# WHEN HEDGE FUNDS MEET TWITTER:
# DOES VOLUNTARY DISCLOSURE OF PORTFOLIO STOCKS MATTER?

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YICHANG LIU

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ADVISORS:
PERVIN SHROFF
JOSHUA MADSEN

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## Dedication

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**Abstract**

After the lifting of the “general solicitation” ban in 2012, hedge funds have started using social media to make disclosures about selected stocks. I examine whether hedge funds use stock tweets to signal their superior stock-picking ability to attract investors. While there is no evidence of hedge funds’ predictive ability for tweeted stocks in general, I find that tweeted portfolio stocks with positive mentions earn positive and significant abnormal returns up to twelve months from the tweeting quarter. Moreover, I find that the abnormal returns for tweeted portfolio stocks are higher relative to those of the fund’s non-tweeted portfolio stocks. Thus, hedge funds appear to be “cherry-picking” portfolio stocks that are expected to perform well to include in their tweets. I further find that funds attract more flows from investors when they tweet, consistent with investors perceiving tweeting hedge funds to be of high quality. In contrast with the superior performance of the tweeted portfolio stocks, tweeting hedge funds’ overall fund performance does not improve after the tweet, so that investors’ expectation about the tweeting fund’s quality is not realized.

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## 1. Introduction

Hedge funds are commonly considered a "black box," partly because they make limited public disclosures. Due to the unique nature of their offerings (i.e., private placements), hedge funds were restricted from making public disclosures to generally solicit or advertise for potential investors under the SEC's Regulation D.[1] The JOBS Act of 2012 lifted the decade-long ban on "general solicitation," allowing hedge funds to publicly communicate through various media outlets. In response to the relaxation of the ban, some hedge funds have started using social media to make investment-related disclosures, often about their views on selected stocks.[2] This paper explores the motivation for hedge funds to make stock-related disclosures on social media. Specifically, I examine whether their disclosures about stocks signal their stock-picking ability and whether this results in greater fund flows from investors.

I focus on hedge funds' use of Twitter which is among the most-used interactive social media platforms both in general and for hedge funds.[3] Besides tweeting general information about the fund and the market, hedge funds tweet their perceptions about selected stocks, not limited to the stocks they own. Existing research finds that investors pay attention to information posted on a firm's social media platform (Blankespoor et al., 2014; Lee et al., 2015; Cao et al., 2021b). Based on my sample, I find that investors take

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[1] The "general solicitation" restriction was intended to prevent funds from touting potentially fraudulent offers or marketing their services to ineligible investors. More details on Regulation D are available at: https://www.investor.gov/introduction-investing/investing-basics/glossary/regulation-d-offerings

[2] Even after the lifting of the ban, hedge funds have typically limited their public disclosures to mentions of selected stocks rather than their overall fund performance likely due to increased compliance costs. Textual analysis of tweets in my sample shows no tweets with disclosures of overall fund performance by hedge funds.

[3] Based on my data, the number of hedge funds that use Twitter exceeds those that use Facebook and YouTube combined. While Twitter specifically tags a post as stock-related, it is difficult to reliably identify such posts on Facebook and YouTube (Jia et al., 2020). Hedge funds also commonly use LinkedIn as a social media platform; however, the exact timing of the creation of posts on LinkedIn is not readily determinable.

notice of stock-related disclosures on social media; tweets of hedge funds that discuss stocks receive significantly more "likes" and "retweets" than tweets that discuss non-stock information. While hedge funds make private communications to their current investors via traditional channels (e.g., investor letters), social media provides an opportunity to reach out to a wider set of potential investors. Typically, investors in hedge funds are wealthy individuals and institutions that are considered "accredited".[4] While such sophisticated investors are more likely to respond to direct solicitation, recent evidence shows that both retail and institutional investors use social media to facilitate their investment decisions (Hu et al., 2021).[5] Thus, it is likely that hedge funds send stock-related tweets to signal their superior stock-picking ability in order to attract investors. I examine whether hedge funds' positive or non-positive mentions of tweeted stocks are consistent with the subsequent performance of these stocks. I also examine whether the abnormal returns to positive (non-positive) tweets of hedge funds' owned stocks are higher (lower) relative to the non-tweeted stocks in their portfolios.

I assemble a novel dataset of hedge funds' social media accounts. I manually collect this information from hedge funds' Form ADV filing with the SEC (Item 1.I of Part 1A) and supplement it using Google search. To identify tweets that contain stock-related information, I use Twitter's "cash tag" feature which allows users to associate the tweets

[4] The SEC's definition of "accredited investors" can be found at: https://www.investor.gov/introduction-investing/general-resources/news-alerts/alerts-bulletins/investor-bulletins/updated-3. While hedge funds are not required to identify their investors in public disclosures, SEC's Division of Investment Management provides summary statistics on various types of investors of qualifying hedge funds. From 2013Q1 to 2021Q4, the top investor categories of qualifying hedge funds are private funds (18.5%), non-profits (13.9%), pension plans (12.9%), U.S. individuals (11.7%), and state/municipal government pension plans (10.6%) (available at https://www.sec.gov/divisions/investment/private-funds-statistics)
[5] A survey by Greenwich Associates reports that almost 80% of institutional investors use social media as part of their regular workflow. Available at https://www.greenwich.com/press-release/social-media-influencing-investment-decisions-global-institutions.

with a specific company. To test if the stock-related tweets signal hedge funds' stock-picking ability, I construct a linguistic measure, *Managers' Perception*, which captures fund managers' positive, neutral, and negative mentions of stocks based on the text of the tweets. I assess abnormal performance of stocks by calculating Fama-French (1993) and Carhart (1997) alphas over different horizons beginning one day after the date of the tweet.

I find that positive mentions of tweeted stocks earn positive and significant abnormal returns for horizons of up to twelve months from the tweet date. However, I find that tweeted stocks with non-positive mentions also earn positive and significant subsequent abnormal returns and the difference in abnormal returns of the positive and non-positive stock tweets is insignificant. In other words, hedge funds' positive versus non-positive mentions of tweeted stocks are unable to differentiate stocks with future positive or non-positive performance. Further examination reveals that hedge funds' positive versus non-positive mentions of tweeted stocks appear to be based on the stock's performance in the three months prior to the tweet date, i.e., the tweets reflect observable information. Hence, the general evidence is inconsistent with the hypothesis that hedge funds' tweets signal their superior stock-picking ability. It is likely that hedge funds' stock tweets do not convey superior information for all stocks that they tweet but only for the stocks they own.[6] Thus, I next examine the subsequent performance of hedge funds' tweeted *portfolio* stocks.

Consistent with Agarwal et al. (2013), I estimate abnormal returns over varying horizons from the beginning of the tweeting quarter. I find that abnormal returns of tweeted portfolio stocks with positive mentions are significantly higher than that of the non-tweeted

[6] I find that hedge funds' tweets of owned stocks tend to mostly convey their positive perception of the stock. I find that, while 57% of tweeted stocks with positive mentions are owned by hedge funds, the corresponding percentage for non-positive mentions is only 17%.

portfolio stocks up to the subsequent twelve months. The difference translates into an economically meaningful magnitude – for horizons ranging from 3 to 12 months, daily Carhart alphas range from 2.95 to 7.58 basis points, equivalent to 7.43% to 19.10% on an annualized basis. Hence, it appears that hedge funds may be "cherry-picking" portfolio stocks that are expected to perform well to include in their tweets.

If the portfolio stock tweets persuade investors of the fund's superior stock-picking ability, I expect investors to respond to the tweets. I first find a positive and significant (insignificant) market reaction to the tweeted stocks with positive (non-positive) mentions around the date of the tweet. Next, I examine whether there is an increase in fund flows from investors when hedge funds tweet portfolio stocks. Hedge funds are likely to tweet only if there are significant benefits in the form of higher fund flows to offset the increase in potential regulatory and compliance costs associated with the use of social media. If hedge funds choose to attract investors through Twitter, they "may have to apply a stricter and more costly process to determine accredited investor status than what they currently use" (SEC, 2013). Moreover, in view of the recent charges brought by the SEC for stock manipulation and "pump-and-dump" schemes on social media platforms,[7] stock tweets by hedge funds may increase the threat of regulatory action. In addition, analogous to analyst forecasts in the firm setting, inaccurate analyses or comments of stocks in the form of tweets may harm the reputation of hedge fund managers (Mikhail et al., 1999; Hong and Kubik, 2003). These costs raise the minimum threshold of the disclosure and should, in expectation, be compensated by additional benefits (e.g., Verrecchia, 1983, 2001). In the case of portfolio stock tweets, hedge funds could benefit by attracting fund flows from

[7] https://www.sec.gov/news/press-release/2022-221

potential investors. Thus, I examine whether fund flows increase when hedge funds tweet their portfolio stocks.

I use flow to funds as a direct measure of investors' actions following the tweets. I find that fund flows are higher in the tweeting quarter (Q0) and the quarter subsequent to it (Q1) relative to non-tweeting quarters. Specifically, hedge funds obtain 5.4% more flows (equivalent to 48.1 million dollars) from investors over the two quarters. The incremental fund flows are both statistically and economically meaningful after controlling for the total number of tweets, the use of other social media, and the use of traditional media by the hedge funds. Difference in differences analysis also indicates higher fund flows for the tweeting funds relative to a control sample of non- tweeting funds matched on size and performance. This result implies that hedge funds are able to convince investors about their stock-picking ability through their portfolio stock tweets, resulting in greater fund flows from investors.

Do hedge fund investors gain if they make investments in hedge funds following the tweets? Interestingly, I find that tweeting hedge funds' abnormal performance is negative and declines in the four quarters after the tweets; the abnormal performance relative to that of non-tweeting funds is also negative. Thus, investors do not gain by investing in tweeting funds following the tweets. Overall, my results imply that hedge funds demonstrate their stock-picking ability in their tweets by cherry-picking certain portfolio stocks in order to attract investors, but the overall performance of the tweeting funds is not as good as that of their tweeted portfolio stocks.

This paper makes several contributions to the existing literature. First, I contribute to the research on hedge fund communication. Due to the unique nature of hedge funds, private communication is the dominating industry practice (Cassar et al. 2018). Research on *public* communication by hedge funds appears only after the Dodd-Frank and the JOBS Acts. While a nascent strand of the literature examines the mandatory SEC filings of hedge funds stipulated by Dodd-Frank (Honigsberg, 2019; Liu et al. 2022), research on their *voluntary* disclosures is limited. This paper addresses this gap in the literature by providing early evidence on hedge funds' voluntary disclosures after the JOBS Act of 2012.

Second, I contribute to the research on firms' use of social media to achieve goals such as reducing information asymmetry (Blankespoor et al., 2014), attenuating negative price impacts (Lee et al., 2015), strategically disseminating financial information (Jung et al., 2018), managing CSR reputation (Crowley et al., 2019), and "badmouthing" industry peers (Cao et al., 2021b). This literature is predicated on the assumption that investors react to useful social media information. It is ex ante unclear whether sophisticated investors that make up a hedge fund's target clientele would react to social media information like typical retail investors. I find that the tweeted information by hedge funds elicits these investors' response in the form of additional fund flows.

Third, I contribute to the research on disclosures of portfolio stocks by hedge funds in a voluntary setting. I find that hedge funds exploit the discretion allowed by the JOBS Act by tweeting information about selected good-performing stocks from their portfolios. By signaling their stock-picking ability for portfolio stocks they are able to attract investors and increase fund flows. From the perspective of investors, however, I find no evidence of an improvement in hedge funds' performance following the tweets. Thus, investors' perception of the hedge fund's stock- picking ability indicated by the portfolio stock tweets is not realized. An implication of this finding is that the discretion allowed by the JOBS Act is used by hedge funds to access more funds to the detriment of investors.

The remainder of this paper proceeds as follows. Section 2 provides institutional background, reviews related literature, and develops the main hypotheses. Section 3 describes the data and sample. Section 4 discusses the empirical results. Section 5 concludes.

## 2. Institutional Background, Literature Review, and Hypotheses Development

### 2.1 Institutional Background

Hedge funds are influential participants in capital markets and play a critical role in the capital formation process. The total AUM (assets under management) of the hedge fund industry grew from $0.36 trillion in 2000 to $4.80 trillion in 2021, equivalent to 20% of the US GDP.[8] Other than the SEC's requirement for hedge funds to disclose their portfolio holdings on a quarterly basis through 13F filings, this industry has largely been unregulated. Under the Securities Act of 1933, any offer or sale of a security must either be registered with the SEC or meet an exemption. Section 4(a)(2) of the Securities Act exempts from registration "transactions by an issuer not involving any public offering", which allows hedge funds and other private funds to avoid the costly registration and disclosure requirements applicable to public issuers of securities.[9] To meet the requirements of the Section 4(a)(2) exemption, hedge fund advisers need to follow conditions outlined by Rule 506 of Regulation D. One of the conditions is that an adviser must not use general solicitation or general advertising to market its securities.[10]

On April 5, 2012, the JOBS Act was signed into law by President Barack Obama.

