**Firms' Tweets and Stock Price Discovery**

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**Abstract**

Do firms’ tweets improve stock price discovery at quarterly earnings announcements? We address this question using a comprehensive sample of 148,656 tweets released by 855 S&P 1500 firms from 2008 through 2021. Firms’ tweets are associated with stronger stock price and volume reactions to earnings announcements. In addition, firms’ tweets reduce investor uncertainty, increase the timeliness and efficiency with which stock prices reflect information in earnings announcements, and reduce the post-earnings-announcement drift. We document that firms’ tweets improve stock price discovery by enhancing firm visibility and increasing retail investor trading, which facilitates faster incorporation of information into stock prices. Our inferences hold in a propensity score matched sample, where firms that use Twitter are matched with similar firms that do not. Our findings are of interest to regulators who wish to improve the informativeness of security prices, investors who are interested in information that affects prices and volume, and managers who seek channels to communicate with investors.

JEL classification: G11, G12, G14, M41

Keywords: Firms’ tweets; Stock price discovery; Informational efficiency of stock prices

**Firms' Tweets and Stock Price Discovery**

## 1 Introduction

We address whether firms' tweets improve stock price discovery at quarterly earnings announcements. In recent years, social media platforms, especially Twitter, have become an important communication channel between firms and investors. In April 2013, the Securities and Exchange Commission (SEC) approved the use of posts on Facebook and Twitter to communicate corporate news, such as periodic firm fundamental performance.[1] Moreover, in the SEC "Compliance and Disclosure Interpretations" (C&DIs), updated on November 6, 2017, which comprise the interpretations of the rules adopted under the Securities Act, the SEC recognizes the growing interest in using technologies such as social media to communicate with investors. According to the C&DIs, the SEC staff will not object to firms' use of social media to convey information about specific investment opportunities (e.g., offers of own securities) to gauge interest among potential investors.[2] However, the official guidance also suggests that firms can be held responsible for information provided in tweets from official Twitter accounts.[3] Despite the increasing importance of social media in capital markets, we lack comprehensive evidence on the effects of firms' use of Twitter on stock price discovery, i.e., whether tweets are informative to investors and whether they improve the informational efficiency of stock prices.

The literature suggests that dissemination of information using Twitter can increase market liquidity and reduce information asymmetry between investors (e.g., Blankespoor, Miller, and White, 2014). However, recent evidence suggests firms might use social media opportunistically to disseminate information (e.g., Jung et al., 2018) and provide voluntary

[1] The official announcement can be found at this webpage.
[2] For more information regarding the C&DIs and related questions and answers, visit this webpage.
[3] Firms cannot simply tweet without a fear of retaliation from the regulator. For example, Elon Musk, the CEO of Tesla Inc., was sued by the SEC for his tweet "would take Tesla private at 420" from August 7, 2018.

disclosures to obtain favorable capital markets outcomes (e.g., Barth et al., 2021). Hence it is unclear whether and how firms' tweets affect stock price discovery.

Investors may not consider information in firms' tweets when making investment decisions. This might be due to the existence of alternative official sources of firm information, and because of the potential opportunism in the tweets. Moreover, even if investors do consider firms' tweets, it is unclear whether tweets hinder or improve the informational efficiency of security prices. On one hand, firms may use Twitter to manage investors' expectations, and thus firms' tweets might provide and disseminate information that results in less informative prices. On the other hand, because firms bear responsibility over information they provide and disseminate in their tweets, it is likely that firms' tweets contain value-relevant information that helps investors analyze and incorporate information into stock prices, resulting in more efficient security prices.

We hypothesize that firms' use of Twitter at quarterly earnings announcements improves stock price discovery. First, we expect firms' tweets to be informative to investors as firms will want to avoid litigation risk and refrain from disseminating or providing information that misrepresents their financial position or performance. Hence, firms' tweets at quarterly earnings announcements are likely to contain value-relevant information for investors. Second, because they appear on a popular social media platform, we expect that firms' tweets at quarterly earnings announcements help disseminate and provide information that is more easily accessible to retail investors (Bushee and Miller, 2012; Blankespoor, deHaan, and Zhu, 2018), increase firm visibility, and engender retail investor trading (Bushee, Cedergren, and Michels, 2020). This in turn will allow faster incorporation of information in earnings announcement into stock prices and result in more informative prices (e.g., Grossman and Stiglitz, 1980; Israeli, Lee, and Sridharan, 2017).

We test our hypothesis in three steps. First, we examine whether firms' tweets are informative to investors. We do so by addressing whether tweets affect the price and volume reactions to quarterly earnings announcements. Second, we examine whether firms' tweets improve the informational efficiency of stock prices. We do so by examining the relation between firms' tweets and two dimensions of stock price informativeness: (1) investor uncertainty about firm value at quarterly earnings announcements and (2) the speed with which stock prices reflect information in quarterly earnings announcements (i.e., the timeliness and efficiency of incorporation of earnings announcement information into stock prices and the post-earnings-announcement drift). Third, we investigate whether firms' tweets are associated with higher firm visibility, higher retail trading volume and whether this increased volume helps explain the improvement in stock price discovery. We test our hypothesis using quarterly earnings announcements, because they provide a salient information event to examine constructs related to stock price discovery.

Consistent with our predictions, we find that firms' tweets are associated with stronger stock price and volume reactions to quarterly earnings announcements. An additional tweet issued by an average firm in our sample during the quarterly earnings announcement period is associated with a 28.4 basis-point increase in absolute abnormal stock return and a 55.6 basis-point increase in abnormal trading volume. Moreover, consistent with firms' tweets improving the informational efficiency of stock prices, we find that they reduce investor uncertainty, increase the timeliness and efficiency with which stock prices reflect information in earnings announcements, and reduce the post-earnings-announcement drift. An additional tweet during the earnings announcement window is associated with an 11.2 basis-point reduction in investor uncertainty, 7.1 basis-point increase in the efficiency with which stock prices incorporate news in earnings announcements, and a 4.6% reduction in the post-earnings-announcement drift.

We also document that firms' tweets enhance firm visibility and improve stock price discovery by increasing retail trading at quarterly earnings announcement. Increased retail trading that is associated with firms' tweets helps explain the stronger stock price and volume reactions to earnings announcements, lower investor uncertainty, and faster incorporation of information in earnings announcements into prices. These findings are consistent with Grossman and Stiglitz (1980) and Israeli et al. (2017), who show that retail trading plays an important role in stock price discovery. The presence of individual investors allows sophisticated investors to incorporate new information into stock prices faster by trading against them. Hence, Twitter, as a popular social media platform, enhances stock price discovery by potentially increasing firm visibility and attracting more retail traders.

A possible concern with our research design is that it might suffer from endogeneity. Because firms self-select whether to use Twitter, one could argue that only firms that have better stock price discovery (i.e., stronger reactions to information in earnings announcements, lower investor uncertainty, and higher information efficiency of stock prices), due to some unique characteristics (e.g., smaller analyst forecast error, higher earnings quality), choose to do so. Such an argument raises concerns that the improved stock price discovery is due to these unique characteristics and not to the use of Twitter. To alleviate this concern, we use propensity score matching to construct a sample of similar firms that differ only in whether they use Twitter to communicate with investors. Our inferences endure. We find support for the hypothesis that firms' tweets at quarterly earnings announcements improve stock price discovery.

Our paper relates to a growing literature that studies the capital market consequences of firms' use of social media, especially Twitter, to communicate with investors. In an early study, using a sample of 102 tech firms with a Twitter account as of September 30, 2009, Blankespoor et al. (2014) find that firms can reduce information asymmetry among investors by more broadly disseminating their news, e.g., sending links to press releases and other disclosures via Twitter to all of the corporate accounts' followers. Cole, Daigle, and Van Ness (2015) document a positive association between a firm's Twitter membership and excess returns and share turnover during the first 24 months of membership. Debreceny, Rahman, and Wang (2021) report that abnormal levels of user-generated tweets and sentiment in tweets over the three days surrounding firms' 8-K filings are positively associated with abnormal returns and trading volume. These studies support the view that firms' tweets might contain information that affects stock returns and trading volume and can help reduce information asymmetry (Ganesh and Iyer, 2021).

Our study contributes to this literature in several ways. First, unlike previous studies, our paper considers a much broader capital market consequence of firms' tweets. We address whether these tweets improve stock price discovery at a major corporate information event, i.e., the quarterly earnings announcement. This is an important distinction, because our study allows us to illuminate how firms' use of Twitter affects the informational efficiency of stock prices. A growing literature suggests firms might use Twitter or implement voluntary disclosure practices opportunistically. For example, Lee, Hutton, and Shu (2015) report that firms use social media to attenuate negative price reactions to consumer product recalls. Jung et al. (2018) find that firms use Twitter to strategically disseminate financial information. Nekrasov, Teoh, and Wu (2022) report that firms include visuals in their tweets to increase the followers' direct engagement (i.e., retweets and likes) with the message. Barth et al. (2021) document that firms strategically release financial information before warrant expiration dates to prevent (induce) warrant exercise when the exercise is antidilutive (dilutive) to shareholders. Hence, the previously reported associations between firms' Twitter use and stock prices and volume do not necessarily imply informationally efficient stock prices; firms might use Twitter to manage investors' expectations and affect stock prices and trading volume in a way that may not result in more informative stock prices.

Second, our study considers two types of tweets: those that disseminate existing information and those that release new information. This feature allows us to explore whether and how the release of different types of information via social media affects stock price discovery. Importantly, our study informs regulators who seek to determine whether and how firms should be allowed to use social media. Third, we investigate how firms' tweets help improve the informational efficiency of stock prices, i.e., improved firm visibility and the channel of increased retail trading. We show that the tweets increase firm visibility and retail trading, which in turn facilitates faster incorporation of the information in quarterly earnings announcements into stock prices. Finally, our study covers a large universe, i.e., firms in the S&P 1500 index, over a long sample period, i.e., from January 2008 through the end of 2021. This allows us to provide insights with stronger external validity and to control for any time trends that likely exist in firms' use of Twitter.[4]

[4] A related growing literature explores whether aggregate information from Twitter or other social platforms (e.g., Estimize or Seeking Alpha) can be used to predict overall stock market or firm performance. For example, Bollen, Mao, and Zeng (2011) find that the aggregate mood in the text of daily tweets can help predict changes in the Dow Jones Index. Mao et al. (2012) report that the daily number of tweets that mention S&P 500 stocks is associated with levels and changes in the S&P 500 Index. Bartov, Faurel, and Mohanram (2018, 2022) document that the aggregate opinion from tweets issued by individuals helps predict forthcoming quarterly earnings, stock returns, announcement bond returns, and credit default swap spreads. Jia et al. (2020) find that Twitter can impede price discovery in the presence of negative rumors released by individual Twitter users surrounding mergers and acquisitions. Our study differs from these studies as we focus on firm-initiated tweets and address whether and how these tweets affect stock price discovery at quarterly earnings announcements.

The paper proceeds as follows. Section 2 explains the research design. Section 3 describes the sample and data and provides descriptive statistics. Section 4 presents the findings, and section 5 provides additional analyses. Section 6 concludes.

## 2 Research design

We test whether firms' tweets improve stock price discovery at quarterly earnings announcements in three steps. First, we examine whether firms' tweets are informative to investors. Second, we examine whether firms' tweets improve the informational efficiency of stock prices (i.e., reduce investor uncertainty about firm value and increase the speed with which stock prices reflect information in quarterly earnings announcements). Third, we identify how firms' tweets affect stock price discovery. We do so by addressing whether firms' tweets improve firm visibility and increase retail trading volume and whether the increase in retail trading that is associated with firms' tweets helps explain the stronger investor reaction to and faster incorporation of information in earnings announcements.

