Tweeting for money: Social media and mutual fund flows*

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Abstract

We investigate whether asset management firms use social media to influence investors' perceptions and attract flows. Combining a database of 1.5 million Twitter posts by mutual fund families managing equity funds in the US from 2009 to 2020 with textual analysis using machine learning methods, we find that investors respond to the tone of these posts. A one standard deviation increase in the positiveness of a family's tweets in a given month increases its assets under management by 10 basis points, or USD 21 million, in the following month. In contrast with other brand awareness measures, Twitter induced flows do not have the sensitivity predicted by lower participation costs. Moreover, positive tweets do not predict higher subsequent fund performance. These results suggest that asset managers use social media to persuade investors rather than to alleviate information asymmetries by either lowering search costs or disclosing privately observed information. Consistently with this explanation, funds struggling to compete for investors' money benefit the most from positive posts on Twitter.

Keywords: social media; Twitter; mutual fund families; mutual fund flows; machine learning; textual analysis.

JEL Classification: G11; G23; D83

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1. Introduction

As of October 2021, more than 4.5 billion people in the world, 70% of the population aged 13 years and older, were using social media to communicate with others, entertain themselves, and stay informed.[1] The growing popularity of social media has raised concerns about their potential to misinform the public and manipulate individuals' opinions and behavior (e.g., Abramowitz, 2017; Aral and Eckles, 2019). In the context of financial markets, the online activities of some high-profile individuals have prompted investigations by the Securities and Exchange Commission (SEC).[2] Also, some firm managers have recognized social media as an opportunity to engage directly with their investors, especially in the midst of the "meme-stock" frenzy.[3]. Indeed, if social media can be used to influence investors' perceptions, then companies issuing securities to the public have strong incentives to become active participants. Beyond anecdotal evidence, do firms use social media to persuade investors? Is this strategy effective? In this paper, we focus on the market for mutual funds and study whether asset management firms use social media to attract money from investors.

As argued by Mullainathan, Schwartzstein, and Shleifer (2008), persuasion in finance involves exploiting investors' biases to change their perceptions. In this sense, social media is an ideal tool for persuasion for asset management firms, as it allows them to communicate with current and prospective investors without the strict constraints imposed by mandatory information disclosures on the timing, content, and framing of information.[4] For instance, firms may choose to communicate only positive information. They may also time their communications to maximize the impact on investors' decisions. And they may frame information in the most favorable way possible.

Asset managers have strong incentives to use social media in order to influence investors' perceptions and increase their assets under management. However, it is unclear whether they will succeed in this endeavor. The mutual fund market is highly regulated and abundant hard information is already available through mandatory disclosures, such as fund prospectuses and statements of additional information. Also, if investors understand the ability of asset management firms to strategically select and frame information, any attempts

[1]Data from datareportal.com (Global Social Media Stats).

[2]Mohamed (2021),"Big Short' investor Michael Burry says he'll stop tweeting after SEC regulators paid him a visit," Businessinsider.com, (https://markets.businessinsider.com/currencies/news/big-short-investor-michael-burry-stop-tweets-sec-regulators-visit-2021-3-1030222890); SEC (2018),"Elon Musk Charged With Securities Fraud for Misleading Tweets," (https://www.sec.gov/news/press-release/2018-219); ; Spichak (2021), "Elon Musk Hopes SEC Will Investigate Him over Dogecoin Tweets: 'It Would Be Awesome'," Newsweek, (https://www.newsweek.com/elon-musk-sec-investigation-dogecoin-bitcoin-cryptocurrency-tweets-1572290).

[3]Gladstone and Schwartzel (2021), "AMC Boss Adam Aron Basks in Meme-Stock Spotlight," Wall Street Journal (https://www.wsj.com/articles/amc-boss-adam-aron-basks-in-meme-stock-spotlight-11622799000)

[4]Note, however, that advertisement and retail investor communication by asset management companies must comply with SEC rule 482 and FINRA rule 2210. In 2003, SEC rule 482 modified the Securities Act of 1933-Section 5 that stated that all fund advertisement must have information that is contained in the statutory prospectus. With rule 482, investment companies are allowed to include information not included in the statutory prospectus. This allows investment companies to include up-to-date information in rule-482 advertisements, such as information about current economic conditions that are not commonly included in a fund's prospectus. FINRA Rule 2210 governs communications with the public including communications with retail and institutional investors. The rule provides standards for the content, approval, recordkeeping and filing of communications with FINRA. The rule prohibits false, exaggerated, unwarranted, and misleading information communications, as well as projections of future performance.

to influence investors could be self-defeating.

The mutual fund industry is an ideal laboratory to study the role of social media communication in financial markets. First, thousands of actively managed mutual funds compete for investors' money. Second, there is asymmetric information about managerial ability and other determinants of fund performance. While asset management companies can closely monitor portfolio managers' decisions and influence their performance through the allocation of resources within the firm, investors can only learn about funds' future expected performance from public information such as past returns and infrequently disclosed portfolio holdings. Another important advantage of the mutual fund setting is that open-end mutual fund shares trade at their net asset value, which makes it possible for researchers to observe directly investors' response to firms' actions by looking at flows of money into and out of mutual funds.

Twitter is also particularly appropriate for our purposes given its rising popularity among investors. Indeed, a number of studies have shown evidence that Twitter activity can predict prices of stocks and other asset classes (Bollen, Mao, and Zeng, 2011; Ranco et al., 2015; You, Guo, and Peng, 2017; Gholampour and van Wincoop, 2017; Gu and Kurov, 2020). Also, the presence of asset management firms in Twitter has grown at a very fast pace in the last years. In our sample, the number of posts on Twitter (tweets) by all mutual fund families went from almost zero prior to 2009 to around 20,000 tweets per month in 2016.

To investigate whether asset management companies influence investors' decisions through social media communications, we build a database of Twitter posts by mutual fund families managing active US equity funds in the US between January 2009 and December 2020. We then employ machine learning algorithms to classify tweets into positive or negative and compute the positiveness of the tone of asset management firms' tweets in a given month. Finally, we merge these data with the CRSP Survivor-Bias-Free US Mutual Fund database, which contains information on fund, manager and family characteristics.

Our results can be summarized as follows. First, 284 of 939 firms managing US diversified equity funds have a Twitter account and post at least one tweet during our sample period. Families that use Twitter tend to manage more assets, more funds, and funds in more investment categories than families that do not use Twitter, which suggests that economies of scale play a role in the decision to implement a social media strategy. Among those firms that use Twitter, more frequent users tend to be younger and to manage more assets and funds with higher past performance, lower expenses, and lower volatility.

We find that a more positive tone in a family's tweets in a given month predicts significantly higher flows to the family's funds in the following month. The increase in flows to the family's funds following tweets with a positive tone is economically significant. A one standard deviation increase in the tone of tweets is associated with an increase in assets under management of 10 basis points (bp) in the following month, or 21 USD million for the average family. This result is robust to different ways of modelling the flow-performance relationship, to controlling for previously documented determinants of mutual fund flows, and to the inclusion of time, fund, and fund family fixed effects. To rule out the possibility that fund families tweet about events that are public knowledge and may be trigger fund flows, we repeat the analysis controlling for known events, such as manager turnover, social media mentions by third parties, and the fraction of funds with very recent stellar performance in the family. In all cases, the association between recent tweets and fund flows survives.

To further investigate the mechanism through which Twitter activity influences fund flows, we obtain data on share purchases and share redemptions from SEC filings until 2016, and run separate regressions for inflows and outflows. We find that positive Twitter posts both increase inflows and decrease outflows.

Our results are consistent with asset management firms using social media to persuade investors, consistent with the theory of Mullainathan et al. (2008). However, we consider two alternative explanations for the results documented in this paper. First, building on the work of Sirri and Tufano (1998), Hortaçsu and Syverson (2004), and Huang, Wei, and Yan (2007), asset management companies could use social media to reduce search costs for investors. This can be achieved by directing investors to information about fund offerings, fees, or past performance, that is already available but difficult to locate for investors. Under this hypothesis, we would expect the *sensitivity* of the flow-performance relation to increase (decrease) for medium (high) performance. With lower search costs, investors can afford studying more funds and discover good investments even if the recent performance has not been spectacular, reducing their salience to few funds with superior performance (Huang, Wei, and Yan (2007)). We find that positiveness has no impact on the sensitivity of the flow-performance relation across the medium or high performance regions thus rejecting this hypothesis.

Second, we explore whether asset management companies use social media to convey to investors information that is not available to the public. More specifically, the model of Dumitrescu and Gil-Bazo (2016) of strategic communication by asset managers predicts that asset management companies will communicate information that is favorable for future fund performance and which is not already publicly available. Since this information is both new and truthful, favorable communications have a positive impact on flows of new money. But the model also implies that asset manager communications have predictive power with respect to future performance, controlling for publicly available information. To test this prediction, we investigate whether more positive tweets predict superior fund performance controlling for well-documented predictors of performance, including possible diseconomies of scale (Berk and Green, 2004; Chen, Hong, Huang, and Kubik, 2004; Pástor, Stambaugh, and Taylor, 2015; Zhu, 2018). We find that the positiveness of an asset management company's tweets does not positively predict future fund performance. This evidence contradicts the information hypothesis.

We investigate if the fund families' ability to persuade investors is persistent or if investors disinvest after realizing the quality of the fund has been overestimated. We extend our analysis to consider the flows to funds over longer horizons. If investors disinvest after realizing a potential investment mistake, we would expect to observe a mean reversion in the impact of positiveness on flows over longer horizons. We find that the impact of positiveness on flows persists for approximately two years, and we find no evidence of mean reversion in horizons up to three years. This evidence suggests persuasion could have a permanent impact on the size of mutual funds. Finally, we perform a placebo test, and repeat our main analysis focusing on index funds. Fund families offering index funds should have no room for persuasion since there is no underlying quality to be inferred by individuals (Mullainathan, Schwartzstein, and Shleifer (2008)). We find that index funds from fund families that post more positive information on Twitter do not receive larger net-flows of capital in subsequent months.

In sum, the empirical evidence documented in this paper does not support the notion that social media communications of asset management firms alleviate information asymmetries between mutual fund companies and investors by either reducing search costs or conveying new information to investors. If the purpose of social media communications is to persuade investors, we would expect social media activity to benefit more those asset managers that experience more difficulties in attracting investors' money. Consistently with this prediction, we find that the link between positive tweets and asset growth is stronger for fund families with younger funds, and funds with less experienced managers. This evidence gives further credence to the persuasion hypothesis.

By unveiling the role of social media communications on mutual fund investors' decisions, our paper contributes to a large literature on the determinants of mutual fund flows (see Christoffersen, Musto, and Wermers 2014, for a survey). More specifically, our paper is related to a number of studies that investigate the role of advertising in the mutual fund industry. Sirri and Tufano (1998) show that marketing effort, as proxied by fund fees, increases fund flows. Jain and Wu (2000) study a sample of 294 funds that are advertised either in Barron's or in Money magazine and find that even though the pre-advertisement performance of these funds is better than the performance of their benchmark, there is no superior performance in the post-advertisement period. Cronqvist (2006) investigates the content of mutual fund advertisements in Sweden and finds that most fund ads are not informative about fund quality. Nevertheless, fund ads influence individuals' portfolio decisions, steering them towards high-fee funds, locally concentrated portfolios, and funds investing in sectors with high recent performance. Gallaher, Kaniel, and Starks (2015) show that mutual fund families' advertising expenditures attract flows to the family's funds as well as to other funds in the industry, reduce redemptions, and increase the convexity of the flow-performance relationship. We contribute to this literature by studying a new and increasingly important means of communication which, unlike traditional media advertising, allows firms to interact directly and in real time with investors. Moreover, we use textual analysis and machine learning to measure the tone of communications.