[8] The AUM data is from Barclay Hedge: https://www.barclayhedge.com/solutions/assets-under-management/ and the GDP data is from St. Louis Fed: https://fred.stlouisfed.org/series/GDP
[9] Explanations of exempted transactions are available at: https://www.law.cornell.edu/uscode/text/15/77d
[10] More details on private placements are available at: https://www.sec.gov/smallbusiness/exemptofferings

The Act was intended to stimulate capital formation for emerging growth companies by easing regulations and access to capital markets. If financial intermediaries such as hedge funds have more capital to invest, it was expected that the real economy and the labor market would benefit from it. Section 201(a)(1) of the JOBS Act directed the SEC to amend Rule 506 of Regulation D under the Securities Act to eliminate the prohibition of general solicitation or general advertising in offerings made under Rule 506. To implement Section 201(a)(1) of the JOBS Act, the SEC added paragraph(c) to Rule 506. Under Rule 506(c), issuers can offer securities through means of general solicitation under conditions where all purchasers in the offering are accredited investors, the issuer takes reasonable steps to verify their accredited investor status, and certain other requirements in Regulation D are satisfied.[11]

The new rule was finally approved by the SEC on September 23, 2013, and since then hedge fund advisers can directly communicate with investors through both physical and electronic means.[12] Hedge funds are also allowed to openly advertise their offerings and services. The SEC expected that the new rule would enable hedge funds "to reach a much greater number of potential investors...thereby increasing their access to sources of capital" (SEC, 2013).

## 2.2 Literature Review

### 2.2.1 The use of social media by firms

Research on firms' use of social media and its effects has burgeoned since the past decade. Blankespoor et al. (2014) examine a sample of technology firms and find that

[11] Rule 506(c) of Regulation D can be found at: https://www.law.cornell.edu/cfr/text/17/230.506

[12] Details of the SEC's rule on *Eliminating the Prohibition Against General Solicitation and General Advertising in Rule 506 and Rule 144A Offerings* are available at: https://www.sec.gov/rules/final/2013/33-9415.pdf

dissemination of firm-initiated news via Twitter improves market liquidity and reduces information asymmetry, particularly for firms that are not highly visible. Lee et al. (2015) examine the use of social media by firms to communicate consumer product recalls that could expose them to reputational damage and legal liability. They find that social media on average attenuates the negative price impact caused by product recalls. Jung et al. (2018) find that firms are less likely to disseminate earnings news on social media when the news is negative. Crowley et al. (2019) find that firms that are weak on corporate social responsibility (CSR) use social media as a tool for "greenwashing". Cao et al. (2021) show that firms use social media to disseminate bad news about their industry peers and find that this strategy obtains positive price reactions in the short term. Nekrasov et al. (2022) find that earnings announcements with visuals on Twitter receive more attention from investors, which leads to a stronger initial response to the earnings news. Overall, the literature shows that social media is widely used by firms as a communication channel and as a strategy to achieve certain goals.

### 2.2.2 The use of social media by mutual funds

Unlike hedge funds which offer private investments to accredited investors, mutual funds offer investment products that are available to the public. Accordingly, mutual funds have not been restricted by the general solicitation and general advertising rule that applied to hedge funds and other private funds. Kim (2017) finds that mutual funds are more likely to establish a Twitter account when they have new funds or star funds. She finds that mutual funds (both new and existing) experience greater fund flows following their usage of Twitter, but the effect is temporary, lasting about six months. She concludes that mutual funds use Twitter as a novel marketing strategy to attract the attention of market participants. Gil-Bazo and Imbet (2022) use textual analysis to study tweets of U.S. mutual funds. They find that a more positive tone of tweets in a month is associated with greater fund flows in the following month, particularly for tweets about financial advice and market commentary. Since the JOBS Act allows public disclosures by hedge funds similar to mutual funds, it is likely that hedge funds also use social media to advertise to potential investors. However, given hedge funds' reliance on private communication to their more sophisticated clientele, it is an open question whether the effects of advertising on social media will be similar for hedge funds.

### 2.2.3 Advertising by hedge funds

Due to their private nature, U.S. hedge funds were prohibited from general solicitation and general advertising prior to the JOBS Act. In countries where such restrictions do not exist, hedge funds have greater flexibility in choosing how to market themselves to the public. Using a cross-country sample, Cumming and Dai (2009) examine how different marketing schemes affect hedge funds' flow-performance sensitivity. They find that distribution through investment managers and fund distribution companies leads to higher flow-performance sensitivity relative to distribution in the form of wrappers (i.e., bundled selling). In the U.S., while hedge funds are now allowed to openly advertise their business and products, private communication is still the dominating industry practice. Anecdotal evidence suggests that hedge funds are often advertised through close networks, which include friends, friends of friends, and relationships introduced through business associates or a third party.[13] Hedge funds typically provide offering memorandum to attract prospective investors and investor letters to give periodic reports to existing investors.

[13] https://www.investmentlawgroup.com/faqs/how-does-a-hedge-fund-raise-money/

Given these features of the U.S. hedge fund industry, it is interesting to examine whether hedge funds' use of social media as an advertising platform has any effect on fund performance and flows.

### 2.3 Hypotheses Development

Research on hedge fund disclosures has been limited since hedge funds have historically relied on non-public disclosures to communicate with investors (e.g., private placement memorandum, investor letters). An exception is the paper by Cassar et al., (2018) which examines hedge funds' quantitative and qualitative disclosures to investors using a proprietary dataset of investor letters. Since the general solicitation ban was removed in 2012 as part of the JOBS Act, some hedge funds have started to use social media, to increase their visibility by making investment-related disclosures. I focus on hedge funds' use of Twitter in this paper since it is among the most-used interactive social media platforms (both in general and for hedge funds). Hedge funds' tweets are often about their views on selected stocks and rarely about their overall fund performance. While the SEC does not explicitly prohibit the public disclosure of overall fund performance, hedge funds are subject to potential SEC enforcement actions and penalties if their disclosures are not in compliance.[14] To avoid compliance costs, hedge funds typically restrict their tweets to information about selected stocks as an alternative way to signal their superior stock picking ability to the public. If hedge funds use their stock tweets to demonstrate their stock-picking ability, I expect that the hedge fund managers' positive or negative perception of

[14] SEC guidance requires hedge funds' disclosures of overall fund performance to include details of benchmarks, relevance and reason for their benchmark choice, reasons for deviations between the fund and the index, reasons for good performance due to extreme events (e.g., IPOs), and labels for historical, hypothetical, "model", or back-tested performance measures separate from actual performance. Moreover, the SEC's quantitative staff tries to identify unusually and improbably positive performance information which may lead to an investigation into non-compliant advertising by hedge funds.

tweeted stocks is consistent with the future performance of these stocks. Therefore, the first hypothesis is as follows (in alternative form):

H1: Tweeted stocks with positive (negative) mentions earn positive (negative) and significant abnormal returns following the tweets.

As hedge funds tweet information on selected stocks including the stocks they own, I examine the performance of tweeted stocks that belong to hedge funds' portfolios. If hedge funds wish to signal their stock-picking ability to investors, it is likely that they will tweet positive information about portfolio stocks that are expected to perform well. To the extent that hedge fund managers can discern more profitable stocks within their portfolio, tweeted portfolio stocks are likely to outperform non-tweeted portfolio stocks. In other words, hedge fund managers may "cherry-pick" portfolio stocks. The second hypothesis is stated as follows (in alternative form):

H2: Tweeted portfolio stocks earn positive and significant abnormal returns relative to non- tweeted portfolio stocks of the same hedge funds following the tweeting quarter.

It is in the interest of a hedge fund to tweet well-performing portfolio stocks so that investors perceive the fund as having stock-picking ability and increase their investment in the fund. Hedge funds will engage in this tweeting strategy only if the benefit in the form of increased fund flows is higher than the potential regulatory and compliance costs of advertising on social media. Consistent with the argument that tweeting can be costly, the SEC recently brought charges relating to the use of social media platforms for stock manipulation and "pump-and-dump" schemes (SEC, 2022). Moreover, analogous to analyst forecasts in the firm setting, inaccurate analyses or comments of stocks in the form of tweets may harm the reputation of hedge fund managers (Mikhail et al., 1999; Hong and

Kubik, 2003). Thus, I expect a significant increase in fund flows to offset the potential costs of tweeting portfolio stocks. The third hypothesis is as follows (in alternative form):

H3: Hedge funds experience higher fund flows when they tweet portfolio stocks.

## 3. Data and Sample Selection

### 3.1 Hedge Funds' Stock Tweets

I start the sample formation process by identifying SEC-registered hedge funds. I obtain a list of SEC-registered investment advisers from the SEC's website and a list of hedge funds from Thomson Reuter's Lipper TASS Hedge Fund Database.[15] I perform a name-by-name merging between the two sources and verify matches using fund locations. The merging process finds 657 hedge funds that are registered with the SEC on October 1, 2013. As registered hedge funds are required to file Form ADV with the SEC, I obtain Form ADV for each of the matched hedge funds using their unique registration identifier.

I collect comprehensive social media information of hedge funds from item 1.I of their Form ADV (Part 1a) and use two additional ways to make sure that the collection of information is complete. When a hedge fund discloses that there are no social media platforms other than a corporate website, I visit their website and look for icons or links to their social media platforms, if any. When a hedge fund claims that it does not have any social media presence (including a website), I google search the name of the hedge fund and the social media platform (e.g., Twitter) to supplement the results obtained from Form ADV. In this paper, I focus on the use of Twitter by hedge funds for the following reasons. First, Twitter is among the most used social media platforms for corporations and also for hedge funds. In my sample, 93 of 657 hedge funds have established a Twitter account.[16]

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[15] The list of SEC-registered investment advisers: https://www.sec.gov/help/foiadocsinvafoiahtm.html

[16] From the 93 hedge funds that have a Twitter account, I exclude 15 funds which have private accounts, or

Second, Twitter provides a historical archive of all user activities. Third, Twitter has a special "cash tag" feature which allows users to associate their tweets with specific companies using a dollar sign followed by a stock ticker. I take advantage of this feature to obtain a list of stock tickers that are mentioned by hedge funds in their tweets.

I obtain the sample tweets (including retweets and replies) of hedge funds between 2013Q3 and 2020Q4. My sample starts in 2013Q3, the quarter when the ban on general solicitation was first lifted by the SEC. I identify tweets that contain at least one "cash tag" in the text with Python and manually remove tweets when the content following the "cash tag" is not a stock ticker. To be included in the empirical analysis, I require the stock tickers mentioned in the tweets to meet the following criteria. The stock needs to be listed on one of the three main U.S. stock exchanges (i.e., NYSE, NASDAQ, and NYSE American, formerly AMEX) during the sample period. Moreover, the stocks must be ordinary common shares (i.e., SHRCD code = 10, 11, 12 in CRSP). These criteria result in a sample of 565 stocks covered in 1,074 tweets by 24 hedge funds.[17] I classify stock mentions as having positive or non-positive tone by manually reading the content of the tweets as explained in detail later.

Table 1 Panel A shows the sample distribution of stock tweets by year. The number of stock tweets increases in the second half of the sample period with an average tweet mentioning 1.3 stocks (untabulated). Panel B tabulates the number of stock tweets by quarter. The tweets are smoothly spread over the four quarters during the sample period, with 256 (23.8%) stock tweets in Q1, 294 (27.4%) stock tweets in Q2, 250 (23.3%) stock

are inactive since the creation of the account (i.e., fewer than 10 tweets posted in total).

[17] Based on the numbers reported by Twitter in June 2023, on average there were 22,946 followers of the hedge funds in my sample since the creation of their Twitter accounts.

tweets in Q3, and 274 (25.5%) stock tweets in Q4. Panel C presents the number of stock tweets by tone. There are 209 (19.5%) stock tweets with a positive mention and 865 (80.5%) with a non-positive mention (i.e., neutral and negative). Appendix 2 provides some examples of stock tweets sent by hedge funds.

### 3.2 13F Portfolio Stocks

I download the quarterly 13F filings of hedge funds in my sample from the SEC EDGAR website. Since 1978, all institutional managers with investment discretion over 100 million U.S. dollars are required to disclose their quarterly portfolios by filing Form 13F with the SEC. Prior research (e.g., Agarwal et al., 2013; Aragon et al., 2013) finds that the original 13F filings may contain errors or undisclosed confidential holdings which are later corrected by 13F amendments. Following these studies, I use 13F amendments instead of the original 13F filings for such cases. I obtain 536 quarterly 13F filings (including amendments) for hedge funds in my sample and only keep an entry of a portfolio stock if the title of the class (column 2 of the 13F filings) indicates that it is common stock. Moreover, as CUSIPs (column 3 of the 13F filings) may change over time, I require that they match a unique permanent identifier of the stocks in CRSP (e.g., PERMNO). These criteria result in a total number of 164,305 13F portfolio stocks at the fund-quarter level. The average number of portfolio stocks held by a tweeting hedge fund in my sample is 307 per quarter and the median number is 244. The average dollar value of the portfolio held by a tweeting hedge fund is 5,023 million per quarter and the median dollar value is 1,523 million. The average dollar value of a portfolio stock held by a tweeting hedge fund is 16.39 million and the median dollar value is 2.57 million.