This three-step approach allows us to consider whether firms' tweets affect two key dimensions of stock price discovery (i.e., informativeness to investors and informational efficiency of stock prices) as well as illuminate the channel (i.e., retail trading volume) through which firms' tweets affect stock price discovery.

### 2.1 Measuring firms' tweets

In our main analyses, we use three variables to capture the key dimensions of firms' tweets at quarterly earnings announcements. The first variable, $Tweets$, measures the number of tweets a firm issues during the earnings announcement period, i.e., the three trading days, $[-1, 1]$, surrounding an earnings announcement day. This variable captures the intensity of firms' use of Twitter at the quarterly earnings announcement. We compute this variable by counting the total number of tweets a firm releases during the earnings announcement window. Because some firms might not release any tweets during an earnings announcement period and because we want to create a continuous variable, we measure $Tweets$ as the natural logarithm of one plus the number of firm-initiated tweets in the $[-1,1]$ window surrounding quarterly earnings announcements.

The second variable, $Dissem$, measures the number of tweets at quarterly earnings announcements that disseminate existing information (e.g., a tweet that contains a link to an earnings announcement report or a retweet). $Dissem$ captures one dimension of the content of firm-initiated tweets at the quarterly earnings announcement. We measure $Dissem$ as the natural logarithm of one plus the number of firm-initiated tweets in the $[-1,1]$ window surrounding the quarterly earnings announcement day that disseminate existing information (Bartov et al., 2018). We determine whether a firm's tweet disseminates existing information through textual analysis of each tweet. Appendix B outlines our methodology to identify $Dissem$ tweets and provides several examples of such tweets. Panel A of the appendix provides the word lists we use to classify the tweets and panel B provides several examples of *Dissem* tweets in our sample.

The third variable, $Fund$, measures the number of tweets at quarterly earnings announcements that provide fundamental information (e.g., a tweet that contains earnings, performance, or trading information). $Fund$ captures another dimension of the content of firm-initiated tweets at quarterly earnings announcement. We measure $Fund$ as the natural logarithm of one plus the number of firm-initiated tweets in the $[-1, 1]$ window surrounding the quarterly earnings announcement that contain fundamental information (Bartov et al. 2018; Nekrasov 2022). We analyze the text of firms' tweets to determine whether a tweet contains fundamental information. Appendix B outlines our methodology for identifying $Fund$ tweets and provides several examples of such tweets. Panel A outlines the lists of words we use to identify *Fund* tweets and panel B provides several examples of *Fund* tweets.

Together, *Dissem* and *Fund* reflect different sub-categories of the *Tweets* variable. Such a disaggregation allows us to illuminate how different tweets' characteristics affect stock price discovery at quarterly earnings announcements.[5]

**2.2 Do firms' tweets inform investors?**

We test whether firms' tweets inform investors by examining whether they are associated with stronger price and volume reactions to earnings announcements. We do so by estimating several versions of the following equation:

$$INFORM_{i,t} = \beta_1 TWITTER_{i,t} + Controls_{i,t} + \alpha_i + \delta_t + \epsilon_{i,t}, \quad (1)$$

where *INFORM* denotes one of the two variables that capture the informativeness of firm *i*'s earnings announcements at quarter *t*: $|CAR[-1,1]|$ and *ATVol*. $|CAR[-1,1]|$ is absolute size- and book-to-market- adjusted stock return (e.g., Daniel et al., 1997). We use absolute, not signed, abnormal stock returns to gauge the price informativeness of firms' tweets because they might contain both positive and negative value-relevant information and because we are interested in studying whether the tweets affect stock prices, regardless of the direction. *ATVol* is abnormal trading volume calculated as the natural logarithm of one plus the share turnover ratio across days [−1, 1], scaled by the average daily turnover ratio across days [−54, −5] relative to the quarterly earnings announcement (e.g., Israeli, Kasznik, and Sridharan, 2022b).

*TWITTER* denotes one of the three measures of firms' tweets: *Tweets*, *Dissem*, and *Fund*. *Controls* denotes a vector of control variables that the literature suggests help explain the price

[5] *Dissem* and *Fund* are not mutually exclusive categories of firms' tweets. As panel B of appendix B shows, it is possible for a *Dissem* tweet to provide fundamental information and thus also be categorized as a *Fund* tweet. It is also possible for a *Fund* tweet to contain a hyperlink and thus also be categorized as a *Dissem* tweet.

and volume reactions to earnings announcements (Barth, Berkovitch, and Israeli, 2023; Israeli et al., 2022b). These include, analyst forecast error, $AFE$, calculated as the decile ranking of the absolute difference between median analyst forecast and actual earnings per share scaled by stock price; profitability, $ROE$; an indicator variable for whether a firm reports a loss, $Loss$; operating accruals, $OAcc$; institutional ownership, $InstOwn$; analyst following, $Analyst$; natural logarithm of equity market value, $Size$; natural logarithm of equity book-to-market ratio, $BTM$; and return momentum, $Mom$. Appendix A provides variable definitions. $\alpha_i$ and $\delta_t$ denote Fama-and-French (1997) 48-industry and quarter fixed effects. These fixed effects are designed to capture industry- and time-specific factors that affect investor reactions to quarterly earnings announcements and are associated with firms' use of Twitter. We base our inferences on *t*-statistics computed using standard errors clustered at the firm and quarter levels.

If firms' tweets are informative to investors, we expect the coefficient on *Tweets* to be positive. In addition, if firms' tweets are informative to investors by serving the dissemination role, we expect the coefficient on *Dissem* to be positive. If fundamental information included in firms' tweets contributes to informativeness of those tweets, we expect the coefficient on *Fund* to be positive.

### 2.3 Firms' tweets and the informational efficiency of prices

We consider two aspects of informational efficiency of stock prices: investor uncertainty about firm value and the speed of incorporation of information in quarterly earnings announcements.

#### 2.3.1 Do firms' tweets reduce investor uncertainty about firm value?

Security prices are expected to be informationally more efficient when investors are more certain about firm value (Sridharan, 2015). Based on this intuition, the first dimension of informational efficiency of stock prices we consider is investor uncertainty at quarterly earnings announcements. It is well documented that investor uncertainty increases at earnings announcements (Patell and Wolfson, 1979; Barth and So, 2014; Gallo et al., 2021). If firms' tweets improve stock price discovery, we expect that the rise in investor uncertainty at earnings announcements will be smaller for firms with more tweets. We test this prediction by estimating several versions of the following equation:

$$IV_{i,t} = \beta_1 TWITTER_{i,t} + Controls_{i,t} + \alpha_i + \delta_t + \epsilon_{i,t}, \tag{2}$$

where $IV$ denotes change in option-implied volatility. Because options are forward-looking, implied volatility better measures investor uncertainty about future stock prices than does historical price volatility. Additionally, option markets are not subject to short sale constraints, which can distort stock prices (Johnson and So, 2012). This helps option prices better reflect current investor perceptions. Moreover, because implied volatility is measured daily, it is useful for examining changes in uncertainty around earnings announcements, within the 3-day window.

We obtain implied volatilities from the OptionMetrics Standardized Options dataset, which provides daily interpolated put and call implied volatilities for at-the-money options with various durations. We measure implied volatility on a given date by averaging the implied volatilities of put and call options with durations of 30 days.[6] The fixed durations implicit in Standardized Options allow us to avoid complications arising from mechanical changes in implied volatility related to option expiration (Patell and Wolfson, 1979). We calculate the change in implied volatility on days $[-1, 1]$ for each firm *i* and quarter *t* earnings announcement.

$$IV_{i,t} = \frac{LogIV_{i,t+1}}{LogIV_{i,t-1}}.$$

[6] We use 30-day options for our main analyses because liquidity in the options market is a decreasing function of option horizon and therefore the most reliable data are available for 30-day options.

The *Controls* vector encompasses all variables previously discussed as controls in equation (1) as well as two additional measures that the literature suggests are associated with the evolution of implied volatilities around earnings announcements and might be associated with firms' use of Twitter. These include the contemporaneous change in market volatility ($VIX_t$) and baseline implied volatility ($IV\_Base_{i,t}$), measured on day $-2$ relative to the earnings announcement date. As in equation (1), we include industry and calendar-quarter fixed effects to capture industry- and time-specific factors that affect investor reactions to quarterly earnings announcements and are associated with firms' use of Twitter. We base our inferences on *t*-statistics computed using standard errors clustered at the firm and quarter levels.

If firms' tweets decrease investor uncertainty, we expect to find a negative coefficient on the three variables that *TWITTER* denotes: *Tweets*, *Dissem*, and *Fund*.

**2.3.2 Do firms' tweets increase the speed of information incorporation into stock prices?**

We test whether firms' tweets increase the speed with which stock prices reflect information in earnings announcements in two ways. First, we examine whether firms' tweets increase the timeliness and efficiency of incorporation of information into stock prices. Second, we test whether firms' tweets reduce the post-earnings-announcement drift.

To test whether tweets increase the timeliness and efficiency of incorporation of information into stock prices, we estimate several versions of the following equation:

$$IPX_{i,t} = \beta_1 TWITTER_{i,t} + Controls_{i,t_{\alpha_i}} + \alpha_i + \epsilon_{i,t}, \tag{3}$$

where $IPX$ denotes one of the two commonly used measures of speed of information incorporation into stock prices, i.e., intraperiod timeliness, *IPT*, and intraperiod efficiency, *IPE* (Blankespoor et al., 2014; Israeli et al., 2022b; Barth et al., 2023; Berkovitch et al., 2023).

*IPT* employes an area-under-the-curve approach to estimate the speed of price discovery during the $[0, 5]$ window relative to a firm's quarterly earnings announcement day. Following the literature, we estimate *IPT* by first calculating the cumulative abnormal return for firm *i* from day zero through day *j*, relative to the quarter *t* earnings announcement ($CAR_{i,t}[0, j]$) as firm *i*'s raw return minus the value-weighted return for a portfolio of firms matched on five-by-five sorts of firm size and market-to-book ratio. We then scale each day *t* cumulative return by the total cumulative return for the $[0, 5]$-day period. Plotting the scaled daily cumulative returns generates a curve that reflects the speed of price discovery. From this curve, *IPT* is calculated as follows:

$$IPT_{i,t} = \sum_{j=0}^{4} \frac{CAR_{i,t}[0,j]}{CAR_{i,t}[0,5]} + 0.5.$$

Higher values of *IPT* indicate that stock prices react sooner to information disclosed during the measurement period. If firms' tweets at quarterly earnings announcements facilitate stock price discovery, they should result in quicker incorporation of information in prices and thus in higher values of *IPT*.

The *IPT* metric assumes there is no overreaction and reversal during the return measurement window. The calculation of *IPT* does not penalize for exceeding the overall cumulative return level. Hence a scenario where returns peak before reversing to a lower long-run steady state would result in a higher *IPT* value. However, this price pattern does not necessarily reflect greater informational efficiency of security prices, particularly relative to the alternative of correctly reaching the appropriate level without overreaction (Thomas and Zhang, 2008). To address this concern, Blankespoor et al. (2018) introduce the following intraperiod efficiency measure, *IPE*:

$$IPE_{i,t} = 1 - \sum_{j=0}^{5} \frac{|CAR_{i,t}[0,5] - CAR_{i,t}[0,j]|}{|CAR_{i,t}[0,5]|}.$$

As with $IPT$, the definition of $IPE$ involves measuring the area under the curve of cumulative abnormal returns during a specified event window, i.e., $[0, 5]$ window in our case. $CAR_{i,t}[0, j]$ measures the cumulative abnormal return for firm *i* from day zero through day *j*, relative to the quarter *t* quarterly earnings announcement, as the firm *i*'s raw return minus the value-weighted return for a portfolio of firms matched on five-by-five sorts of firm size and market-to-book ratio. Unlike *IPT*, *IPE* penalizes overreactions and reversals, such that only a price response that reaches its cumulative day 5 value on day 1 has *IPE* = 1. To confirm that our inferences endure when we use this alternative conceptualization of speed, we also estimate equation (3) using *IPE* as a dependent variable, instead of *IPT*.

