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Follow Me on Twitter: Attracting Mutual Fund Investor Attention through Social Media

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Follow Me on Twitter: Attracting Mutual Fund Investor Attention through Social Media

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Management

by

Sora Kim

Dissertation Committee:
Professor Zheng Sun, Chair
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2017

DEDICATION

To

My beloved parents, Jiahn Choi and Jung Yeol Kim

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Finance

ABSTRACT OF THE DISSERTATION

Follow Me on Twitter:
Attracting Mutual Fund Investor Attention through Social Media

By

Sora Kim

Doctor of Philosophy in Management

University of California, Irvine, 2017

Professor Zheng Sun, Chair

This paper studies mutual funds' use of social media (Twitter) as a new marketing instrument and its effects on the behavior of mutual fund investors. Using hand-collected data from Twitter regarding 175 mutual fund families, I find that mutual fund families are more likely to introduce Twitter when they have star funds in the family and when they are introducing new funds. The average inception size of new funds after a family joined Twitter is significantly larger than before joining Twitter. Moreover, mutual fund families using Twitter receive higher subsequent flows relative to other similar non-Twitter families. These incremental flows disappear six months after the introduction of Twitter. The higher flows are not entirely driven by the flows to the newly launched funds, as pre-existing funds also experience higher flows after introducing Twitter. The flow effect is especially pronounced for young funds within a family. Overall, the evidence suggests that mutual funds strategically use the introduction of Twitter to capture investors' attention and attract flows.

1 Introduction

Advances in technology, such as computers or the Internet have been largely changing not only our daily lives, but also the structure and the behavior of financial markets. Social media, such as Twitter, Facebook, and YouTube, is one of the most important examples of such technology development. In the past decade, the advent of social media has transformed communications across a host of industries by providing an excellent platform to share and diffuse information to a wide audience. Social media has also gained great importance in the business world as a revolutionary marketing tool (Larcker et al., 2012), a new outlet for investor relations, and an effective recruiting and networking channel (Li, 2015). An overwhelming majority (96%) of marketers responding to a 2015 survey are using social media to market their businesses (Stelzner, 2015) and more than half of S&P 1,500 firms had joined either Twitter or Facebook by 2013 (Jung et al., 2015). The popularity of social media as a powerful source of disseminating information has been noted by professional money managers as well. A recent Bloomberg Business article reports that hedge funds are planning to launch a fund that will use consumer sentiment and trader behavior estimated from social media data to bet on and against U.S. stocks (Willmer, 2015).[1]

Despite the popularity and the significance of social media in the real world, the literature has little knowledge about how social media impacts the financial market, and the usage of social media by mutual funds has never been explored. In this paper, I investigate the determinants of mutual funds' usage of social media and its effectiveness on fund flows. This study focuses on Twitter out of the many social networking services as Twitter appears to be the preferred social media platform of mutual funds. Since its launch in 2006, Twitter has become one of the biggest social networking services in the United States and had grown to more than 320 million active users as of September 2015.[2] Moreover, Twitter was the number one social media service adopted by S&P 1,500 companies in 2013 (Jung et al., 2015). Twitter also appears to be the most popular social

[1] According to Willmer (2015), Tashtego, a hedge fund company based in Boston, is setting up a Social Equities Fund, which will rely on algorithms using investment decisions on consumer sentiments from social media and is looking to raise around $1 billion. Tashtegos strategy involves tracking all-purpose social networks such as Twitter and Facebook, and online communities set up specifically for investors to share and follow each others trading ideas.

[2] Twitter is a free online social networking and microblogging service where users post and interact with messages, "Tweets," restricted to 140 characters. Users access Twitter through its website interface, SMS, or a mobile device app. Twitter was created in March 2006 and rapidly gained worldwide popularity. In 2012, out of about 500 million accounts, more than 140 million active users posted 340 million Tweets a day. In 2013, Twitter was one of the ten most-visited websites (`www.alexa.com/topsites`). See more information at `https://about.twitter.com/company`.

media of choice for corporate investor relations (Hogan, 2011). For empirical analyses, I use mutual fund data from the Center for Research in Security Prices (CRSP) for the period from October 2008 to December 2015 as mutual funds have introduced Twitter since October 2008.

Using hand-collected data, I find that 30% of mutual fund families have created at least one account on social networking services across the broad universe of U.S. mutual funds. One natural question that has arisen is what makes mutual funds start (or prevents them from) communicating through social media. Mutual funds might use social media as a new way of marketing to attract more money from existing or potential investors. Previous studies have shown that advertising activities by mutual funds are associated with higher fund flows (e.g., Barber et al., 2005; Jain and Wu, 2000).[3] However, advertising through traditional outlets such as TV commercials or printed advertisements in newspapers or magazines is inarguably expensive.[4] On the other hand, advertising via social networking services is almost costless compared to traditional advertising channels, although it is not completely costless. Even apart from the direct expense of managing social media accounts, advertising via social media could indirectly impose costs since companies are likely to be penalized for their low or suspended activities on their social media accounts due to the multi-way and viral nature of social media. Therefore, mutual funds might want to strategically use (or not to use) this pioneering marketing instrument to attract more money.

More specifically, a fund family might opportunistically employ this new communication tool to attract new capital by introducing social media when the fund family is on average doing well as mutual fund flows chase past performance. This is plausible in that advertising decisions are made at a fund family level and the vast majority of social media accounts I have found are for a fund family rather than a specific fund. There is evidence that the pre-advertising performance of mutual funds is significantly higher than that of the benchmarks while the superior performance disappears in the post-advertisement period, which implies that the fund family chooses to advertise funds

[3] The Securities and Exchange Commission ("SEC") Rule 206(4)-1 defines "advertising" as "any notice, circular, letter or other written communication addressed to more than one person, or any notice or other announcement in any publication or by radio or television, which offers (1) any analysis, report, or publication concerning securities, or which is to be used in making any determination as to when to buy or sell any security, or which security to buy or sell, or (2) any graph, chart, formula, or other device to be used in making any determination as to when to buy or sell any security, or which security to buy or sell, or (3) any other investment advisory service with regard to securities." See `http://www.regulatorycompliance.com/newsletter/2009/January/advertising.html` for more detail.

[4] According to Gallaher et al. (2008), mutual funds spent over $1 billion on print advertising alone over the period 1997-2001.

with superior past performance (Jain and Wu, 2000). This suggests that fund families are able to attract new money based on the family's superior past performance using timely publication to the broader public through social networking.

On the other hand, a fund family may also want to use social media to attenuate the negative impact of bad performance. It is more likely that existing customers, or at least ones who already know the fund family, are following it through social media. Unlike traditional advertising channels such as newspapers or TV commercials, a corporation's social media platform has limited access. People may be able to find it via a link on the company's website or by directly searching for a fund name or a fund family name on social media, which implies that mutual funds are likely to use social networking services in order to manage existing investors. Stelzner (2015) finds in his recent survey report that most marketers (69%) are using social media to develop loyal fans. The interactive feature of social media can be particularly effective in developing loyal customers. Moreover, social media is likely to be a useful channel within the context of crisis as it facilitates direct and timely broadcasting of the firm's intended message to a broad audience (Lee et al., 2015). Lee et al. (2015) documents that corporations with social media platforms experience a less pronounced negative price reaction to their product recall announcements than firms without social media accounts.

The two objectives of social media usage by mutual funds, achieving new investors by broadcasting good performance and developing loyal existing customers even with bad performance, are not mutually exclusive and can be concurrently pursued. The convex relation between past performance and fund flows creates an incentive to seek these two seemingly incompatible goals. The convex relationship indicates that the top performing funds disproportionately attract new money relative to the worst performing funds.[5] This generates the so-called star phenomenon that a funds stellar performance has a positive spillover effect on the flows of other funds in the family with no negative effect from poor performance. (Nanda et al., 2004). Gaspar et al. (2006) provides evidence that mutual fund families actively pursue a family-level strategy of favoring "high family value" funds by transferring performance from "low family value" funds. This incentive is reinforced by the stylized fact that investors seem to first choose a fund family rather an individual

[5]The convex relation between fund flows and past performance is documented by Brown et al. (1996), Chevalier and Ellison (1997), and Sirri and Tufano (1998).

fund (Massa, 2003). Given this, fund families might want to employ Twitter as an affordable marketing tool to amplify the positive spillover effect from star performance. Even with an on average poor performance, fund families are likely to attract more new money or minimize the outflow of capital by propagating star performance through social media along with conventional advertising instruments.

Lastly, mutual funds may strategically time the introduction of their social media and choose when they have a high need to broadcast information about their funds. One example is when mutual fund families are launching (or have just launched) an unusually large number of new funds. There must be considerable limited attention on new funds, and social media can be an affordable, yet fast way to broadcast about new funds to reduce the limited attention. Another example is that fund families might start or increase activities on social media when the overall stock market is performing well to attract new investment from people who are chasing the entire market performance and are allocating their capital between the stock market and the bond market.