Our paper is most closely related to the study of Hillert, Niessen-Ruenzi, and Ruenzi (2018). These authors use textual analysis to determine the tone of shareholders' letters from asset management companies and their impact on fund flows. The authors find a positive association between tone and subsequent flows. Using daily information about flows for a subsample of funds, they also provide evidence that the reaction to shareholder letters appears right after shareholder letters are sent to investors, and reverts around five days after shareholders receive the letter. The authors also find evidence that funds that address their shareholders in a more personal manner, have better subsequent performance on average. Although shareholder letters provide some freedom to managers to communicate to shareholders, they are part of the shareholder's report (Form N-CSR and N-CSRS filings) and highly regulated by the SEC in terms of their frequency, format and content. Like Hillert, Niessen-Ruenzi, and Ruenzi (2018), we find that fund families that post more positive information receive higher net flows and experience fewer redemptions. However, we find that the relation between positiveness of tweets and flows does not revert after a few days. Moreover, we find that these communications are not informative with respect to future fund performance.

Our paper also contributes more generally to the literature on non-mandatory corporate disclosures (Kim and Verrecchia, 1991; Dye and Sridhar, 2004; Dye and Sridhar, 2004; Cornelli, Kominek, and Ljungqvist, 2013; Bertomeu and Marinovic, 2016), and to the recent literature of textual analysis in Finance and Accounting (see Loughran and McDonald, 2016 for a survey of the literature). The study of Blankespoor, Miller, and White (2014) is particularly relevant to our paper. These authors show that when public firms use Twitter to disseminate firm-initiated news, information asymmetries decline as evidenced by narrower bid-ask spreads. In contrast, our results suggest that Twitter does not help alleviate information asymmetries in the mutual fund industry.

2. Data

In this section, we present the data used in the analysis. We draw on two data sets, the CRSP Survivor-Bias-Free US Mutual Fund database and a database of tweets from January 2009 to December 2020 posted by mutual fund families. From the former, we obtain information at the share class level on returns, assets under management, investment category, expenses, and age. Even though our Twitter database starts in 2009, we collect mutual fund data from 2006 so we can use three years of prior historical data to estimate risk-adjusted returns.

To construct variables at the mutual fund level, we follow the same share aggregation procedure as in Gil-Bazo and Ruiz-Verdú (2009). For our main analysis we keep only non index US equity funds following CRSP style level one. To avoid discrepancies between the objective reported by CRSP and the lipper classification of the fund we manually discard those funds whose lipper objective class name does not correspond to an equity fund. Among these funds we discard less than one percent of the funds that are classified as municipal debt funds, money market funds, debt funds, and funds focusing on other securities. Total Net Assets (TNA) of a fund are the sum of the TNA under each share class. Returns and expense ratios are TNA-weighted averages across all share classes in the fund. The age of the fund is the age of the oldest share class in the fund. Following Berk and van Binsbergen (2016) and Pastor, Stambaugh, and Taylor (2015) we drop observations where funds have less than 15 million USD in TNA.

To create some of our variables, we aggregate data at the fund family level based on the CRSP identifier mgmt_code. TNA at the family level is the sum of the TNA of each fund in the family, the age of the fund family is the age of the oldest fund in the family, and flows, expenses and returns are weighted averages across all funds in the family (based on the TNA of each fund in the family).[5]

For a subsample of funds, and until 2016, we obtain data on inflows and outflows, as in Christoffersen, Evans, and Musto (2013) and Ha and Ko (2019). These data can be obtained from SEC's N-SAR form, Item 28, which includes cash-flow information on a monthly basis at the portfolio level.[6]

Given the findings of Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016) that investors appear to use the CAPM to evaluate mutual fund performance, throughout the paper we focus on CAPM alphas as a determinant of flows, although we test the robustness of our results to using the three-factor and four-factor models of Fama and French (1993) and Carhart (1997) to estimate performance.[7] We compute the risk-adjusted return, $\hat{\alpha}_{it}$, of fund i in month t as the intercept plus the residual of the CAPM model:

$$\hat{\alpha_{it}} = r^e_{it} - \hat{\beta_{it}} r^e_{mt}, \tag{1}$$

where r^e_{it} is the excess return of fund i at month t over the risk free rate and r^e_{mt} is the excess return of the market portfolio over the risk free rate. We obtain the monthly risk-free rate and the market portfolio return from Prof. Kenneth French's website and $\hat{\beta_{it}}$ is estimated for each fund and month t by running OLS rolling regressions of excess returns on market excesss return over the three-year period ending in month $t-1$. If less than three years of data are available in a given window, we require the fund to have at least 30 months of data and run the regressions with the data available.

To construct the Twitter database of mutual fund families we obtain the names of all asset management companies in the CRSP database managing US equity funds. Then, we perform a manual search through each one of the family names represented in the variable mgmt_name in the CRSP database and group similar names using the CRSP aggregation variable mgmt_code. Finally, we search for each family's Twitter account in the asset management company's website.

Once the list of Twitter accounts is collected, we web scrape all tweets from accounts that are active

[5] We compute flows at the family level using a weighted average of the flows of each fund in the family since we discard money market, bond, and hybrid funds from the sample before aggregation.

[6] We thank Yeonjeong Ha and Kwangsoo Ko for kindly sharing their data with us.

[7] Evans and Sun (2020) show that mutual fund flows have become more sensitive to three-factor abnormal returns since Morningstar changed its methodology to compute fund ratings to account for funds' investment style.

in 2018 and in 2021, and keep only unique tweets. It is important to notice that if a fund family that was active in the past decided to cancel its Twitter account we would not be able to get this information. The web-scraping procedure downloads tweets historically starting from the most recent tweet up to the first one. Web-scraping algorithms can get banned temporarily and the download procedure may stop prematurely. To ensure we download all information, we compare the last tweet obtained for each company with the true first tweet of the account provided by Twitter.[8] Our database contains 1,592,486 tweets from 284 different usernames, from January 2009 to December 2020.

The procedure used to measure the positiveness of tweets is explained in detail in the Appendix and can be summarized as follows. To determine the tone of a tweet, we use a training sample with previously manually classified tweets. We consider both the occurrence of a word in the text and its Part of Speech (POS) as features.[9] To avoid any subjectivity in choosing the machine learning algorithm to classify the tweets, we use six different algorithms and select for each tweet the most voted label among them. If three algorithms classify a tweet as positive and three as negative, we consider the tweet to have a neutral tone. Using this voting scheme, all tweets in our sample are classified as either positive, neutral or negative. The approach also provides us with a measure of confidence in the classification. In particular, we define the confidence of classifying tweet k as c as:

$$w_k^c = \frac{\text{Number of algorithms that classify tweet } k \text{ with label } c}{\text{Total number of algorithms}} \tag{2}$$

We then define the positiveness of a family's tweets in month t as follows:

$$\text{Positiveness}_t = \ln\Big(\frac{1+M_t^p}{1+M_t^n}\Big), \tag{3}$$

where $M_t^p(M_t^n)$ is the weighted count of positive (negative) tweets of that family in one month:

$$M_t^p = \sum_{k\in\mathcal{D}(t)} w_k^p x_k^p,\ M_t^n = \sum_{k\in\mathcal{D}(t)} w_k^n x_k^n, \tag{4}$$

where $D(t)$ is a monthly time interval, x_k^p (x_k^n) is an indicator variable that takes the value of 1 if tweet k at time t is positive (negative), and w_k^p (w_k^n) is the confidence in the tweet's positive (negative) label given the level of agreement among all classifiers for a particular tweet as in equation (2). Our measure of Positiveness is closely related to that employed by Antweiler and Frank (2004), but is more appropriate for handling Twitter accounts with zero tweets.

[8]The first tweet of any active account was found using the webpage https://discover.twitter.com/first-tweet, which is no longer available, although other websites provide the same service.

[9]Part of Speech is one of the grammatical groups, such as noun, verb, and adjective, into which words are divided depending on their use. Retrieved from: https://dictionary.cambridge.org/dictionary/english/part-of-speech

Figure (1) displays the total number of tweets across all mutual fund families, as well as the weighted count of positive and negative tweets per month. The figure shows a sharp increase in Twitter usage by mutual fund families, with a peak in 2016. As expected, positive tweets predominate over tweets classified as negative.

Out of 939 fund families in the final CRSP sample, 284 fund families tweet at least once during the sample period. This is the subsample we use in most of our analysis. To understand how this subsample differs from the rest, Table (1) presents descriptive statistics of both fund and family characteristics for the Twitter subsample and the full sample. At the fund level, there are no clear differences between funds managed by fund families in the Twitter subsample an funds in the entire sample. However, at the family level differences between fund families in both samples become more evident. Fund families in the Twitter subsample are on average older, manage more assets, more funds, and funds in more different investment categories.

We show how our classification procedure works in practice by examining two tweets posted by asset management companies in our sample. The first example presented in Figure (2) corresponds to a post written by Northern Trust which is classified as negative by the six algorithms. The features (*challenge*, *Noun Singular*) together with (*growth*, *Noun Singular*) are informative enough to make all algorithms coincide with the classification. The second tweet presented in Figure (3) written by State Farm is classified as positive with a confidence of 1. In this tweet the features (*outperforms*, *Verb 3rd person singular*), (*industry*, *Noun Singular*), and (*average*, *Noun Singular*) are informative enough to make all algorithms coincide with the classification.

3. Determinants of Twitter activity by mutual fund families

We start our analysis by investigating which families are more likely to use Twitter. Although social media communication has low explicit costs, the implicit costs are non-trivial. Managing a social media communication strategy requires that social media managers coordinate with the marketing department and senior management in the process of setting goals, creating contents, and engaging with the public. In addition, contents need to be created, the firm's social media presence must be promoted, technological support is required, and the whole process must be carefully monitored and evaluated. Since such costs are likely to have a fixed component, we expect large asset management firms to be more likely to have a social media presence and use it actively. To explore this conjecture, in addition to the amount of assets under management to proxy for size, we use the number of funds and the number of different categories (both in logs) in which families offer funds. We also study whether younger firms are more likely to use Twitter since younger families have more incentives to gain visibility among investors. Finally, we control for the characteristics of funds in the family: asset-weighted average CAPM alpha over the previous 12 months; asset-weighted average expense ratio; number of funds in the family that charge loads (in logs); and asset-weighted average volatility of fund returns in the previous 12 months.

We analyze both the extensive and the intensive margins of families' Twitter usage. More specifically, in our tests, we employ two different dependent variables. The first variable, Twitter, is an indicator that equals one if the fund family has a Twitter account and uses it at least once in our sample period. The second variable, Number of Tweets, is defined for each family and month and is computed as the natural logarithm of 1 plus the number of Tweets posted by the family in that month.