### 3.3 Tweeted Portfolio Stocks

As hedge funds could comment on any stocks (not just the ones they own), I merge the tweeted stocks with 13F portfolio stocks to understand the extent to which tweeted stocks are also held by the hedge funds (see Figure 1). I find that 41% of tweeted stocks are also owned by hedge funds (untabulated). The top five tweeting hedge funds are Gator Capital Management, Horizon Kinetics, Kerrisdale Advisers, GAM investments, and AlphaOne Capital Partners. The top five tweeted portfolio stocks are Apple Inc., Amazon.com Inc., Meta Platforms Inc., Amerco, and Alphabet Inc.

## 4. Empirical Results

### 4.1 Tweeted Stocks

#### 4.1.1 Characteristics of Tweeted Stocks

Table 2 Panel A presents the industry distribution of the tweeted stocks (based on their two-digit SIC code). Tweeted stocks are more likely to be in finance, insurance, real estate industries (39.3%), manufacturing industry (22.4%) and services industry (16.1%). Panel B reports the characteristics of the tweeted stocks. The mean (median) size (market capitalization) of the tweeted stocks is \$87,221 (\$8,313) million at the end of the tweeting quarter. Both the mean and the median are over ten times larger when compared with the size of stocks from the Compustat/CRSP universe, indicating that large cap stocks are more likely to be included in the tweets of hedge funds. The mean (median) book-to-market ratio of the tweeted stocks is 0.65 (0.48) and is insignificantly different from that of the Compustat/CRSP universe. The mean ROA of the tweeted stocks is a small positive and around 1.7% higher than that of the Compustat/CRSP universe. The mean (median) return volatility of the tweeted stocks is 0.10 (0.08), lower than that of the Compustat/CRSP universe. The abnormal return of tweeted stocks in the quarter prior to the tweet is -0.002, slightly lower than that of the Compustat/CRSP universe. Tweeted stocks have higher liquidity and higher momentum when compared with stocks from the Compustat/CRSP universe. Overall, relative to the Compustat/CRSP universe, the tweeted stocks are larger in size, with a slightly higher ROA but lower return performance prior to the tweet.

Table 2 Panel C compares the characteristics of the two groups of tweeted stocks partitioned on the *Managers' Perception* measure. To capture managers' optimism/pessimism towards the tweeted stocks, I construct a linguistic measure based on the text of the tweets. As more than one stock might be mentioned in a tweet, I read all the tweets and assign a value between 0 and 1 to each stock mentioned in the tweet (1 for optimistic, 0.5 for neutral, and 0 for pessimistic). I aggregate this measure at the quarterly level when a stock is mentioned in multiple tweets by a hedge fund during a quarter. Among 565 tweeted stocks, I classify 148 stocks as having positive mentions and 417 stocks as having non-positive mentions (i.e., neutral or negative).[18] From Panel C, I find that tweeted stocks with positive mentions are significantly larger than those with non-positive mentions. Moreover, tweeted stocks with positive (non-positive) mentions have positive (negative) ROA and recent return performance.

#### 4.1.2 Performance of Tweeted Stocks

I examine if stocks tweeted by the hedge funds signal the funds' stock-picking ability. If tweeted stocks indicate hedge funds' superior stock-picking ability, I hypothesize that their

[18] I validate my manual classification by measuring the tone of the stock tweets by textual analysis using the sentiment word lists developed by Loughran and McDonald (2011, 2016). I focus on tweets that only cover a single stock to minimize misclassification errors when multiple stocks are covered by a tweet. I find that using the manual classification versus the textual analysis yields a consistency rate of 72%.

perceptions of the tweeted stocks are predictive of the future performance of these stocks. To assess abnormal stock performance, I calculate two commonly used metrics in the literature, Fama-French (1993) and Carhart (1997) daily alphas, as follows.

$$r_{i,t} - r_{f,t} = \alpha_i + \sum_{j=1}^{J} \beta_i^j F_t^j + \varepsilon_{i,t} \quad (1)$$

$r_{i,t}$ is the return for stock *i* on date *t* and $r_{f,t}$ is the date-*t* risk-free rate (one-month treasury bill rate). $F_t^j$ represents *j* factors including the date-*t* excess return on the market (MRTRF), small minus big (SMB) and high minus low book-to-market (HML) for the estimation of Fama-French alphas, and including the fourth momentum factor (UMD) for the estimation of Carhart alphas. $\beta_i^j$ represents the *j* factor loadings for stock *i*. The abnormal performance is assessed over horizons of different lengths following the tweet date.[19]

Table 3 reports results of hypothesis 1 examining the stock-picking ability conveyed by hedge funds' tweets. Panel A reports the daily Fama-French and Carhart alphas for tweeted stocks with positive mentions for horizons subsequent to the tweet date. The daily Fama-French (Carhart) alphas are 3.98 (4.29), 3.28 (3.51), 3.29 (3.30), and 2.72 (2.74) basis points over three months, six months, nine months, and twelve months, respectively; the corresponding annualized abnormal returns are 10.03% (10.81%), 8.27% (8.85%), 8.29% (8.32%), and 6.85% (6.90%), respectively. Thus, these results show that tweeted stocks with positive mentions earn positive future abnormal returns. Table 3 Panel B presents the results of tweeted stocks with non-positive mentions. The abnormal returns of these stocks are also significantly positive over all horizons. Moreover, the difference in alphas of the positive versus non-positive mentions is insignificant for all horizons,

[19] If a stock is tweeted more than once by a hedge fund during a quarter, I choose the date when the stock is tweeted for the first time during that quarter for the calculation of the abnormal performance.

suggesting that hedge fund managers' perceptions of tweeted stocks are unable to differentiate stocks with future positive or non-positive performance.

As shown in column (1) of Panel A, the daily Fama-French (Carhart) alpha is positive at +6.00 (+5.37) basis points for tweeted stocks with positive mentions in the three months prior to the tweet date (-3m), while, as shown in column (1) of Panel B, it is negative at -3.07 (-3.24) basis points for tweeted stocks with non-positive mentions in the prior three months. Thus, hedge fund managers' perceptions as reflected in stock tweets appear to be based on historical information.[20]

In summary, I find no evidence of stock-picking ability indicated by hedge funds' stock tweets in general. In the section that follows, I test whether hedge finds' tweets of their *portfolio* stocks are predictive of the future performance of these stocks.

### 4.2 Tweeted Portfolio Stocks

#### 4.2.1 Characteristics of Tweeted Portfolio Stocks

In this section, I examine the characteristics of tweeted portfolio stocks and the remaining stocks held by hedge funds but not mentioned in a tweet (non-tweeted portfolio stocks). Among stocks that are owned by the hedge funds, the emphasis on some stocks in the form of tweet mentions might indicate greater importance of these stocks relative to others. I thus conjecture that hedge funds are more likely to tweet stocks for which they have a large position in their portfolio. To examine this, I rank the dollar value of all portfolio stocks of

[20] From Table 3 Panel B, the abnormal returns of tweeted stocks with non-positive mentions experience negative to positive return reversals from month -3 to month +3. Month-by-month analysis reveals that the reversal takes place gradually over the three-month period for tweets with non-positive mentions, and also for tweets with negative and neutral mentions when analyzed separately (untabulated). While the general mean reversion pattern in returns is consistent with prior research (e.g., Mukherji, 2011), I find that the return reversal for negative mentions is mainly driven by stocks whose earnings news changes from negative to positive in the 3 months subsequent to the tweet.

a hedge fund at the quarterly level and construct an indicator variable *Top10* which takes a value of 1 if the dollar value of a stock is ranked in the top ten among all of the fund's stock holdings in a quarter. Table 4 Panel A shows that the mean value of the *Top10* variable is 0.43 for tweeted portfolio stocks while the mean is only 0.02 for non-tweeted portfolio stocks. In addition, univariate comparisons show that tweeted portfolio stocks have a larger market capitalization and a higher ROA than non-tweeted portfolio stocks. Table 4 Panel B formally establishes the relationship between a hedge fund's portfolio stock tweeting decision and stock characteristics using multivariate regressions. The model specification is as follows.

$$Tweeted\ Portfolio\ Stocks_{i,j,q} = Stock\ Characteristics_{i,q} + \delta_q + \theta_{ind} + \varepsilon_{i,j,q} \quad (2)$$

$Tweeted\ Portfolio\ Stocks_{i,j,q}$ is an indicator variable that takes a value of 1 if stock *i* is both tweeted and held by a hedge fund $j$ in quarter $q$. $Stock\ Characteristics_{i,q}$ are a vector of characteristics of stock *i* in quarter $q$. $\delta_q$ and $\theta_{ind}$ are the quarter and industry dummies or fixed effects. Table 4 Panel B reports the results of a linear probability model in column (1). I find that the coefficient estimate on the *Top10* variable is 0.019, positive and significant at the 1% level, showing that tweeted portfolio stocks are more likely to be ranked at the top of the portfolio than non-tweeted portfolio stocks. In addition, the coefficient on *B/M* is positive and significant, suggesting that the tweeted portfolio stocks are likely to be securities that are undervalued by the market. I also find that hedge funds are likely to tweet stocks with higher *Volatility* and larger market capitalization. Column 2 presents logit regression results which are substantially similar to the linear regression results. Taken together, among all their portfolio stocks, hedge funds are more likely to tweet undervalued and risky large-cap stocks in which they have large positions. Table 4

Panel C further partitions the tweeted portfolio stocks into positive mentions and non-positive mentions. Other than volatility and the probability of being among the top ten stocks in the quarterly portfolio, the characteristics of tweeted portfolio stocks with positive mentions are insignificantly different from those of non-positive mentions.

### 4.2.2 Performance of Tweeted Portfolio Stocks

Next, I examine the performance of tweeted portfolio stocks relative to that of non-tweeted portfolio stocks. If hedge funds wish to signal their stock-picking ability to investors, it is likely that they will tweet more and positively about portfolio stocks that are expected to perform well. From Table 2 Panel C, positive stock tweets only account for 26% of all stock tweets unconditional on the portfolio ownership (148 out of 565 tweeted stocks), while in contrast, from Table 4 Panel C, the positive tweets on portfolio stocks account for over half of the tweets on portfolio stocks (85 out of 157 tweeted portfolio stocks). I hypothesize that stocks receiving positive mentions have stronger performance than non-tweeted portfolio stocks. Similar to the calculations in section 4.1, I assess abnormal returns of tweeted and non-tweeted portfolio stocks using Fama-French (1993) and Carhart (1997) alphas. Consistent with Agarwal et al., (2013), I calculate the abnormal performance over horizons of different lengths assuming that the stocks are held at the beginning of the tweeting quarter. Table 5 reports the results.

The top panel of Table 5 Panel A uses the Fama-French alphas for the comparison and the bottom panel uses the Carhart alphas. Regardless of the measure, tweeted portfolio stocks that receive positive mentions outperform non-tweeted portfolio stocks in all horizons. The Fama- French (Carhart) daily alpha is 8.68 (8.39) basis points for tweeted portfolio stocks over a three- month horizon and translates to an annualized abnormal return of 21.87% (21.14%). In contrast, the Fama-French (Carhart) alpha is only 1.20 (0.81) basis points for non-tweeted portfolio stocks over the same period and translates to an annualized abnormal return of 3.02% (2.04%). The daily difference is 7.48 (7.58) basis points and translates to an annualized difference of 18.85% (19.10%) which is statistically and economically meaningful. The annualized difference in abnormal returns between the two groups of stocks is 9.05% (9.42%) over a six-month horizon, 7.08% (7.43%) over a nine-month horizon, and 7.61% (7.53%) over a twelve-month horizon.

Results in panel B show that the abnormal returns of tweeted portfolio stocks with non- positive mentions are not statistically different from those of non-tweeted portfolio stocks. This is in contrast with the findings for tweeted portfolio stocks with positive mentions. Taken together, the findings show that stocks receiving positive mentions have stronger performance than non- tweeted portfolio stocks, which suggests that hedge funds may be "cherry-picking" portfolio stocks that are expected to perform well to include in their tweets.