$TWITTER$, our explanatory variable of interest, denotes one of the three measures of firms' use of Twitter at quarterly earnings announcements: *Tweets*, *Dissem*, or *Fund*. If firms' tweets improve the informational efficiency of stock prices, by increasing the timeliness and efficiency with which prices reflect information in quarterly earnings announcements, we expect $\beta_1$ to be positive. The *Controls* vector includes the same control variables as in equation (1) (Berkovitch et al., 2023). As in other estimations, we include Fama-and-French (1997) 48-industry and calendar-quarter fixed effects to capture industry- and time-specific factors that affect the speed with which stock prices reflect information in quarterly earnings announcements and are associated with firms' use of Twitter. We base our inferences on *t*-statistics computed using standard errors clustered at the firm and quarter levels.

To test whether firms' tweets help reduce the post-earnings-announcement drift, we estimate several versions of the following equation:

$$CAR[2, 20]_{i,t} = \beta_1 TWITTER_{i,t} + \beta_2 AFE_{i,t} + \beta_3 TWITTER_{i,t} \times AFE_{i,t} + Controls_{i,t_{\alpha_i}} + \alpha_i + \epsilon_{i,t}, \quad (4)$$

where $CAR[2,20]$ is the cumulative abnormal return during the $[2,20]$ period after the quarterly earnings announcement. We use the $[2,20]$ window because research documents that most of the information from quarterly earnings announcements is incorporated during this period (Bamber, 1987; Barth et al., 2020).

*TWITTER* is one of our three measures of firm use of Twitter, i.e., *Tweets*, *Dissem*, or *Fund*, and *AFE* is analyst forecast error. As in equation (1), *Controls* denotes control variables that the literature suggests help explain the post earnings-announcements returns. In this equation, the coefficient of interest is $\beta_3$, i.e., the coefficient on the interaction between *AFE* and a measure of firms' use of Twitter. If firms' tweets help improve the informativeness of stock prices, the incorporation of information on earnings news in quarterly earnings announcements into stock prices should be faster, and thus $\beta_3$ should be negative.[7]

**2.4 Firm visibility and the role of retail trading volume**

The final step in our research design focuses on the role of retail trading volume in the hypothesized relation between firms' tweets and stock price discovery. To facilitate this channel, we first examine whether firms' tweets are associated with heightened firm visibility at quarterly earnings announcements. Specifically, we re-estimate equation (1) using standardized unexpected volume, *SUV,* as the dependent variable. *SUV* is calculated as the ratio between total trading volume during days $[-1, 1]$ that cannot be explained by positive or negative stock returns during the measurement window, and the standard deviation of residuals from a regression of trading volume on positive and negative stock returns during days $[-54, -5]$ relative to the earnings announcement date. Because *SUV* is orthogonal to stock returns, *SUV* captures

[7] To ensure that our inferences are insensitive to the choice of earnings news variable, i.e., *AFE*, in untabulated analyses, we replace *AFE* with $CAR[-1,1]$. This approach uses the abnormal return during the earnings announcement window, i.e., days [-1, 1], as an earnings news variable that is associated with future returns (Barth et al., 2023).

abnormal trading volume that is closely related to an improvement in a firm's visibility rather to change in its fundamentals (Lerman, Livnat, and Mendenhall, 2010; Israeli, Kaniel, and Sridharan, 2022a). A positive coefficient on *Tweets*, *Dissm*, or *Fund*, would indicate that firms' use of Twitter during the quarterly earnings announcement window increases firm visibility.

Once we establish the link between firms' use of Twitter and firm visibility, we turn to the investigation of the role retail traders play in the price discovery process. We implement this by first assessing whether firms' tweets increase retail trading volume at quarterly earnings announcements. Next, we examine whether the part of retail trading volume that is associated with firms' tweets helps explain the stronger investor reaction to and faster incorporation of information in quarterly earnings announcements.

Specifically, we employ a two-stage least square (2SLS) approach, where we first regress abnormal retail trading volume, *ARVol*, on one of the three measures of firms' use of Twitter, *Tweets*, *Dissem*, and *Fund* and then use the fitted values of *ARVol* as an explanatory variable. In the first stage, we estimate the following equation:[8]

$$ARVol_{i,t} = \beta_1 TWITTER_{i,t} + Controls_{i,t_{\alpha_i}} + \alpha_i + \delta_t + \epsilon_{i,t}, \tag{5a}$$

where *TWITTER* denotes one of the three measures of firm's use of Twitter and *ARVol* is abnormal retail volume during days $[-1, 1]$. Consistent with the measurement of *ATVol*, *ARVol* is the ratio between retail trading volume during days $[-1, 1]$ and the mean retail trading volume in the preceding two trading months $[-54, -5]$ (Israeli et al., 2022b; Barth et al., 2023). We follow Boehmer et al. (2016) and Blankespoor et al. (2018) to identify retail trading volume on the relevant trading days. *Controls* denotes a vector of control variables as defined above. $\alpha_i$ and

[8] We use *ARVol*, and not *SUV*, to establish the channel through which firms' tweets improve stock price discovery, because *ARVol* is a cleaner measure of retail trading volume. While *SUV*, as a measure of firm visibility, appeals to retail investor trading because visibility is likely to affect mostly retail investors, it includes both retail and non-retail investor trading.

$\delta_t$ denote industry and quarter fixed effects. Retail investors have fewer resources at their disposal compared to institutional investors, thus a free and widely used social platform that disseminates and provides firm information can help them increase their capital market activity (Blankespoor et al., 2014). Therefore, we expect to find a positive association between firms' tweets and retail trading volume.

Next, we use fitted values from equation (5a) to re-estimate equations (1) through (3):

$$OUTCOME_{i,t} = \beta_1 \widehat{ARVol}_{TWITTERi,t} + Controls_{i,t} + \alpha_i + \delta_t + \epsilon_{i,t}, \qquad (5b)$$

where *OUTCOME* denotes one of the following measures we use to estimate the effect of firms' tweets on stock price discovery: $|CAR[-1,1]|$, *ATVol*, *IV*, and *IPE*.[9] $\widehat{ARVol}_{TWITTER}$ is the fitted value of *ARVol* as obtained from equation (5a) using one of the measures of firms' use of Twitter, i.e., *Tweets*, *Dissem*, *Fund*. It is designed to substitute the *TWITTER* variable we use in equations (1) through (3). Following Chen et al. (2022), we use bootstrapping to adjust the second-stage standard errors for the first-stage estimation. A positive (negative) coefficient on $\beta_1$ in the estimations in which $|CAR[-1,1]|$, *ATVol*, or *IPE (IV)* is the dependent variable will indicate that the part of retail trading volume that is explained by firms' tweets helps explain the associations between firms' tweets and price discovery at quarterly earnings announcements.

In addition to equations (1) through (3), we estimate equation (4) as follows:

$$CAR[2,20]_{i,t} = \beta_1 \widehat{ARVol}_{TWITTERi,t} + \beta_2 AFE_{i,t} + \beta_3 \widehat{ARVol}_{TWITTERi,t} \times AFE_{i,t}$$
$$+ Controls_{i,t} + \alpha_i + \delta_t + \epsilon_{i,t}. \qquad (5c)$$

In this equation, our coefficient of interest is $\beta_3$. A negative coefficient on $\beta_3$ will indicate that the part of retail trading volume that explained by firms' tweets helps explain the smaller post-

[9] For the sake of brevity and to facilitate exposition, from this stage onward, we use *IPE* as a measure of the speed of incorporation of information at quarterly earnings announcements into stock prices. Our inferences endure when we use *IPT* instead.

earnings-announcement drift experienced by firms that tweet at quarterly earnings announcements.

## 3 Sample, data, and descriptive statistics

### 3.1 Sample and data

Our study uses a sample of S&P 1500 firms, whose value represents approximately 90% of the market capitalization of all US stocks. We begin by identifying firms that were included in the S&P 1500 index at any point between the years 2008–2021. We obtain for these firms quarterly fundamental information from Compustat, stock price data from CRSP, analyst data from IBES, institutional ownership data from Thomson Reuters, and option implied volatility from OptionMetrics for the fiscal quarters between the first quarter of 2008 and the fourth quarter of 2021. The intersection of these databases results in a sample of 1,867 unique firms and 77,863 firm-quarter observations.[10] Following prior literature, to address the construct of stock price discovery using a sample of firms with sufficient information at quarterly earnings announcements, we require firms to have size and market-to-book adjusted returns of at least 2% during the $[0,5]$ window, at least one analyst following, and non-missing fundamental information. These filters result in a final sample of 1,844 unique firms and 41,531 firm-quarter observations. Table 1 outlines the sample selection process and provides the composition of additional subsamples we use in our analyses.

For each firm in the sample of 1,844 firms, we identify whether, during the period between 2008 and 2021, it had an official corporate Twitter account.[11] To ensure we provide a

[10] The number of firms differs from 1500 because during the sample period some firms entered and exited the S&P 1500 index, but they are still included in our initial sample.
[11] As Table 1 explains, we apply this process to the initial sample of 1,867 firms, resulting in 881 Twitter users. However, the final sample comprises 1,844 firms and 855 Twitter users. The list of firms and their corresponding Twitter accounts is available from the authors upon request.

comprehensive search, we check both the Twitter website for a corporate account and a firm's website to identify any existing Twitter activity. Using this approach, we can match 855 firms to their respective Twitter accounts.[12] We then use the web scraping platform Stevesie to collect all tweets issued by these firms during the $[-1, 1]$ days around quarterly earnings announcements between 2008 and 2021.[13] The final sample consists of 1,844 firms, of which 855 have active Twitter accounts. These firms issued 148,656 tweets during the three trading days surrounding the earnings announcement days, i.e., days $[-1, 1]$ around each announcement.

Table 2 panel A presents the sample composition for each year-quarter in the sample. Twitter use by firms rose in popularity throughout our sample period together with a growing number of tweets. In the first quarter of 2008, only 0.26% of firms in our sample had an active Twitter account, and these firms tweeted six times only. In the first quarter of 2014 (the fourth quarter of 2018), 37.4% (48.5%) of firms had active Twitter accounts and these firms tweeted 3,146 (3,177) times. These figures persist until the end of our sample period. Panel A also reveals that most tweets disseminate existing information and the fraction of tweets that contain fundamental information has grown. For example, while in the first quarter of 2014, 26.26% of tweets contain fundamental information, in the fourth quarter of 2018, 33.18% of tweets contain fundamental information. Appendix B outlines the procedures and the vocabularies we use to classify firms' tweets into the two categories and provides several examples for dissemination and fundamental tweets.

Panel B presents the number of Twitter users within each Fama-and-French (1997) 48 industry. Noticeably, not all industries show the same rate of Twitter use. For example, only

[12] To further complete this process, we follow Guindy (2021) and use Google to search for the existence of active Twitter accounts for firms that either do not have an official website or do not mention Twitter on their website.
[13] https://stevesie.com/cloud/apis/twitter

11.8% of firms in the "steel works etc." industry and 20% of firms in "printing and publishing" industry maintain an active Twitter account in our sample. Conversely, 43.5% of firms in the "business services" industry and 57.9% of firms in the "tobacco products" industry use Twitter.