We start by estimating a cross-sectional linear probability model with the Twitter indicator as the dependent variable using the full sample. Fund-level explanatory variables are first computed for each family and month. All variables are then aggregated at the family level by computing their time-series means within each family. Estimation results are presented in Panel A of Table (2). Family age and lagged flows are not associated with having a Twitter account. However, all three proxies for family size are positively and significantly associated with the family's presence in Twitter. In other words, smaller management companies are less likely to consider Twitter as a way of communicating with investors. There is no significant association between fund characteristics and a Twitter account.

We then regress the natural logarithm of one plus the Number of Tweets on the same set of explanatory variables as in the previous regression, but defined at the family-month level, and lagged one month with respect to the dependent variable. In this case, we naturally restrict the sample to families with Twitter$=1$. We include family and time fixed effects and compute robust standard errors clustered at the month level. Estimation results are presented in Table (2). Conditional on having a Twitter account, both younger and larger firms tend to tweet more frequently. As for fund characteristics, families with better-performing funds and families with less expensive funds also tweet more. Return volatility, on the other hand, is negatively associated with the intensity of Twitter activity. We find no evidence that fund families with larger recent flows use Twitter more intensively.

These results suggest that economies of scale are a key determinant of social media usage by asset managers. Conditional on having presence on Twitter, its usage appears to respond not only to cost considerations but also to the potential benefits of social media for firms: gaining visibility for younger firms, publicizing good performance, and raising assets for low-fee funds.

4. Twitter activity and fund flows

In this section we study how flows of new money to mutual funds respond to posts of fund families on Twitter. Following the literature, we compute netflows to fund i between month t and month $t+1$ as the growth rate in total net assets net of the fund's return:

$$\text{Flows}_{i,t+1} = \frac{\text{TNA}_{i,t+1} - \text{TNA}_{it}(1 + r_{i,t+1})}{\text{TNA}_{it}}, \tag{5}$$

where TNA_{it} is the total net assets of fund i at the end of month t, and $r_{i,t+1}$ is the fund's monthly return. To minimize the impact of outliers - mostly small funds with large percentage of inflows or outflows - we follow the literature and winsorize flows at the 1% level.

We begin our analysis by studying how the number of tweets by an asset management firm in a given month is related to flows to funds in that family in the following month, controlling for fund performance and other well-documented flow determinants.[10] Like Sirri and Tufano (1998), we allow for a convex flow-performance relationship. To model dependence on performance, we employ two different approaches. First, we define the variable Rank_{it} as the ranking of fund i's CAPM alpha in the 12-month period ending in month t against all other funds in the same Lipper category, normalized to be between $1/N$ (lowest performing fund) and 1 (highest performing fund), where N denotes the number of funds in the corresponding category and month.

Second, we use objective-adjusted abnormal return (OAR) as an alternative to performance rank. As argued by Ha and Ko (2019), OAR accounts for the potentially large dispersion in the cross-section of fund performance and its impact on the flow-performance relationship. We compute OAR_{it} by standardizing the 12-month CAPM alpha to have zero mean and unit standard deviation across all funds in the same investment category.

For both $\text{Performance}_{it} \in \{\text{Rank}_{it}, \text{OAR}_{it}\}$, we compute the following variables:

$$\begin{aligned}
\text{Low Performance}_{it} &= \min(\text{Performance}_{it}, p20) \\
\text{Mid Performance}_{it} &= \min(\text{Performance}_{it} - \text{Low Performance}_{it}, p80 - p20) \\
\text{High Performance}_{it} &= \text{Performance}_{it} - \text{Mid Performance}_{it} - \text{Low Performance}_{it},
\end{aligned} \tag{6}$$

where $p20, p80$ denote the 20th and 80th percentiles, respectively, of either the cross-sectional distribution of performance rank or OAR.

We first analyze the link between the the tone of tweets posted by a fund family and subsequent flows.

[10] Henceforth, we restrict the sample to funds in fund families that have tweeted at least once between 2009 and December 2020.

More specifically, we estimate the regression equation:

$$
\begin{aligned}
\text{Flows}_{i,t+1} = \gamma_0 &+ \gamma_1 \times \text{Positiveness}_{it} \\
&+ \gamma_2 \times \text{Low Performance}_{it} + \gamma_3 \times \text{Mid Performance}_{it} + \gamma_4 \times \text{High Performance}_{it} \\
&+ \gamma_5 \times X_{it} + \delta_{t+1} + \lambda_i + \mu_{cat} + \theta_{fam} + \nu_{i,t+1},
\end{aligned} \tag{7}
$$

where $\text{Flows}_{i,t+1}$ is in %. Low, Mid, and High Performance are calculated using both Rank and OAR based on 12-month CAPM alphas as in Equation (6). Following the large literature on the determinants of fund flows, the vector of lagged controls, X_{it}, includes the natural logarithm of the fund's total net assets, the fund's expense ratio, the fund's age (log of months since inception), and flows into the fund. Controls also include flows to funds in the same investment category in month $t+1$ and the standard deviation of returns in the 12-month period from $t-11$ to t. Importantly, we control for family size (log of assets under management) and family age (age of the family's oldest fund), since we know from the previous section that these variables are associated with the family's decision to use Twitter. In some specifications we control for Twitter Activity defined as the natural logarithm of one plus the number of tweets in a month, in order to study if investors react to the number of tweets or to their content.[11] δ_{t+1}, λ_i, μ_{cat}, and θ_{fam} denote month, fund, investment category, and family fixed effects, respectively.[12] Finally, $\nu_{i,t+1}$ denotes the error term.

We estimate equation (7) using pooled OLS and compute robust standard errors clustered at the month, fund family, and month-fund family levels. Table (3) presents the results. To model dependence of flows on performance we use OAR in columns (1)-(3) and Rank in columns (4)-(6). In column (1) we do not include Number of Tweets or Positiveness. As previously documented in the literature, we find a convex relation between flows and performance. Fund size, flows to funds in the same category, and volatility are all negatively associated with flows. Flows are persistent as evidenced by the positive and significant coefficient on lagged flows. Finally, younger funds and larger families capture more flows.

In column (2), we include Positiveness, as in equation (7). The coefficient on Positiveness is positive and statistically significant at the 1% level, which suggests that flows respond to a positive tone in asset management companies' tweets. Note that this association cannot be driven by fund or family time-invariant characteristics that determine both the tone of families tweets and fund flows. It is not driven either by larger or younger companies' tendency to tweet more. In column (3) we control for the number of tweets (in logs) to discard that our results are being driven an increase in visibility and not by the content of tweets. The coefficient on Positiveness is positive and statistically significant at the 5% level.

In columns (4) to (6), we show estimation results when we use Rank instead of OAR. Although the

[11]We don't include an specification considering only the number of tweets instead of positiveness as both variables are highly correlated.

[12]In our sample, some funds change investment categories through time.

relation between flows and performance appears to be more convex, consistent with the results of Ha and Ko (2019), the association between Positiveness and Flows is robust to modelling the flow-performance relationship in this way. In particular, the estimated coefficient on Positiveness have the same magnitude and significance.

In unreported results, we repeat the analysis using the three-factor and four-factor models of Fama and French (1993) and Carhart (1997), respectively, to compute both Rank and OAR. Our conclusions are qualitatively and quantitatively similar.

In terms of the economic magnitude of the association, using the average estimated coefficient of columns (2) and (5), a one standard deviation increase in Positiveness (0.74 for the Twitter subsample) corresponds to an increase in subsequent flows of 0.06% (= 0.08×0.74), which for the average fund in the Twitter sample corresponds to an increase of USD 739,080 per month (= 0.06%$\times$ USD 1231.8 millions).

To gauge the economic impact of Twitter posts' tone for the average family, we need to estimate the marginal effect of positiveness on flows at the family level. In Table (4) we estimate a version of equation (**??**) where all variables are collapsed at the family-month level. In column (1) we use OAR and include time fixed effects but not family fixed effects.[13] The estimated coefficient on Positiveness$_{it}$ is statistically significant at the 1% level. Using the estimation in column (2), a one standard deviation increase in Positiveness$_{it}$ is associated with an increase of 0.148% (=0.19% $\times$ 0.78) in family flows, which given the average assets under management per family of USD 7.44 billion represents an increase in assets of USD 11 million.[14] In column (2), we add family fixed effects and estimate an almost identical coefficient on Positiveness, that is also statistically significant at the 1% level. Therefore, the association between Positiveness and flows to the family's funds is not driven by some unobservable time-invariant family characteristic. Results in columns (3) and (4) are obtained using Rank to model the flow-performance relationship and suggest a slightly stronger association between Positiveness and Flows, both with and without family fixed effects.

The results of Table (3) and Table (4) are consistent with social media influencing investor behavior. However, there is an alternative explanation for the positive association between Positiveness and fund flows. It could be that positive posts by asset management companies simply disseminate important information that is already public knowledge and that determines flows of money to mutual funds. To investigate this possibility, we evaluate whether the positive link between Twitter post tone and fund flows survives the inclusion of some variables that potentially impact fund flows. More specifically, we repeat the analysis controlling for: i) a change in the previous month in the fund's management company and the fund's portfolio manager, which can be perceived by investors as a positive signal for future returns (Khorana, 2001); ii) the number and tone of tweets by third parties that mention the fund family in the previous month; and iii)

[13]Naturally, the regression equation does not include fund fixed effects or investment objective fixed effects.

[14]One reason why the estimated increase in percentage flows is larger for the average family than for the average individual fund is that families with fewer funds, which are underrepresented in fund-level regressions, benefit more from positive tweets. We explore this possibility in Section 7.

the fraction of funds in the family with monthly CAPM alpha in the top 5% of their investment category in the previous month (Nanda, Wang, and Zheng, 2004). Results in Table (5) indicate that the association between Positiveness and fund flows is still positive, similar in magnitude, and statistically significant at the 1% level after controlling for those performance-relevant events. Therefore, the coefficient on Positiveness is not simply picking up the effect of those events on fund flows.

To give more credence to our main results, in Table (6)we repeat specification (7) considering only index funds. As argued by Mullainathan, Schwartzstein, and Shleifer (2008), the success of persuasion depends on the ability to exploit biases in how individuals perceive the quality of a product. Since there is no idiosyncratic quality in indexed funds, as they restrict their operations to replicate an index, persuasion should not be attainable in this setting. As exposed in Columns (2,3,5,and 6) indexed funds' investors do not react to the tone of tweets nor to the number of tweets posted by fund families.

5. Analysis of inflows and outflows

In this section we investigate whether Positiveness influences net flows by encouraging purchases of fund shares, discouraging redemptions, or both.