#### 4.2.3 Tweeting Hedge Funds' Stock Trading Activities

I examine whether hedge funds' trading activities are consistent with the sentiment expressed by their portfolio stock tweets. Table 6 presents the changes in the positions of tweeted portfolio stocks across quarters for the sample of the tweeting hedge funds. The top (bottom) panel shows changes in positions of tweeted portfolio stocks with positive (non-positive) mentions during the tweeting quarter (3m) and quarters following the tweeting quarter (6m, 9m, 12m). I find that tweeting hedge funds are more likely to increase (decrease) the holdings of stocks with positive (non-positive) mentions rather than decrease (increase) the holdings during the tweeting quarter. For both positive mentions and non-positive mentions, hedge funds gradually decrease their holdings of stocks in quarters following the tweeting quarter, possibly due to the turnover effect as documented in the hedge fund literature (e.g., Griffin and Xu, 2009).[21]

### 4.3 Market Reaction to Hedge Funds' Portfolio Stock Tweets

In this section, I examine whether investors react to the hedge funds' portfolio stock tweets. I perform an event study to examine if hedge funds' tweets result in price reactions in the capital market. I separately examine samples of tweeted portfolio stocks with positive and non-positive mentions. I exclude confounding events including earnings press releases, stock repurchases, mergers and acquisitions (M&As), and initial public offerings (IPOs) that are announced within a [-5, 5] window surrounding the date of the tweet. I exclude the tweet if two or more hedge funds comment on the same stock on the same day. To calculate abnormal returns (ARs) and cumulative abnormal returns (CARs), I use an estimation window from 300 to 91 days prior to the event date. I estimate abnormal returns using the market model (i.e., CAPM) as well as market-adjusted returns for three event windows of different lengths.

Table 7 presents the results of the event study. Panel A reports the market reaction to portfolio stock tweets with positive mentions. I find that the market reacts positively to stock tweets over event windows [0, 0], [0, 2], and [0, 5]. Based on the market model, the mean CAR is 58 basis points and significant at the 5% level on date 0 when the stocks are tweeted. The mean CAR for the [0, 2] window is also significant and increases to 88 basis points. The mean CAR for the [0, 5] window is 77 basis points but is insignificant. The

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[21] The decreasing pattern of portfolio stock holdings in subsequent quarters for the tweeted stocks with negative mentions (one-sixth of the sample of non-positive mention stocks) is similar to that of stocks with neutral tweets (untabulated).

results using market-adjusted returns are similar to those using the market model. Panel B tabulates market reactions to portfolio stock tweets with non-positive mentions. In contrast with the results in Panel A, I find the mean CAR for non-positive mentions to be insignificant during all three event windows.[22] Overall, my results show that investors react to tweets of portfolio stocks when hedge fund managers' perception of the stock is positive.

### 4.4 Portfolio Stock Tweets and Fund Flows

In this section, I examine the hypothesis that hedge funds experience higher fund flows when they tweet their portfolio stocks. Table 8 provides descriptive statistics of the characteristics of tweeting hedge funds. In Panel A, I find that the average size (AUM) of the tweeting hedge funds is $390.3 million which is slightly larger than that of funds in the TASS universe ($326.4 million). The average age of the tweeting hedge funds is 12.3 years, which is 3.8 years older than that of funds in the TASS universe. The average number of total restrictions (in days) are similar between the tweeting hedge funds and the fund universe (165.4 v. 177.6). Tweeting hedge funds charge lower management fees (1.3% v. 1.4%), higher incentive fees (15.2% v. 13.6%), and are less likely to use a highwater mark (0.44 v. 0.57) when compared with funds in the TASS universe. The average percentage of funds that use leverage are similar between the two groups. Panel B presents descriptive statistics at the fund-quarter level. I find that the mean fund flows are negative (-0.04) for tweeting funds over the sample period. An average tweeting hedge fund posts information on portfolio stocks in 17% of the quarters and non-stock information in 83% of the quarters. Examples of non-stock information that is tweeted include funds receiving professional

[22] More than half (54%) of the non-positive mentions of portfolio stocks in this market reaction test are neutral, which may explain the insignificant reaction. When analyzing only the stocks with negative mentions, I find a negative but insignificant market reaction in all event windows.

awards, introducing a CSR report, or sharing its firm culture and employee programs. Panel B also provides summary statistics for the group of matched control funds. The details of selecting control funds are provided later in this section.

I use flow to funds and the following specification to examine investors' response when hedge funds tweet their portfolio stocks.

$$Fund\ Flows_{j,q} = Stock\ Tweeting\ Quarters_j + Other\ Tweeting\ Quarters_j + \sum_{n\in 1,2,3} FRankn_{j,q-1} + Fund\ Characteristics_{j,q} + Total\ Number\ of\ Tweets_{j,q} + Traditional\ Media_{j,q} + Other\ Social\ Media_{j,q} + \delta_{Fund} + \theta_{QuarterXStyle} + \varepsilon_{j,q} \quad (3)$$

$Fund\ Flows_{j,q}$ is the flow of capital to fund $j$ in quarter $q$.[23] $Stock\ Tweeting\ Quarters_j$ is an indicator that takes a value of 1 for the tweeting quarter $q$ (when hedge fund $j$ posts at least one tweet about their portfolio stocks) and for the immediately following quarter, $q+1$. $Other\ Tweeting\ Quarters_j$ is an indicator that takes a value of 1 for quarter $q$ (when hedge fund $j$ has at least one non-stock related tweet) and for the immediately following quarter $q+1$. $\sum_{n\in 1,2,3} FRankn_{j,q-1}$ is the fractional ranking of fund performance in quarter $q-1$ to capture investors' return-chasing behavior (Brown et al., 2008, 2012; Dimmock and Gerken, 2015; Franzoni and Giannetti, 2019). $Fund\ Characteristics_{j,q}$ include the natural logarithm of fund size and fund age. In addition, I control for the total amount of information from a hedge fund's tweets during a quarter by including the $Total\ Number\ of\ Tweets_{j,q}$ variable. As activities from other media outlets may also affect fund flows, I include an indicator variable that reflects a hedge fund's use of other social media (e.g., Facebook, YouTube)

[23] While ideally the flows should be measured after the tweet date, due to data limitations I use quarterly flows starting with the tweeting quarter (following prior literature, e.g., Franzoni and Giannetti 2019).

during a quarter and if a hedge fund has annual advertising expenditures on traditional media (e.g., newspapers, radio, television).[24] I include fund fixed effects and style×quarter fixed effects in all specifications.[25]

Table 9 presents the empirical results. Panel A column 1 shows the effect of tweeting portfolio stocks on fund flows after controlling for past fund performance, fund characteristics, and the use of other media channels. The coefficient on *Stock Tweeting Quarters* is 0.056, significant at the 1% level, indicating that hedge funds on average obtain 5.6% more flows from investors in the tweeting and subsequent quarter relative to other quarters. The magnitude of increase in fund flows is equivalent to 49.9 million dollars which is economically meaningful.[26] Consistent with prior research (e.g., Brown et al., 2008, 2012), I find that hedge fund investors chase past returns. The coefficient on the *FRank1* variable is positive and significant at the 5% level. Column 2 shows the effect of hedge funds' portfolio stock tweets on fund flows after controlling for tweeted non-stock information (*Other Tweeting Quarters*). As in column (1), the coefficient on *Stock Tweeting Quarters* is 0.054 (equivalent to 48.1 million dollars) and is significant at the 1% level, while *Other Tweeting Quarters* has an insignificant coefficient. Thus, the increase in fund flows results only from portfolio stock tweets and not from tweets of non-stock information.

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[24] I obtain the data on advertising expenditures of traditional media from Ad$pender, a commonly used database in marketing research. Ad$pender keeps track of advertising expenditures for over 3 million brands across 18 media categories such as television, magazines, radio, and newspapers. I search for the names of hedge funds in the database and check if a fund reports annual advertising expenditures on a traditional media outlet during the sample period.

[25] Style fixed effect controls for the effect of hedge funds' investment strategy (e.g., long/short equity hedge, event driven, global macro) on fund flows.

[26] $49.9m = 0.056* $891.23m. Note that since *Fund Flows* is scaled by lagged AUM (mean of $891.23m), I obtain the dollar increase by adjusting for the denominator of *Fund Flows*. However, I cannot rule out the possibility of an omitted variable (e.g., news in the tweeting quarter) driving the relation between portfolio stock tweets and fund flows.

Next, to examine whether the fund flows in the tweeting quarters for the tweeting hedge funds are driven by quarter effects, I compare the treatment sample with a matched control sample of funds that never tweet in my sample period (non-tweeting hedge funds). Specifically, for each tweeting fund, I select non-tweeting hedge funds of the same style that fall within [75%, 125%] of the size (AUM) of the tweeting fund. Of these non-tweeting hedge funds, I select the fund with the closest return performance to the tweeting fund at the beginning of the tweeting quarter. Column 3 shows the effect on fund flows in the tweeting quarters for the tweeting funds relative to matched non-tweeting funds. The coefficient on the interaction term *Stock Tweeting Quarters X Tweeting Funds* is 0.041, significant at the 5% level, indicating that when hedge funds tweet their portfolio stocks, fund flows are higher relative to the matched non-tweeting funds. The results from Table 9 collectively suggest that tweeting portfolio stocks likely attracts investors and increases fund flows to hedge funds.[27]

I further examine the persistence of the effect of portfolio stock tweets on fund flows. For this test, I remove portfolio stock tweets with overlapping pre-tweeting period (-3, -2, -1) and post-tweeting period (+2, +3, +4). I include three additional indicator variables in regression (3) – *Post2, Post3, Post4,* which represent the second, third, and fourth quarters after the tweeting quarter. If the effect of portfolio stock tweets on fund flows persists beyond the first quarter subsequent to the tweeting quarter, I expect that one or more of the *Post* variables will be significantly positive. If the effect of portfolio stock tweets on fund flows is only temporary, I expect that most or all of the *Post* variables will

[27] These results do not suggest that investors make their investment decisions upon seeing the tweets without learning about a hedge fund from alternative sources. Holding other factors constant (e.g., performance), a hedge fund is more likely to attract investors if it discusses portfolio stocks on social media, which triggers investors' investment decisions.

be insignificant. The results are shown in Table 9 Panel B. In columns 1 and 2, I find that the coefficients of *Post2*, *Post3*, *Post4* are insignificantly different from zero. The results suggest that the effect of portfolio stock tweets on fund flows does not persist beyond the first quarter subsequent to the tweeting quarter. In column 3, I compare the tweeting hedge funds with a matched control sample of non-tweeting hedge funds. I find that the interaction terms between *Post3* (*Post4*) and *Tweeting Funds* are marginally negative at the 10% level. The results indicate that tweeting hedge funds might in fact experience fund outflows in the post-tweeting period when compared with non-tweeting hedge funds. Taken together, the evidence suggests that the effect of portfolio stock tweets on fund flows is temporary.

### 4.5 Hedge Fund Performance

The previous section shows that hedge funds obtain incremental fund flows following their tweets. An interesting question to ask is whether hedge fund investors' gain by making investments in tweeting funds after the tweets. I address this question by examining hedge fund performance around the tweeting quarters.

To assess the abnormal performance of hedge funds, I calculate the Fung and Hsieh (2001, 2004) seven-factor alpha. I regress fund returns in excess of the risk-free rate on an equity market factor (the Standard &Poor's 500 index of monthly total return less the risk-free rate), a size spread factor (Russell 2000 index monthly total return less Standard & Poor's 500 monthly total return), a bond market factor (the monthly change in the 10-year Treasury constant maturity yield), a credit spread factor (the monthly change in the Moody's Baa yield less 10-year Treasury constant maturity yield), a bond-trend following factor, a currency-trend following factor, and a commodity-trend following factor. Betas are calculated using a rolling window of the previous 24 months.[28] The abnormal performance of hedge funds is assessed over four quarters following the tweeting quarter, Q0.

The first row in Table 10 presents the abnormal returns of tweeting funds. Their average abnormal performance during the tweeting quarter is 16.82 basis points. However, the positive performance is not sustained in the post-tweeting quarters. The average monthly abnormal performance in the first quarter subsequent to the tweeting quarter (i.e., Q1) is -11.40 basis points. The cumulative abnormal returns are -2.45, -13.52, and -5.99 basis points for the second (Q2), third (Q3), and fourth (Q4) quarters subsequent to the tweeting quarter. The average abnormal performance of the tweeting funds is also negative in the quarter prior to the tweeting quarter. Overall, the results suggest that hedge funds time their portfolio stock tweets in quarters when the overall fund performance is good. However, the fund does not maintain the good performance after the tweeting quarter.

The second row shows the average abnormal performance of the matched non-tweeting funds as a comparison. Non-tweeting funds' abnormal performance in Q1 is -9.31 basis points. Their cumulative abnormal returns are -2.30, -0.21, and -6.08 basis points for Q2, Q3, and Q4, respectively. Comparing the performance of the tweeting funds and the matched non-tweeting funds, I find that while both samples experience a negative performance in the post-tweeting quarters, the performance of tweeting funds is more negative in general (though insignificant) than that of non-tweeting funds. Note that, in the tweeting quarter, the performance of the matched non-tweeting funds is similar to that of tweeting funds by construction. In sum, the results show that the overall performance of

[28] The bond-trend following factor, currency-trend following factor, and commodity-trend following factor are available from David Hsieh's Data Library https://people.duke.edu/~dah7/HFRFData.htm

tweeting funds is not as good as that of their tweeted stocks. Thus, it appears that investors do not gain by investing in the tweeting funds following the tweets. In other words, investors' perception of the hedge fund's stock-picking ability indicated by the portfolio stock tweets is not realized.