In our analyses, we include year-quarter and industry fixed effects to account for the time and industry differences in firms' use of Twitter. In addition, we examine whether our inferences hold for different tweets classifications.

### 3.2 Descriptive statistics

Table 3 provides descriptive statistics for the variables in our main analyses. Panel A (Panel B) presents distributional statistics (Pearson and Spearman correlations). Panel A reveals that, on average, firms tweet 3.58 times during the earnings announcement window, i.e., days $[-1, 1]$. On average, a firm publishes 3 tweets classified as disseminating information and 1 tweet that contains fundamental information. During this window, firms experience an average abnormal stock return of 0.48% (mean $CAR[-1, 1]$ = 0.48; mean $|CAR[-1, 1]|$ = 7.27), and total trading volume that is two times higher than the average total trading volume during the quarter (mean *ATVol* = 1.05, which represents a mean of 2 without the natural logarithm transformation). Stock prices reflect, on average, 64% of information in quarterly earnings announcements in an efficient manner (mean *IPE* = 0.64). In addition, on average, firms in our sample experience standardized unexpected trading volume (abnormal retail trading volume) that is 76% (20%) higher than that during the $[-54, -5]$ trading day window (mean *SUV* = 1.76; mean *ARVol* = 0.76, which represents a mean of 1.2 without the natural logarithm transformation). Panel A also reveals that, on average, firms are profitable (mean *ROE* = 0.02), with only 17% reporting quarterly losses (mean *Loss* = 0.17), are followed by more than seven analysts (mean number of analysts is 7.08), and exhibit substantial institutional ownership (mean *InstOwn* = 0.77).

Panel B reveals that, consistent with firms' tweets informing investors, *Tweets* is positively correlated with abnormal trading volume. The Pearson (Spearman) correlation between *Tweets* and *ATVol* is 0.08 (0.10).[14] Furthermore, there is a positive relation between firms' tweets and measures of informational efficiency of stock prices. The Pearson (Spearman) correlation between *Tweets* with *IPT* is 0.03 (0.04) and between *Tweets* and *IPE* is 0.07 (0.07). In addition, consistent with firms' tweets reducing investor uncertainty, there is a negative correlation between firms' tweets and investor uncertainty (Pearson = −0.14, Spearman = −0.17). Panel B also shows that firm tweets are associated with higher firm visibility (Pearson (Spearman) corr. between *Tweets* and *SUV* is 0.11 (0.10)) and heightened retail investor trading (Pearson (Spearman) corr. between *Tweets* and *ARVol* is 0.09 (0.10)) at quarterly earnings announcements.

## 4 Findings

### 4.1 Evidence on the informativeness of tweets

Table 4 presents summary statistics from the estimations of equation (1). Columns (1) and (2) ((3) and (4)) present summary statistics when the dependent variable is $|CAR[-1,1]|$ (*ATVol*). Columns (1) and (3) include a strict set of control variables that the literature suggests are associated with returns at quarterly earnings announcements and might be associated with firms' use of Twitter. Columns (2) and (4) add additional control variables designed to capture

[14] According to panel B of table 3, the unconditional Pearson (Spearman) correlation between *Tweets* and absolute abnormal stock return, $|[CAR[-1, 1]|$, is negative, i.e., −0.05 (−0.04). This is because, unconditionally, firms that use Twitter have lower abnormal returns during earnings announcements. However, table 4 indicates that controlling for variables that capture firm characteristics as well as firm information environment and are related to abnormal returns at earnings announcements, *Tweets* is significantly positively associated with $|[CAR[-1, 1]|$.

the informational environment of the firm, i.e., institutional ownership, number of analysts following, book-to-market, and momentum. As columns (1) and (2) indicate, the number of tweets generated by firms during the $[-1, 1]$ window around quarterly earnings announcements is significantly positively associated with higher absolute abnormal returns (coefs. = 0.17 and 0.14; t-stats = 4.21 and 3.66). These coefficients imply that for an average firm in our sample, one additional tweet during the earnings announcement window is associated with a 28.4 basis-point increase in the absolute abnormal stock return during the $[-1, 1]$ window.[15]

Similarly, columns (3) and (4) indicate that firms' tweets are associated with higher unexpected trading volume at quarterly earnings announcements (coefs. = 0.01 and 0.01; t-stats = 4.48 and 4.10). These results suggest that for an average firm in our sample, one additional tweet during the earnings announcement window is associated with a 55.6 basis-point increase in abnormal trading volume at the quarterly earnings announcement.

Taken together, consistent with our hypothesis, the results in table 4 for stock returns and trading volume indicate that firms' tweets are informative to investors, as they affect both abnormal stock returns and trading volume at quarterly earnings announcements.

**4.2 Evidence on the effect of firms' tweets on stock price informativeness**

Table 5 presents summary statistics from the estimations of equation (2). The outcome variable of interest in these estimations is investor uncertainty, *IV*. Column (1) presents the findings from a regression model that uses a strict set of control variables, and column (2) adds control variables that capture the information environment of the firm. In both columns, the findings indicate that firms' tweets are significantly negatively associated with investor

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[15] We reach this result by multiplying the coefficient on *Tweets* (0.14) by the mean of $|CAR[-1, 1]|$ (7.27) and then multiplying it by 27.9. For an average firm in our sample, an increase in one tweet is equivalent to an increase in 27.9% in the number of tweets (1/3.58). We use the same calculation with necessary adjustments to quantify the associations between one additional tweet for an average firm in our sample and *ATVol*, *IPT*, and *IPE.*

uncertainty at quarterly earnings announcements (coefs. = −0.004 and −0.004; t-stats = −4.80 and −4.64). The results indicate that an additional tweet during the earnings announcement window is associated with an 11.2 basis-point reduction in investor uncertainty.[16]

Table 6 presents summary statistics from estimations that examine the relation between firms' tweets and stock price informativeness. Panel A presents summary statistics for equation (3), which focuses on the timeliness and efficiency with which stock prices reflect information in quarterly earnings announcements. Columns (1) and (2) present results using *IPT*, i.e., earnings timeliness, as the dependent variable. The results indicate that one additional tweet issued by an average firm in our sample during the earnings announcement window is associated with a 3.6 basis-point increase in the timeliness with which stock prices reflect information in quarterly earnings announcements (coefs. = 0.03 and 0.03; t-stats = 2.36 and 2.33). Columns (3) and (4) present results using *IPE*, i.e., earnings efficiency, as the dependent variable. The inferences endure when using this measure of speed with which stock prices reflect information in quarterly earnings announcements (coefs. = 0.003 and 0.004; t-stats = 2.18 and 2.34). The results in column (4) suggest that for an average firm in our sample, one additional tweet is associated with a 7.1 basis-point increase in the efficiency with which stock prices reflect information in quarterly earnings announcements.

Table 6 panel B presents regression summary statistics for equations (4a) and (4b), where the outcome variable of interest is returns during the post-earnings-announcement period, $CAR[2,20]$. Column (1) presents results for equation (4a), where *AFE* is interacted with *Tweets.* Consistent with our hypothesis, the coefficient on the interaction term is significantly negative,

[16] We reach this result by multiplying the coefficient on *Tweets* (−0.004) by 27.9 (for an average firm in our sample, an increase in one tweet is equivalent to an increase in 27.9% in the number of tweets, i.e., 1/3.58).

indicating that an additional tweet issued by an average firm in our sample is associated with a reduction of 4.6% in the post-earnings announcement drift (coef. = $-0.32$; t-stat = $-2.30$).[17] As a validation test, column (2) presents results for equation (4b), where $CAR[-1, 1]$, and not $AFE$, serves as a variable that captures the earnings news during quarterly earnings announcement, is interacted with *Tweets.* The coefficient on the interaction term is significantly negative (coef. = $-0.01$; t-stat = $-2.05$), indicating that an additional tweet by an average firm in the sample is associated with a 3.9% decrease in post-earnings announcement drift.

Taken together, the results in tables 5 and 6 indicate that firms' use of Twitter at quarterly earnings announcements improves the informational efficiency of stock prices. Specifically, firms' tweets reduce investor uncertainty, increase the speed with which information in quarterly earnings announcements is incorporated into stock prices, and reduce the post-earnings announcement drift.

**4.3 Evidence on the role of specific tweet characteristics**

Up to this stage, we use *Tweets*, i.e., the number of tweets a firm releases during quarterly earnings announcements, to measure firms' use of Twitter. To illuminate whether different tweet characteristics affect stock price discovery, we analyze the text within firms' tweets and classify them with respect to their attributes as tweets that disseminate existing information, *Dissem*, or tweets that provide fundamental information, *Fund*. We do so following Bartov et al. (2018) and Nekrasov et al. (2022). Appendix B outlines our classification methodology to identify *Dissem* and *Fund* tweets, the lists of words we use in our textual analysis and provides several examples of different types of tweets. We hypothesize that both *Dissem* and *Fund* tweets help improve

[17] We obtain this by dividing the coefficient estimate on the interaction between *Tweets* and *AFE* (-0.32) by the coefficient estimate on *AFE* (1.38) and multiplying the ratio by the difference between log(1+4.58) and log(1+3.58). (i.e., the difference in log when an average firm in our sample issues one additional tweet).

stock price discovery. This is because both types of tweets released by firms during the earnings-announcement window contain value-relevant information that helps investors better analyze and incorporate information in quarterly earnings announcements into stock prices.

Table 7 panel A presents regressions summary statistics for equation (1) using *Dissem* and *Fund* as measures of firms' use of Twitter instead of *Tweets*. The outcome variables are $|CAR[-1,1]|$ and *ATVol.* Consistent with our hypothesis, the results in panel A indicate that both dissemination of existing information and provision of fundamental information in firms' Tweets inform investors. The coefficients on *Dissem* and *Fund* are significantly positive for both absolute abnormal return (coefs. = 0.14 and 0.15; t-stats = 3.37 and 2.55) and abnormal trading volume (coefs. = 0.04 and 0.02; t-stats = 4.15 and 1.73). Panel B presents regression summary statistics for equations (2) and (3), where the dependent variables are *IV* or *IPE*.[18] Consistent with our hypothesis and our findings in table 5 and table 6 panel A, both *Dissem* and *Fund* are associated with lower investor uncertainty (coefs. = $-0.004$ and $-0.003$; t-stats = $-4.58$ and $-2.59$) and faster incorporation of information in quarterly earnings announcements (coefs. = 0.004 and 0.01; t-stats = 2.39 and 2.51). Panel C presents regressions summary statistics for equation (4a), where $CAR[2,20]$ is the dependent variable. The significantly negative coefficients on the interaction terms between *AFE* and *Dissem* or *Fund* (coefs. = $-0.37$ and $-0.34$; t-stats = $-2.55$ and $-1.81$) indicate that both types of firm tweets are associated with lower post-earnings announcement drift. In untabulated analyses we also estimate equation (4b) in which we interact *Dissem* or *Fund* with $CAR[-1,1]$. Our inference that both types of firm tweets are associated with lower post-earnings announcement drift remain the same.

[18] As we explain in section 2.3.2, prior literature suggests that *IPE* is a superior measure of the speed of information incorporation into stock price. Hence, and for the sake of brevity, in the current and subsequent analyses we tabulate regression summary statistics from the estimation of equation (3) using *IPE* as the dependent variable. Our inferences remain the same if we use *IPT* instead.