More specifically, we define Inflows and Outflows for fund i in month $t+1$ as:

$$\text{Inflows}_{i,t+1} = \frac{\text{New Sales}_{i,t+1}}{\text{TNA}_{i,t}} \tag{8}$$

$$\text{Outflows}_{i,t+1} = \frac{\text{Redeemed Cash}_{i,t+1}}{\text{TNA}_{i,t}} \tag{9}$$

As argued by Ha and Ko (2019) inflows and outflows are simultaneously determined by investors' rebalancing strategies. This mutual dependence between inflows and flows is tackled by performing a two-stage least square estimation. We follow closely Ha and Ko (2019) and run the following OLS regressions for inflows and outflows separately:

$$\text{Inflows}_{i,t+1} = a + \sum_{s=0}^{11} b_s \text{Inflows}_{i,t-s} + cX_{it} + \nu_{i,t+1}, \tag{10}$$

$$\text{Outflows}_{i,t+1} = a + \sum_{s=0}^{11} b_s \text{Outflows}_{i,t-s} + cX_{it} + \nu_{i,t+1}, \tag{11}$$

where X_{it} contains the same controls used in the flow regressions.

We then use the fitted values of the dependent variables $\widehat{\text{Inflows}}_{t+1}$ and $\widehat{\text{Outflows}}_{t+1}$ to estimate residual inflows and outflows:

$$\text{Inflows}_{i,t+1} = a + b\widehat{\text{Outflows}}_{t+1} + \epsilon^{I}_{i,t+1} \tag{12}$$

$$\text{Outflows}_{i,t+1} = a + b\widehat{\text{Inflows}}_{t+1} + \epsilon^{O}_{i,t+1} \tag{13}$$

Finally, fitted residual inflows, $\widehat{\epsilon}^{I}_{i,t+1}$, and outflows, $\widehat{\epsilon}^{O}_{i,t+1}$, are regressed on Positiveness and performance (Rank and OAR):

$$\begin{aligned}
\widehat{\epsilon}^{I}_{i,t+1} &= \gamma_0 + \gamma_1 \times \text{Positiveness}_t \\
&\quad + \gamma_2 \times \text{Low Performance}_{it} + \gamma_3 \times \text{Mid Performance}_{it} + \gamma_4 \times \text{High Performance}_{it} + \nu_{i,t+1} \\
\widehat{\epsilon}^{O}_{i,t+1} &= \gamma_0 + \gamma_1 \times \text{Positiveness}_t \\
&\quad + \gamma_2 \times \text{Low Performance}_{it} + \gamma_3 \times \text{Mid Performance}_{it} + \gamma_4 \times \text{High Performance}_{it} + \nu_{i,t+1}
\end{aligned} \tag{14}$$

In Table (7), we show estimation results for inflows in columns (1) and (2). The estimated coefficients for both OAR and Rank confirm the existence of a convex relationship between inflows and performance, consistent with Christoffersen, Evans, and Musto (2013). The coefficient on Positiveness is positive and significant at the 1% level. In columns (3) and (4) we show estimation results for outflows. We find a statistically significant and negative association between Positiveness and outflows. The association is similar in magnitude and statistical significance to that between Positiveness and fund inflows. Therefore, social media communications appear to increase net flows not only by fostering purchases of new shares but also by deterring investors from redeeming old shares.

6. Alternative hypotheses

The results presented in the previous sections are consistent with the persuasion hypothesis of Mullainathan et al. (2008). In this section, we consider two alternative explanations. First, building on the work of Sirri and Tufano (1998), Hortaçsu and Syverson (2004), and Huang, Wei, and Yan (2007), asset management companies could use social media to reduce search costs for investors. This can be achieved by directing investors to information about fund offerings, fees, or past performance, that is already available but difficult to locate for investors. In the model of Huang, Wei, and Yan (2007), a reduction in search costs increases the sensitivity of flows to medium performance and decreases the sensitivity of flows to high-performance. In their model, as participation costs decrease, investors can afford studying more funds and discover better investments even if the recent performance of their funds have not been superior. This expansion in the set of potential funds to invest in reduces the allocation of few funds with superior performance. Table (10) extends specification (7) and interacts Positiveness with the three regions of performance. Columns

(1) and (3) present the base specification without interactions, and columns (2) and (4) present the results interacting Positiveness with performance. We find that positiveness only increases the sensitivity of flow to low performance and has no impact on the sensitivity of medium nor high performance. Even if the reduction in search costs makes low performance funds more attractive to investors, we should expect a reduction in the salience of better performing funds as investors remove them from their portfolios. Therefore we discard the search cost hypothesis.

Second, we explore the notion that asset management companies use social media to convey to investors relevant information that is not available to the public. More specifically, the model of Dumitrescu and Gil-Bazo (2016) of strategic communication by asset managers predicts that asset management companies will communicate information that is favorable for future fund performance and which is not already publicly available. Since in equilibrium communications are truthful and favorable, they should have a positive impact on flows of new money. But such communications should also possess predictive ability with respect to future fund performance. To test this prediction of the model, we regress one-month ahead performance on Positiveness while controlling for past performance and fund and family characteristics that have been documented in the literature to predict performance. We also allow for time, fund, investment category, and family fixed effects. One difficulty that arises with this test is the fact that net performance is partially determined by investors' reaction. In particular, if there are diseconomies of scale in asset management, fund performance will deteriorate as money flows to funds that are expected to outperform (Berk and Green, 2004). To account for that possibility, we control for lagged assets under management as well as recent fund flows.

Therefore, we estimate the regression equation:

$$\hat{\alpha}_{t+1} = \rho_0 + \rho_1 \alpha_{i,t-3:t} + \rho_2 \text{Positiveness}_{i,t} + \rho_3 X_{it} + \delta_{t+1} + \lambda_i + \mu_{cat} + \theta_{fam} + \nu_{i,t+1}, \tag{15}$$

where $\alpha_{i,t-3:t}$ is the fund's abnormal return in the previous three months. δ_{t+1}, λ_i, μ_{cat}, and θ_{fam} denote time, fund, investment category, and family fixed effects, respectively. X_{it} is a vector of control variables that includes: fund size; expense ratio; flows (in month t); portfolio turnover; 12-month return volatility; an indicator variable that equals one if the fund charges loads; fund age; family size and family age. Standard errors are clustered at the fund, month, and fund-month levels.

Table (8) shows the estimation results. In columns (1) and (2) we use CAPM alphas both as the dependent variable and as a control (in this case, measured over the previous three months), whereas in columns (3) and (4) we use Carhart's (1997) four-factor alphas. In columns (1) and (3) we do not include fund fixed effects, so we are asking whether positive tweets allow investors to identify funds that will outperform their peers in the following months.

Without fund fixed effects, the estimated coefficient on past recent performance is significant and positive for CAPM alpha (column 1), and for past four-factor alpha (column 3), which suggests that cross-sectional differences in four-factor alphas, and in CAPM alphas, persist in the short term. When we include fund fixed effects (columns 2 and 4), the estimated coefficient on past performance is positive and significant for CAPM alpha but not for four factor alpha. Also, fund performance declines in with fund size both in the cross section and in the time series, which is consistent with prior studies (e.g., Chen, Hong, Huang, and Kubik, 2004). Expense ratios are negatively related to performance in the cross-section, but not in the time series. Finally, the family's assets under management are negatively related to fund performance.

In terms of our variable of interest, Positiveness, the coefficients on this variable are negative and not significant. This implies that funds in families that post more positive tweets do not outperform in the following month either in the cross-section or in the time-series. The results therefore do not support the idea that positive tweets help investors select funds that will either outperform their peers or deliver higher performance than in other periods. In other words, asset management firms do not seem to use social media to convey private information about future fund performance.

7. Further evidence of social media as a persuasion tool

If the main purpose of social media communications is not to reduce information asymmetries but to persuade investors to purchase mutual funds, then asset management firms that have more difficulties competing for investors' money in terms of objective signals of performance are the ones that can potentially benefit the most from using social media for persuasion purposes.

To test this conjecture, we estimate again our baseline flow regressions augmented with interactions of Positiveness with two proxies of difficulty in raising funds: fund age, and manager's tenure. Since the managerial ability of younger funds or from fund managers with less experience in the fund is more difficult to infer by investors, it is expected that these funds have more difficulty in raising funds. Table (9) shows the estimation results. The coefficient on the interaction between Positiveness and Tenure (defined as the number of years since the manager took office) is negative and statistically significant at the 5% significance level. A one standard deviation decrease in the tenure of managers below its mean increases the coefficient of positiveness by 0.06. The coefficient on the interaction term of Positiveness with the age of the fund in months (in logs) is negative and significant at the 1% level. A one standard deviation decrease in the age of the fund increases the coefficient of positiveness by 0.0585. In sum, the results of (9) are consistent with persuasion being more effective for funds that struggle to compete and those that target retail investors.

Finally, if investors realize that the inferred quality of mutual funds was overestimated, we should expect investors to disinvest in the future. We document that the impact of positiveness on flows is persistent and does not revert in the following years. Table (11) estimates specification (7) considering net flows to funds for different horizons of 6 month intervals. Columns (1) to (4) show that the reaction of investors to positiveness can be tracked up to two years in the future. The impact of positiveness in the subsequent six and twelve months is positive and statistically significant at the 1% level, while for horizons of 18 and 24 months it is significant at the 5% and 10% respectively. Finally for horizons of more than two years the coefficient of positiveness on net flows is positive but not significant.

8. Conclusions

Social media provide asset managers with a powerful tool to circumvent constraints on traditional mandatory disclosures and persuade investors. We find that a positive tone of Twitter posts predicts subsequent an increase in flows to the fund not explained by performance or fund characteristics, that is statistically and economically significant.

However, we do not find that Twitter is consistent with a reduction in search costs as the tone of these tweets have no impact on the medium nor higher ranges of the flow-performance relation. We cannot find, either, any evidence that the tone of Twitter communications contains valuable information about future fund performance, as one would expect if social media were used to convey new information to investors.

Therefore, our results suggest that asset management companies use Twitter as a way to improve investors' perception of the quality of their asset management services. Consistently with this hypothesis, we show that the benefit of positive tweets concentrates in families managing funds that struggle to compete and those that cater to retail investors.

Clients of mutual fund management firms could benefit a great deal from the enhanced, more frequent, and easier-to-access information that social media can provide. Instead, the results of our paper suggest that incentives to influence investors' perceptions dominate incentives to alleviate information asymmetries.