### 4.6 Robustness Checks

I perform a battery of tests on the main results of this paper which are reported in Tables 11 and 12. In Table 11, I provide robustness checks on the results of differences in abnormal returns between tweeted portfolio stocks and non-tweeted portfolio stocks over different horizons, and they remain robust in all the following scenarios. Panel A (panel B) reports results for tweeted portfolio stocks with positive (non-positive) mentions. In Panel (1), I exclude stock-quarters that only have retweets and/or replies; in Panel (2), I exclude hedge funds that jointly file their 13F with other investment advisers; in Panel (3), I exclude quarterly 13Fs filed by hedge funds that changed their name during the sample period; in Panel (4), I exclude hedge funds that are based outside the U.S. (five from the U.K. and two from Canada) and only include hedge funds whose headquarters are in the U.S.; in Panel (5), I exclude hedge funds whose Twitter usernames are the funds but display names are the CEOs; in Panel (6), I exclude a handful of hedge funds that conduct other businesses in addition to being hedge funds and only include pure-play hedge funds in my sample. In Table 12, I provide robustness checks on the results of regression (3) showing the association between portfolio stock tweets and fund flows. Similar to Table 11, I exclude retweets and/or replies in column (1), joint filers in column (2), name changers in column (3), non-U.S. funds in column (4), CEO display names in column (5), and conglomerate funds in column (6). The results of fund flows remain robust in all the above scenarios.

## 5. Conclusion

In this paper, I examine how hedge funds respond to a recent regulatory change that lifted the long- time ban on general solicitation and general advertising. I study hedge funds' use of Twitter to make disclosures about selected stocks. I first examine whether hedge funds' positive or non- positive mentions of the tweeted stocks are consistent with the subsequent performance of these stocks. I find that hedge funds' tweeted stocks with positive mentions earn positive and significant abnormal returns up to twelve months from the tweet date. However, I find that abnormal returns are also significantly positive for tweeted stocks with non-positive mentions. It thus appears that hedge funds' mentions of tweeted stocks are unable to differentiate stocks with future positive or non-positive performance. In fact, it appears that their perceptions of tweeted stocks are simply based on historical information.

While there is no evidence of stock-picking ability for tweeted stocks in general, I examine whether hedge funds' tweets of their portfolio stocks are predictive of the future performance of these stocks. I find that subsequent abnormal returns of tweeted portfolio stocks with positive mentions are significantly higher relative to a sample of non-tweeted portfolio stocks. The difference translates into an economically meaningful magnitude and suggests that hedge funds may be "cherry-picking" portfolio stocks that are expected to perform well to include in their tweets.

If the portfolio stock tweets persuade investors of hedge funds' stock-picking ability, I expect that investors will react to the tweets and will increase fund flows to the tweeting hedge fund. I find a positive and significant market reaction to portfolio stock tweets with positive mentions and insignificant reaction to tweets with non-positive mentions. Further, I find that hedge funds obtain more flows from investors in the tweeting quarter and one quarter subsequent to it. Difference in differences analysis also indicates higher fund flows for the tweeting funds relative to a control sample of non-tweeting funds matched on size and performance. While this result suggests that investors perceive tweeting hedge funds to be of high quality, I do not find an improvement in the tweeting hedge funds' performance after the tweet; their abnormal performance in the post-tweeting quarters is lower than that of the non-tweeting hedge funds in general. Thus, it appears that investors do not gain by investing in the tweeting funds following the tweets.

This paper makes several contributions to the literature. First, I contribute to research on hedge fund communication. Due to the unique nature of hedge funds, private communication is the dominating industry practice and research on the public communication by hedge funds is limited. I address this gap in the literature by providing early evidence on hedge funds' voluntary disclosures after the JOBS Act of 2012. Second, I contribute to the research on firms' use of social media to achieve their goals. Consistent with existing literature which finds that investors react to useful social media information, I show that information on portfolio stocks tweeted by hedge funds elicits investor response in the form of additional fund flows. Third, I contribute to the research on disclosures of portfolio stocks by hedge funds in a voluntary setting. I find that hedge funds exploit the discretion allowed by the JOBS Act by tweeting information about selected good-performing stocks from their portfolios to the detriment of investors.

I note some caveats to my study. First, although the ban on general solicitation is lifted, not many hedge funds use stock tweets to advertise or attract investors.[29] Thus, my evidence is based on a small subset of the hedge fund industry. Second, the tweeting hedge

[29] Although few in number, two-thirds of the stock tweeting hedge funds fall in the top tercile of AUM within my sample of SEC registered hedge funds.

funds in my sample send tweets for only a small number of stocks in their portfolio. In ongoing work, I intend to extend my analyses to other social media platforms besides Twitter in order to obtain a larger sample, more powerful tests, and more generalizable results.

**Figure 1 Comparing Different Groups of Stocks**

The following figure illustrates different groups of stocks in this paper. The circle on left represents tweeted stocks. The circle on the right represents tweeting hedge funds' 13F portfolio stocks. At the intersection of the two circles is tweeted portfolio stocks.

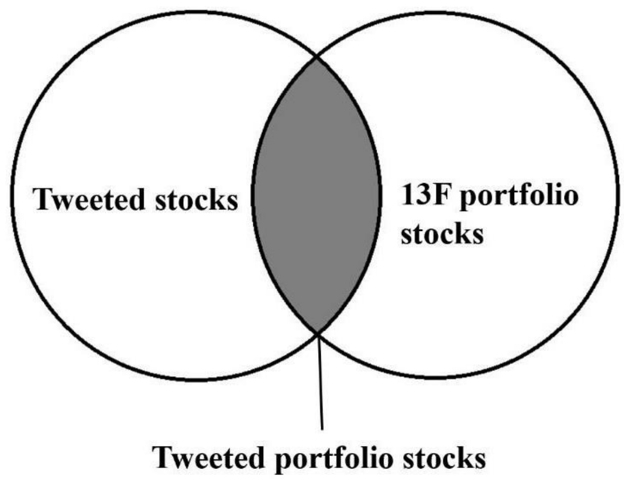

**Table 1 Stock Tweets**

Panel A of this table reports the yearly frequency of stock tweets posted by hedge funds during the sample period. The number of tweets in 2013 excludes the first and second quarters that are prior to the sample period. Panel B and C present the number of stock tweets by quarter and tone.

| | **# of tweets** | **Yearly percentage (%)** |
|---|---|---|
| **Total** | **1,074** | **100.0** |
| ***Panel A: Stock Tweets By Year*** | | |
| 2013 | 22 | 2.1 |
| 2014 | 110 | 10.2 |
| 2015 | 75 | 7.0 |
| 2016 | 171 | 15.9 |
| 2017 | 226 | 21.0 |
| 2018 | 179 | 16.7 |
| 2019 | 158 | 14.7 |
| 2020 | 133 | 12.4 |
| ***Panel B: Stock Tweets By Quarter*** | | |
| Q1 | 256 | 23.8 |
| Q2 | 294 | 27.4 |
| Q3 | 250 | 23.3 |
| Q4 | 274 | 25.5 |
| ***Panel C: Stock Tweets by Tone*** | | |
| Positive | 209 | 19.5 |
| Non-positive | 865 | 80.5 |

**Table 2 Summary Statistics: Tweeted Stocks**

Panel A of this table tabulates the industry distribution of the tweeted stocks. Panel B provides summary statistics on the characteristics of tweeted stocks and comparisons with the stocks from the Compustat-CRSP universe during the sample period. Multiple tweets on the same stock from the same hedge funds in a quarter are considered one observation. Tweets on one stock from the same hedge funds across quarters are considered different observations. There are also limited number of situations when a stock is tweeted by more than one hedge fund during the same quarter, which are considered different observations. Panel C compares the characteristics of tweeted stocks with positive mentions and those with non-positive mentions. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level for the mean difference t-tests. Variable definitions can be found in Appendix 1.

**Panel A: Industry Distribution of Tweeted Stocks (two-digit SIC)**

| **Industry** | **# of tweeted stocks** | **Percentage (%)** |
|---|---|---|
| Mining & Construction | 15 | 2.7 |
| Manufacturing | 127 | 22.4 |
| Transportation & Public Utilities | 57 | 10.1 |
| Wholesale & Retail Trade | 52 | 9.2 |
| Finance, Insurance, Real Estate | 222 | 39.3 |
| Services | 91 | 16.1 |
| Public Administration | 1 | 0.2 |
| **Total** | 565 | 100.0 |

**Panel B: Characteristics of Tweeted Stocks**

| | | Tweeted stocks | | Compustat/CRSP | | Mean Diff. |
|---|---|---|---|---|---|---|
| | N | Mean | Median | Mean | Median | Test |
| Size (in millions) | 565 | 87220.9 | 8313.0 | 7023.6 | 777.7 | 80197.3*** |
| B/M | 565 | 0.65 | 0.48 | 0.63 | 0.48 | 0.02 |
| ROA | 565 | 0.0002 | 0.004 | -0.017 | 0.003 | 0.017 |
| Volatility | 565 | 0.10 | 0.08 | 0.13 | 0.10 | -0.02*** |
| Recent Performance | 565 | -0.002 | -0.004 | 0.002 | -0.01 | -0.004 |
| Illiquidity | 565 | 0.003 | 0.0002 | 2.35 | 0.07 | -2.35*** |
| Momentum | 545 | 0.07 | -0.01 | -0.002 | -0.06 | 0.07** |

**Panel C: Characteristics of Tweeted Stocks – Positive Mentions v. Non-Positive Mentions**

| | Positive Mentions | | Non-positive Mentions | | Mean Diff. |
|---|---|---|---|---|---|
| | Mean | Median | Mean | Median | Test |
| Size (in millions) | 119871.5 | 9366.3 | 75632.6 | 7730.8 | 44238.9** |
| B/M | 0.57 | 0.42 | 0.68 | 0.49 | -0.11 |
| ROA | 0.012 | 0.009 | -0.004 | 0.003 | 0.016 |
| Volatility | 0.097 | 0.086 | 0.103 | 0.082 | -0.007 |
| Recent Performance | 0.015 | 0.011 | -0.008 | -0.007 | 0.022 |
| Illiquidity | 0.0029 | 0.0002 | 0.0033 | 0.0002 | -0.0004 |
| Momentum | 0.11 | 0.05 | 0.06 | -0.03 | 0.05 |
| N | 148 | | 417 | | |

**Table 3 Tweeted Stocks and the Stock-Picking Ability of Hedge Funds**

This table reports the abnormal returns of tweeted stocks with positive/non-positive mentions. The abnormal returns are measured using the Fama-French (1993) and Carhart (1997) alphas. Daily alphas (in percentage points) are calculated by running regressions over horizons of different lengths (e.g., three months, six months, nine months, twelve months) starting from the first date after the tweets. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level for the signed t-tests.

**Panel A: Tweeted Stocks with Positive Mentions**

| | **Return Horizons** | | | | |
|---|---|---|---|---|---|
| | **-3m (pre)** | **3m** | **6m** | **9m** | **12m** |
| *Fama-French Alphas* | | | | | |
| Daily abnormal returns | **0.0600**** | **0.0398*** | **0.0328**** | **0.0329***** | **0.0272***** |
| Annualized abnormal returns | 15.12% | 10.03% | 8.27% | 8.29% | 6.85% |
| p-value (alpha > 0) | 0.013 | 0.083 | 0.031 | 0.006 | 0.006 |
| # of tweeted stocks | 148 | 148 | 147 | 147 | 147 |
| | | | | | |
| *Carhart Alphas* | | | | | |
| Daily abnormal returns | **0.0537**** | **0.0429*** | **0.0351**** | **0.0330***** | **0.0274***** |
| Annualized abnormal returns | 13.53% | 10.81% | 8.85% | 8.32% | 6.90% |
| p-value (alpha > 0) | 0.023 | 0.084 | 0.023 | 0.007 | 0.007 |
| # of tweeted stocks | 148 | 148 | 147 | 147 | 147 |

**Panel B: Tweeted Stocks with Non-Positive Mentions**

| | Return Horizons | | | | |
|---|---|---|---|---|---|
| | **-3m (pre)** | **3m** | **6m** | **9m** | **12m** |
| *Fama-French Alphas* | | | | | |
| Daily abnormal returns | **-0.0307*** | **0.0311**** | **0.0332***** | **0.0398***** | **0.0362***** |
| Annualized abnormal returns | -7.74% | 7.84% | 8.37% | 10.03% | 9.12% |
| p-value (alpha < 0) | 0.055 | 0.968 | 0.999 | 1.000 | 1.000 |
| p-value (diff. pos v. non-pos) | **0.006** | 0.395 | 0.507 | 0.652 | 0.729 |
| # of tweeted stocks | 417 | 417 | 417 | 417 | 413 |
| | | | | | |
| *Carhart Alphas* | | | | | |
| Daily abnormal returns | **-0.0324**** | **0.0312**** | **0.0313***** | **0.0384***** | **0.0338***** |
| Annualized abnormal returns | -8.16% | 7.86% | 7.89% | 9.68% | 8.52% |
| p-value (alpha < 0) | 0.049 | 0.968 | 0.997 | 1.000 | 1.000 |
| p-value (diff. pos v. non-pos) | **0.009** | 0.365 | 0.429 | 0.616 | 0.663 |
| # of tweeted stocks | 417 | 417 | 417 | 417 | 413 |

**Table 4 Tweeted Portfolio Stocks v. Non-Tweeted Portfolio Stocks**

Panel A provides summary statistics on the characteristics of tweeted portfolio stocks and non-tweeted portfolio stocks of hedge funds that tweet. Panel B provides the multivariate results. The dependent variable is an indicator that takes a value of 1 is a tweeted stock is owned by the tweeting hedge fund during the tweeting quarter. The stock characteristics of interest include Top10, B/M, Volatility, Size, Recent Performance, ROA, Illiquidity, and Momentum. Standard errors for the regressions are clustered at the stock level. Industry and quarter fixed effects (dummies) are included. Panel C compares the characteristics of tweeted portfolio stocks with positive mentions and those with non-positive mentions. Variable definitions can be found in Appendix 1. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level.