Together the results in table 7 indicate that our inferences regarding firms' tweets, i.e., informativeness to investors and improvement in informational efficiency of stock prices, endure when we use other measures of firms' use of Twitter: *Dissem* and *Fund*.[19] These findings suggest that during the earnings announcement window different tweet characteristics play role in stock price discovery. Importantly, the findings indicate that our inference that firms' tweets improve stock price discovery is not limited to a particular measure of firms' use of Twitter.

### 4.4 Firm visibility and the role of retail trading volume

To identify how firms' use of Twitter improves stock price discovery, we start by examining whether firms' tweets are associated with heightened firm visibility, i.e., we estimate the relation between firms' tweets and a measure of firm visibility, *SUV*. Next, we implement a two-stage regression approach using abnormal retail trading volume to identify the channel through which Twitter affects stock price discovery. Specifically, we first estimate the relation between firms' tweets and abnormal retail trading volume at quarterly earnings announcements, and then use the portion of abnormal retail volume that is explained by *Tweets*, *Dissem*, or *Fund* to estimate equations (1) through (4), which examine whether firms' tweets are informative to investors and whether they improve the informational efficiency of stock prices. These stages allow us to examine whether the portion of retail trading volume that is explained by firms' tweets helps explain the observed associations between tweets and measures of informativeness to investors as well as informational efficiency of stock prices.

Table 8 presents regression summary statistics from estimating equation (1) using *SUV* as the outcome variable of interest. Column (1) presents results using *Tweets* as the focal variable,

[19] From a statistical point of view, this is not surprising because *Tweets*, *Dissem*, and *Fund* appear to be significantly highly correlated. The Pearson correlation between *Tweets* and *Dissem* is 0.96 and between *Tweets* and *Fund* is 0.81. The Pearson correlation between *Dissem* and *Fund* is 0.74.

indicating that firms' tweets are positively associated with *SUV* (coef. = 0.05; t-stat = 3.55). Columns (2) and (3) present results using alternative measures of firms' tweets, i.e., *Dissm* and *Fund*. The results indicate that as with overall tweets, the different tweet classifications are also positively associated with increased firm visibility (coefs. = 0.06 and 0.05; t-stats = 3.54 and 2.44). Together, the results in table 8 indicate that firms that use Twitter during the quarterly earnings announcement window enjoy higher visibility.

Table 9, panel A, presents summary statistics from estimating the first stage regressions in which abnormal retail trading volume is the dependent variable. Column (1) presents results using *Tweets* as the focal variable, and columns (2) and (3) use *Dissem* and *Fund* to measure firms' use of Twitter. The results indicate that the three measures of firms' use of Twitter are significantly positively associated with abnormal retail trading volume (t-stats = 3.13, 2.87, and 1.76). This suggests that firms' tweets attract retail investors to trade at quarterly earnings announcements.[20]

Table 9, panel B, presents the results using the fitted values from the analyses in panel A as measures of firms' use of Twitter in equations (1) through (3) instead of *Tweets*, *Dissem* or *Fund*. The results indicate that the portion of abnormal retail trading volume that is explained by the different types of firms' use of Twitter—*Tweets*, *Dissem*, or *Fund*—is associated with higher absolute abnormal return (t-stats = 3.66, 3.38, and 2.60) and higher abnormal trading volume (t-stats = 3.99, 3.90, and 1.75). Table 9, panel C, presents results using investor uncertainty and *IPE* as the dependent variables. As before, the results indicate that, an increase in abnormal retail volume, attributable to the firms' use of Twitter, is associated with lower investor uncertainty (t-

[20] Blankespoor et al. (2014) do not find an association between firms' use of Twitter and retail investor activity. However, the authors attribute this to the trade-size cutoff approach they use to identify retail trading activity. Prior literature documents that this approach captures retail trades only partially (Barber, Odean, and Zhu, 2009; Campbell, Ramadorai, and Schwartz, 2009).

stats = −4.81, −4.74, and −2.65) and higher speed with which stock prices reflect information in earnings announcements (t-stats = 2.12, 2.20, and 2.42).

Table 9, panel D, presents summary statistics from estimating equation (5c). The coefficients on the interaction terms between measures of abnormal retail trading volume instrumented by *Tweets, Dissem*, *or Fund* and *AFE* are all negative and significant (t-stats = −2.40, −2.27, and −2.23). These results further indicate that the increased retail trading volume that is associated with firms' tweets helps reduce the post-earnings-announcement drift. The sum of the coefficients on *AFE* and the interaction of *AFE* with the fitted values of Twitter variables from our first stage estimation are statistically not different from zero (p-vals = 0.49, 0.47, 0.49). These findings suggest the portion of retail trading volume explained by the firms' use of Twitter helps eliminate the post-earnings announcement drift.

Taken together, the evidence in tables 8 and 9 show that firms' tweets are associated with heightened firm visibility and an increase in abnormal retail trading volume. The increase in retail trading volume explained by measures of firms' use of Twitter (i.e., *Tweets*, *Dissem*, or *Fund*) helps explain the reduction in investor uncertainty, the faster incorporation of information in quarterly earnings announcements, and the lower post-earnings-announcement drift. These findings support the view that firms' tweets increase retail investor trading, which helps improve the stock price discovery process at quarterly earnings announcements.

## 5 Additional analyses and robustness tests

### 5.1 Firms' tweets and stock price discovery in propensity score matched sample

A possible concern with our inferences is that they are based on a sample of firms that can choose whether to use Twitter. One might argue that only firms with better stock price discovery choose to use Twitter. To address this concern, we use a propensity score matched sample of 26,902 firm-quarter observations that contains firms that share similar characteristics (e.g., analyst forecast error, earnings quality, and institutional ownership) and differ mainly in whether they use Twitter at quarterly earnings announcements. Specifically, we match firms based on the fundamental performance and information environment variables that we use in our main analyses as controls.

Table 10, panel A, presents summary statistics for the full sample and the matched sample along with the differences between key control variables. The matching process eliminates significant economic differences between the two subsamples. In particular, it eliminates the statistical significance of four variables (i.e., *AFE*, *OAcc*, *InstOwn*, and *Mom*), and, for the remaining variables, the differences are much smaller between the full and matched samples, eliminating the existing economic significance (e.g., difference in *ROE* dropped from −0.012 to −0.006; difference in *Size* dropped from −1.160 to −0.609).[21]

Table 10, panel B, presents summary statistics from estimating our main specifications using a propensity score matched sample. Columns (1) and (2) present results of estimating equation (1). These columns indicate that firms' tweets are positively associated with both abnormal return and unexpected volume at quarterly earnings announcements (coefs. = 0.17 and 0.01; t-stats = 4.18 and 4.01). Column (3) indicates that firms' tweets reduce investor uncertainty (coef. = −0.003; t-stat = −4.21), column (4) indicates that firms' tweets improve the efficiency with which stock prices reflect information in quarterly earnings announcements (coef. = 0.003; t-stat = 2.10), and column (5) suggests firms' tweets are associated with greater visibility (coef. = 0.04; t-stat = 2.86). Taken together, the results in panel B suggest that all our inferences hold in this sample as well. This alleviates the concern that the self-selection of firms into Twitter users

[21] In untabulated analyses, we also match firms using more parsimonious sets of variables (e.g., only performance measures such as *ROE*). These approaches yield the same inferences.

at quarterly earnings announcements explains our results and indicates that self-selection is not likely the primary driver of our inference that firms' tweets help improve stock price discovery.

### 5.2 Alternative fixed effects structures

In our main analyses, we include industry fixed effects and calendar-quarter fixed effects to absorb any industry-specific or time-specific invariant characteristics of firms that may relate to their use of Twitter and stock price discovery. To ensure that our findings are not limited to a particular fixed effects structure, in untabulated analyses, we estimate all our equations using five alternative fixed effects structures. First, following deHaan (2021), we estimate the equations without any fixed effects. Second, we use an alternative industry classification scheme and replace the industry fixed effects based on Fama and French (1997) 48 industries classification to Fama and French (1997) 30 industries classification. Third, we replace the industry and calendar-quarter fixed effects with calendar-quarter-industry fixed effects. Finally, we estimate the equations with industry fixed effects or calendar-quarter fixed effects separately. Our findings reveal that the relation between *Tweets* and various measures of stock price discovery remain the same. Overall, these analyses provide additional support to our hypothesis that firms' use of Twitter helps improve stock price discovery.

### 5.3 Alternative measurement of the earnings announcement window

Following prior literature and to make sure we properly capture the events related to firms' quarterly earnings announcements, in our main analyses, we use the three trading-day window, i.e., days $[-1, 1]$, as the quarterly earnings announcement period during which we measure our key variables.

Accordingly, we measure the number of tweets issued by firms as well as other event-related variables, e.g., $|CAR[-1, 1]|$, *ATVol*, *IV*, and *SUV* during this three-day window. To ensure that our inferences are not driven by this choice of an earnings announcement window, we consider an alternative earnings announcement period using a two-day window, i.e., days [0, 1] surrounding the earnings announcement day. During the two-day earnings announcement window firms in our sample provide 103,034 tweets in total and 2.5 tweets on average (compared to a total of 148,656 tweets and 3.58 tweets on average during the three-day window). Untabulated analyses indicate that our inferences remain the same when we use the shorter period to measure our key variables.

**6. Summary and concluding remarks**

We address whether firms' tweets improve stock price discovery at quarterly earnings announcements. We measure firms' tweets using the number of tweets a firm issues during the quarterly earnings announcement period. We also consider alternative measures of tweets, i.e., the number of tweets that disseminate existing information or provide fundamental information.

Using a sample of 41,531 firm-quarter observations from 1,844 S&P 1,500 firms, of which 855 use Twitter, issuing 148,656 tweets between 2008–2021, we find that firms' tweets are informative to investors (i.e., significantly positively associated with measures of investor reaction to earnings announcements). We further find that firms' use of Twitter reduces investor uncertainty, increases the speed with which stock prices reflect information in quarterly earnings announcements, reduces the post-earnings-announcement drift, and increases firm visibility.

We show that the positive association between firms' tweets and abnormal retail trading volume helps explain this capital market benefit, i.e., improved price discovery. The positive association with abnormal retail trading helps explain the stronger price reaction and trading volume at quarterly earnings announcements as well as the reduced investor uncertainty and improved stock price informativeness.

Our findings illuminate whether firms' communication using social media is informative to investors and whether it enhances the informational efficiency of stock prices. Our inference that firms' use of Twitter improves stock price discovery at a major corporate information event, i.e., quarterly earnings announcement, is of interest to regulators who wish to enhance the informativeness of security prices, investors who are interested in information that affects prices and volume, and managers who seek channels to communicate with investors. Overall, our study advances our understanding of the implications of social media use on capital markets.

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# Tables

## Table 1: Sample selection process

| | No. of firms | No. of firms using Twitter | No. of Obs. | No. of Obs. using Twitter | No. of Tweets |
|---|---|---|---|---|---|
| Participants of the S&P 1,500 during the sample period | 1,867 | 881 | 77,863 | 25,167 | 275,838 |
| Raw return at quarterly earnings announcements of at least 2% (necessary to compute $IPT$ and $IPE$ measures) | 1,855 | 873 | 49,144 | 15,459 | 170,123 |
| Followed by at least 1 analyst | 1,849 | 867 | 48,134 | 15,288 | 168,870 |
| Non-negative book value of equity | 1,847 | 864 | 47,834 | 15,166 | 167,555 |
| Non-missing fundamental information (Full Sample) | 1,844 | 855 | 41,531 | 13,451 | 148,656 |
| Non-missing data on retail volume (necessary to compute $ARVol$) | 1,840 | 849 | 38,221 | 12,194 | 130,978 |
| Non-missing data on implied volatility (necessary to compute $IV$) | 1,797 | 840 | 36,023 | 11,733 | 135,238 |

This table presents the sample selection process we implement to obtain the samples we use in the analyses.