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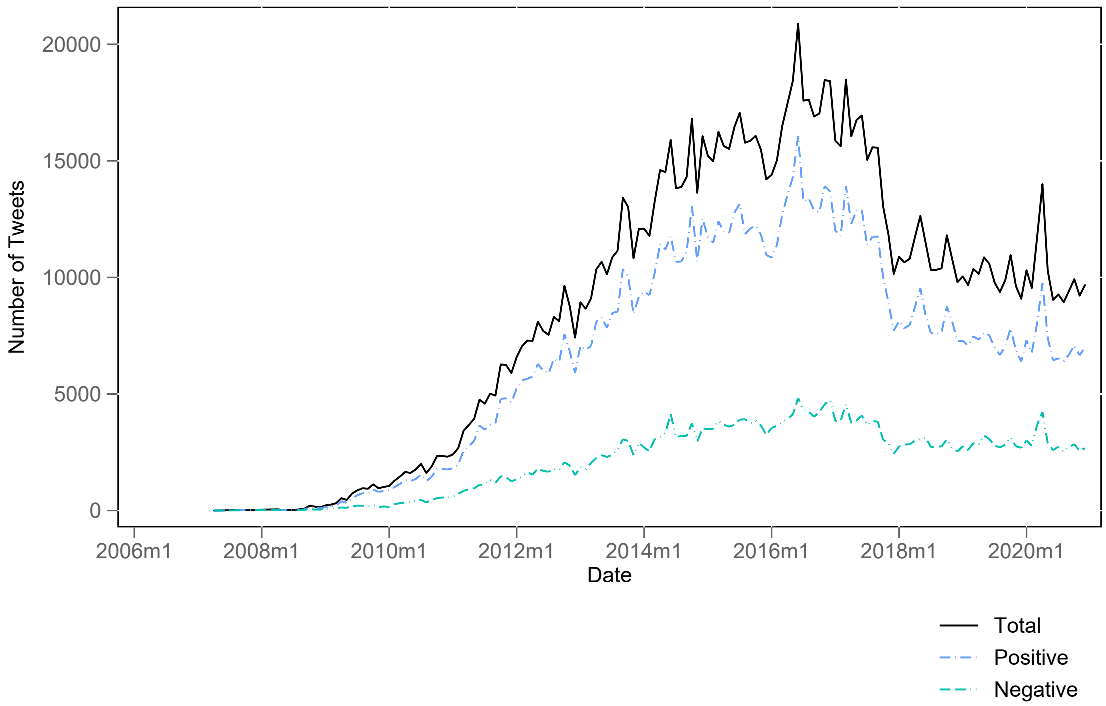

Figure 1: Evolution of tweets by fund families through time. The figure shows the number of tweets by fund families per month. The solid black line shows the total number of tweets obtained based on the fund family identifier mgmt_cd for the entire CRSP database. The dot-dashed line and the dashed line represent out of the entire sample the number of tweets classified as positive and negative, respectively.

Tweets from asset management companies

Figure 2: Tweet classified as negative with a confidence of 1. The tweet was written by asset management company Northern Trust (@NorthernTrust) on October 1 2013.

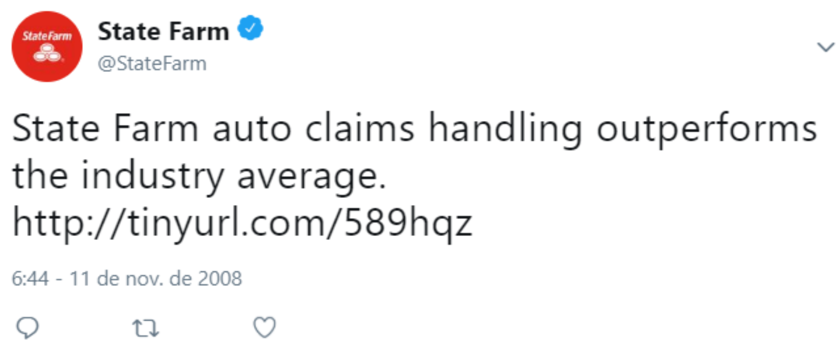

Figure 3: Tweet classified as positive with a confidence of 1. The tweet was written by asset management company State Farm (@StateFarm) on November 11 2008.

Table 1: Descriptive Statistics, Fund Family characteristics

	Twitter Subsample						Full Sample					
Variable	mean	median	s.d.	p1	p99	N	mean	median	s.d.	p1	p99	N
Fund Level												
Positiveness	0.78	0.77	0.75	-0.16	2.53	1212755	0.45	0.00	0.69	0.00	2.39	2099985
Performance %	-0.17	-0.09	2.20	-6.01	5.37	1068237	-0.17	-0.10	2.54	-6.22	5.61	1805722
Age	11.80	10.08	9.33	0.50	47.00	1212755	11.56	10.00	8.94	0.42	42.50	2099985
Flows %	0.32	-0.32	6.69	-17.35	28.82	1199360	0.24	-0.40	6.98	-19.55	31.07	2071800
Expense ratio	0.01	0.01	0.01	0.00	0.02	1212755	0.01	0.01	0.01	0.00	0.02	2099985
Total Net Assets (USD Millions)	1156.45	153.10	5886.72	15.80	17713.70	1212755	884.21	134.00	4650.09	15.70	12861.90	2099985
Average Front Load	0.04	0.04	0.01	0.01	0.05	220112	0.04	0.04	0.01	0.01	0.05	289131
Average Back Load	0.02	0.02	0.01	0.00	0.02	137451	0.02	0.02	0.01	0.00	0.02	240483
Turnover	0.67	0.38	3.04	0.00	5.10	1212755	0.59	0.30	2.54	0.00	4.93	2099985
Tenure (Months)	97.61	86.00	63.09	8.00	284.00	1041448	97.31	85.00	64.65	8.00	292.00	1478642
Flows Category	-0.00	-0.01	0.10	-0.17	0.22	1212667	-0.00	-0.01	0.71	-0.16	0.19	2099785
Flows %	0.32	-0.32	6.69	-17.35	28.82	1199360	0.24	-0.40	6.98	-19.55	31.07	2071800
Fund Family Level												
Positiveness	0.59	0.00	0.75	-0.51	2.51	22379	0.20	0.00	0.52	0.00	2.19	65877
Number of tweets per month	30.30	2.00	70.24	0.00	322.00	22379	10.29	0.00	43.38	0.00	191.00	65877
Age (Years)	30.79	22.50	24.97	2.67	90.08	22379	23.17	18.00	20.12	2.58	87.17	65877
Family Size (USD Billions)	8.05	8.03	2.65	2.93	14.05	22379	6.79	6.53	2.52	2.83	13.08	65877
Number of Funds	52.03	12.00	87.14	1.00	415.00	22379	24.25	4.00	58.15	1.00	271.00	65877
Number of Investment Categories	13.72	6.00	15.92	1.00	69.00	22379	7.49	3.00	11.63	1.00	55.00	65877
CAPM monthly alpha %	-0.00	-0.00	0.01	-0.02	0.02	22379	-0.00	-0.00	0.01	-0.02	0.02	65877
Funds with loads %	25.72	14.94	29.32	0.00	100.00	22379	28.99	12.65	35.48	0.00	100.00	65877
Expense Ratio	1.05	1.00	1.32	0.11	2.21	22379	1.14	1.10	0.85	0.11	2.47	65877
Volatility %	4.01	3.62	2.09	0.84	10.68	22379	4.25	3.80	2.36	0.77	11.55	65877
Unique fund families						284						939

Note: This table contains summary statistics of fund and fund family characteristics for two samples. The first sample, Twitter Subsample, consists of fund families managing US equity funds that have tweeted at least once from January 2009 to October 2017. The Full Sample includes all families managing US equity funds in the same period. The first set of rows show descriptive statistics for variables computed at the fund-month level. Performance is the monthly CAPM alpha computed from the asset-weighted average return of all share classes of the fund. Age is the number of years since the inception of the oldest share class in the fund. Flows is the fund's monthly growth in the fund's total net assets net of the fund's return. Expense ratio is the asset-weighted average across all share classes of the fund, expressed in decimal units. Total Net Assets is the sum of total net assets of all share classes of the fund. Front-end and back-end loads denote the asset-weighted average of the maximum loads across all share classes. Turnover denotes the annual turnover of the fund's portfolio. Tenure is the number of months since the manager took over the fund. Flows Category denotes the relative flows to all the funds in the same Lipper investment category as the fund in question. The second set of rows display family characteristics. Number of Tweets in the total number of posts on Twitter by the family in a given month. Positiveness is defined as in equation (3). Family Age is the age in years of the family's oldest fund. Family Size is the sum of Total Net Assets across all of the family's funds. Number of Funds is the total number of funds managed by the family. Number of Investment Categories is the number of different Lipper investment categories to which the family's funds belong. Funds with loads is the percentage of funds in the family that charge either front-end or back-end load. Expense Ratio is the Asset weighted average of the expense ratios of all funds within each fund family. Volatility is the asset weighted average of the rolling 12 month volatility of the returns of each fund within each family presented in percentage.

Table 2: Determinants of Twitter Activity

	(1) Twitter	(2) Twitter	(3) Twitter	(4) # of Tweets	(5) # of Tweets	(6) # of Tweets
Family Age	-0.001	-0.009	0.003	-0.243***	-0.134**	-0.109**
	(0.024)	(0.023)	(0.023)	(0.062)	(0.057)	(0.055)
Family Size	0.056***			0.208***		
	(0.009)			(0.014)		
Number of Funds		0.115***			0.153***	
		(0.017)			(0.027)	
Number of Inv. Categories			0.146***			0.087**
			(0.025)			(0.034)
CAPM alpha	531.311*	552.999*	550.134*	583.785***	621.282***	626.322***
	(300.430)	(295.398)	(298.155)	(183.372)	(199.727)	(201.368)
Expense Ratio	-0.792	-3.695	-3.558	-4.294***	-4.441***	-4.427***
	(3.371)	(3.205)	(3.234)	(0.260)	(0.275)	(0.280)
Funds with loads	0.038	0.043	0.039	0.027	-0.022	-0.041
	(0.040)	(0.040)	(0.040)	(0.053)	(0.053)	(0.052)
Volatility	-1.587*	-1.636*	-1.611*	-7.097***	-7.520***	-7.679***
	(0.830)	(0.852)	(0.849)	(1.191)	(1.228)	(1.232)
Lagged flows	45.324	51.163	48.440	-5.022***	-3.600**	-3.448**
	(36.595)	(33.905)	(35.161)	(1.488)	(1.477)	(1.462)
Observations	814	814	814	22139	22139	22139
Adjusted R^2 (%)	8.69	9.72	8.39	70.24	70.03	70.01
Time FE	No	No	No	Yes	Yes	Yes
Family FE	No	No	No	Yes	Yes	Yes
Estimation	Cross	Cross	Cross	Panel	Panel	Panel
Sample	Full	Full	Full	Twitter	Twitter	Twitter

Note: This table shows estimation results for regressions of Twitter activity on family characteristics. Columns (1) to (3) display results for cross-sectional regressions of a dummy variable that equals 1 if a fund family has tweeted at least once in our sample, on family characteristics. Columns (4) to (6) provide results of running a regression of the natural logarithm of one plus the number of tweets (# of Tweets) posted by a fund family in a given month on fund family characteristics. In columns (1) to (3) explanatory variables are averaged across time for each family. In columns (4) to (6) the unit of observation is family-month and family characteristics are lagged one month. Flows to the family are calculated using equation (5) with the Total Net Assets of the fund family and the asset-weighted average return of the family. Family Age is the natural logarithm of one plus the age of the oldest fund in the family in years. Family size is the natural logarithm of all the total net assets managed by the company in USD millions. Number of Funds is the log of the number of funds managed by the family. Inv. Categories denotes the log of the number of different Lipper investment categories across all funds in the family. The CAPM alpha is the asset-weighted average 12-month CAPM alpha across funds in the family. Expense Ratio is is the asset-weighted average of expense ratios across funds in the family. Funds with loads denotes the percentage of funds in the family that charge front-end or back-end loads. Volatility is the asset-weighted average of each fund's 12-month rolling volatility of returns. In columns (1) to (3) robust standard errors are presented in parentheses, while in columns (4) to (6) robust standard errors are clustered at the time level. *** p<0.01, ** p<0.05, *p<0.1.