The empirical results support the conjecture that motivation is induced by the convex flow-performance relationship and the star fund phenomenon. Mutual fund families are more likely to introduce Twitter when they have at least one star fund in the family. This implies that mutual funds seem to intend to gain new money flows from their top performing funds and enjoy spillover effects by exploiting social media to amplify that effect. Consistent with the notion of the star fund spillover effect (Nanda et al., 2004), fund families with larger assets under management, with a longer history, and that offer more diverse styles are more likely to use Twitter. I also find that fund families are more likely to introduce Twitter when they are about to launch (or have recently launched) many new funds. This evidence suggests that mutual funds strategically select when to introduce Twitter and choose when they have a high need for advertising.

I examine the effect of Twitter on fund flows using a difference-in-differences methodology in a regression framework. Mutual funds' use of Twitter is associated with the increase in subsequent flows compared to their matched fund families, yet the incremental flows disappear six months after the opening of Twitter. This suggests that the additional flows after joining Twitter only last for a relatively short period of time and do not come from Tweeting itself. The incremental flows are strongest in both magnitude and significance three months after the introduction of Twitter, which accounts for 10.43% of additional flows annually. To address the possibility that the positive relation between the introduction of Twitter and subsequent flows is entirely driven by flows to newly launched funds, I repeat the same analysis only on flows to pre-existing funds (or styles) and find consistent results.

I also investigate whether the introduction of Twitter has an impact on flows to relatively young funds. I compare the inception sizes of new funds after joining Twitter with their sizes before among fund families that eventually introduce Twitter by the end of the sample period. The results show that the average inception size of new funds after the opening of a Twitter account is significantly larger than its benchmark. The difference in inception size is huge in that the average inception size after introducing Twitter is almost double the inception size before introducing Twitter. In addition, I test whether the adoption of Twitter attracts incremental flows to young funds (defined as funds that are 12 months old or younger) compared to old funds (defined as funds that are older than 12 months) using the difference-in-differences methodology. I find that young funds receive both higher average percentage flows and higher average dollar flows relative to old funds after the initiation of Twitter compared to before. Young funds attract 350% or $3.2 million additional monthly flows relative to old funds after the introduction of Twitter. Together, consistent with the limited attention story, younger funds enjoy even higher money inflow after they join Twitter.

Previous research on social media in the context of financial markets is sparse, with a few notable exceptions. Lee et al. (2015) documents that corporate use of social media attenuates the negative price reaction to consumer product recalls. Blankespoor et al. (2014) reports that tech firms can lower information asymmetry by more broadly disseminating links to firm-initiated press releases through Twitter. Jung et al. (2015) finds similar evidence for a much broader set of samples that disclosing earnings announcements through social media improves the firm's information environment. Other studies such as Bollen et al. (2011), Zhang et al. (2011), Chen et al. (2014), and Bartov et al. (2015) mostly focus on the predictable power of aggregated information inferred from analyzing content on social media. To the best of my knowledge, this paper first investigates the use of social media in the mutual fund industry and its effects on the behavior of mutual funds and mutual fund investors.

Apart from the aforementioned literature on social media, this paper also adds new evidence to the literature on advertising. Extensive literature on advertising in general has shown that firms pay a high advertising cost to signal their quality (Kirmani and Wright, 1989) and to build a brand reputation and a loyal customer base (Barone et al., 2005). While prior research has established the incentives for and effectiveness of high-cost advertising, whether low-cost advertising also works is relatively under explored due to lack of data. Using data from social media as an affordable marketing tool, this paper provides new evidence that low-cost advertising successfully attracts customers' attention as well. In the context of the mutual fund literature, previous studies on mutual fund advertising focus on advertising activities via traditional channels such as print advertising, and find a significant positive association between advertising activities and subsequent flows (Jain and Wu (2000), Korkeamaki et al. (2007), and Gallaher et al. (2008)) This study is the first attempt to investigate mutual fund advertising strategies using social media, a widely adopted new marketing instrument, and their effects on mutual fund flows.

This study also contributes to the literature on mutual funds' strategic behaviors. Massa (2003) finds evidence of family driven heterogeneity among funds and shows that mutual fund families actively exploit it to increase the degree of fund proliferation. Nanda et al. (2004) finds that spillovers from star performance induce lower ability families to pursue star-creating strategies by increasing the variations in investment strategies. Gaspar et al. (2006) documents that mutual fund families strategically transfer performance across member funds to favor those more likely to increase overall family profits. Consistent with the previous findings, this study shows that mutual fund families strategically introduce Twitter to attain investor attention and attract more flows.

Finally, this research contributes to the vast literature on investors' limited attention. Sirri and Tufano (1998) finds that mutual fund investors disproportionately invest more in high performing funds while failing to flee from low performing funds at the same rate. The authors also show that high-fee funds that presumably make more concerted marketing efforts enjoy a much stronger performance-flow relationship than do their rivals. Nanda et al. (2004) finds a strong positive spillover effect from a star fund to other funds in the family, which induces lower ability families to pursue star-creating strategies. This study provides consistent evidence in line with the findings of Sirri and Tufano (1998) and Nanda et al. (2004), which suggests that mutual funds exploit social media to attract extra money from the convex performance-flow relationship and the spillover effect from star performance.

The rest of the paper is organized as follows. Section 2 describes the data and summary statistics. Section 3 explores empirical evidence on determinants of mutual funds' Twitter usage.

Section 4 and Section 5 investigate the effect of Twitter on fund flows and on flows to young funds, respectively. Section 6 concludes.

2 Data

2.1 Twitter Data

I started by searching for the Twitter accounts of 696 management companies with a non-missing management company name and with at least one live fund. The search process was conducted by using the management company name, fund name, and contact information from CRSP. If a management company's website address is available in CRSP, I checked whether the website has a link to its Twitter account. If there is a link to their Twitter account, that account is included in the sample. If there is no link on the website or no website information available in CRSP, I manually searched management company names using Twitter search. The searched Twitter account is included in the sample only if the contact information (the website address, the phone number, or the address of the headquarters) on the Twitter profile page matches the corresponding information from CRSP. If multiple Twitter accounts are found for one management company, I took only the one that is the most representative (the one with the longest history or with the largest number of followers, but not specifically for recruiting or customer services). I also excluded any Twitter account which was not in English, that is protected, or that has never Tweeted. The final sample consists of 210 Twitter accounts out of 696 management companies.

Among 210 Twitter accounts, only 23.36% of accounts are verified by Twitter.[6] Among the 210 Twitter accounts, 78.57% are found through the link on the company's website. Among the top 10% accounts with the largest number of followers, 31.33% are for companies also offering retail banking or insurance. Similarly, among the top 10% accounts with the largest number of Tweets, 52.38% are for companies servicing retail banking or insurance. For those companies that also service the retail banking or insurance sectors, but that operate only one Twitter account for the whole company, it is hard to separate the portion of mutual funds. Moreover, those accounts are

[6] Twitter verifies accounts to establish the authenticity of the identities of key individuals and brands on Twitter. Twitter verifies accounts on an ongoing basis and concentrates on highly sought users in music, acting, fashion, government, politics, religion, journalism, media, sports, business and other key interest areas. Twitter does not accept requests for verification from the general public. You can also find more information at `https://support.twitter.com/groups/31-twitter-basics/topics/111-features/articles/119135-about-verified-accounts`.

likely to have a lot of followers seeking information on their retail banking or insurance division.[7] I discard those accounts to minimize the effect from their business other than mutual funds, which results in total 175 Twitter accounts in my sample.

Table 1 presents the time trend of Twitter accounts run by mutual funds for each year from 2008 to September 2015. Mutual funds joined Twitter for the first time in October 2008.[8] The number of newly launched accounts peaked during 2009-2011. The number of first-Tweeted accounts peaked between 2011-2013, and it has been a small degree of slow down since 2014. It is quite noticeable that some Twitter accounts had been inactive before they started Tweeting. Indeed, the average number of days until first-Tweeting is approximately 263 days and the median is 65 days. The average number of Tweets posted by mutual funds per year over the whole sample period is approximately 380 Tweets. The average number of followers at the end of 2015 is approximately 17,993 followers (median of 766 followers). The average number of Tweets and the average number of followers scaled by the number of days from the accounts initial date are 1.14 and 9.20, respectively, suggesting that Twitter accounts managed by mutual funds on average post one Tweet per day and attract nine followers per day.

2.2 Sample Statistics

The entire sample consists of 86,163 monthly fund-family-level observations from November 2008 to December 2015. The primary data source for mutual funds is the Center for Research in Security Prices (CRSP) U.S. Mutual Fund Database. The sample covers all of the types of mutual funds found in CRSP, including index funds, foreign funds, bond funds, balanced funds and defunct funds. Table 2 provides the summary statistics for the mutual fund families who have Twitter accounts (Twitter=1) compared to those who do not have Twitter accounts (Twitter=0) over the period of one year before each fund family started Tweeting ranging from December 2007 to November 2014. There are a total of 142 mutual fund families operating Twitter accounts out of 1,058 fund families.