**Panel A: Characteristics of Tweeted Portfolio Stocks and Non-tweeted Portfolio Stocks**

| | Tweeted Port. Stocks | | Non-tweeted Port. Stocks | | Mean Diff. |
|---|---|---|---|---|---|
| | Mean | Median | Mean | Median | Test |
| Top 10 | 0.43 | 0.00 | 0.02 | 0.00 | 0.41*** |
| B/M | 0.50 | 0.38 | 0.48 | 0.36 | 0.03 |
| Volatility | 0.09 | 0.08 | 0.10 | 0.08 | 0.00 |
| Size (in millions) | 196,203 | 34,066 | 28,829 | 4,868 | 167,373*** |
| Recent Performance | 0.03 | 0.01 | 0.02 | 0.00 | 0.01 |
| ROA | 0.02 | 0.01 | 0.01 | 0.01 | 0.01** |
| Illiquidity | 0.002 | ~0.000 | 0.020 | ~0.000 | -0.018 |
| Momentum | 0.15 | 0.06 | 0.08 | 0.02 | 0.07* |
| N | 157 | | 164,148 | | |

**Panel B: Multivariate Results – Characteristics of Tweeted Portfolio Stocks**

| | DV=**1**(Tweeted Portfolio Stocks) | |
|---|---|---|
| | (1) | (2) |
| Top10 | 0.019*** | 2.816*** |
| | (0.003) | (0.350) |
| B/M | 0.001*** | 0.669** |
| | (0.000) | (0.262) |
| Volatility | 0.018*** | 13.83*** |
| | (0.004) | (2.487) |
| Log(size) | 0.0006*** | 0.453*** |
| | (0.000) | (0.116) |
| Recent Performance | -0.0004 | -0.212 |
| | (0.001) | (0.479) |
| ROA | 0.006 | 6.647* |
| | (0.004) | (4.035) |
| Illiquidity | 0.005** | -0.607 |
| | (0.003) | (4.472) |
| Momentum | 0.0001 | 0.110 |
| | (0.000) | (0.286) |
| Estimation Method | OLS | Logit |
| Industry & Quarter | Yes | Yes |
| Adjusted/Pseudo $R^2$ | 0.01 | 0.19 |
| Observations | 137,861 | 120,259 |

**Panel C: Characteristics of Tweeted Portfolio Stocks – Positive/Non-positive Mentions**

| | Positive Mentions | | Non-positive Mentions | | Mean Diff. |
|---|---|---|---|---|---|
| | Mean | Median | Mean | Median | Test |
| Top 10 | 0.49 | 0.00 | 0.36 | 0.00 | 0.13* |
| B/M | 0.49 | 0.38 | 0.52 | 0.39 | -0.03 |
| Volatility | 0.10 | 0.09 | 0.09 | 0.08 | 0.01* |
| Size (in millions) | 190,238 | 13,520 | 203,244 | 76,612 | -13,006 |
| Recent Performance | 0.029 | 0.014 | 0.034 | 0.013 | -0.005 |
| ROA | 0.017 | 0.010 | 0.017 | 0.016 | 0.000 |
| Illiquidity | 0.001 | 0.0001 | 0.003 | ~0.000 | -0.002 |
| Momentum | 0.18 | 0.08 | 0.11 | 0.05 | 0.07 |
| N | 85 | | 72 | | |

**Table 5 Stock Performance: Tweeted Portfolio Stocks v. Non-Tweeted Portfolio Stocks**

This table compares the abnormal returns of tweeted portfolio stocks and non-tweeted portfolio stocks of hedge funds that tweet. The abnormal returns are measured using the Fama-French (1993) and Carhart (1997) alphas. Daily alphas (in percentage points) are calculated by running regressions over horizons of different lengths assuming the holdings at the beginning of the quarter when the tweets are posted. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level for the signed t-tests.

**Panel A: Tweeted Portfolio Stocks with Positive Mentions**

| | **Return Horizons** | | | |
|---|---|---|---|---|
| | **3m** | **6m** | **9m** | **12m** |
| *Daily Fama-French Alphas* | | | | |
| Tweeted port. stocks | **0.0868*** ** | **0.0425** ** | **0.0358** ** | **0.0340** ** |
| Non-tweeted port. stocks | 0.0120*** | 0.0066*** | 0.0077*** | 0.0038*** |
| Difference in mean | **0.0748*** ** | **0.0359** ** | **0.0281** ** | **0.0302** ** |
| Annualized - tweeted stocks | 21.87% | 10.71% | 9.02% | 8.57% |
| Annualized - non-tweeted | 3.02% | 1.66% | 1.94% | 0.96% |
| Annualized diff. in mean | 18.85% | 9.05% | 7.08% | 7.61% |
| p-value (diff. > 0) | 0.005 | 0.044 | 0.045 | 0.018 |
| # of tweeted portfolio stocks | 85 | 85 | 85 | 85 |
| # of non-tweeted port. stocks | 6,586 | 6,603 | 6,569 | 6,535 |
| | | | | |
| *Daily Carhart Alphas* | | | | |
| Tweeted port. stocks | **0.0839*** ** | **0.0415** ** | **0.0347** ** | **0.0326** ** |
| Non-tweeted port. stocks | 0.0081*** | 0.0041** | 0.0052*** | 0.0027** |
| Difference in mean | **0.0758*** ** | **0.0374** ** | **0.0295** ** | **0.0299** ** |
| Annualized - tweeted stocks | 21.14% | 10.46% | 8.74% | 8.22% |
| Annualized - non-tweeted | 2.04% | 1.03% | 1.31% | 0.68% |
| Annualized diff. in mean | 19.10% | 9.42% | 7.43% | 7.53% |
| p-value (diff. > 0) | 0.004 | 0.039 | 0.041 | 0.021 |
| # of tweeted portfolio stocks | 85 | 85 | 85 | 85 |

| | | | | |
|---|---|---|---|---|
| # of non-tweeted port. stocks | 6,586 | 6,603 | 6,569 | 6,535 |

**Panel B: Tweeted Portfolio Stocks with Non-Positive Mentions**

| | Return Horizons | | | |
|---|---|---|---|---|
| | **3m** | **6m** | **9m** | **12m** |
| *Daily Fama-French Alphas* | | | | |
| Tweeted port. stocks | **0.0073** | **0.0172** | **0.0163** | **0.0128** |
| Non-tweeted port. stocks | 0.0120*** | 0.0066*** | 0.0077*** | 0.0038*** |
| Difference in mean | **-0.0047** | **0.0105** | **0.0087** | **0.0090** |
| Annualized - tweeted stocks | 1.84% | 4.33% | 4.11% | 3.23% |
| Annualized - non-tweeted | 3.02% | 1.66% | 1.94% | 0.96% |
| Annualized diff. in mean | -1.18% | 2.67% | 2.17% | 2.27% |
| p-value (diff. > 0) | 0.560 | 0.322 | 0.314 | 0.284 |
| p-value (diff. pos v. non-pos) | 0.051 | 0.188 | 0.209 | 0.141 |
| # of tweeted portfolio stocks | 72 | 72 | 72 | 72 |
| # of non-tweeted port. stocks | 6,586 | 6,603 | 6,569 | 6,535 |
| | | | | |
| *Daily Carhart Alphas* | | | | |
| Tweeted port. stocks | **0.0078** | **0.0142** | **0.0132** | **0.0099** |
| Non-tweeted port. stocks | 0.0081*** | 0.0041** | 0.0052*** | 0.0027** |
| Difference in mean | **-0.0003** | **0.0100** | **0.0080** | **0.0071** |
| Annualized - tweeted stocks | 1.97% | 3.58% | 3.33% | 2.49% |
| Annualized - non-tweeted | 2.04% | 1.03% | 1.31% | 0.68% |
| Annualized diff. in mean | -0.08% | 2.55% | 2.02% | 1.81% |
| p-value (diff. > 0) | 0.504 | 0.331 | 0.332 | 0.327 |
| p-value (diff. pos v. non-pos) | 0.059 | 0.179 | 0.191 | 0.129 |
| # of tweeted portfolio stocks | 72 | 72 | 72 | 72 |
| # of non-tweeted port. stocks | 6,586 | 6,603 | 6,569 | 6,535 |

**Table 6 Tweeted Portfolio Stocks and Trading Activities**

This table reports the changes in hedge funds' positions in tweeted portfolio stocks during the tweeting quarter (3m) and in quarters following the tweeting quarter (6m, 9m, 12m) relative to the beginning of the tweeting quarter.

| | Return Horizons | | | |
|---|---|---|---|---|
| | 3m | 6m | 9m | 12m |
| *Positive mentions* | | | | |
| Increase | 45 (53%) | 32 (38%) | 29 (34%) | 24 (28%) |
| No change | 3 (4%) | 7 (8%) | 7 (8%) | 7 (8%) |
| Decrease | 37 (44%) | 46 (54%) | 49 (58%) | 54 (64%) |
| # of tweeted port. stocks | 85 | 85 | 85 | 85 |
| | | | | |
| *Non-positive mentions* | | | | |
| Increase | 33 (46%) | 30 (42%) | 24 (33%) | 22 (31%) |
| No change | 4 (6%) | 6 (8%) | 8 (11%) | 10 (14%) |
| Decrease | 35 (49%) | 36 (50%) | 40 (56%) | 40 (56%) |
| # of tweeted port. stocks | 72 | 72 | 72 | 72 |

**Table 7 Market Reaction to the Tweeted Portfolio Stocks**

This table reports cumulative abnormal returns (CARs) around the event date when hedge funds tweet their portfolio stocks. The abnormal returns are calculated using the market model (CAPM) and market-adjusted model (in excess of the CRSP value-weighted market returns) with an estimation window from 300 to 91 days prior to the event date. Tweets that fall within [-5, +5] days of earnings press releases, share repurchases, M&As, and IPOs of the tweeted stocks are excluded from this test. The number of observations in the table refers to the number of events when a hedge fund mentions a portfolio stock in the tweets. Standard errors of the t-tests are in the parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level.

**Panel A: Tweeted Portfolio Stocks with Positive Mentions**

| | **Market Model** | | **Market-Adjusted Return** | |
|---|---|---|---|---|
| **Windows** | Number | Mean CAR | Number | Mean CAR |
| **[0,0]** | 83 | 0.0058** | 83 | 0.0058** |
| | | (0.0026) | | (0.0026) |
| **[0,2]** | 83 | 0.0088** | 83 | 0.0103*** |
| | | (0.0034) | | (0.0034) |
| **[0,5]** | 83 | 0.0077 | 83 | 0.0094 |
| | | (0.0089) | | (0.0089) |

**Panel B: Tweeted Portfolio Stocks with Non-Positive Mentions**

| | **Market Model** | | **Market-Adjusted Return** | |
|---|---|---|---|---|
| **Windows** | Number | Mean CAR | Number | Mean CAR |
| **[0,0]** | 83 | 0.0025 | 83 | 0.0032 |
| | | (0.0035) | | (0.0035) |
| **[0,2]** | 83 | 0.0017 | 83 | 0.0039 |
| | | (0.0039) | | (0.0036) |
| **[0,5]** | 83 | -0.0017 | 83 | 0.0037 |
| | | (0.0053) | | (0.0047) |

**Table 8 Summary Statistics: Fund Characteristics**

Panel A of this table provides summary statistics on the characteristics of tweeting hedge funds during the tweeting quarters and comparisons with funds from the Lipper TASS universe during the sample period. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level for the mean difference t-tests. Panel B provides summary statistics at fund-quarter level.