## Table 2: Firms' use of Twitter at quarterly earnings announcements

### Panel A: Firms and tweets in each year-quarter in the sample

| Year-Quarter | Firms | Twitter Users | Tweets | Dissemination | Fundamental |
|---|---|---|---|---|---|
| 2008Q1 | 783 | 2 | 6 | 0 | 2 |
| 2008Q2 | 902 | 2 | 5 | 0 | 0 |
| 2008Q3 | 882 | 8 | 133 | 4 | 43 |
| 2008Q4 | 945 | 18 | 174 | 8 | 72 |
| 2009Q1 | 983 | 37 | 252 | 25 | 100 |
| 2009Q2 | 1,001 | 72 | 618 | 67 | 193 |
| 2009Q3 | 926 | 48 | 331 | 36 | 132 |
| 2009Q4 | 848 | 33 | 143 | 21 | 55 |
| 2010Q1 | 773 | 33 | 111 | 14 | 41 |
| 2010Q2 | 819 | 73 | 262 | 29 | 102 |
| 2010Q3 | 841 | 119 | 749 | 139 | 221 |
| 2010Q4 | 813 | 154 | 1,309 | 218 | 342 |
| 2011Q1 | 805 | 172 | 1,582 | 311 | 505 |
| 2011Q2 | 709 | 170 | 1,612 | 321 | 426 |
| 2011Q3 | 771 | 211 | 2,188 | 951 | 667 |
| 2011Q4 | 814 | 227 | 2,135 | 1,670 | 559 |
| 2012Q1 | 767 | 227 | 2,328 | 1,954 | 653 |
| 2012Q2 | 758 | 239 | 2,764 | 2,172 | 711 |
| 2012Q3 | 829 | 277 | 3,008 | 2,525 | 818 |
| 2012Q4 | 652 | 235 | 2,878 | 2,424 | 709 |
| 2013Q1 | 664 | 226 | 2,761 | 2,347 | 709 |
| 2013Q2 | 692 | 235 | 3,272 | 2,625 | 879 |
| 2013Q3 | 779 | 285 | 3,124 | 2,682 | 879 |
| 2013Q4 | 799 | 288 | 4,143 | 3,567 | 1,153 |
| 2014Q1 | 685 | 256 | 3,146 | 2,785 | 826 |
| 2014Q2 | 705 | 272 | 3,977 | 3,561 | 967 |
| 2014Q3 | 763 | 309 | 4,874 | 4,368 | 1,313 |
| 2014Q4 | 763 | 296 | 4,406 | 3,810 | 1,133 |
| 2015Q1 | 742 | 301 | 3,851 | 3,350 | 1,252 |
| 2015Q2 | 703 | 311 | 5,013 | 4,514 | 1,217 |
| 2015Q3 | 784 | 329 | 4,314 | 3,874 | 1,206 |
| 2015Q4 | 785 | 340 | 4,802 | 4,406 | 1,302 |
| 2016Q1 | 728 | 294 | 4,191 | 3,784 | 1,226 |
| 2016Q2 | 742 | 336 | 4,917 | 4,480 | 1,269 |
| 2016Q3 | 754 | 348 | 4,215 | 3,827 | 1,097 |
| 2016Q4 | 740 | 344 | 4,173 | 3,817 | 1,158 |
| 2017Q1 | 675 | 301 | 3,949 | 3,696 | 1,071 |
| 2017Q2 | 690 | 321 | 3,924 | 3,676 | 1,118 |
| 2017Q3 | 690 | 325 | 3,923 | 3,719 | 1,099 |
| 2017Q4 | 774 | 348 | 4,433 | 4,079 | 1,354 |
| 2018Q1 | 656 | 293 | 3,005 | 2,856 | 1,014 |
| 2018Q2 | 710 | 326 | 3,819 | 3,538 | 1,303 |
| 2018Q3 | 720 | 332 | 3,603 | 3,184 | 1,243 |
| 2018Q4 | 656 | 318 | 3,177 | 2,891 | 1,054 |
| 2019Q1 | 635 | 293 | 2,870 | 2,649 | 1,019 |
| 2019Q2 | 604 | 291 | 2,550 | 2,329 | 962 |
| 2019Q3 | 627 | 313 | 2,537 | 2,263 | 958 |
| 2019Q4 | 669 | 320 | 2,934 | 2,653 | 1,083 |
| 2020Q1 | 582 | 292 | 2,333 | 2,143 | 821 |
| 2020Q2 | 675 | 327 | 2,646 | 2,414 | 1,009 |
| 2020Q3 | 638 | 325 | 2,476 | 2,217 | 999 |
| 2020Q4 | 615 | 320 | 2,666 | 2,395 | 1,017 |
| 2021Q1 | 577 | 304 | 2,601 | 2,107 | 1,027 |
| 2021Q2 | 635 | 326 | 2,612 | 2,328 | 993 |
| 2021Q3 | 638 | 328 | 2,339 | 2,076 | 953 |
| 2021Q4 | 616 | 321 | 2,492 | 2,110 | 1,008 |

## Table 2 (continued): Firms' use of Twitter at quarterly earnings announcements

### Panel B: Firm-quarter observations and tweets across the Fama-French 48 industries

| Industry | Firms | Twitter Users | Tweets | Dissemination | Fundamental |
|---|---|---|---|---|---|
| Fabricated Products | 28 | 11 | 40 | 36 | 11 |
| Precious Metals | 28 | 19 | 245 | 203 | 163 |
| Tobacco Products | 38 | 22 | 124 | 89 | 98 |
| Agriculture | 57 | 18 | 140 | 118 | 14 |
| Coal | 63 | 12 | 123 | 78 | 58 |
| Candy and Soda | 110 | 52 | 847 | 700 | 259 |
| Recreation | 129 | 93 | 1,553 | 1,169 | 285 |
| Textiles | 148 | 57 | 1,013 | 704 | 141 |
| Beer and Liquor | 152 | 55 | 842 | 724 | 467 |
| Defense | 161 | 34 | 248 | 237 | 62 |
| Real Estate | 161 | 46 | 718 | 677 | 363 |
| Shipbuilding, Railroad Equipment | 162 | 57 | 726 | 697 | 217 |
| Electrical Equipment | 189 | 24 | 124 | 119 | 58 |
| Non-Metallic and Industrial Metal Mining | 202 | 7 | 21 | 21 | 15 |
| Shipping Containers | 210 | 78 | 411 | 364 | 158 |
| Printing and Publishing | 231 | 47 | 349 | 317 | 85 |
| Rubber and Plastic Products | 264 | 93 | 531 | 481 | 149 |
| Aircraft | 378 | 127 | 1,378 | 1,057 | 794 |
| Entertainment | 404 | 150 | 2,662 | 2,392 | 340 |
| Other | 476 | 207 | 1,576 | 1,309 | 519 |
| Business Supplies | 490 | 183 | 1,412 | 1,247 | 372 |
| Personal Services | 499 | 133 | 1,133 | 676 | 415 |
| Consumer Goods | 642 | 185 | 1,888 | 1,512 | 358 |
| Restaurants, Hotels, Motels | 649 | 210 | 1,580 | 1,221 | 195 |
| Steel Works Etc | 677 | 80 | 176 | 165 | 84 |
| Apparel | 718 | 307 | 2,413 | 1,874 | 340 |
| Healthcare | 763 | 175 | 1,604 | 1,316 | 572 |
| Construction | 765 | 194 | 1,685 | 1,290 | 523 |
| Construction Materials | 800 | 100 | 674 | 639 | 203 |
| Automobiles and Trucks | 826 | 160 | 834 | 707 | 309 |
| Food Products | 828 | 189 | 1,948 | 1,498 | 858 |
| Measuring and Control Equipment | 958 | 325 | 3,038 | 2,687 | 670 |
| Communication | 959 | 353 | 4,117 | 3,227 | 1,127 |
| Utilities | 1,186 | 359 | 2,591 | 1,953 | 1,022 |
| Chemicals | 1,191 | 371 | 2,133 | 1,862 | 892 |
| Transportation | 1,214 | 339 | 2,598 | 2,257 | 722 |
| Trading | 1,248 | 401 | 5,425 | 4,532 | 2,512 |
| Medical Equipment | 1,327 | 334 | 2,761 | 2,337 | 1,007 |
| Petroleum and Natural Gas | 1,355 | 330 | 2,379 | 2,084 | 1,141 |
| Machinery | 1,369 | 483 | 3,505 | 3,162 | 1,233 |
| Wholesale | 1,427 | 431 | 3,634 | 3,340 | 1,050 |
| Pharmaceutical Products | 1,579 | 484 | 5,226 | 4,156 | 1,987 |
| Insurance | 1,777 | 556 | 4,478 | 3,651 | 1,354 |
| Computers | 1,958 | 848 | 11,982 | 10,064 | 3,638 |
| Retail | 2,390 | 1,001 | 10,400 | 8,567 | 1,713 |
| Electronic Equipment | 2,662 | 949 | 9,465 | 8,292 | 2,869 |
| Banking | 3,184 | 805 | 6,745 | 5,571 | 2,135 |
| Business Services | 4,499 | 1,957 | 39,161 | 34,630 | 11,485 |

This table presents statistics for firms' use of Twitter in the full sample. Panel A presents the total number of firms in each year-quarter along with the number of firms using Twitter in each period, the number of tweets overall, the number of tweets that disseminate information and the number of tweets that contain fundamental information. Panel B presents the total number of observations in each Fama and French (1997) 48-industry classification along with the number of observations using Twitter and the above mentioned tweet classifications. See Appendix A for definitions of all

## Table 3: Descriptive statistics

### Panel A: Distributional statistics of key variables

| | Obs. | Mean | Median | StDev |
|---|---|---|---|---|
| Outcome variables | | | | |
| $CAR[-1,1]$ | 41,531 | 0.48 | 0.55 | 9.32 |
| $ATVol$ | 41,531 | 1.05 | 1.01 | 0.30 |
| $IV$ | 36,078 | −0.08 | −0.07 | 0.11 |
| $IPT$ | 41,531 | 4.30 | 4.31 | 1.81 |
| $IPE$ | 41,531 | 0.64 | 0.70 | 0.26 |
| $CAR[2,20]$ | 41,531 | 0.22 | −0.11 | 8.62 |
| $SUV$ | 41,531 | 1.76 | 1.68 | 1.75 |
| $ARVol$ | 38,221 | 0.76 | 0.73 | 0.22 |
| Twitter variables | | | | |
| $Tweets$ | 41,531 | 0.65 | 0 | 1.08 |
| $Dissem$ | 41,531 | 0.59 | 0 | 1.02 |
| $Fund$ | 41,531 | 0.34 | 0 | 0.69 |
| Control variables | | | | |
| $AFE$ | 41,531 | −0.01 | 0 | 0.05 |
| $ROE$ | 41,531 | 0.02 | 0.03 | 0.07 |
| $Loss$ | 41,531 | 0.17 | 0 | 0.38 |
| $OAcc$ | 41,531 | −0.01 | −0.01 | 0.03 |
| $InstOwn$ | 41,531 | 0.77 | 0.83 | 0.21 |
| $Analyst$ | 41,531 | 2.08 | 2.20 | 0.81 |
| $Size$ | 41,531 | 7.84 | 7.70 | 1.66 |
| $BTM$ | 41,531 | −0.77 | −0.71 | 0.83 |
| $Mom$ | 41,531 | 0.07 | 0.05 | 0.31 |

## Table 3 (continued): Descriptive statistics

### Panel B: Correlations

| | Tweets | \|CAR[-1, 1]\| | ATVol | IV | IPT | IPE | SUV | ARVol |
|---|---|---|---|---|---|---|---|---|
| $Tweets$ | | −0.05 | 0.08 | −0.14 | 0.03 | 0.07 | 0.11 | 0.09 |
| $\|CAR[-1,1]\|$ | −0.04 | | 0.48 | 0.01 | 0.29 | 0.24 | 0.01 | 0.21 |
| $ATVol$ | 0.10 | 0.43 | | −0.08 | 0.19 | 0.20 | 0.57 | 0.22 |
| $IV$ | −0.17 | −0.02 | −0.13 | | −0.04 | −0.03 | −0.10 | −0.08 |
| $IPT$ | 0.04 | 0.45 | 0.28 | −0.05 | | 0.35 | 0.08 | 0.08 |
| $IPE$ | 0.07 | 0.42 | 0.30 | −0.03 | 0.50 | | 0.09 | 0.07 |
| $SUV$ | 0.10 | 0.03 | 0.67 | −0.11 | 0.09 | 0.13 | | 0.06 |
| $ARVol$ | 0.10 | 0.19 | 0.15 | −0.11 | 0.10 | 0.10 | 0.04 | |

This table presents distributional statistics for the variables used in the study. Panel A presents descriptive statistics for control, Twitter use, and outcome variables used in the analyses. Panel B presents correlations for the Twitter and outcome variables. See Appendix A for definitions of all variables.