In general, mutual fund families with Twitter accounts are larger in terms of family size as well

[7] One example of a Twitter account for a company that also offers retail banking is Citi group. Its Twitter account has more than 670,000 followers which is more than one and a half times larger than the highest number of followers of mutual funds' Twitter accounts that neither offer retail banking nor insurance.

[8] Twitter started their services in July 2006.

as in the average fund size relative to those not having Twitter accounts. Mutual fund families operating Twitter accounts are generally older and offer more funds and more diverse styles in the family than their counterparts. It is interesting to note that cross-fund return volatility within a fund family is significantly higher for fund families that use Twitter, while there is no difference in average time-series return volatility between the two groups. This implies the existence of externality from a spillover effect on flows within a fund family. Nanda et al. (2004) finds that a star fund attracts flows not only to itself but also to other funds in the family, and mutual fund families purse strategies to take advantage of the intra-family spillover effect by increasing the cross-fund return standard deviation.[9] Mutual funds seeking those strategies might employ social media such as Twitter as a way to selectively broadcast their winning funds' performance and maximize additional money coming from the spillover effect.

More interestingly, mutual fund families running Twitter accounts are higher in the average style-adjusted return and in the highest fund return within a family, and are more likely to be a star family compared to their counterparts.[10] This leads to a similar conjecture that one motivation for mutual funds' use of Twitter could be to attract more investor attention by broadcasting their superior performance. Mutual funds might strategically choose when to initiate their social networking services and select a time after which they are overall performing well, after they have one fund that has been doing very well, or when they have at least one star fund in the family. It is also noteworthy that fund families with Twitter accounts tend to have more index funds but less growth funds compared to those without Twitter accounts. The higher percentage of index funds might have something to do with the fact that Twitter transmits only up to 140 characters of text at a time. Due to this limitation, Twitter might be more appropriate to communicate relatively straightforward information such as Dow Jones Index movements than more complicated information such as in-depth analysis of the performance of growth stocks. Moreover, index funds are virtually indifferent across products and the only point of difference is the management fee that the management company charges. For indifferentiable products such as index funds, the attention effect coming from broadcasting or advertising would be most critical in attracting more customers

[9] According to Nanda et al. (2004), star funds are defined as the top 5% of performers with the highest average raw returns or the highest average four-factor alphas over the previous 12 months within the same investment category.

[10] A fund family is defined as a star family if it has at least one star fund under management following Nanda et al. (2004).

than its competitors. Therefore, it is plausible that mutual fund families with a higher percentage of index funds are more willing to use Twitter in order to effectively and quickly convey information about their index funds to their potential or existing customers.

3 Determinants of Mutual Funds' Twitter Usage

Based on inspiration from the sample statistics, I investigate the determinants of mutual funds' use of Twitter. Using the Cox proportional hazards regression model, also called the Cox regression, I examine factors that might reflect motivations for fund families' introduction of Twitter. Survival analysis is an approach to modeling the impact of risk factors on the amount of time to the occurrence of an event. Events are defined by a transition from one discrete state to another at an instantaneous moment in time.[11] This study defines events as the introduction of Twitter by mutual funds and mutual funds transit from a state not running a Twitter account to a state running a Twitter account. In survival analysis, ordinary least squares regression methods fall short because the time to the event is typically not normally distributed, and the Cox proportional hazards regression model remains the dominant analysis method.[12]

The Cox regression models the incidence or hazard rate, i.e., the number of new openings of a Twitter account by mutual funds per population at-risk per unit time. The hazard function here is the probability that if a mutual fund family has not introduced Twitter at t, they will experience the event (the introduction of Twitter) in the next instant. Then, the Cox proportional hazards model is defined as follows:

Let $\lambda(t|X_{1i}, X_{2i}, \cdots, X_{Ki})$ denote the hazard function for ith fund family at time t, where the K regressors are denoted as $X_{1i}, X_{2i}, \cdots, X_{Ki}$ and $i = 1, 2, \cdots, n$. The baseline hazard function at time t, i.e., when $X_{1i} = 0, X_{2i} = 0, \cdots, X_{Ki} = 0$, is denoted as $\lambda_0(t)$. This baseline hazard function is comparable to the intercept term in a multiple regression or logistic regression model. The hazard ratio, $\lambda_1(t)/\lambda_0(t)$ is considered the relative risk of an event which occurs at time t. Then, the log of the hazard ratio, or the hazard function divided by the baseline hazard function

[11] For a detailed illustration, see Smith et al..

[12] `http://www.ats.ucla.edu/stat/sas/seminars/sas_survival/`.

at time t, is a linear combination of parameters and regressors as follows:

$$\log\left(\frac{\lambda(t|X_{1i}, X_{2i}, \cdots, X_{Ki})}{\lambda_0(t)}\right) = \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_K X_{Ki}. \tag{1}$$

The proportional hazards regression model can be viewed as a function of relative risk based on the fact that the ratio of hazard functions can be regarded as a ratio of risk functions. Changes in a covariate have a multiplicative impact on the baseline risk. The model with regard to the hazard function at time t is:

$$\lambda(t|X_{1i}, X_{2i}, \cdots, X_{Ki}) = \lambda_0(t) \exp(\beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_K X_{Ki}). \tag{2}$$

In this setting, no particular probability model is chosen to represent the time to the introduction of Twitter. Instead, the Cox proportional hazards model has an important assumption: the hazard for any fund family is a fixed proportion of the hazard for any other families. Note that if $\lambda_0(t)$ is the hazard function for a subject with all the predictor values equal to zero and $\lambda_1(t)$ is the hazard function for a subject with other values for the predictor variables, then the hazard ratio is determined only by the predictors and not by time t. This implies that if a covariate doubles the risk of the event on day one, it also doubles the risk of the event on any other day.[13]

The dependent variable of the Cox regression is the time length to open a Twitter account times the censoring variable which equals one if a fund family runs a Twitter account, otherwise it equals zero. Here the right censoring technique is applied as time terminates before all the outcomes of interest (the introduction of Twitter) are observed. The time to join Twitter terminates on September 2015 as the search for Twitter accounts held by mutual funds was conducted up to that time. Explanatory variables of interest $(X_{1i}, X_{2i}, \cdots, X_{Ki})$ included in the regression are family size, average fund size, age, number of funds, number of different styles, number of newly launched funds, turnover, expense ratio, 12b-1 fee, flows to family, past performance measured by the average style-adjusted return, return volatility, an indicator variable for a star family, and the percentage of retail/bond/growth/income/index funds.

Table 3 presents the Cox proportional hazards regression results for the probability of intro-

[13] `https://onlinecourses.science.psu.edu/stat507/node/81.`

ducing Twitter on a set of explanatory variables. The interpretation of the measures of association given by the Cox hazards model as "relative risk" type ratios is desirable in explaining the probability of event for a set of covariates of interest, so hazard ratios are reported in parentheses. The hazard ratio is equal to e^{β}, where β is the parameter estimate from the regression. The results support a motivation induced by the convex flow-performance relationship and the star fund phenomenon. Mutual fund families are more likely to launch their Twitter accounts when they have at least one star fund in the family and when there are diverse styles within a family. This implies that mutual funds are likely to seek the goal of gaining investor attention by boasting of its high-performing funds through social media. Consistent with the notion of star funds' spillover effect that was previously documented in Nanda et al. (2004), fund families that offer more diverse styles are more likely to introduce Twitter. Nanda et al. (2004) also finds that fund families pursue star-creating strategies by increasing the cross-fund return standard deviation and the number of funds in the family. In addition, Gaspar et al. (2006) documents that mutual fund families strategically transfer performance across member funds in the family to favor those more likely to boost the entire family profits and this cross-fund subsidization is pronounced for large families with many funds. My evidence supports the findings of Nanda et al. (2004) and Gaspar et al. (2006) and implies that mutual fund families may employ social media in amplifying the effectiveness of their star-creating or family-value maximizing strategies.

Another prominent result from Table 3 is that fund families which have recently launched (or are about to launch) multiple new funds are more likely to introduce Twitter as well. This suggests that fund families may time the initiation of Twitter to take advantage of this one-time opportunity of introducing a new communication channel when they have a high need for advertising. This confirms the findings from previous studies that mutual funds undertake advertising to attract additional money, although those studies are based on the impact of traditional outlets such as TV commercials or printed advertisements in newspapers or magazines.[14] It is interesting to note that in an unreported analysis, a dummy variable indicating whether a fund family recently launched (or is about to launch) a new fund in the family is not associated with a greater tendency to join Twitter. Since the introduction of Twitter is practically a one-time opportunity to enjoy attention from an extensive customer base, fund families might not want to waste this opportunity on a small

[14] See Barber et al. (2005) and Jain and Wu (2000) for more detail.

event such as launching only one or a few funds. Mutual fund families may wait and choose to begin Tweeting when they have a plan to launch an unusually large number of new funds in the family to maximize the attention effect they get from introducing Twitter.