**Panel A: Characteristics of Tweeting Hedge Funds**

| | | Tweeting Funds | | TASS Funds | | Mean Diff. |
|---|---|---|---|---|---|---|
| | N | Mean | Median | Mean | Median | Test |
| Size (millions) | 61 | 390.3 | 10.2 | 326.4 | 28.8 | 63.9 |
| Age (years) | 61 | 12.3 | 10.4 | 8.5 | 7.6 | 3.8*** |
| Total Restrictions (days) | 61 | 165.4 | 78.0 | 177.6 | 75.0 | -12.2 |
| Management Fees (%) | 61 | 1.3 | 1.25 | 1.4 | 1.5 | -0.1* |
| Incentive Fees (%) | 61 | 15.2 | 20 | 13.6 | 20 | 1.6** |
| Highwater Mark | 61 | 0.44 | 0.00 | 0.57 | 1.00 | -0.13*** |
| Leveraged | 61 | 0.49 | 0.00 | 0.47 | 0.00 | 0.02 |

**Panel B: Fund-quarter Summary Statistics**

| | N | Mean | Std Dev. | $10^{th}$%ile | Median | $90^{th}$ %ile |
|---|---|---|---|---|---|---|
| *Treatment funds* | | | | | | |
| Fund Flows | 1036 | -0.04 | 0.14 | -0.16 | -0.02 | 0.03 |
| Stock Tweeting Quarters | 1036 | 0.17 | 0.38 | 0.00 | 0.00 | 1.00 |
| Other Tweeting Quarters | 1036 | 0.83 | 0.38 | 0.00 | 1.00 | 1.00 |
| FRank1 | 1036 | 0.27 | 0.10 | 0.09 | 0.33 | 0.33 |
| FRank2 | 1036 | 0.14 | 0.15 | 0.00 | 0.08 | 0.33 |
| FRank3 | 1036 | 0.06 | 0.10 | 0.00 | 0.00 | 0.24 |
| Total Tweets | 1036 | 48.09 | 146.61 | 0.00 | 8.00 | 67.00 |
| Size (in millions) | 1036 | 1201.77 | 6115.49 | 1.08 | 12.57 | 420.00 |
| Age (in years) | 1036 | 11.81 | 5.30 | 6.00 | 11.33 | 17.83 |
| | | | | | | |
| *Control funds* | | | | | | |
| Fund Flows | 538 | -0.01 | 0.10 | -0.08 | -0.01 | 0.04 |
| FRank1 | 538 | 0.27 | 0.11 | 0.07 | 0.33 | 0.33 |
| FRank2 | 538 | 0.17 | 0.15 | 0.00 | 0.17 | 0.33 |
| FRank3 | 538 | 0.06 | 0.11 | 0.00 | 0.00 | 0.26 |
| Size (in millions) | 538 | 387.02 | 1236.26 | 5.15 | 65.51 | 378.66 |
| Age (in years) | 538 | 14.06 | 5.68 | 7.17 | 13.71 | 21.00 |

**Table 9 Fund Flows and Portfolio Stock Tweets**

Panel A analyzes the effect of hedge funds' portfolio stock tweets on fund flows. The dependent variable, Fund Flows, is a continuous variable that measures a fund's net flows at the quarterly level. The independent variable, Stock Tweeting Quarters, is an indicator variable that takes a value of 1 for quarters when a hedge fund tweets on a portfolio stock. The subsequent quarter is also assigned a value of 1 to allow time for investors to adjust their portfolio decisions. Control variables include Other Tweeting Quarters, fund performance in the past quarter (the FRank measures), Log(size), Log(age), the total number of tweets, the use of other social media, and the use of traditional media by the funds. Panel B analyzes the persistence of the effect of hedge funds' portfolio stock tweets on fund flows. *Post2*, *Post3*, *Post4*, are indicator variables that take a value of 1 for the second, third, and fourth quarters after a stock tweeting quarter. Portfolio stock tweets with overlapping pre-tweeting period (-3, -2, -1) and post-tweeting period (+2, +3, +4) are excluded from this test. Variable definitions can be found in Appendix 1. Standard errors are clustered at the fund level. Fund fixed effects and style-quarter fixed effects are included in all specifications. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level.

**Panel A: Fund Flows and Portfolio Stock Tweets – Tweeting Quarters**

| | (1) | (2) | (3) |
|---|---|---|---|
| Stock Tweeting Quarters | 0.056*** | 0.054*** | -0.009 |
| | (0.019) | (0.019) | (0.029) |
| Other Tweeting Quarters | | -0.008 | |
| | | (0.038) | |
| Stock Quarters X Tweeting Funds | | | 0.041** |
| | | | (0.017) |
| FRank1 | 0.213** | 0.413** | 0.071 |
| | (0.098) | (0.179) | (0.072) |
| FRank2 | 0.050 | -0.193 | 0.026 |
| | (0.054) | (0.124) | (0.040) |
| FRank3 | -0.030 | 0.078 | 0.010 |
| | (0.051) | (0.125) | (0.036) |
| Log (size) | 0.050*** | 0.053*** | 0.062*** |
| | (0.018) | (0.017) | (0.018) |
| Log (age) | -0.091** | -0.091** | -0.109*** |
| | (0.040) | (0.037) | (0.041) |
| | | | |
| Stock Tweeting Quarters X FRank | Yes | Yes | Yes |
| Other Tweeting Quarters X FRank | No | Yes | No |
| Fund FE | Yes | Yes | Yes |
| Style X Quarter FE | Yes | Yes | Yes |
| Log (# of tweets) | Yes | Yes | No |
| Traditional Media | Yes | Yes | No |
| Other Social Media | Yes | Yes | No |

| | | | |
|---|---|---|---|
| Adjusted $R^2$ | 0.20 | 0.20 | 0.18 |
| Observations | 992 | 992 | 1,540 |

**Panel B: Fund Flows and Portfolio Stock Tweets – Post-Tweeting Quarters**

| | (1) | (2) | (3) |
|---|---|---|---|
| Stock Tweeting Quarters | 0.051** | 0.050** | -0.003 |
| | (0.020) | (0.020) | (0.032) |
| Post2 | 0.075 | 0.071 | 0.041 |
| | (0.047) | (0.045) | (0.071) |
| Post3 | 0.084 | 0.089 | 0.075* |
| | (0.076) | (0.078) | (0.040) |
| Post4 | -0.025 | -0.022 | 0.039 |
| | (0.047) | (0.045) | (0.049) |
| Stock Quarters X Tweeting Funds | | | 0.036* |
| | | | (0.020) |
| Post2 X Tweeting Funds | | | -0.039 |
| | | | (0.031) |
| Post3 X Tweeting Funds | | | -0.081* |
| | | | (0.044) |
| Post4 X Tweeting Funds | | | -0.030* |
| | | | (0.017) |
| FRank1 | 0.292** | 0.407* | 0.118 |
| | (0.123) | (0.225) | (0.085) |
| FRank2 | -0.001 | -0.194 | 0.004 |
| | (0.093) | (0.155) | (0.050) |
| FRank3 | -0.007 | 0.112 | -0.009 |
| | (0.087) | (0.144) | (0.047) |
| Log (size) | 0.052** | 0.054*** | 0.063*** |
| | (0.019) | (0.018) | (0.020) |
| Log (age) | -0.090** | -0.090** | -0.117** |
| | (0.039) | (0.037) | (0.044) |
| Post X FRank | Yes | Yes | Yes |
| Stock Tweeting Quarters X FRank | Yes | Yes | Yes |
| Other Tweeting Quarters | No | Yes | No |
| Other Tweeting Quarters X FRank | No | Yes | No |
| Fund FE | Yes | Yes | Yes |
| Style X Quarter FE | Yes | Yes | Yes |
| Log (# of tweets) | Yes | Yes | No |
| Traditional Media | Yes | Yes | No |
| Other Social Media | Yes | Yes | No |
| Adjusted $R^2$ | 0.19 | 0.19 | 0.16 |
| Observations | 740 | 740 | 1,262 |

**Table 10 Hedge Fund Performance and Stock Tweeting Behavior**

This table reports the abnormal returns of tweeting hedge funds around the tweeting quarters. The abnormal returns are measured using the Fung and Hsieh (2001, 2004) seven-factor alphas. Monthly alphas are calculated by running rolling regressions. Q0 represents the tweeting quarters and Q1 is the first quarter after a tweeting quarter. Q(-1) is the first quarter before a tweeting quarter. The abnormal returns shown in the Q2 column are the average monthly returns of Q1 and Q2 (i.e., cumulative starting from Q1). Calculations are similar for other quarters. Matched non-tweeting funds for comparison are selected based on these criteria: (1) Fund size falls within [75%, 125%] of the tweeting fund; (2) fund performance is closest to that of the tweeting fund at the beginning of the tweeting quarter; (3) fund style is the same as that of the tweeting fund. The number of observations in this table is at the fund-quarter level (i.e., a fund posting tweets in different quarters are considered different observations). *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level for the signed t-tests.

| | **Return Horizons** | | | | | |
|---|---|---|---|---|---|---|
| | **Q(-1)** | **Q0** | **Q1** | **Q2** | **Q3** | **Q4** |
| *Monthly Fung & Hsieh Alphas* | | | | | | |
| Tweeting Funds | **-0.4246*** ** | **0.1682** | **-0.1140** | **-0.0245** | **-0.1352** ** | **-0.0599** |
| Non-tweeting Funds | -0.2580* | 0.1620 | -0.0931 | -0.0230 | -0.0021 | -0.0608 |
| Difference in mean | **-0.1665** | **0.0062** | **-0.0208** | **-0.0015** | **-0.1331** | **0.0009** |
| Annualized differences | -2.00% | 0.074% | -0.250% | -0.018% | -1.597% | 0.011% |
| P-value (tweeting funds > 0) | 0.998 | 0.129 | 0.786 | 0.597 | 0.983 | 0.813 |
| P-value (non-tweeting funds > 0) | 0.920 | 0.200 | 0.688 | 0.567 | 0.508 | 0.770 |
| P-value (diff.>0) | 0.754 | 0.490 | 0.535 | 0.504 | 0.883 | 0.497 |
| # of observations (tweeting) | 206 | 208 | 190 | 178 | 174 | 169 |
| # of observations (non-tweeting) | 113 | 109 | 104 | 101 | 100 | 97 |

**Table 11 Stock Performance – Robustness**

This table compares the abnormal returns of tweeted portfolio stocks and non-tweeted portfolio stocks of hedge funds that tweet and provides robustness checks of the results in Table 5. The abnormal returns are measured using the Carhart (1997) alphas. Daily alphas (in percentage points) are calculated by running regressions over horizons of different lengths assuming the holdings at the beginning of the quarter when the tweets are posted. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level for the signed t-tests.

**Panel A: Tweeted Portfolio Stocks with Positive Mentions**

| | **Return Horizons** | | | |
|---|---|---|---|---|
| | **3m** | **6m** | **9m** | **12m** |
| *(1) Exclude retweets and replies* | | | | |
| Tweeted port. stocks | **0.0888*** ** | **0.0531** ** | **0.0409*** ** | **0.0383*** ** |
| Non-tweeted port. stocks | -0.0024 | -0.0022 | 0.0019 | 0.0005 |
| Difference in mean | **0.0912*** ** | **0.0553** ** | **0.0390** ** | **0.0378** ** |
| # of tweeted portfolio stocks | 56 | 56 | 56 | 56 |
| # of non-tweeted port. stocks | 4,895 | 4,892 | 4,867 | 4,843 |
| | | | | |
| *(2) Exclude joint filers* | | | | |
| Tweeted port. stocks | **0.0884*** ** | **0.0405*** | **0.0393** ** | **0.0354** ** |
| Non-tweeted port. stocks | 0.0061* | 0.0033 | 0.0058*** | 0.0043** |
| Difference in mean | **0.0823*** ** | **0.0372*** | **0.0335** ** | **0.0311** ** |
| # of tweeted portfolio stocks | 78 | 78 | 78 | 78 |
| # of non-tweeted port. stocks | 5,372 | 5,369 | 5,342 | 5,315 |
| | | | | |
| *(3) Exclude name changers* | | | | |
| Tweeted port. stocks | **0.0751** ** | **0.0402*** | **0.0364*** | **0.0333** ** |
| Non-tweeted port. stocks | 0.0134*** | 0.0080*** | 0.0078*** | 0.0046** |
| Difference in mean | **0.0617** ** | **0.0322*** | **0.0287*** | **0.0287** ** |
| # of tweeted portfolio stocks | 70 | 70 | 70 | 70 |

| | | | | |
|---|---|---|---|---|
| # of non-tweeted port. stocks | 4,892 | 4,890 | 4,861 | 4,835 |
| | | | | |
| *(4) Exclude non-US funds* | | | | |
| Tweeted port. stocks | **0.1019*** ** | **0.0540** ** | **0.0412** ** | **0.0415*** ** |
| Non-tweeted port. stocks | 0.0101*** | 0.0080*** | 0.0081*** | 0.0059*** |
| Difference in mean | **0.0917*** ** | **0.0460** ** | **0.0331** ** | **0.0356** ** |
| # of tweeted portfolio stocks | 71 | 71 | 71 | 71 |
| # of non-tweeted port. stocks | 5,030 | 5,027 | 4,995 | 4,966 |
| | | | | |
| *(5) Exclude CEO display names* | | | | |
| Tweeted port. stocks | **0.1032** ** | **0.0406* ** | **0.0427** ** | **0.0340** ** |
| Non-tweeted port. stocks | 0.0053* | 0.0018 | 0.0018 | -0.0006 |
| Difference in mean | **0.0979*** ** | **0.0388* ** | **0.0409** ** | **0.0346** ** |
| # of tweeted portfolio stocks | 60 | 60 | 60 | 60 |
| # of non-tweeted port. stocks | 5,918 | 5,916 | 5,884 | 5,851 |
| | | | | |
| *(6) Exclude conglomerate funds* | | | | |
| Tweeted port. stocks | **0.0938*** ** | **0.0448** ** | **0.0342* ** | **0.0299** ** |
| Non-tweeted port. stocks | 0.0126*** | 0.0068*** | 0.0088*** | 0.0060*** |
| Difference in mean | **0.0813*** ** | **0.0381** ** | **0.0253* ** | **0.0239* ** |
| # of tweeted portfolio stocks | 76 | 76 | 76 | 76 |
| # of non-tweeted port. stocks | 4,508 | 4,506 | 4,485 | 4,464 |