Table 3: Flows and Twitter Activity

	(1)	(2)	(3)	(4)	(5)	(6)
Positiveness		0.08***	0.06**		0.08***	0.06**
		(0.02)	(0.03)		(0.02)	(0.03)
Number of tweets			0.01			0.01
			(0.01)			(0.01)
Low OAR	0.33***	0.33***	0.33***			
	(0.03)	(0.03)	(0.03)			
Mid OAR	0.66***	0.66***	0.66***			
	(0.02)	(0.02)	(0.02)			
High OAR	0.77***	0.77***	0.77***			
	(0.04)	(0.04)	(0.04)			
Low Rank				2.72***	2.72***	2.72***
				(0.23)	(0.23)	(0.23)
Mid Rank				1.59***	1.59***	1.59***
				(0.06)	(0.06)	(0.06)
High Rank				8.75***	8.77***	8.76***
				(0.46)	(0.46)	(0.46)
Size	-0.71***	-0.71***	-0.71***	-0.72***	-0.71***	-0.71***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Flows to the same category	-2.37***	-2.38***	-2.38***	-2.38***	-2.38***	-2.39***
	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)
Volatility	-11.12***	-11.12***	-11.13***	-9.08***	-9.07***	-9.07***
	(1.18)	(1.18)	(1.18)	(1.18)	(1.18)	(1.18)
Expense ratio	2.15	2.20	2.12	2.53	2.58	2.50
	(2.23)	(2.23)	(2.23)	(2.26)	(2.26)	(2.25)
Age	-1.95***	-1.95***	-1.95***	-1.98***	-1.98***	-1.98***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
Family Size	0.17***	0.17***	0.17***	0.17***	0.17***	0.17***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Family Age	-0.26***	-0.27***	-0.27***	-0.27***	-0.28***	-0.29***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Past Flows	0.14***	0.14***	0.14***	0.14***	0.14***	0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	12.96***	12.96***	12.94***	12.40***	12.40***	12.38***
	(0.92)	(0.92)	(0.92)	(0.92)	(0.92)	(0.92)
Observations	455071	455071	455071	455071	455071	455071
Adjusted R^2 (%)	12.28	12.29	12.29	12.22	12.23	12.23
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Inv. Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund Family FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows estimation results for regressions of mutual fund flows (in %) on Number of Tweets, Positiveness, and control variables. Flows are computed using equation (5). Number of Tweets is computed as the natural logarithm of one plus the number of tweets posted by the fund's fund family in the previous month. Positiveness is computed in the previous month as in equation (3). Low, Mid, and High Performance are computed using objective adjusted 12-month CAPM alphas (normalized to have zero average and unit standard deviation across all funds with the same Lipper class investment objective). Low, Mid, and High Ranks are computed using ranks based on the 12-month CAPM alpha of each fund under the same Lipper class investment objective. Size is the natural logarithm of the total net assets under management of a fund in the previous month. Flows to the same category are computed as the percentage of contemporaneous net flows to all funds with the same Lipper class investment objective. Volatility is the 12 month rolling volatility of returns. Expense Ratio is in decimal units. Age is the natural logarithm of the age of the fund in months. Lagged Flows denotes one-month lagged flows to the fund. Family size is the natural logarithm of the assets under management by the fund family in the previous month, and family age is the natural logarithm of one plus the age of the family in months. Robust standard errors, clustered at the month, fund family, and month-fund family levels, are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Flows and Positiveness (Fund family level)

	(1)	(2)	(3)	(4)
Positiveness	0.10***	0.12***	0.13***	0.14***
	(0.03)	(0.04)	(0.03)	(0.04)
Low OAR - Family	0.82***	0.70***		
	(0.11)	(0.12)		
Mid OAR - Family	0.27***	0.27***		
	(0.08)	(0.08)		
High OAR - Family	0.69***	0.79***		
	(0.12)	(0.12)		
Low Rank - Family			-6.07***	-5.61***
			(0.80)	(0.83)
Mid Rank - Family			2.41***	2.17***
			(0.22)	(0.22)
High Rank - Family			6.01***	8.63***
			(1.39)	(1.48)
Family Size	-0.01	-0.27***	-0.00	-0.25***
	(0.01)	(0.07)	(0.01)	(0.07)
Volatility - Family	4.24*	-5.51	0.53	-5.55
	(2.36)	(4.04)	(2.32)	(4.01)
Expense Ratio - Family	-19.64**	20.29	-27.80***	27.17
	(9.37)	(23.30)	(9.30)	(23.14)
Age - Family	-0.22***	-0.29**	-0.23***	-0.33**
	(0.04)	(0.13)	(0.04)	(0.14)
Flows Category - Family	0.64**	-0.56	0.55**	-0.56
	(0.25)	(0.59)	(0.25)	(0.58)
Flows - Family(t)	0.31***	0.26***	0.32***	0.26***
	(0.02)	(0.02)	(0.02)	(0.02)
Constant	1.38***	3.57***	1.59***	3.54***
	(0.22)	(0.85)	(0.23)	(0.86)
Observations	22140	22137	22140	22137
Adjusted R^2 (%)	16.34	19.41	16.18	19.36
Time FE	Yes	Yes	Yes	Yes
Fund Family FE	No	Yes	No	Yes

Note: This table shows estimation results for regressions of mutual fund flows (in %) on Positiveness and control variables. Flows are computed using equation (5). Positiveness is computed in the previous month as in equation (3). Family-level aggregated variables including flows are asset-weighted averages across funds in the family, except for Family Size, which is the natural logarithm of the sum of all the TNAs among the funds in the family, and Family Age, which is the natural logarithm of one plus the age of the oldest fund in months. Low, Mid, and High Performance are computed using objective adjusted 12-month CAPM alphas (normalized to have zero average and unit standard deviation across all funds with the same Lipper class investment objective). Low, Mid, and High Ranks are computed using ranks based on the 12-month CAPM alpha of each fund under the same Lipper class investment objective. Size is the natural logarithm of the total net assets under management of a fund in the previous month. Flows to the same category are computed as the percentage of contemporaneous net flows to all funds with the same Lipper class investment objective. Volatility is the 12 month rolling volatility of returns. Expense Ratio is in decimal units. Age is the natural logarithm of the age of the fund in months. Lagged Flows denotes one-month lagged flows to the fund. Family size is the natural logarithm of the assets under management by the fund family in the previous month, and family age is the natural logarithm of one plus the age of the family in months. Robust standard errors, clustered at the month, fund family, and month-fund family levels, are shown in parentheses. *** p<0.01, ** p<0.05, *p<0.1

Table 5: Flows, Positiveness and Fundamental Information

	(1)	(2)	(3)	(4)	(5)
Positiveness	0.07***	0.07***	0.08***	0.07***	0.07***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Change Family	-0.28				
	(0.20)				
Change Manager		-1.11**			
		(0.55)			
Number of external tweets			-0.08*		
			(0.04)		
External Positiveness				-0.01	
				(0.06)	
Fraction Top Funds					0.49***
					(0.15)
Low Rank	2.70***	2.69***	2.70***	2.69***	2.68***
	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)
Mid Rank	1.59***	1.59***	1.59***	1.59***	1.59***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
High Rank	8.71***	8.70***	8.72***	8.71***	8.66***
	(0.46)	(0.46)	(0.46)	(0.46)	(0.46)
Size	-0.71***	-0.71***	-0.71***	-0.71***	-0.71***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Flows to the same category	-2.36***	-2.36***	-2.37***	-2.36***	-2.36***
	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)
Volatility	-8.88***	-8.89***	-8.89***	-8.88***	-8.91***
	(1.18)	(1.18)	(1.18)	(1.18)	(1.18)
Expense ratio	2.78	2.77	2.71	2.77	2.74
	(2.29)	(2.29)	(2.29)	(2.29)	(2.28)
Age	-1.98***	-1.98***	-1.98***	-1.98***	-1.97***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Family Size	0.15***	0.15***	0.15***	0.15***	0.15***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Family Age	-0.28***	-0.28***	-0.27***	-0.28***	-0.28***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Past Flows	0.14***	0.14***	0.14***	0.14***	0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	455071	455071	455071	455071	455071
Adjusted R^2 (%)	12.19	12.2	12.19	12.19	12.2
Time FE	Yes	Yes	Yes	Yes	Yes
Fund Family FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes

Note: This table shows estimation results for regressions of mutual fund flows (in %) on Number of Tweets, Positiveness, and control variables. Flows are computed using equation (5). Number of Tweets is computed as the natural logarithm of one plus the number of tweets posted by the fund's fund family in the previous month. Positiveness is computed in the previous month as in equation (3). Low, Mid, and High Performance are computed using objective adjusted 12-month CAPM alphas (normalized to have zero average and unit standard deviation across all funds with the same Lipper class investment objective). Low, Mid, and High Ranks are computed using ranks based on the 12-month CAPM alpha of each fund under the same Lipper class investment objective. Size is the natural logarithm of the total net assets under management of a fund in the previous month. Flows to the same category are computed as the percentage of contemporaneous net flows to all funds with the same Lipper class investment objective. Volatility is the 12 month rolling volatility of returns. Expense Ratio is in decimal units. Age is the natural logarithm of the age of the fund in months. Lagged Flows denotes one-month lagged flows to the fund. Family size is the natural logarithm of the assets under management by the fund family in the previous month, and family age is the natural logarithm of one plus the age of the family in months. Change Family indicates if the fund has changed fund family (measured as mgmt_cd) in the last month, Change Manager indicates if the fund has changed manager in the last month, the number of external tweets is computed as the natural logarithm of the number of external mentions retrieved from the fund, external positiveness is defined as in equation 3 using external tweets, fraction of top funds is the fraction of funds in the fund family that are in the top 5% performance percentile in the month across all funds in the same Lipper category. Robust standard errors, clustered at the month, fund family, and month-fund family levels, are shown in parentheses. *** p<0.01, ** p<0.05, *p<0.1

Table 6: Flows and Twitter Activity (Index Funds)