4 The Use of Twitter and Mutual Fund Flows

In this section, I test whether the use of Twitter by mutual funds actually leads to higher fund flows at a family level. To avoid the possibility that the results are affected by substantial differences in fund family characteristics between fund families operating Twitter accounts and those which do not, I conduct a difference-in-differences analysis in a regression framework following Bertrand and Mullainathan (2003). For each treated fund family i with a Twitter account, I look at the monthly fund flows over the n-month period prior to the introduction of Twitter and compare them with the monthly fund flows over the n-month period following the introduction of Twitter. A control group is selected with fund families that are of similar size, turnover, and expense ratio, but which do not use Twitter. Specifically, matched fund family i is in the same quintile of assets under management (TNA), in the same quintile of turnover, and in the same quintile of expense ratio as treated fund family i over the previous n months before the introduction of Twitter for the $(-n, +n)$ window. If multiple fund families satisfy the aforementioned criteria, I rank fund families based on the absolute difference in the average monthly fund flows in the months prior to the introduction of Twitter and choose the fund family with the smallest difference compared to treated fund family i. There are no meaningful differences in fund family size, turnover, or expense ratio between treated fund families and matched fund families. To minimize the effect of confounding factors, the months when a fund family starts Tweeting are discarded. These restrictions and matching procedures lead to a final sample of 1,871 fund family-month observations for the (–12,+12) window.

In fund family-month panel data, a general form of the regression I estimate is:

$$Flow_{it} = \alpha_i + \alpha_t + \beta Twitter_{it} + \gamma X_{it} + \varepsilon_{it}. \tag{3}$$

where i indexes fund families, t indexes time, α_i and α_t are fund family and year fixed effects, X_{it} are control variables, $Twitter_{it}$ is a dummy variable that takes the value of one if fund family i

has started Tweeting in time t, and ε_{it} is an error term. This methodology allows full control of fixed differences between treated and control fund families via the fund family fixed effects. The year fixed effects take care of aggregate fluctuations over time. The control variables (X_{it}) include Star family, Past performance, Log size, Log number of styles, Log age, Turnover, Expense ratio, and Volatility. Specifically, a fund family is defined as a star family if it has at least one star fund under management. Star funds are defined as the top 5% of performers with the highest average returns over the previous 12 months within the same investment category (Nanda et al., 2004). Past performance is the average style-adjusted return over the previous 12 months. Log size is the logarithm of the fund family's total net assets (summed over all funds). Log number of styles is the logarithm of the number of different styles offered by a fund family. Log age is the logarithm of the age of the oldest fund in a fund family. Turnover and Expense ratio are the weighted average of corresponding values of all member funds in the family. Volatility is the standard deviation of monthly returns over the past 12 months. The coefficient estimate for $Twitter_{it}$, β, provides an estimate for the relation between the introduction of Twitter and subsequent fund flows.

One caveat of my methodology is that, because the introduction of Twitter is endogenous, the results presented in this paper do not prove causality. Although I control for many possibly significant factors, there can be still unobserved factors that may affect both the decision to use Twitter and the fund flows. To prove whether the introduction of Twitter has an effect on fund flows, using an instrument that affects the decision to use Twitter but does not affect fund flows should be considered. The location of headquarters (whether it is close to technology hubs such as Silicon Valley) and the CEO's age or experience are potential instruments that can be further studied.

4.1 The Use of Twitter and Fund Flows

Table 4 presents the regression results for the relation between the introduction of Twitter and subsequent flows at the family level. I find a significant positive association between the initiation of Twitter and flows from one month after the initiation. The relation is strongest in both magnitude and significance three months after joining Twitter. The estimated coefficient indicates that a fund family that has started Tweeting receives 10.43% of additional flows annually, relative to before Tweeting and its matched fund family, for three months after the introduction of Twitter. The incremental flows, however, drop to approximately 3.66% and disappear altogether 12 months after joining Twitter. Overall, the association between the introduction of Twitter and subsequent flows draws a concave curve over time as the relation is minimal for one month, strongest after three months, then drops down slightly in six months, after which it completely fades away. This concave pattern over time suggests that the relation mainly comes from the introduction of Twitter rather than from Tweeting itself.[15]

The higher subsequent flows after introducing Twitter are likely to be a pure attention effect because I did not find any significant relations between the introduction of Twitter and flow-performance sensitivity/flow-star effect sensitivity/performance. Table A1 presents the regression results for the relation between the introduction of Twitter and fund flow-performance sensitivity. The overall insignificant coefficients for the interactions between the Twitter dummy and fund performance quintiles indicate that mutual fund investors do not change their sensitivity to funds' performance after the introduction of Twitter.[16] Table A2 shows the regression results for the relation between the introduction of Twitter and fund flow-star effect sensitivity. Similarly, the insignificant coefficients on the interaction between the Twitter dummy and a star family indicator variable imply that fund investors do not invest more or less money in star funds after the introduction of Twitter. Table A3 provides the regression results for the relation between the introduction of Twitter and mutual funds performance. The results show that the average performance of mutual funds after joining Twitter is not different from that before joining Twitter. This indicates that mutual funds using Twitter are not more skilled compared to those not using Twitter. Together with the results from Table 4, the overall evidence suggests that the increased subsequent flows after the introduction of Twitter come from attracting more attention from investors and are not related to funds' performance or fund managers' ability.

4.2 The Use of Twitter and Pre-existing Fund Flows

Evidence in Section 3 suggests that mutual fund families are likely to introduce Twitter when they are launching new funds in the family. One may question whether the positive association between

[15]In an unreported analysis, I test whether the monthly number of Tweets a fund family posted has an effect on its subsequent flows, and find insignificant results.

[16]The fund performance quintiles, High performance, Second performance, Mid performance, Forth performance, and Low performance, are computed following the methodology in Sirri and Tufano (1998).

the introduction of Twitter and subsequent flows found in Section 4.1 is possibly driven by flows to newly launched funds. To address this concern, I separate out flows to newly launched funds within different windows and repeat the same regression analysis as in Section 4.1 but only on flows to pre-existing funds in the family. Table 5 shows the regression results for the relation between the introduction of Twitter and pre-existing fund flows. The positive association holds for flows to pre-existing funds in the family and only the magnitude is slightly lower, or similar, depending on time windows. The concave pattern over time holds as well, but only the coefficient for the (–12, +12) window is now marginally significant. As a robustness check, I also test the relation between the introduction of Twitter and subsequent flows to pre-existing styles in the family. As shown in Table 6, the positive association holds for flows to pre-existing styles in the family as well, but the magnitude is a little smaller. The concave pattern over time pretty much holds as well, but the coefficient for the (–1, +1) window becomes insignificant. Together, the above evidence confirms that the positive relation between the introduction of Twitter and subsequent flows is not entirely driven by money to new funds (or styles) in the family.

5 The Use of Twitter and Flows to Young Funds

In this section, I investigate whether the introduction of Twitter has an impact on flows to relatively young funds. In previous sections, I found evidence that mutual funds tend to open their Twitter accounts when they are about to launch (or have recently launched) new funds in the family and the initiation of Twitter actually attracts incremental flows in the subsequent period. Therefore, one question that naturally arises is whether the introduction of Twitter leads additional flows to new funds as well. This is a particularly interesting subject to explore because generally, younger funds tend to suffer more from limited attention from investors than matured funds. If Twitter indeed improves mutual fund investors' limited attention, I hypothesize that the flow effect from Twitter would be stronger when limited attention is greater.

5.1 The Use of Twitter and Funds' Inception Size

It is well documented in the previous literature that mutual funds' past performance affects flows.[17] The inception size of a new fund is a perfect subject through which to explore the attention effect from Twitter since the inception size is defined as the TNA at the end of the month in which a fund appears for the first time, thus there is no past performance that influences subsequent flows. Moreover, potential investors are likely to have very limited information on new funds. Therefore, the inception size is free of many factors that may affect flows such as past performance, fund age, or fund size in the previous period, and possibly reflects only the attention effect from all marketing efforts, including traditional TV commercials. To see whether Twitter attracts additional money to newly launched funds and to prevent any substantial difference between fund families using Twitter and those which do not from affecting the results, I only look at fund families that had introduced Twitter at the end of the sample period and compare the average inception size before the introduction of Twitter with that after. Naturally, more after-Twitter observations occur later than before-Twitter observations, so an increasing trend in the inception size over time may significantly affect the results. To address this possibility, I first take the average of the inception size each year and calculate the differences between the average inception size after the introduction of Twitter and one before, and then average again across time.