**Panel B: Tweeted Portfolio Stocks with Non-Positive Mentions**

| | Return Horizons | | | |
|---|---|---|---|---|
| | **3m** | **6m** | **9m** | **12m** |
| *(1) Exclude retweets and replies* | | | | |
| Tweeted port. stocks | **0.0387** | **0.0010** | **0.0052** | **0.0033** |
| Non-tweeted port. stocks | -0.0024 | -0.0022 | 0.0019 | 0.0005 |
| Difference in mean | **0.0411** | **0.0032** | **0.0033** | **0.0029** |
| # of tweeted portfolio stocks | 50 | 50 | 50 | 50 |
| # of non-tweeted port. stocks | 4,895 | 4,892 | 4,867 | 4,843 |
| | | | | |
| *(2) Exclude joint filers* | | | | |
| Tweeted port. stocks | **0.0070** | **0.0157** | **0.0152** | **0.0198*** |
| Non-tweeted port. stocks | 0.0061* | 0.0033 | 0.0058*** | 0.0043** |
| Difference in mean | **0.0008** | **0.0124** | **0.0095** | **0.0155** |
| # of tweeted portfolio stocks | 57 | 57 | 57 | 57 |
| # of non-tweeted port. stocks | 5,372 | 5,369 | 5,342 | 5,315 |
| | | | | |
| *(3) Exclude name changers* | | | | |
| Tweeted port. stocks | **0.0067** | **0.0149** | **0.0135** | **0.0088** |
| Non-tweeted port. stocks | 0.0134*** | 0.0080*** | 0.0078*** | 0.0046** |
| Difference in mean | **-0.0068** | **0.0068** | **0.0057** | **0.0043** |
| # of tweeted portfolio stocks | 56 | 56 | 56 | 56 |
| # of non-tweeted port. stocks | 4,892 | 4,890 | 4,861 | 4,835 |
| | | | | |
| *(4) Exclude non-US funds* | | | | |
| Tweeted port. stocks | **0.0070** | **0.0310*** | **0.0210** | **0.0187** |
| Non-tweeted port. stocks | 0.0101*** | 0.0080*** | 0.0081*** | 0.0059*** |
| Difference in mean | **-0.0031** | **0.0230** | **0.0129** | **0.0128** |

| | | | | |
|---|---|---|---|---|
| # of tweeted portfolio stocks | 55 | 55 | 55 | 55 |
| # of non-tweeted port. stocks | 5,030 | 5,027 | 4,995 | 4,966 |
| | | | | |
| *(5) Exclude CEO display names* | | | | |
| Tweeted port. stocks | **0.0398** | **0.0112** | **0.0156** | **0.0123** |
| Non-tweeted port. stocks | 0.0053* | 0.0018 | 0.0018 | -0.0006 |
| Difference in mean | **0.0345** | **0.0095** | **0.0138** | **0.0129** |
| # of tweeted portfolio stocks | 45 | 45 | 45 | 45 |
| # of non-tweeted port. stocks | 5,918 | 5,916 | 5,884 | 5,851 |
| | | | | |
| *(6) Exclude conglomerate funds* | | | | |
| Tweeted port. stocks | **-0.0052** | **0.0052** | **0.0068** | **0.0006** |
| Non-tweeted port. stocks | 0.0126*** | 0.0068*** | 0.0088*** | 0.0060*** |
| Difference in mean | **-0.0178** | **-0.0015** | **-0.0021** | **-0.0054** |
| # of tweeted portfolio stocks | 65 | 65 | 65 | 65 |
| # of non-tweeted port. stocks | 4,508 | 4,506 | 4,485 | 4,464 |

**Table 12 Fund Flows – Robustness**

This table analyzes the effect of hedge funds' portfolio stock tweets on fund flows and provides robustness checks of the results in Table 9 Panel A column (1). The dependent variable, Fund Flows, is a continuous variable that measures a fund's net flows at the quarterly level. The independent variable, Stock Tweeting Quarters, is an indicator variable that takes a value of 1 for quarters when a hedge fund tweets on a portfolio stock. The subsequent quarter is also assigned a value of 1 to allow time for investors to adjust their portfolio decisions. Control variables include fund performance in the past quarter (the FRank measures), Log(size), Log(age), the total number of tweets, the use of other social media, and the use of traditional media by the funds. In column (1) of this table, I exclude stock-quarters that only have retweets and/or replies; in column (2), I exclude hedge funds that jointly file their 13F with other investment advisers; in column (3), I exclude hedge funds that change their names during the sample period; in column (4), I exclude non-US hedge funds; in column (5), I exclude hedge funds whose Twitter display names are the CEOs; in column (6), I exclude hedge funds that are part of a financial conglomerate. Variable definitions can be found in Appendix 1. Standard errors are clustered at the fund level. Fund fixed effects and style-quarter fixed effects are included in all specifications. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Stock Tweeting Quarters | 0.062*** | 0.054** | 0.083*** | 0.071** | 0.031** | 0.065*** |
| | (0.023) | (0.023) | (0.026) | (0.030) | (0.014) | (0.019) |
| FRank1 | 0.216** | 0.102 | 0.152 | 0.058 | 0.256** | 0.262** |
| | (0.099) | (0.095) | (0.158) | (0.133) | (0.108) | (0.097) |
| FRank2 | 0.043 | 0.082 | 0.117* | 0.097 | 0.075 | -0.077 |
| | (0.056) | (0.056) | (0.062) | (0.075) | (0.059) | (0.072) |
| FRank3 | -0.024 | -0.080* | -0.061 | -0.102* | -0.036 | 0.037 |
| | (0.054) | (0.043) | (0.055) | (0.057) | (0.060) | (0.062) |
| Log (size) | 0.050*** | 0.035 | 0.041** | 0.039 | 0.051*** | 0.060*** |
| | (0.018) | (0.023) | (0.019) | (0.037) | (0.018) | (0.012) |
| Log (age) | -0.089** | -0.129*** | -0.094** | -0.102** | -0.028 | -0.116*** |
| | (0.041) | (0.025) | (0.045) | (0.045) | (0.079) | (0.026) |
| | | | | | | |
| Stock Tweeting Qtrs X FRank | Yes | Yes | Yes | Yes | Yes | Yes |
| Fund FE | Yes | Yes | Yes | Yes | Yes | Yes |

| | | | | | | |
|---|---|---|---|---|---|---|
| Style X Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Log (# of tweets) | Yes | Yes | Yes | Yes | Yes | Yes |
| Traditional Media | Yes | Yes | Yes | Yes | Yes | Yes |
| Other Social Media | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.20 | 0.21 | 0.19 | 0.20 | 0.20 | 0.25 |
| Observations | 980 | 707 | 798 | 609 | 906 | 691 |

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## Appendix 1: Variable Definitions

This appendix provides the definitions of variables used in the main analyses of the paper.

| **Stock Level** | |
|---|---|
| *Managers' Perception* | A numerical variable between 0 and 1 that measures the average level of optimism of a stock based on a hedge fund's tweets in a quarter. |
| *Top10* | An indicator variable that takes a value of 1 if the total dollar value of a stock is ranked top ten among all the stock holdings of a hedge fund in its quarterly 13F filings. |
| *Recent Performance* | The cumulative stock returns during the past three months prior to the quarter-end portfolio date of the 13F filings in excess of the cumulative CRSP value-weighted market returns during the same period. |
| *ROA* | The return on total assets of a stock during a quarter. |
| *Size* | The total market capitalization of a stock at the quarter-end in millions of U.S. dollars. |
| *B/M* | The book-to-market ratio of a stock at the quarter-end. |
| *Volatility* | The standard deviation of stock returns of the past 36 months prior to the quarter-end. |
| *Illiquidity* | The Amihud (2002) illiquidity measure calculated as quarterly average of absolute stock returns divided by the product of daily stock prices and trading volume, then multiplied by $10^6$. |
| *Momentum* | The cumulative stock returns during the 12 months prior to the quarter-end adjusted by the CRSP value-weighted market returns during the same period. |
| *Fama-French Alpha* | Stock returns in excess of the risk-free rate are regressed on the excess return on the market (MRTRF), small minus big (SMB), high minus low (HML) over horizons of different lengths. |
| *Carhart Alpha* | Stock returns in excess of the risk-free rate are regressed on the excess return on the market (MRTRF), small minus big (SMB), high minus low (HML), and momentum (UMD) over horizons of different lengths. |
| *CAR* | The abnormal returns are calculated using the market model (CAPM) and market-adjusted model (in excess of the CRSP value-weighted market returns) with an estimation window from 300 to 91 days prior to the event date. |
| **Fund Level** | |
| *Tweeting Funds* | An indicator variable that takes a value of 1 if a hedge fund ever tweets its portfolio stocks during the sample period. |

| | |
|---|---|
| *Fund Flows* | Fund quarterly flows, computed as [AUM(q) - AUM(q - 1) × (Returns (q) + 1)] / AUM(q - 1). AUM (q) is the fund AUM at the end of quarter q. Returns (q) are calculated by compounding (Returns (m) + 1) within quarter q. |
| *Stock Tweeting Quarters* | An indicator variable that takes a value of 1 if when a hedge fund makes at least one tweet on their portfolio stocks during a quarter. The subsequent quarter is also assigned a value of 1 to allow time for investors to adjust their portfolio decisions. |
| *Other Tweeting Quarters* | An indicator variable that takes a value of 1 if when a hedge fund makes at least one non-stock tweet during a quarter. The subsequent quarter is also assigned a value of 1. |
| *Post2, Post3, Post4* | The second, third, and fourth quarters after a stock tweeting quarter. |
| *FRank Terciles* | The fractional ranking of quarterly fund performance. Specifically, FRank1 = min(FRank, 1/3), FRank2 = min(FRank - FRank1, 1/3), and FRank3 = min(FRank - FRank1 - FRank2, 1/3). |
| *Size* | Fund's assets under management (AUM) in millions of dollars. |
| *Age* | Number of years since inception of hedge fund. |
| *Total Restrictions* | Sum of lockup period, redemption notice period, and redemption frequency, where the lockup period refers to the number of days before an investment can be withdrawn, redemption notice period refers to the number of days required to inform a hedge fund of a future withdrawal, and redemption frequency refers to the minimum number of days required between two withdrawals. |
| *Management Fees* | Percentage of fund's net asset value charged by the hedge fund. |
| *Incentive Fees* | Percentage of profits charged by the hedge fund. |
| *Highwater Mark* | An indicator variable that takes a value of one if a fund uses a highwater mark to calculate incentive fees. |
| *Leveraged* | An indicator variable that takes a value of one if a fund uses leverage. |
| *Total number of tweets* | The total number of tweets sent by a tweeting hedge fund in a quarter. |
| *Traditional Media* | An indicator variable that takes a value of one if a hedge fund has annual advertising expenditure according to the ad$pender database. |
| *Other Social Media* | An indicator variable that takes a value of one if a hedge fund has posts on Facebook and/or YouTube during a quarter. |

## Appendix 2: Examples of Tweets Sent by Hedge Funds

This appendix provides a few examples of tweets sent by the hedge funds in my sample. The tickers after the "dollar signs" refer to the stocks that are covered in (also the subjects of) the tweets.

[1] Facebook has focused in the right order on the right things, says GAM's Mark Hawtin via @BloombergTV $FB

[2] Less investment and more debt (to pay dividends) is only a short term solution to mask massive earnings decline $XOM

[3] $WBS reported this morning, strong growth in HSA division. Deposits up 20% y/y, accounts up 25%, HSA pretax income up 113% (incl acq growth)

[4] We value core $ADMS at $65/sh. But its pipeline is also undervalued. Assuming 50% prob of success, we see an add'l $37/sh, for $100 total.

[5] Newmont reports best quarter in its history on rising gold price #Gold $NEM

[6] $KFY also owns an under followed RPO asset that's reported 20% compounded growth for five straight years. RPO assignments can last 3-5 years and provide higher visibility than traditional executive staffing. KFY signed $118m worth of long term RPO contracts last quarter.