**Table 4: Informativeness of firms' tweets at quarterly earnings announcements**

| | $\|CAR[-1,1]\|$ | | $ATVol$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Tweets$ | 0.17*** | 0.14*** | 0.01*** | 0.01*** |
| | (0.04) | (0.04) | (0.003) | (0.003) |
| $AFE$ | 2.01*** | 2.12*** | 0.05*** | 0.07*** |
| | (0.16) | (0.15) | (0.01) | (0.01) |
| $ROE$ | −0.02 | −0.24 | 0.16*** | 0.08* |
| | (0.83) | (0.86) | (0.04) | (0.04) |
| $Loss$ | 0.07 | 0.01 | −0.02** | −0.03*** |
| | (0.14) | (0.14) | (0.01) | (0.01) |
| $OAcc$ | −6.09*** | −5.14*** | −0.24*** | −0.10 |
| | (1.29) | (1.30) | (0.08) | (0.08) |
| $Size$ | −0.78*** | −1.09*** | 0.002 | −0.03*** |
| | (0.04) | (0.05) | (0.002) | (0.003) |
| $InstOwn.$ | | 0.05 | | 0.05*** |
| | | (0.21) | | (0.01) |
| $Analyst$ | | 0.80*** | | 0.07*** |
| | | (0.08) | | (0.01) |
| $BTM$ | | −0.11 | | −0.03*** |
| | | (0.08) | | (0.004) |
| $Mom$ | | 0.29 | | 0.02** |
| | | (0.19) | | (0.01) |
| Industry FE | Yes | Yes | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes | Yes |
| Observations | 41,531 | 41,531 | 41,531 | 41,531 |
| Adjusted $R^2$ | 0.13 | 0.14 | 0.16 | 0.18 |

This table presents regression summary statistics from estimating equation (1) showing the association between the number of firm issued tweets, $Tweets$ and absolute earnings-announcement return, $|CAR[-1,1]|$, and abnormal trading volume, $ATVol$. Industry fixed effects are based on the Fama and French (1997) 48-industry classification. Standard errors clustered by firm and year-quarter appear in parentheses. *, **, *** indicate significance at 10%, 5%, and 1%. The sample comprises of 41,531 observations from 1,844 U.S. firms from 2008 to 2021. See Appendix A for definitions of all variables.

**Table 5: Firms' tweets and investor uncertainty**

| | *IV* | |
|---|---|---|
| | (1) | (2) |
| *Tweets* | $-0.004^{***}$ | $-0.004^{***}$ |
| | (0.001) | (0.001) |
| *VIX* | $0.21^{***}$ | $0.21^{***}$ |
| | (0.02) | (0.02) |
| *IV_Base* | $-0.12^{***}$ | $-0.12^{***}$ |
| | (0.02) | (0.02) |
| *AFE* | 0.003 | $-0.001$ |
| | (0.002) | (0.002) |
| *ROE* | $-0.11^{***}$ | $-0.09^{***}$ |
| | (0.01) | (0.01) |
| *Loss* | $0.02^{***}$ | $0.02^{***}$ |
| | (0.002) | (0.002) |
| *OAcc* | $0.23^{***}$ | $0.20^{***}$ |
| | (0.02) | (0.03) |
| *Size* | $-0.01^{***}$ | $-0.01^{***}$ |
| | (0.001) | (0.001) |
| *InstOwn* | | $-0.02^{***}$ |
| | | (0.003) |
| *Analyst* | | $-0.01^{***}$ |
| | | (0.002) |
| *BTM* | | $0.01^{***}$ |
| | | (0.001) |
| *Mom* | | 0.003 |
| | | (0.003) |
| Industry FE | Yes | Yes |
| Year-Quarter FE | Yes | Yes |
| Observations | 36,023 | 36,023 |
| Adjusted $R^2$ | 0.17 | 0.18 |

This table presents regression summary statistics from equation (2) showing the association between the number of firm issued tweets, *Tweets*, and Investor Uncertainty, *IV*. Industry fixed effects are based on the Fama and French (1997) 48-industry classification. Standard errors clustered by firm and year-quarter appear in parentheses. *, **, *** indicate significance at 10%, 5%, and 1%. The sample comprises of 36,023 observations from 1,798 U.S. firms from 2008 to 2021. See Appendix A for definitions of all variables.

**Table 6: Firms' tweets and stock price informativeness**

**Panel A: Timeliness and efficiency of incorporation of earnings news into stock prices**

| | $IPT$ | | $IPE$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Tweets$ | 0.03** | 0.03** | 0.003** | 0.004** |
| | (0.01) | (0.01) | (0.002) | (0.002) |
| $AFE$ | 0.08* | 0.10** | 0.0001 | 0.01 |
| | (0.04) | (0.04) | (0.005) | (0.005) |
| $ROE$ | 0.56** | 0.47* | 0.07** | 0.04 |
| | (0.26) | (0.28) | (0.03) | (0.03) |
| $Loss$ | −0.08* | −0.09** | −0.02*** | −0.03*** |
| | (0.04) | (0.04) | (0.01) | (0.01) |
| $OAcc$ | −0.12 | 0.03 | −0.07* | −0.05 |
| | (0.39) | (0.40) | (0.04) | (0.04) |
| $Size$ | 0.02** | 0.002 | 0.01*** | 0.01*** |
| | (0.01) | (0.01) | (0.001) | (0.002) |
| $InstOwn$ | | 0.29*** | | 0.04*** |
| | | (0.07) | | (0.01) |
| $Analyst$ | | 0.04 | | −0.002 |
| | | (0.03) | | (0.003) |
| $BTM$ | | −0.03 | | −0.01*** |
| | | (0.02) | | (0.003) |
| $Mom$ | | −0.04 | | −0.01 |
| | | (0.05) | | (0.01) |
| Industry FE | Yes | Yes | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes | Yes |
| Observations | 41,531 | 41,531 | 41,531 | 41,531 |
| Adjusted $R^2$ | 0.02 | 0.02 | 0.05 | 0.05 |

## Table 6 (continued): Firms' tweets and stock price informativeness

### Panel B: Post earnings announcement drift

| | $CAR[2,20]$ | |
|---|---|---|
| | (1) | (2) |
| $Tweets \times AFE$ | $-0.32^{**}$ | |
| | (0.14) | |
| $Tweets \times CAR[-1,1]$ | | $-0.01^{**}$ |
| | | (0.01) |
| $Tweets$ | 0.02 | 0.03 |
| | (0.04) | (0.04) |
| $AFE$ | $1.38^{***}$ | $1.18^{***}$ |
| | (0.27) | (0.25) |
| $CAR[-1,1]$ | $0.04^{***}$ | $0.05^{***}$ |
| | (0.01) | (0.01) |
| $ROE$ | $5.59^{***}$ | $5.57^{***}$ |
| | (1.38) | (1.38) |
| $Loss$ | $-0.24$ | $-0.25$ |
| | (0.35) | (0.35) |
| $OAcc$ | $-20.78^{***}$ | $-20.76^{***}$ |
| | (2.91) | (2.90) |
| $Size$ | $-0.15^{**}$ | $-0.15^{**}$ |
| | (0.07) | (0.07) |
| $InstOwn$ | 0.04 | 0.04 |
| | (0.24) | (0.24) |
| $Analyst$ | 0.21 | 0.21 |
| | (0.13) | (0.13) |
| $BTM$ | $0.54^{***}$ | $0.54^{***}$ |
| | (0.12) | (0.12) |
| $Mom$ | $-0.66$ | $-0.65$ |
| | (0.54) | (0.54) |
| Industry FE | Yes | Yes |
| Year-Quarter FE | Yes | Yes |
| Observations | 41,531 | 41,531 |
| Adjusted $R^2$ | 0.02 | 0.02 |

This table presents regression summary statistics from estimating equations (3) and (4). Panel A presents summary statistics from estimating equation (3) and shows the association between firm issued tweets, $Tweets$ and intraperiod timeliness of prices, $IPT$, and intraperiod efficiency, $IPE$. Panel B presents summary statistics from estimating equation 4 and shows the association between firm issued tweets, $Tweets$ and post-earnings-announcement return, $CAR[2,20]$. Industry fixed effects are based on the Fama and French (1997) 48-industry classification. Standard errors clustered by firm and year-quarter appear in parentheses. *, **, *** indicate significance at 10%, 5%, and 1%. The sample comprises of 41,531 observations from 1,844 U.S. firms from 2008 to 2021. See Appendix A for definitions of all variables.

**Table 7: Tweets' characteristics and stock price discovery**

**Panel A: Tweets' characteristics and their informativeness to investors**

| | $\lvert CAR[-1,1]\rvert$ | | $ATVol$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Dissem* | $0.14^{***}$ | | $0.04^{***}$ | |
| | (0.04) | | (0.01) | |
| *Fund* | | $0.15^{**}$ | | $0.02^{*}$ |
| | | (0.06) | | (0.01) |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes | Yes |
| Observations | 41,531 | 41,531 | 41,531 | 41,531 |
| Adjusted $R^2$ | 0.13 | 0.13 | 0.15 | 0.15 |

**Panel B: Tweets' characteristics and informational efficiency of stock prices**

| | $IV$ | | $IPE$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Dissem* | $-0.004^{***}$ | | $0.004^{**}$ | |
| | (0.001) | | (0.002) | |
| *Fund* | | $-0.003^{**}$ | | $0.01^{**}$ |
| | | (0.001) | | (0.002) |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes | Yes |
| Observations | 36,023 | 36,023 | 41,531 | 41,531 |
| Adjusted $R^2$ | 0.18 | 0.17 | 0.05 | 0.05 |

**Table 7 (continued): Tweets' characteristics and stock price discovery**

**Panel C: Tweets' characteristics and post-earnings announcement drift**

| | $CAR[2,20]$ | |
|---|---|---|
| | (1) | (2) |
| $Dissem \times AFE$ | $-0.37^{**}$ | |
| | (0.15) | |
| $Fund \times AFE$ | | $-0.34^{*}$ |
| | | (0.19) |
| $AFE$ | $1.39^{***}$ | $1.30^{***}$ |
| | (0.27) | (0.26) |
| Tweets main effects | Yes | Yes |
| Controls | Yes | Yes |
| Industry FE | Yes | Yes |
| Year-Quarter FE | Yes | Yes |
| Observations | 41,531 | 41,531 |
| Adjusted $R^2$ | 0.02 | 0.02 |

This table presents regression summary statistics from estimating equations (1) through (4) showing the association between the characteristics of firms' tweets and measures of stock price discovery. Firm tweets are classified as disseminating existing information, $Dissem$, or containing fundamental information, $Fund$. Panel A presents regression summary statistics from estimating equation(1). Columns (1) and (2) use abnormal return at quarterly earnings announcements, $CAR[-1,1]$, and columns (3) and (4) use abnormal trading volume, $ATVol$. Panel B presents regression summary statistics from estimating equations (2) and (3). Columns (1) and (2) use investor uncertainty at quarterly earnings announcements, $IV$, and columns (3) and (4) use intraperiod efficiency $IPE$. Panel C presents regressions summary statistics from estimating equation (4). Columns (1) and (2) use post-earnings announcement return, $CAR[2,20]$. Industry fixed effects are based on the Fama and French (1997) 48-industry classification. Standard errors clustered by firm and year-quarter appear in parentheses. *, **, *** indicate significance at 10%, 5%, and 1%. The sample comprises of 41,531 (36,023) observations from 1,844 (1,798) U.S. firms from 2008 to 2021. See Appendix A for definitions of all variables.