Table 7 shows the relative inception size of new funds after introducing Twitter compared to that before. Before Twitter presents an average inception size of new funds for fund families that have not yet joined Twitter while After Twitter reports an average inception size of new funds for fund families that have started Tweeting. The results indeed find evidence of the attention effect from Twitter on incoming money to newly launched funds. The average inception size after the introduction of Twitter is significantly larger, and more than double its counterpart. The difference in average inception size is about $15.2 million, which is huge considering the fact that the average inception size before the introduction of Twitter is $11.1 million.

[17] For example, see Sirri and Tufano (1998), Berk and Green (2004), Nanda et al. (2004), and Del Guercio and Tkac (2008) for more detail.

5.2 The Use of Twitter and Flows to Young Funds

In this section, I take a more rigorous approach to investigating the effect of Twitter on flows to young funds up to 12 months after their inception. Specifically, I use a difference-in-differences methodology to test whether the adoption of Twitter attracts incremental flows to young funds relative to those of old funds. Young funds are defined as any fund that is 12 months old or younger, and old funds are defined as any fund that is older than 12 months. Again, I only consider fund families that had introduced Twitter at the end of the sample period to eliminate the possibility that any substantial difference between fund families using Twitter and those that do not has an effect on the results. In addition, to address the concern that the significant difference in fund size between young funds and old funds possibly affects the results, I try to match old funds to each young fund by size. Specifically, for each young fund, I first select old funds that are from the same management company and in the same TNA quintile each month. If multiple old funds are selected, I rank funds based on the absolute difference in TNA in that month and choose the fund with the smallest difference compared with the young fund. However, I still observe meaningful differences in fund size across young funds and old funds even after conducting the aforementioned matching procedures. Since the conventional measure for fund flows is the percentage flows which are incremental cash inflows scaled by TNA at the beginning of each month, significant differences in fund size may considerably affect the results. To avoid that possibility I also look at dollar flows, which are just incremental cash inflows not scaled by fund size, as well as percentage flows. To find the effect of Twitter on flows to young funds, I compare flows to young funds relative to flows to old funds after joining Twitter with those before joining Twitter and calculate the difference-in-differences. To illustrate, I first calculate the relative flows to young funds compared to old funds both after and before the introduction of Twitter by subtracting the average flows to old funds from the average flows to young funds for both groups. Then I subtract the relative flows to young funds compared to old funds before introducing Twitter from the relative flows to young funds compared to old funds after introducing Twitter. To address a potential autocorrelation issue across young funds and old funds, Newey-West standard errors are used to compute t-statistics for each estimate.

In Table 8, Panel A reports the average percentage flows to young funds and to old funds before joining Twitter and after joining Twitter and Panel B reports the average dollar flows to young funds and to old funds before joining Twitter and after joining Twitter. The difference-in-differences estimates reported in the last column are significant and economically huge for both percentage flows and dollar flows. The difference-in-differences estimate for percentage flows implies that young funds receive 350% additional monthly flows relative to old funds after the introduction of Twitter compared to before. Similarly, the difference-in-differences estimate for dollar flows indicates that young funds attract $3.2 million more each month relative to old funds after the initiation of Twitter compared to before. Together, the results provide evidence for the fact that mutual funds are actually benefiting from using Twitter by receiving greater capital to their younger funds. These findings confirm the limited attention hypothesis as the effect is stronger for younger funds with a higher degree of limited attention.

6 Conclusion

This paper studies mutual funds' use of social media (Twitter) as a new marketing instrument and its effects on the behavior of mutual fund investors and the behavior of mutual funds. Using data collected from Twitter, I find that mutual funds are more likely to introduce Twitter when they have star funds in the family. This implies that fund families employ social media to amplify the positive spillover effect from star performance. Mutual funds are also more likely to introduce Twitter when they are about to launch (or have recently launched) new funds, which indicates that mutual funds strategically time the introduction of Twitter and choose when they can benefit from it most.

Mutual funds' use of Twitter is associated with the increase in subsequent flows compared to their matched fund families, yet the incremental flows disappear six months after introducing Twitter. To address the possibility that the positive association between the introduction of Twitter and subsequent flows is driven by flows to newly launched funds, I repeat the same analysis only on flows to pre-existing funds (or styles) and find consistent results. I also investigate whether the use of Twitter attracts additional flows to relatively young funds and determine if the effect is greater for younger funds with a higher degree of limited attention. I show that the average inception size of new funds after joining Twitter is significantly larger than one before. Moreover, young funds receive considerably higher average percentage flows and average dollar flows relative to old funds after the introduction of Twitter compared to before. This greater magnitude supports the limited attention hypothesis.

One big question to be answered is what mutual funds post on their Twitter accounts and whether the content of Tweets matters. I downloaded all Tweets posted for my entire sample from the time of initiation of each account. Looking at the actual posts on Twitter by mutual funds will greatly help to understand the following questions: what do mutual funds communicate through social media? What is the role of social media? Do mutual funds strategically pick information to manage investors' expectations about their performance? Textual analysis can be conducted for more in-depth analyses. For example, to further examine the motivation induced by the star phenomenon, I will look for Twitter posts broadcasting their star performance and see whether these lead to higher fund flows. Mutual funds may also use Twitter to blame external factors, such as the overall stock market performance or industry performance for their poor returns. To examine this possibility, I will see whether Tweets more frequently include words such as "market" or "industry" when mutual funds experience bad performance.

In future research, other social networking service platforms operated by mutual funds are also interesting to look at as they have distinctive and different features that may affect mutual fund investors' behavior. When a fund family is running multiple social media accounts, I am usually able to find a link to other social media accounts on the website as well. Aside from Twitter, LinkedIn, Facebook, and YouTube are the most popular social media platforms among mutual funds. Facebook is very similar to Twitter, but is more oriented toward personal communications among family and friends. LinkedIn is a specialized service for recruiting and networking. YouTube is especially interesting in that the platform is mainly used for sharing videos in contrast to other social media services. Verbal communications or image transfer through video may more effectively convey the intended messages.

Another interesting topic for future research is mutual/hedge fund managers' personal Twitter accounts. While searching for mutual fund companies' Twitter accounts, I found mutual fund managers' personal Twitter accounts and a few fund families even have a link to those personal accounts (most likely a founder or a CEO) on the company website. Also, since hedge funds are not allowed to advertise, hedge fund managers may operate their personal Twitter accounts as a way to indirectly advertise their hedge funds. Fund managers may also use social media for their own personal purposes, such as to leverage greater bargaining power. Another hypothesis is that overconfident fund managers may more actively communicate through social media. This is particularly interesting to look at because overconfidence is hard to measure even though overconfidence in the financial market is widely documented.

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Table 1. Time trend of mutual funds' Twitter accounts

This table documents the time trend of mutual funds' Twitter accounts from 2008 to September 2015. The number of newly joined firms shows the number of mutual funds' Twitter accounts that are created for the first time each year and the number of first-Tweeting firms shows the number of mutual funds' Twitter accounts that post their very first Tweet on their account each year. The number of newly joined firms and the number of first-Tweeting firms in 2015 are up to September of 2015.

Year	Number of newly joined firms	Number of first -Tweeting firms	Average number of Tweets	Total number of Tweets
2008	3	2	97.500	195
2009	36	19	220.200	4,404
2010	29	21	215.150	8,606
2011	37	32	296.000	21,608
2012	25	29	520.860	52,086
2013	19	32	636.595	80,211
2014	18	24	535.764	79,293
2015 (by September)	8	16	520.736	82,797
Total	175	175	380.351	329,200

Table 2. Summary statistics

This table presents the summary statistics for mutual fund families in the period of one year before each fund family started Tweeting which ranges from December 2007 to November 2014. The average fund family statistics are reported for all fund families with Twitter accounts (Twitter=1), as well as for those not having Twitter accounts (Twitter=0). Size is the fund family's total net assets in millions of dollars (summed over all funds). Age is defined as the age in years of the oldest fund in the family. Turnover, expense ratio, 12b-1 fee, raw return, and style-adjusted return are the weighted average of corresponding values of all member funds in the family. Return volatility and flow volatility are measured over the previous 12 months. Cross-sectional return volatility measures cross-sectional dispersion across funds in a family. According to Nanda et al. (2004), star funds are defined as the top 5% of performers with the highest average returns over the previous 12 months within the same investment category. A fund family is defined as a star family if it has at least one star fund under management. Turnover, expense ratio, and 12b-1 fee are year-end measures. All other variables are measured on a monthly basis. Robust standard errors are clustered at the fund family level. Significance levels at 10%, 5%, and 1% are denoted by *, ** and ***, respectively.