	(1)	(2)	(3)	(4)	(5)	(6)
Number of tweets		0.05			0.05	
		(0.03)			(0.03)	
Positiveness			0.08			0.07
			(0.06)			(0.06)
Low OAR	0.45***	0.45***	0.45***			
	(0.11)	(0.11)	(0.11)			
Mid OAR	0.54***	0.54***	0.54***			
	(0.07)	(0.07)	(0.07)			
High OAR	1.20***	1.20***	1.20***			
	(0.12)	(0.12)	(0.12)			
Low Rank				5.69***	5.69***	5.68***
				(1.02)	(1.03)	(1.03)
Mid Rank				1.37***	1.37***	1.37***
				(0.18)	(0.18)	(0.18)
High Rank				9.56***	9.56***	9.56***
				(1.10)	(1.10)	(1.10)
Size	-1.02***	-1.02***	-1.02***	-1.02***	-1.02***	-1.01***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Flows to the same category	-2.31***	-2.30***	-2.31***	-2.35***	-2.35***	-2.35***
	(0.46)	(0.47)	(0.47)	(0.46)	(0.46)	(0.46)
Volatility	-1.87	-1.87	-1.93	-1.26	-1.26	-1.31
	(3.49)	(3.49)	(3.49)	(3.47)	(3.47)	(3.47)
Expense ratio	-69.58	-70.01	-69.16	-64.60	-65.02	-64.24
	(54.02)	(54.03)	(54.16)	(54.48)	(54.50)	(54.60)
Age	-0.51*	-0.52*	-0.50*	-0.59**	-0.59**	-0.58**
	(0.28)	(0.28)	(0.28)	(0.28)	(0.28)	(0.28)
Family Size	0.60***	0.62***	0.61***	0.58***	0.60***	0.58***
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
Family Age	0.88***	0.88***	0.89***	0.90***	0.89***	0.90***
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
Past Flows	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-3.24	-3.56	-3.41	-4.15	-4.45*	-4.29
	(2.58)	(2.61)	(2.60)	(2.62)	(2.65)	(2.64)
Observations	96676	96676	96676	96690	96690	96690
Adjusted R^2 (%)	8.03	8.04	8.04	7.92	7.93	7.92
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Inv. Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund Family FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows estimation results for regressions of mutual fund flows (in %) on Number of Tweets, Positiveness, and control variables only for index funds. Flows are computed using equation (5). Number of Tweets is computed as the natural logarithm of one plus the number of tweets posted by the fund's fund family in the previous month. Positiveness is computed in the previous month as in equation (3). Low, Mid, and High Performance are computed using objective adjusted 12-month CAPM alphas (normalized to have zero average and unit standard deviation across all funds with the same Lipper class investment objective). Low, Mid, and High Ranks are computed using ranks based on the 12-month CAPM alpha of each fund under the same Lipper class investment objective. Size is the natural logarithm of the total net assets under management of a fund in the previous month. Flows to the same category are computed as the percentage of contemporaneous net flows to all funds with the same Lipper class investment objective. Volatility is the 12 month rolling volatility of returns. Expense Ratio is in decimal units. Age is the natural logarithm of the age of the fund in months. Lagged Flows denotes one-month lagged flows to the fund. Family size is the natural logarithm of the assets under management by the fund family in the previous month, and family age is the natural logarithm of one plus the age of the family in months. Robust standard errors, clustered at the month, fund family, and month-fund family levels, are shown in parentheses. *** p<0.01, ** p<0.05, *p<0.1

Table 7: Inflows, Outflows, and Positiveness

	Inflows		Outflows	
	(1)	(2)	(3)	(4)
Positiveness	0.11***	0.08***	-0.06***	-0.05***
	(0.02)	(0.02)	(0.01)	(0.01)
Low OAR	0.26***		-0.58***	
	(0.03)		(0.04)	
Mid OAR	0.66***		-0.31***	
	(0.03)		(0.02)	
High OAR	0.94***		-0.08**	
	(0.07)		(0.04)	
Low Rank		1.81***		-4.53***
		(0.26)		(0.27)
Mid Rank		1.88***		-0.61***
		(0.09)		(0.06)
High Rank		9.35***		-1.28**
		(1.03)		(0.50)
Observations	44943	44943	44943	44943
Adjusted R^2 (%)	4.43	3.96	2.53	2.43

Note: This table shows estimation results for regressions of residual inflows and residual outflows (both in %) on Positiveness and fund performance. In a first stage (not reported) Inflows (Out- flows) are regressed on 12 lags of the variable and controls: Size, the natural logarithm of the total net assets under management of a fund in the previous month; Flows to the same category, the percentage of contemporaneous net flows to all funds with the same Lipper class investment objec- tive; Volatility, the 12 month rolling volatility of returns; Expense Ratio, in decimal units; Age, the natural logarithm of the age of the fund in months; one-month lagged flows to the fund; Family size, the natural logarithm of the assets under management by the fund family in the previous month; and Family age, the natural logarithm of one plus the age of the family in months. In a second stage (not reported) we regress Inflows (Outflows) on the fitted values of Ouflows (Inflows) estimated in the first stage. Fitted residuals from the regression are then regressed on Positiveness and the three performance variables. Positiveness is computed in the previous month as in equation (3). Low, Mid, and High Performance are computed using objective adjusted 12-month CAPM alphas (normalized to have zero average and unit standard deviation across all funds with the same Lipper class investment objective). Low, Mid, and High Ranks are computed using ranks based on the 12-month CAPM alpha of each fund under the same Lipper class investment objective. OLS robust standard errors in parentheses. *** p<0.01, ** p<0.05, *p<0.1

Table 8: Positiveness and Subsequent Fund Performance

	(1) α_{t+1}	(2) α_{t+1}	(3) α^{4F}_{t+1}	(4) α^{4F}_{t+1}
Positiveness	-0.000	-0.003	-0.003	-0.006
	(0.006)	(0.007)	(0.005)	(0.006)
$\alpha_{t-3\to t}$	0.021***	0.012***		
	(0.003)	(0.003)		
$\alpha^{4F}_{t-3\to t}$			0.008**	-0.001
			(0.004)	(0.004)
Size	-0.004*	-0.086***	-0.004**	-0.094***
	(0.002)	(0.006)	(0.002)	(0.005)
Expense ratio	-4.493***	0.913	-4.696***	1.156
	(0.866)	(0.913)	(0.788)	(0.911)
Past Flows	0.000	-0.001**	0.001***	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Turnover	-0.006***	-0.007*	-0.006***	0.001
	(0.002)	(0.004)	(0.002)	(0.003)
Number of Funds	0.000*	0.000*	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Category Share	0.194**	-0.002	0.201***	0.067
	(0.098)	(0.275)	(0.076)	(0.228)
% of new funds	0.000	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Number of tweets	0.004	0.004	-0.001	-0.001
	(0.003)	(0.003)	(0.002)	(0.003)
Volatility	-2.573*	-1.794	-0.428	0.115
	(1.346)	(1.575)	(1.331)	(1.571)
Family Size	-0.057***	-0.027**	-0.074***	-0.041***
	(0.011)	(0.014)	(0.009)	(0.011)
Family Age	-0.024	-0.040*	-0.011	-0.024
	(0.019)	(0.022)	(0.016)	(0.018)
Charges loads	0.001	0.002	0.006	0.007
	(0.007)	(0.042)	(0.006)	(0.036)
Age fund	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Retail	-0.012	-0.002	-0.015*	-0.005
	(0.011)	(0.012)	(0.009)	(0.009)
Constant	0.786***	0.889***	0.797***	0.922***
	(0.157)	(0.196)	(0.129)	(0.160)
Observations	505979	505958	505979	505958
Adjusted R^2 (%)	8.67	8.58	6.18	6.11
Time FE	Yes	Yes	Yes	Yes
Investment Category FE	Yes	Yes	Yes	Yes
Fund FE	No	Yes	No	Yes
Fund Family FE	Yes	Yes	Yes	Yes

Note: This table shows estimation results of regressions of fund's monthly alpha (in %) on Positiveness, past performance, and control variables. Positiveness is defined as in equation (3). Per- formance is defined in two ways: The CAPM abnormal return compounded over the last three months $\alpha(t3 : t)$ and the four-factor abnormal return compounded over the last three months $\alpha(t3 : t)$. Size is the natural logarithm of the total net assets of the fund. The expense ratio is in decimal units. Lagged Flows are the net flows to the fund in the previous month. Turnover is the fund's portfolio turnover. Volatility is the 12-month rolling volatility of returns. Charges Loads is a dummy that equals 1 if the fund charges either front-end or back-end loads. Age is the natural logarithm of the age of the fund in months. Family size is the natural logarithm of the total net assets of the fund family. Family Age is the natural logarithm of the age of the family in months. Robust standard errors clustered at the family, month, and family-month levels are presented in parentheses. *** p<0.01, ** p<0.05, *p<0.1

Table 9: Flows, Positiveness and Fund Characteristics

	(1)	(2)
Positiveness	0.13***	0.53***
	(0.04)	(0.16)
Low OAR	0.33***	0.33***
	(0.03)	(0.03)
Mid OAR	0.68***	0.66***
	(0.02)	(0.02)
High OAR	0.78***	0.77***
	(0.04)	(0.04)
Size	-0.70***	-0.71***
	(0.03)	(0.03)
Flows to the same category	-2.19***	-2.38***
	(0.27)	(0.27)
Volatility	-11.35***	-11.15***
	(1.09)	(1.18)
Expense ratio	4.48*	2.43
	(2.35)	(2.23)
Age	-1.90***	-1.90***
	(0.11)	(0.11)
Age		0.00
		(.)
Family Size	0.21***	0.17***
	(0.04)	(0.05)
Family Age	-0.24**	-0.27***
	(0.10)	(0.09)
Past Flows	0.14***	0.14***
	(0.01)	(0.01)
Tenure	0.01	
	(0.00)	
Positiveness × Tenure	-0.01**	
	(0.00)	
Positiveness × Age		-0.09***
		(0.03)
Constant	11.95***	12.74***
	(0.89)	(0.93)
Observations	402194	455071
Adjusted R^2 (%)	12.05	12.29
Time FE	Yes	Yes
Inv. Category FE	Yes	Yes
Fund FE	Yes	Yes
Fund Family FE	Yes	Yes

Note: This table shows estimation results for regressions of mutual fund flows (in %) on Number of Tweets, Positiveness, and control variables. Flows are computed using equation (5). Number of Tweets is computed as the natural logarithm of one plus the number of tweets posted by the fund's fund family in the previous month. Positiveness is computed in the previous month as in equation (3). Low, Mid, and High Performance are computed using objective adjusted 12-month CAPM alphas (normalized to have zero average and unit standard deviation across all funds with the same Lipper class investment objective). Low, Mid, and High Ranks are computed using ranks based on the 12-month CAPM alpha of each fund under the same Lipper class investment objective. Size is the natural logarithm of the total net assets under management of a fund in the previous month. Flows to the same category are computed as the percentage of contemporaneous net flows to all funds with the same Lipper class investment objective. Volatility is the 12 month rolling volatility of returns. Expense Ratio is in decimal units. Age is the natural logarithm of the age of the fund in months. Lagged Flows denotes one-month lagged flows to the fund. Family size is the natural logarithm of the assets under management by the fund family in the previous month, and family age is the natural logarithm of one plus the age of the family in months. Tenure is the number of years that the current manager has been employed. Robust standard errors, clustered at the month, fund family, and month-fund family levels, are shown in parentheses. *** p<0.01, ** p<0.05, *p<0.1

