begin{array}{c} 0.182 \\ 6.458 \end{array}$	$\begin{array}{c} 0.182 \\ 6.458 \end{array}$		$\begin{array}{c} 0.182 \\ 6.458 \end{array}$				
Obs. Adj. R^2	$598,363 \\ 0.104$	$597,524 \\ 0.140$		$\begin{array}{c} 438,\!485 \\ 0.093 \end{array}$	$\begin{array}{c} 438,\!485 \\ 0.093 \end{array}$	$519,866 \\ 0.101$	$519,866 \\ 0.101$	

TABLE C.12: Fund Flows and Data Technologies after TensorFlow, without Growth Funds: This table replicates the findings in Section 4.4 (Table 7 in the main text) removing growth funds from the sample. This robustness address the concern that results in Table 7 are driven by TensorFlow affecting flows to growth funds only. Specifically, this table shows results of OLS panel regression in which the dependent variable is the one-month-ahead flow for share class j of fund i. Columns (1) and (2) follow specification in equation (5), while columns (3) to (6) follow (6). In columns (3) and (4) the continuous treatment z_i is the (log) number of months between the first data technology adoption and TensorFlow's release. Columns (5) and (6) use the number of data technologies installed as of TensorFlow's release, as continuous treatment z_i . DATA_{i,t} is a dummy equal to one if fund i has a data technology in place at month t. See Section 3.2 for details on data technologies. The fund-month control variables (omitted for brevity) include a fund's size (logAUM), expense ratio, (log) age, flows, turnover, CAPM alpha, 12b-1 fees, and the coefficient of data competition (equation (8)) in month t. The monthly sample include equity mutual funds and ETFs, excluding growth funds, from March 1993 to December 2022, which did not adopt a data technology after June 2015 (i.e., six-months before TensorFlow's release). All standard errors are two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	CAPM alpha		FF-3 alpha		FF-5 alpha	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathrm{DATA}_{i,t}$	0.0003^{**} (0.0001)		$0.0002 \\ (0.0001)$		-0.0000 (0.0002)	
$\overline{\mathrm{DATA}}_{i,t}$		$0.0000 \\ (0.0001)$		$\begin{array}{c} 0.0001 \\ (0.0002) \end{array}$		-0.0002 (0.0002)
Estimator	OLS	RD	OLS	RD	OLS	RD
Controls	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Fund FE	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Time FE	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Outcome mean	0.0010	0.0010	-0.0012	-0.0012	0.0012	0.0012
Outcome SE	0.0252	0.0252	0.0363	0.0363	0.0558	0.0558
Obs. Adj. R^2 First stage F-stat	971,918 0.1199 -	971,918 -0.0067 7,421.13	971,918 0.5019 -	971,918 -0.0081 7,421.13	971,918 0.6377 -	971,918 -0.0080 7,421.13

TABLE C.13: **Performance and Data Technologies**: This table shows results of regression in which the dependent variable is the one-month-ahead fund performance. Columns (1), (3), and (5) report results for OLS regressions, while columns (2), (4), and (6) use the recursive demeaning approach (RD) in Pástor, Stambaugh and Taylor (2015) which accounts for the positive contemporaneous correlation between fund size and unexpected returns. The regressors are a dummy equal to one if a fund *i* has a data technology in place at month *t* (DATA_{*i*,*t*}), 12b-1 fees, and controls for fund-month characteristics (omitted for brevity). See Section 3.2 for details on data technologies. The control variables include a fund's size (*logAUM*), (*log*) age, flows, turnover, and performance in month *t*. I use CAPM alpha (columns (1) and (2)), FF-3 factors alpha (columns (3) and (4)), and FF-5 factors alpha (columns (5) and (6)) as proxy of funds' performance. The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022. All standard errors are two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	Fund Flows _{<i>i</i>,<i>t</i>+1} (%)				
	Retail Funds		Institutio	nal Funds	
	(1)	(2)	(3)	(4)	
$\mathrm{DATA}_{i,t}$	0.161^{**} (0.075)	0.190^{**} (0.076)	0.027 (0.121)	-0.012 (0.123)	
12b-1 $\mathrm{Fees}_{i,t}$	-0.598^{**} (0.246)	-0.635^{**} (0.250)	-0.139 (0.434)	-0.194 (0.439)	
Controls	\checkmark	\checkmark	\checkmark	\checkmark	
Fund FE	\checkmark	\checkmark	\checkmark	\checkmark	
Time FE	\checkmark	×	\checkmark	×	
Category×Time FE	×	\checkmark	×	\checkmark	
Outcome mean	0.421	0.421	0.746	0.746	
Outcome SE	7.930	7.930	8.421	8.421	
Obs. Adj. R^2	$407,509 \\ 0.136$	$\begin{array}{c} 406,755 \\ 0.161 \end{array}$	$188,295 \\ 0.113$	$185,928 \\ 0.123$	

TABLE C.14: Retail and Institutional Aggregation and Data Technologies: This table shows results of OLS panel regression in which the dependent variable is the one-month-ahead fund expense ratio. Columns (1) and (2) report results aggregating observations for retail share classes only, while columns (2) and (4) for institutional share classes only. The regressors are a dummy equal to one if a fund *i* has a data technology in place at month *t* (DATA_{*i*,*t*}), 12b-1 fees, and controls for fund-month characteristics (omitted for brevity). See Section 3.2 for details on data technologies. The control variables include a fund's size (*logAUM*), (*log*) age, flows, turnover, and CAPM alpha in month *t*. The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022. All standard errors are two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

	Fund Flows _{<i>i</i>,<i>t</i>+1} (%)				
	(1)	(2)	(3)	(4)	
Exp. $\text{Ratio}_{i,t}$	-1.249^{***} (0.100)	-1.114^{***} (0.086)	-1.249^{***} (0.089)	-1.114^{***} (0.096)	
Exp. $\text{Ratio}_{i,t} \times \text{DATA}_{i,t}$		-0.246^{***} (0.062)		-0.246^{***} (0.079)	
Controls	\checkmark	\checkmark	\checkmark	\checkmark	
Fund FE	\checkmark	\checkmark	\checkmark	\checkmark	
$Time \ FE$	\checkmark	×	\checkmark	×	
Category×Time FE	×	\checkmark	×	\checkmark	
Outcome mean	0.222	0.222	0.222	0.222	
Outcome SE	6.295	6.295	6.295	6.295	
Obs.	971,984	971,079	971,984	971,079	
Adj. R^2	0.112	0.141	0.112	0.141	

TABLE C.15: Fund Flows Semi-Elasticity and Data Technologies: This table shows results of OLS panel regression in which the dependent variable is the one-month-ahead fund fund flows. The regressors are a the fund expense ratio (in %), a dummy equal to one if a fund *i* has a data technology in place at month t (DATA_{*i*,*t*}), an interaction term with the fund expense ratio and the dummy, 12b-1 fees, and controls for fund-month characteristics (omitted for brevity). See Section 3.2 for details on data technologies. The control variables include a fund's size (*logAUM*), (*log*) age, flows, turnover, and CAPM alpha in month t. The monthly sample include equity mutual funds and ETFs from March 1993 to December 2022. All standard errors are two-way clustered by fund and month (in parentheses). *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.