	Twitter=0	Twitter=1	Diff$(1-0)$	t-statistic
Size ($ million)	7,725.13	43,736.32	36,011.19***	2.9838
Average fund size ($ million)	425.3193	682.6357	257.3164**	2.1364
Number of funds per family	6.3177	37.3611	31.0433***	7.2295
Number of styles per family	1.8379	5.6878	3.8498***	11.4004
Age (years)	14.0425	29.4789	15.4364***	6.3460
Turnover	1.1130	1.2034	0.0905	0.3087
Expense ratio	0.0140	0.0115	-0.0025***	-3.7510
12b-1 fee	0.0032	0.0036	0.0004**	2.0983
Raw return	0.0041	0.0059	0.0018	1.5505
Style-adjusted return	-0.0014	-0.0004	0.0010**	2.1534
Return volatility	0.0415	0.0402	-0.0014	-0.6097
Cross-fund return volatility	0.0154	0.0186	0.0033**	2.4699
Highest raw return	0.0194	0.0448	0.0254***	7.6948
Highest style-adjusted return	0.0108	0.0326	0.0217***	7.2437
Flow to family (scaled by Size)	0.0526	0.0231	-0.0295*	-1.7887
Flow to family ($ million)	5.5369	40.6217	35.0848	0.3841
Flow volatility	0.1274	0.0518	-0.0755	-1.5596
Percentage of retail funds	0.4604	0.4813	0.0209	0.6149
Percentage of index funds	0.0429	0.0930	0.0501**	2.2604
Percentage of growth funds	0.4660	0.3662	-0.0998***	-2.9944
Percentage of income funds	0.0285	0.0237	-0.0049	-0.4880
Percentage of bond funds	0.2432	0.2819	0.0387	1.3531
Percentage of star funds	0.0580	0.0436	-0.0144	-1.5212
Percentage of star family	0.0941	0.3322	0.2381***	11.4027
Number of fund families	1,058	142		

Table 3. Determinants of mutual funds' Twitter usage

This table presents the regression results for the probability of introducing Twitter by mutual funds on a set of explanatory variables using the Cox proportional hazards model. The dependent variable is the product of a time length for a fund family to introduce Twitter with a dummy variable indicating whether a fund family joined Twitter at the end of the sample period. Log size is the logarithm of the fund family's total net assets (summed over all funds). Log age is the logarithm of the age of the oldest fund in a fund family. Log number of styles is the logarithm of the number of different styles offered by a fund family. The number of newly launched funds is the total number of funds that are introduced in a family over each window scaled by the total number of existing funds in that family. Turnover, expense ratio, 12b-1 fee, style-adjusted return are the weighted average of corresponding values of all member funds in the family. Volatility is the standard deviation of monthly returns over the past 12 months. Star funds are defined as the top 5% of performers with the highest average returns over the previous 12 months within the same investment category. A fund family is defined as a star family if it has at least one star fund under management. The hazard ratios are reported in parentheses. Significance levels at 10%, 5%, and 1% are denoted by *, ** and ***, respectively.

	Months				
	(−1, +1)	(−3, +3)	(−6, +6)	(−12, +12)	(−18, +18)
Log size	0.2158	0.2022	0.0820	0.0724	0.0607
	(1.2409)	(1.2241)	(1.0854)	(1.0751)	(1.0626)
Log average fund size	-0.0162	0.0122	0.1202	0.1532	0.0303
	(0.9839)	(1.0123)	(1.1278)	(1.1655)	(1.0308)
Log age	0.0913	0.1712	0.0969	0.1418	0.1868
	(1.0956)	(1.1868)	(1.1018)	(1.1523)	(1.2054)
Log number of funds	-0.1183	-0.0920	-0.0462	-0.0591	-0.0064
	(0.8884)	(0.9121)	(0.9548)	(0.9426)	(0.9936)
Log number of styles	0.9013**	0.8409**	1.0087***	1.1108***	1.1124***
	(2.4629)	(2.3186)	(2.7420)	(3.0368)	(3.0416)
Number of newly launched funds	13.3119***	6.5831***	5.5720***	4.2358***	3.2000***
	(604,326)	(722.80)	(262.97)	(69.12)	(24.53)
Turnover	0.0407	0.0422	0.0298	0.0137	-0.0344
	(1.0416)	(1.0431)	(1.0302)	(1.0137)	(0.9662)
Expense ratio	39.8746	34.1429	10.3859	33.7593	41.1021
	(2.08E+17)	(6.73E+14)	(3.24E+04)	(4.59E+14)	(7.09E+17)
12b-1 fee	25.0831	8.0670	33.3498	35.5721	-1.5432
	(7.82E+10)	(3.19E+03)	(3.05E+14)	(2.81E+15)	(0.2137)
Flows to family	0.0928	0.0344	0.0391	0.0713	0.0603
	(1.0973)	(1.0350)	(1.0399)	(1.0739)	(1.0621)
Style-adjusted return	85.3813*	34.7929	71.1925*	52.3773	45.0474
	(1.20E+37)	(1.29E+15)	(8.29E+30)	(5.59E+22)	(3.66E+19)
Highest style-adjusted return	-0.1801	-0.8786	0.3187	-0.2824	3.9880
	(0.8352)	(0.4154)	(1.3753)	(0.7540)	(53.9473)
Volatility	19.4663*	21.0523**	22.3184**	19.2979*	9.8783**
	(2.85E+08)	(1.39E+09)	(4.93E+09)	(2.40E+08)	(19,503)
Star family	1.5522***	1.4261***	1.6591***	1.7612***	1.4411***
	(4.7219)	(4.1625)	(5.2543)	(5.8197)	(4.2254)
Percentage of bond funds	1.0477*	0.9717	0.8869	0.8701	0.4845
	(2.8510)	(2.6424)	(2.4277)	(2.3871)	(1.6234)
Percentage of growth funds	-0.4161	-0.4026	-0.6301	-0.6439	-1.2375**
	(0.6596)	(0.6686)	(0.5325)	(0.5253)	(0.2901)
Percentage of income funds	-0.9091	-0.8954	-1.1314	-0.8979	-2.0905
	(0.4029)	(0.4084)	(0.3226)	(0.4074)	(0.1236)
Percentage of index funds	0.6626	0.8122	0.5466	0.8072	0.2955
	(1.9399)	(2.2528)	(1.7274)	(2.2415)	(1.3438)
Percentage of retail funds	0.4376	0.5996	0.7140	0.6333	0.4557
	(1.5489)	(1.8214)	(2.0421)	(1.8839)	(1.5773)
Observations	511	511	511	511	509

Table 4. The use of Twitter and mutual fund flows

This table presents the regression results for the relation between the introduction of Twitter and subsequent fund flows. The dependent variable is monthly family-level flows. Twitter is a dummy variable indicating whether a fund family uses Twitter. Star funds are defined as the top 5% of performers with the highest average returns over the previous 12 months within the same investment category. A fund family is defined as a star family if it has at least one star fund under management. Past performance is the average style-adjusted return over the previous 12 months. Log size is the logarithm of the fund family's total net assets (summed over all funds). Log number of styles is the logarithm of the number of different styles offered by a fund family. Log age is the logarithm of the age of the oldest fund in a fund family. Turnover and Expense ratio are the weighted average of corresponding values of all member funds in the family. Volatility is the standard deviation of monthly returns over the past 12 months. Robust standard errors clustered on fund family are reported in parentheses. Significance levels at 10%, 5%, and 1% are denoted by *, ** and ***, respectively.

	Months				
	(−1, +1)	(−3, +3)	(−6, +6)	(−12, +12)	(−18, +18)
Twitter	0.0071*	0.0083***	0.0069**	0.0030	0.0010
	(0.0038)	(0.0026)	(0.0028)	(0.0032)	(0.0040)
Star family	0.0040	-0.0009	0.0020	-0.0029	0.0045
	(0.0087)	(0.0028)	(0.0021)	(0.0024)	(0.0036)
Past performance	-0.0664	0.0511**	0.0837**	0.1590***	0.0884
	(0.1290)	(0.0257)	(0.0332)	(0.0332)	(0.0898)
Log size	-0.0017	-0.0139	-0.0309*	-0.0566***	-0.0155
	(0.0336)	(0.0114)	(0.0164)	(0.0210)	(0.0173)
Log number of styles	-0.0215	0.0171	0.0331	-0.0281	0.0215
	(0.0166)	(0.0254)	(0.0226)	(0.0178)	(0.0177)
Log age	0.0055	0.0049	0.0238**	0.0175**	0.0062
	(0.0220)	(0.0079)	(0.0113)	(0.0079)	(0.0037)
Turnover	-0.0096	-0.0022	-0.0049*	-0.0134**	-0.0047
	(0.0143)	(0.0033)	(0.0028)	(0.0055)	(0.0041)
Expense ratio	1.8250	0.4750	0.6160	-3.4620**	10.5500
	(3.9680)	(1.2020)	(1.4600)	(1.6500)	(6.7920)
Volatility	0.3380	0.0836	0.0381	-0.3530**	-0.1750
	(0.2710)	(0.1470)	(0.2000)	(0.1410)	(0.2530)
Observations	345	881	1,423	1,871	1,014

Table 5. The use of Twitter and flows to pre-existing funds

This table presents the regression results for the relation between the introduction of Twitter and subsequent flows to pre-existing funds. The dependent variable is monthly family-level flows to pre-existing funds. Twitter is a dummy variable indicating whether a fund family uses Twitter. Star funds are defined as the top 5% of performers with the highest average returns over the previous 12 months within the same investment category. A fund family is defined as a star family if it has at least one star fund under management. Past performance is the average style-adjusted return over the previous 12 months. Log size is the logarithm of the fund family's total net assets (summed over all funds). Log number of styles is the logarithm of the number of different styles offered by a fund family. Log age is the logarithm of the age of the oldest fund in a fund family. Turnover and Expense ratio are the weighted average of corresponding values of all member funds in the family. Volatility is the standard deviation of monthly returns over the past 12 months. Number of new funds is the total number of funds that are introduced in a family over each window. Robust standard errors clustered on fund family are reported in parentheses. Significance levels at 10%, 5%, and 1% are denoted by *, ** and ***, respectively.