Table 10: Sensitivity of Positiveness Induced Flows

	(1)	(2)	(3)	(4)
Positiveness	0.081***	0.123***	0.080***	-0.047
	(0.022)	(0.047)	(0.022)	(0.048)
Low OAR	0.330***	0.270***		
	(0.030)	(0.041)		
Mid OAR	0.658***	0.622***		
	(0.023)	(0.034)		
High OAR	0.772***	0.805***		
	(0.039)	(0.057)		
Positiveness × Low OAR		0.080**		
		(0.036)		
Positiveness × Mid OAR		0.041		
		(0.029)		
Positiveness × High OAR		-0.041		
		(0.053)		
Low Rank			2.724***	2.162***
			(0.227)	(0.316)
Mid Rank			1.590***	1.575***
			(0.059)	(0.087)
High Rank			8.766***	9.222***
			(0.459)	(0.701)
Positiveness × Low Rank				0.712***
				(0.270)
Positiveness × Mid Rank				0.015
				(0.073)
Positiveness × High Rank				-0.526
				(0.621)
Size	-0.706***	-0.708***	-0.712***	-0.714***
	(0.029)	(0.029)	(0.029)	(0.029)
Expense ratio	2.199	2.194	2.582	2.557
	(2.227)	(2.228)	(2.256)	(2.254)
Past Flows	0.142***	0.142***	0.143***	0.143***
	(0.005)	(0.005)	(0.005)	(0.005)
Volatility	-11.122***	-11.163***	-9.069***	-9.087***
	(1.184)	(1.184)	(1.184)	(1.185)
Family Size	0.165***	0.165***	0.171***	0.170***
	(0.046)	(0.046)	(0.046)	(0.046)
Family Age	-0.268***	-0.270***	-0.283***	-0.284***
	(0.091)	(0.091)	(0.091)	(0.091)
Flows to the same category	-2.378***	-2.376***	-2.385***	-2.384***
	(0.270)	(0.270)	(0.270)	(0.270)
Age	-1.950***	-1.946***	-1.985***	-1.981***
	(0.105)	(0.105)	(0.105)	(0.105)
Constant	12.962***	12.945***	12.403***	12.506***
	(0.924)	(0.924)	(0.924)	(0.924)
Observations	455071	455071	455071	455071
Adjusted R^2 (%)	12.29	12.29	12.23	12.23
Time FE	Yes	Yes	Yes	Yes
Investment Category FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Fund Family FE	Yes	Yes	Yes	Yes

Note: This table shows estimation results for regressions of mutual fund flows (in %) on Number of Tweets, Positiveness, and control variables. Flows are computed using equation (5). Number of Tweets is computed as the natural logarithm of one plus the number of tweets posted by the fund's fund family in the previous month. Positiveness is computed in the previous month as in equation (3). Low, Mid, and High Performance are computed using objective adjusted 12-month CAPM alphas (normalized to have zero average and unit standard deviation across all funds with the same Lipper class investment objective). Low, Mid, and High Ranks are computed using ranks based on the 12-month CAPM alpha of each fund under the same Lipper class investment objective. Size is the natural logarithm of the total net assets under management of a fund in the previous month. Flows to the same category are computed as the percentage of contemporaneous net flows to all funds with the same Lipper class investment objective. Volatility is the 12 month rolling volatility of returns. Expense Ratio is in decimal units. Age is the natural logarithm of the age of the fund in months. Lagged Flows denotes one-month lagged flows to the fund. Family size is the natural logarithm of the assets under management by the fund family in the previous month, and family age is the natural logarithm of one plus the age of the family in months. Robust standard errors, clustered at the month, fund family, and month-fund family levels, are shown in parentheses. *** p<0.01, ** p<0.05, *p<0.1

Table 11: Positiveness and Flows' Reversion

	(1) 6	(2) 12	(3) 18	(4) 24	(5) 30	(6) 36
Positiveness	0.409***	0.639***	0.589**	0.646*	0.657	0.155
	(0.101)	(0.199)	(0.293)	(0.388)	(0.478)	(0.577)
Size	-9.674***	-29.154***	-55.898***	-87.838***	-124.296***	-163.950***
	(0.166)	(0.367)	(0.587)	(0.861)	(1.202)	(1.600)
Expense ratio	-8.007	-15.517	23.600	-401.274	-1257.724***	-2008.095***
	(15.051)	(28.461)	(27.092)	(315.326)	(422.644)	(516.525)
Past Flows	0.572***	0.904***	1.082***	1.120***	1.096***	1.124***
	(0.017)	(0.030)	(0.041)	(0.052)	(0.063)	(0.072)
Volatility	-72.564***	-103.576***	-146.304***	-219.624***	-342.098***	-443.435***
	(5.624)	(9.718)	(14.021)	(18.993)	(26.424)	(34.952)
Family Size	2.003***	5.775***	8.748***	11.784***	14.192***	16.962***
	(0.244)	(0.460)	(0.742)	(1.066)	(1.395)	(1.772)
Family Age	-1.258***	-3.016***	-4.307***	-3.638***	-5.017***	-8.444***
	(0.391)	(0.659)	(0.982)	(1.343)	(1.748)	(2.111)
Low OAR	1.668***	2.416***	3.103***	3.499***	4.015***	4.691***
	(0.117)	(0.225)	(0.356)	(0.495)	(0.580)	(0.726)
Mid OAR	4.181***	7.387***	9.960***	11.454***	12.017***	13.045***
	(0.102)	(0.194)	(0.296)	(0.393)	(0.495)	(0.609)
High OAR	4.395***	7.077***	10.044***	12.008***	12.564***	10.532***
	(0.193)	(0.377)	(0.609)	(0.784)	(0.907)	(1.024)
Flows to the same category	-9.030***	-12.071***	-15.894***	-17.906***	-22.328***	-19.011***
	(1.011)	(1.764)	(2.534)	(3.253)	(3.986)	(4.973)
Age	-9.522***	-14.242***	-18.104***	-19.654***	-17.779***	-10.692***
	(0.469)	(0.893)	(1.382)	(1.901)	(2.462)	(3.060)
Constant	83.674***	180.821***	321.819***	475.519***	666.501***	858.847***
	(4.175)	(7.464)	(12.023)	(17.089)	(23.031)	(29.549)
Observations	427992	396686	366542	337504	310046	283924
Adjusted R^2 (%)	28.91	39.92	49.01	56.09	61.45	66.04
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Investment Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund Family FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows estimation results for regressions of mutual fund flows (in %) on Number of Tweets, Positiveness, and control variables. Flows are computed using equation (5) for different horizons. Number of Tweets is computed as the natural logarithm of one plus the number of tweets posted by the fund's fund family in the previous month. Positiveness is computed in the previous month as in equation (3). Low, Mid, and High Performance are computed using objective adjusted 12-month CAPM alphas (normalized to have zero average and unit standard deviation across all funds with the same Lipper class investment objective). Low, Mid, and High Ranks are computed using ranks based on the 12-month CAPM alpha of each fund under the same Lipper class investment objective. Size is the natural logarithm of the total net assets under management of a fund in the previous month. Flows to the same category are computed as the percentage of contemporaneous net flows to all funds with the same Lipper class investment objective. Volatility is the 12 month rolling volatility of returns. Expense Ratio is in decimal units. Age is the natural logarithm of the age of the fund in months. Lagged Flows denotes one-month lagged flows to the fund. Family size is the natural logarithm of the assets under management by the fund family in the previous month, and family age is the natural logarithm of one plus the age of the family in months. Robust standard errors, clustered at the month, fund family, and month-fund family levels, are shown in parentheses. *** p<0.01, ** p<0.05, *p<0.1

Appendix

Since the language used in tweets is limited by the 140-character length restriction, just the presence of words might not be informative enough to classify them.[15] At the same time the *informality* of communications increases the use of words with less defined tonal categories, and provides less informative features to predict labels. To obtain a more informative set of features from tweets, we consider both the appearance of a word as well as its role in the sentence - also known as Part of Speech (POS).

We use six different algorithms: Naive-Bayes classifier, Multinomial-Naive-Bayes classifier, Bernoulli Naive-Bayes classifier, Stochastic Gradient Descent, Support Vector Machines, and Logistic Regression. We then consider a voting scheme that consists of classifying each tweet with the most voted label among the different algorithms. If three algorithms classify a tweet as positive and three as negative, we consider the tweet to have a neutral tone. The procedure also provides us with a measure of agreement between the algorithms.

We start by extracting two important features of each tweet: Words, and Part of Speech (POS). We start by applying a tokenization based on regular expressions to automatically split the text into words. We proceed by using a POS tagger (an algorithm that tags each word with its more likely POS) to identify the role of each word within the sentence. The following example describes the procedure we use:

Figure 4: Example of a financial tweet posted by Bloomberg @business on September 27 2017, 14:00.

The first step consists of tokenizing the tweet to isolate its components. We use a special tokenization procedure to account for hyperlinks, emoticons, and punctuation. The tokenization splits the tweet as follows:

> Fidelity, Chairman, and, CEO, Abigail, Johnson, discusses, the, struggle, between, active
> and, passive, investing, https://www.bloomberg.com/...

Once the tweet is tokenized, we apply a POS tagger which applies an optimization algorithm that maximizes the likelihood of tuples of the form $(token, POS)$ to appear in a sentence. After the POS tagger is applied,

[15] Twitter changed to 240 the character limit of tweets only starting in 2017.

the tweet becomes:

$$\underbrace{\text{Fidelity}}_{\text{proper noun, singular}} \quad \underbrace{\text{Chairman}}_{\text{proper noun, singular}} \quad \underbrace{\text{and}}_{\text{coordinating conjunction}} \quad \underbrace{\text{CEO}}_{\text{proper noun, singular}} \quad \underbrace{\text{Abigail}}_{\text{proper noun, singular}}$$

$$\underbrace{\text{Johnson}}_{\text{proper noun, singular}} \quad \underbrace{\text{discusses}}_{\text{verb, 3rd person, singular, present}} \quad \underbrace{\text{the}}_{\text{determiner}} \quad \underbrace{\text{struggle}}_{\text{noun singular}}$$

$$\underbrace{\text{between}}_{\text{preposition/subordinating conjunction}} \quad \underbrace{\text{active}}_{\text{adjective}} \quad \underbrace{\text{and}}_{\text{coordinating conjunction}} \quad \underbrace{\text{passive}}_{\text{adjective}} \quad \underbrace{\text{investing}}_{\text{noun singular}}$$

$$\underbrace{\text{https://www.bloomberg.com/...}}_{\text{noun singular}}$$

After tokenizing and extracting the POS of every tweet in our database we proceed to extract the most common features. We do this by calculating the frequency of each tuple $(token, POS)$ and select the most common 4000 features.

The machine learning algorithms we use are supervised algorithms. They require an initial set of tweets labelled whether they are positive or negative. The algorithms then find common patters which are applied to classify unlabelled tweets. We train our algorithms with a sample of 10,000 tweets manually classified by two research assistants (undergraduate students in economics and management science respectively). To ensure the training sample has enough tweets from all possible categories in both dimensions we randomly select them from the accounts of the Financial Times (FT) and The Wall Street Journal (WSJ). We use this source of tweets instead of those posted by fund families since negative information is less likely to be disclosed.

Using this methodology we classify each tweet into two tone categories $\{\text{positive}, \text{negative}\}$ using our training sample. For each classification, we obtain a measure of confidence based on the degree of agreement among the classifiers. Below, we present two tweets posted by financial media, and two tweets posted by asset management companies to show the rationale behind estimating the confidence in our classifications. The two tweets written by our external sources, are classified according to their tone. The first tweet (**??**) posted by Financial News, is classified as positive with a confidence of one for containing the features (*Why*, *Adverb*), (*rule*, *Verb*), (*Wall*, *Noun Singular*), and (*Street*, *Noun Singular*), which are enough to make all algorithms coincide with a positive classification. The last tweet, posted also by Financial News (**??**), is classified as negative only with a confidence of only 4 out of 6 algorithms. The tweet can be understood as containing negative information, although from the machine learning algorithms the only word that is informative about the negative tone is *scorn*.