	Months				
	(–1, +1)	(–3, +3)	(–6, +6)	(–12, +12)	(–18, +18)
Twitter	0.0074**	0.0068***	0.0062**	0.0052*	0.0014
	(0.0036)	(0.0021)	(0.0025)	(0.0027)	(0.0036)
Star family	0.0029	-0.0034	0.0010	-0.0020	0.0041
	(0.0091)	(0.0025)	(0.0019)	(0.0022)	(0.0033)
Past performance	-0.0883	0.0509**	0.0800**	0.1190***	0.1060
	(0.1290)	(0.0204)	(0.0321)	(0.0255)	(0.0783)
Log size	-0.0068	-0.0187*	-0.0293*	-0.0313*	-0.0106
	(0.0345)	(0.0110)	(0.0164)	(0.0158)	(0.0151)
Log number of styles	-0.0197	0.0045	0.0293	-0.0061	0.0167
	(0.0218)	(0.0205)	(0.0226)	(0.0153)	(0.0155)
Log age	0.0007	0.0014	0.0223**	0.0127***	0.0053
	(0.0235)	(0.0075)	(0.0109)	(0.0032)	(0.0035)
Turnover	-0.0077	-0.0038	-0.0035	-0.0069*	-0.0033
	(0.0139)	(0.0026)	(0.0022)	(0.0041)	(0.0032)
Expense ratio	1.7870	0.2090	1.0570	-2.4490*	8.0890
	(4.7090)	(1.2290)	(1.5000)	(1.2680)	(5.3000)
Volatility	0.2840	0.0006	0.0296	-0.2360	-0.1420
	(0.2760)	(0.1200)	(0.1970)	(0.1480)	(0.2180)
Number of new funds	0.0007	0.0023	-0.0008	-0.0024	0.0001
	(0.0031)	(0.0024)	(0.0009)	(0.0023)	(0.0001)
Observations	345	881	1,423	1,871	1,014

Table 6. The use of Twitter and flows to pre-existing styles

This table presents the regression results for the relation between the introduction of Twitter and subsequent fund flows to pre-existing styles. The dependent variable is monthly family-level flows to pre-existing styles. Twitter is a dummy variable indicating whether a fund family uses Twitter. Star funds are defined as the top 5% of performers with the highest average returns over the previous 12 months within the same investment category. A fund family is defined as a star family if it has at least one star fund under management. Past performance is the average style-adjusted return over the previous 12 months. Log size is the logarithm of the fund family's total net assets (summed over all funds). Log number of styles is the logarithm of the number of different styles offered by a fund family. Log age is the logarithm of the age of the oldest fund in a fund family. Turnover and Expense ratio are the weighted average of corresponding values of all member funds in the family. Volatility is the standard deviation of monthly returns over the past 12 months. Number of new styles is the total number of styles that are introduced in a family over each window. Robust standard errors clustered on fund family are reported in parentheses. Significance levels at 10%, 5%, and 1% are denoted by *, ** and ***, respectively.

	Months				
	(–1, +1)	(–3, +3)	(–6, +6)	(–12, +12)	(–18, +18)
Twitter	0.0056	0.0069***	0.0046*	0.0056**	0.0007
	(0.0037)	(0.0023)	(0.0026)	(0.0027)	(0.0036)
Star family	0.0060	-0.0004	0.0009	-0.0017	0.0047
	(0.0092)	(0.0028)	(0.0023)	(0.0023)	(0.0032)
Past performance	-0.0763	0.0562**	0.0968***	0.1120***	0.1050
	(0.1290)	(0.0249)	(0.0305)	(0.0265)	(0.0739)
Log size	-0.0040	-0.0120	-0.0264*	-0.0351**	-0.0132
	(0.0337)	(0.0111)	(0.0152)	(0.0155)	(0.0169)
Log number of styles	-0.0313	0.0022	0.0343	-0.0062	0.0183
	(0.0196)	(0.0201)	(0.0219)	(0.0150)	(0.0151)
Log age	0.0174	0.0084	0.0218*	0.0184***	0.0060*
	(0.0237)	(0.0082)	(0.0112)	(0.0046)	(0.0031)
Turnover	-0.0056	-0.0019	-0.0027	-0.0077*	-0.0039
	(0.0137)	(0.0033)	(0.0020)	(0.0041)	(0.0032)
Expense ratio	4.6700	0.1960	0.4520	-2.3460*	8.2500
	(5.0300)	(1.0780)	(1.1490)	(1.1900)	(4.9640)
Volatility	0.5070*	0.1520	0.1740	-0.2160	-0.1460
	(0.2990)	(0.1370)	(0.1660)	(0.1360)	(0.2210)
Number of new styles	-0.0492	0.0069	0.0006	-0.0079	-0.0025**
	(0.0337)	(0.0048)	(0.0044)	(0.0077)	(0.0010)
Observations	345	881	1,423	1,871	1,014

Table 7. The use of Twitter and funds' inception size

This table presents the relative inception size of new funds after joining Twitter compared to that before joining Twitter among fund families that had introduced Twitter at the end of the sample period. Before Twitter reports the average inception size of new funds for fund families that have not yet introduced Twitter while After Twitter reports the average inception size of new funds for fund families that have started Tweeting. Inception size is a fund's total net assets in millions of dollars at the end of the first month when the fund was offered. Standard errors are reported in parentheses. Significance levels at 10%, 5%, and 1% are denoted by *, ** and ***, respectively.

	Before Twitter	After Twitter	Diff (After – Before)
Inception size ($ million)	11.0960	26.3093	15.2133***
	(17.7209)	(27.3443)	(0.9635)
Observations	1,002	1,216	

Table 8. The use of Twitter and flows to young funds

This table presents both percentage flows and dollar flows (in $ million) to young funds relative to old funds after the introduction of Twitter compared with those before the introduction of Twitter. Panel A reports the average percentage flows to young funds and to old funds before joining Twitter and after joining Twitter and Panel B reports the average dollar flows to young funds and to old funds before joining Twitter and after joining Twitter. Before Twitter reports the average flows to young (old) funds for fund families that have not yet introduced Twitter while After Twitter reports the average flows to young (old) funds for fund families that have started Tweeting. Young denotes funds that are 12 months old or younger while Old denotes funds that are more than 12 months old. Young and old funds are selected from the same fund family and matched by size each month. Newey-West standard errors are reported in parentheses. Significance levels at 10%, 5%, and 1% are denoted by *, ** and ***, respectively.

	Before Twitter		After Twitter		(Young, After – Old, After)
	Old	Young	Old	Young	– (Young, Before – Old, Before)
Panel A: Monthly percentage flows scaled by fund size					
Flow (scaled)	0.0463	3.2832	0.0394	6.7668	3.4905***
Newey-West SD	(0.0148)	(0.8196)	(0.0152)	(2.0119)	(0.2385)
Panel B: Monthly dollar flows					
Flow (in $ million)	1.1042	13.1591	0.6012	15.8523	3.1962***
Newey-West SD	(0.5072)	(1.4011)	(0.3840)	(2.7038)	(0.3348)
Observations	135	135	78	78	

Table A1. The use of Twitter and flow-performance sensitivity

This table presents the regression results for the relation between the introduction of Twitter and family-level fund flow-performance sensitivity. The dependent variable is monthly family-level flows. Twitter is a dummy variable indicating whether a fund family has a Twitter account. A fund familys fractional rank represents its percentile performance relative to other fund families in the same period, and ranges from 0 to 1. In this table, fractional ranks are defined on the basis of a fund families previous 12 month style-adjusted return. The coefficients on fractional ranks are estimated using a piecewise linear regression framework over five quintiles. The regression includes interaction terms that are the product of a dummy variable Twitter with fund performance quintiles. Log size is the logarithm of the fund family's total net assets (summed over all funds). Log age is the logarithm of the age of the oldest fund in a fund family. Turnover and expense ratio are the weighted average of corresponding values of all member funds in the family. Volatility is the standard deviation of monthly returns over the past 12 months. Robust standard errors clustered on fund family are reported in parentheses. Significance levels at 10%, 5%, and 1% are denoted by *, ** and ***, respectively.

	Months				
	(−1, +1)	(−3, +3)	(−6, +6)	(−12, +12)	(−18, +18)
Twitter x High performance	0.0535	-0.0274	0.1210	0.1300	-0.1660
	(0.1320)	(0.0961)	(0.1460)	(0.1700)	(0.2020)
Twitter x Second performance	-0.0761	0.0166	-0.0189	-0.0051	0.0848
	(0.0630)	(0.0452)	(0.0437)	(0.0616)	(0.0582)
Twitter x Mid performance	0.1050**	0.0202	-0.0244	0.0448	0.0173
	(0.0510)	(0.0379)	(0.0482)	(0.0427)	(0.0424)
Twitter x Forth performance	-0.1850	-0.0052	0.0684	-0.0492	-0.0704
	(0.1150)	(0.0703)	(0.0689)	(0.0450)	(0.0745)
Twitter x Low performance	-0.0461	-0.0925	-0.0168	-0.0658	0.0972
	(0.1840)	(0.1100)	(0.1280)	(0.0464)	(0.1680)
Twitter	0.0375	0.0237	0.00178	0.0173**	-0.0088
	(0.0271)	(0.0146)	(0.0165)	(0.0071)	(0.0310)
High performance	-0.1040	0.0472	0.0803	0.0292	0.2160
	(0.1240)	(0.0767)	(0.0484)	(0.0686)	(0.1840)
Second performance	0.0619*	0.0322	0.0238	0.0321	0.0093
	(0.0360)	(0.0277)	(0.0185)	(0.0222)	(0.0264)
Mid performance	0.0144	-0.0336	0.0599*	0.0067	0.0466
	(0.0380)	(0.0227)	(0.0346)	(0.0192)	(0.0298)
Forth performance	0.0423	0.0528	-0.0402	0.0098	-0.0166
	(0.0541)	(0.0427)	(0.0478)	(0.0266)	(0.0312)
Low performance	-0.0805	-0.0451	-0.0210	0.1110***	-0.0965
	(0.1320)	(0.0498)	(0.0742)	(0.0362)	(0.1020)
Log size	-0.0136	-0.0103	-0.0309*	-0.0556**	-0.0146
	(0.0316)	(0.0120)	(0.0164)	(0.0215)	(0.0180)
Log number of styles	-0.0197	0.0199	0.0338	-0.0278	0.0247
	(0.0155)	(0.0253)	(0.0225)	(0.0173)	(0.0192)
Log age	0.0213	0.0048	0.0228**	0.0161*	0.0064*
	(0.0171)	(0.0070)	(0.0107)	(0.0085)	(0.0034)
Turnover	-0.0183	-0.0015	-0.0040	-0.0120**	-0.0024
	(0.0139)	(0.0032)	(0.0028)	(0.0052)	(0.0038)
Expense ratio	0.5710	0.4020	-0.3260	-2.7280*	11.0000*
	(3.5250)	(1.1410)	(1.4200)	(1.4730)	(6.4330)
Volatility	0.3960	0.1280	0.0257	-0.3510**	-0.2180
	(0.2880)	(0.1600)	(0.1970)	(0.1560)	(0.2260)
Observations	345	881	1,423	1,871	1,014

Table A2. The use of Twitter and star phenomenon

This table presents the regression results for the relation between the introduction of Twitter and family-level fund flow-star effect sensitivity. The dependent variable is monthly family-level flows. Twitter is a dummy variable indicating whether a fund family has a Twitter account. Star funds are defined as the top 5% of performers with the highest average returns over the previous 12 months within the same investment category. A fund family is defined as a star family if it has at least one star fund under management. The regression includes an interaction term that is the product of a dummy variable Twitter with a star family dummy. Past performance is the average style-adjusted return over the previous 12 months. Log size is the logarithm of the fund family's total net assets (summed over all funds). Log age is the logarithm of the age of the oldest fund in a fund family. Turnover and expense ratio are the weighted average of corresponding values of all member funds in the family. Volatility is the standard deviation of monthly returns over the past 12 months. Robust standard errors clustered on fund family are reported in parentheses. Significance levels at 10%, 5%, and 1% are denoted by *, ** and ***, respectively.

	Months				
	(−1, +1)	(−3, +3)	(−6, +6)	(−12, +12)	(−18, +18)
Twitter x Star family	-0.0047	-0.0007	0.0035	0.0159***	-0.0016
	(0.0073)	(0.0043)	(0.0041)	(0.0046)	(0.0030)
Twitter	0.0096	0.0087**	0.0051	-0.0052	0.0021
	(0.0059)	(0.0041)	(0.0038)	(0.0042)	(0.0046)
Star family	0.0047	-0.0008	0.0012	-0.0072***	0.0050
	(0.0084)	(0.0032)	(0.0021)	(0.0025)	(0.0040)
Past performance	-0.0692	0.0513**	0.0841**	0.1560***	0.0889
	(0.1290)	(0.0255)	(0.0330)	(0.0303)	(0.0903)
Log size	-0.0007	-0.0139	-0.0310*	-0.0565***	-0.0156
	(0.0332)	(0.0114)	(0.0165)	(0.0202)	(0.0173)
Log number of styles	-0.0230	0.0168	0.0333	-0.0266	0.0215
	(0.0163)	(0.0252)	(0.0226)	(0.0167)	(0.0179)
Log age	0.0037	0.0049	0.0242**	0.0173**	0.0061
	(0.0226)	(0.0079)	(0.0114)	(0.0075)	(0.0038)
Turnover	-0.0102	-0.0022	-0.0050*	-0.0136**	-0.0047
	(0.0144)	(0.0033)	(0.0028)	(0.0053)	(0.0041)
Expense ratio	1.8930	0.4850	0.6050	-3.5650**	10.5700
	(3.9610)	(1.2040)	(1.4620)	(1.5970)	(6.7820)
Volatility	0.3280	0.0832	0.0410	-0.3540***	-0.1730
	(0.2690)	(0.1460)	(0.1980)	(0.1310)	(0.2560)
Observations	345	881	1,423	1,871	1,014

Table A3. The use of Twitter and mutual fund performance

This table presents the regression results for the relation between the introduction of Twitter and mutual funds' performance. The dependent variable is the weighted average of monthly style-adjusted return. Twitter is a dummy variable indicating whether a fund family has a Twitter account. Star funds are defined as the top 5% of performers with the highest average returns over the previous 12 months within the same investment category. A fund family is defined as a star family if it has at least one star fund under management. Past performance is the average style-adjusted return over the previous 12 months. Log size is the logarithm of the fund family's total net assets (summed over all funds). Log age is the logarithm of the age of the oldest fund in a fund family. Turnover and expense ratio are the weighted average of corresponding values of all member funds in the family. Volatility is the standard deviation of monthly returns over the past 12 months. Robust standard errors clustered on fund family are reported in parentheses. Significance levels at 10%, 5%, and 1% are denoted by *, ** and ***, respectively.

	Months				
	(–1, +1)	(–3, +3)	(–6, +6)	(–12, +12)	(–18, +18)
Twitter	0.0012	0.0011	0.0005	0.0010	-0.0014*
	(0.0026)	(0.0012)	(0.0011)	(0.0012)	(0.0008)
Star family	-0.0015	-0.0010	0.0011	0.0001	-0.0007
	(0.0036)	(0.0015)	(0.0012)	(0.0007)	(0.0007)
Past performance	-0.0345	-0.0908***	-0.0684***	-0.0202*	-0.0389
	(0.0579)	(0.0142)	(0.0200)	(0.0106)	(0.0365)
Log size	-0.0407**	-0.0124**	-0.0133***	-0.0088***	-0.0052**
	(0.0165)	(0.0050)	(0.0043)	(0.0021)	(0.0020)
Log number of styles	-0.0361**	-0.0117	-0.0130	0.0123*	0.0092**
	(0.0157)	(0.0089)	(0.0080)	(0.0070)	(0.0039)
Log age	-0.0026	-0.0024	0.0025	0.0018	0.0006
	(0.0051)	(0.0035)	(0.0032)	(0.0015)	(0.0020)
Turnover	0.0005	-0.0044**	0.0010	-8.19E-05	0.0032
	(0.0007)	(0.0019)	(0.0008)	(0.0002)	(0.0030)
Expense ratio	-1.5620	-2.7530***	-2.9930***	-1.4420**	-0.9610
	(3.3690)	(1.0150)	(0.7150)	(0.6160)	(1.1470)
Volatility	-0.1030	0.0022	0.0874	0.0619	0.0865
	(0.1400)	(0.0536)	(0.0644)	(0.0470)	(0.0978)
Observations	347	876	1,401	1,902	1,021