## Table 8: Firms' tweets and visibility

| | $SUV$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $Tweets$ | 0.05*** | | |
| | (0.01) | | |
| $Dissem$ | | 0.06*** | |
| | | (0.02) | |
| $Fund$ | | | 0.05** |
| | | | (0.02) |
| $AFE$ | 0.14*** | 0.14*** | 0.15*** |
| | (0.04) | (0.04) | (0.04) |
| $ROE$ | 0.34 | 0.34 | 0.33 |
| | (0.21) | (0.21) | (0.21) |
| $Loss$ | −0.08** | −0.08** | −0.08** |
| | (0.03) | (0.03) | (0.04) |
| $OAcc$ | −0.13 | −0.14 | −0.13 |
| | (0.38) | (0.38) | (0.38) |
| $Size$ | 0.06*** | 0.06*** | 0.06*** |
| | (0.02) | (0.02) | (0.02) |
| $InstOwn$ | 0.42*** | 0.42*** | 0.42*** |
| | (0.07) | (0.07) | (0.07) |
| $Analyst$ | 0.32*** | 0.32*** | 0.32*** |
| | (0.03) | (0.03) | (0.03) |
| $BTM$ | −0.06*** | −0.06*** | −0.07*** |
| | (0.02) | (0.02) | (0.02) |
| $Mom$ | 0.10** | 0.10** | 0.10** |
| | (0.04) | (0.04) | (0.04) |
| Controls | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes |
| Observations | 38,251 | 38,251 | 38,251 |
| Adjusted $R^2$ | 0.13 | 0.13 | 0.13 |

This table presents regression summary statistics from estimating equation (5) showing the association between firms' use of Twitter, $Tweets$, and the tweets' characteristics, $Dissm$ and $Fund$, and standardized unexpected volume, $SUV$. Industry fixed effects are based on the Fama and French (1997) 48-industry classification. Standard errors clustered by firm and year-quarter appear in parentheses. *, **, *** indicate significance at 10%, 5%, and 1%. The sample comprises of 41,531 observations from 1,844 U.S. firms from 2008 to 2021. See Appendix A for definitions of all variables.

**Table 9: Firms' tweets, retail investors, and stock price discovery**

**Panel A: Firms' tweets and retail trading volume**

| | $ARVol$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $Tweets$ | 0.01*** | | |
| | (0.002) | | |
| $Dissem$ | | 0.01*** | |
| | | (0.002) | |
| $Fund$ | | | 0.005* |
| | | | (0.003) |
| Controls | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes |
| Observations | 38,221 | 38,221 | 38,221 |
| Adjusted $R^2$ | 0.12 | 0.12 | 0.12 |

**Table 9 (continued): Firms' tweets, retail investors, and stock price discovery**

**Panel B: Retail trading volume as a channel through which firms' tweets affect stock prices and trading volume**

| | $\lvert CAR[-1,1]\rvert$ | | | $ATVol$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\widehat{RetVol}_{Tweets}$ | 21.83*** | | | 1.54*** | | |
| | (5.97) | | | (0.39) | | |
| $\widehat{RetVol}_{Dissem}$ | | 21.23*** | | | 1.64*** | |
| | | (6.28) | | | (0.42) | |
| $\widehat{RetVol}_{Fund}$ | | | 33.62** | | | 1.45* |
| | | | (12.94) | | | (0.83) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 38,221 | 38,221 | 38,221 | 38,221 | 38,221 | 38,221 |
| Adjusted $R^2$ | 0.13 | 0.13 | 0.13 | 0.18 | 0.18 | 0.18 |

**Table 9 (continued): Firms' tweets, retail investors, and stock price discovery**

**Panel C: Retail trading volume as a channel through which firms' tweets affect the informational efficiency of stock prices**

| | *IV* | | | *IPE* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\widehat{RetVol}_{Tweets}$ | $-0.60^{***}$ | | | $0.51^{**}$ | | |
| | (0.12) | | | (0.24) | | |
| $\widehat{RetVol}_{Dissem}$ | | $-0.65^{***}$ | | | $0.57^{**}$ | |
| | | (0.14) | | | (0.26) | |
| $\widehat{RetVol}_{Fund}$ | | | $-0.68^{**}$ | | | $1.26^{**}$ |
| | | | (0.26) | | | (0.52) |
| Controls | $Yes$ | $Yes$ | $Yes$ | $Yes$ | $Yes$ | $Yes$ |
| Industry FE | $Yes$ | $Yes$ | $Yes$ | $Yes$ | $Yes$ | $Yes$ |
| Year-Quarter FE | $Yes$ | $Yes$ | $Yes$ | $Yes$ | $Yes$ | $Yes$ |
| Observations | 32,920 | 32,920 | 32,920 | 38,221 | 38,221 | 38,221 |
| Adjusted $R^2$ | 0.18 | 0.18 | 0.18 | 0.05 | 0.05 | 0.05 |

**Table 9 (continued): Retail investors, firms' tweets, and stock price discovery**

**Panel D: Retail trading volume as a channel through which firms' tweets affect the post earnings announcement drift**

| | $CAR[2,20]$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\widehat{RetVol}_{Tweets} \times AFE$ | $-7.26^{**}$ | | |
| | (3.24) | | |
| $\widehat{RetVol}_{Dissem} \times AFE$ | | $-7.34^{**}$ | |
| | | (3.24) | |
| $\widehat{RetVol}_{Fund} \times AFE$ | | | $-7.25^{**}$ |
| | | | (3.26) |
| $AFE$ | $6.81^{**}$ | $6.87^{**}$ | $6.80^{**}$ |
| | (2.64) | (2.64) | (2.66) |
| Tweets main effects | $Yes$ | $Yes$ | $Yes$ |
| Controls | $Yes$ | $Yes$ | $Yes$ |
| Industry FE | $Yes$ | $Yes$ | $Yes$ |
| Year-Quarter FE | $Yes$ | $Yes$ | $Yes$ |
| Observations | 38,221 | 38,221 | 38,221 |
| Adjusted $R^2$ | 0.02 | 0.02 | 0.02 |

This table presents summary statistics from estimating a two-stage least square approach. Estimates are produced using firms' use of Twitter, $Tweets$ and the characteristics of the tweets, $Dissm$ and $Fund$. Panel presents regression summary statistics from estimating equation 6(a) for the first stage of the process and shows the association between $Tweets$, $Dissm$, and $Fund$ and abnormal retail volume, $ARVol$. Panels B through D present regression summary statistics from estimating equation (6b), using the fitted values from the first stage. They show the association between the portion fo abnormal retail volume that is explained by the firms' use of Twitter and absolute abnormal return, $|CAR[-1,1]$, abnromal trading volume, $ATVol$, investor uncertainty, $IV$, intraperiod efficiency, $IPE$, and post-earnings announcement return, $CAR[2,20]$. Industry fixed effects are based on the Fama and French (1997) 48-industry classification. Standard errors clustered by firm and year-quarter appear in parentheses. *, **, *** indicate significance at 10%, 5%, and 1%. The sample comprises of 38,221 (32,920) observations from 1,840 (1,791) U.S. firms from 2008 to 2021. See the Appendix A for definitions of all variables.

## Table 10: Firms' tweets and stock price discovery in a propensity score matched sample

### Panel A: Descriptive statistics

| | Full sample | | | Matched sample | | |
|---|---|---|---|---|---|---|
| | Non-Users | Users | *Diff.* | Non-Users | Users | *Diff.* |
| *Obs.* | 27,486 | 13,326 | | 13,326 | 13,326 | |
| *AFE* | -0.007 | -0.005 | −0.002*** | −0.005 | −0.005 | 0.000 |
| *ROE* | 0.023 | 0.034 | −0.012*** | 0.028 | 0.034 | -0.006*** |
| *Loss* | 0.182 | 0.132 | 0.050*** | 0.151 | 0.132 | 0.019*** |
| *OAcc* | −0.014 | −0.013 | −0.001*** | −0.013 | −0.013 | 0.000 |
| *InstOwn* | 0.764 | 0.788 | −0.024*** | 0.785 | 0.788 | -0.002 |
| *Analyst* | 1.947 | 2.376 | −0.430*** | 2.150 | 2.376 | -0.226*** |
| *Size* | 7.489 | 8.649 | −1.160*** | 8.040 | 8.649 | -0.609*** |
| *BTM* | −0.674 | −0.986 | 0.313*** | −0.840 | −0.986 | 0.147*** |
| *Mom* | 0.062 | 0.084 | −0.022*** | 0.081 | 0.084 | -0.003 |

**Table 10 (continued): Firms' tweets and stock price discovery in a propensity score matched sample**

**Panel B: Regressions analyses using propensity score matched sample**

| | $\|CAR[-1,1]\|$ | $ATVol$ | $IV$ | $IPE$ | $SUV$ |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| $Tweets$ | 0.17*** | 0.01*** | −0.003*** | 0.003** | 0.04*** |
| | (0.04) | (0.003) | (0.001) | (0.002) | (0.01) |
| $ROE$ | −0.54 | 0.05 | −0.05*** | 0.05 | 0.33 |
| | (0.99) | (0.06) | (0.02) | (0.04) | (0.32) |
| $Loss$ | 0.78*** | 0.001 | 0.02*** | −0.02*** | −0.08* |
| | (0.16) | (0.01) | (0.003) | (0.01) | (0.04) |
| $Size$ | −1.20*** | −0.04*** | −0.01*** | 0.01*** | 0.04* |
| | (0.06) | (0.004) | (0.002) | (0.002) | (0.02) |
| $Analyst$ | 0.83*** | 0.08*** | −0.01*** | −0.003 | 0.36*** |
| | (0.11) | (0.01) | (0.003) | (0.004) | (0.04) |
| $BTM$ | −0.09 | −0.02*** | 0.01*** | −0.01* | −0.06** |
| | (0.09) | (0.005) | (0.001) | (0.003) | (0.02) |
| $\Delta VIX$ | | | 0.21*** | | |
| | | | (0.02) | | |
| $BaseIV$ | | | −0.15*** | | |
| | | | (0.03) | | |
| Industry FE | Yes | Yes | Yes | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 26,902 | 26,902 | 23,654 | 26,902 | 26,902 |
| Adjusted $R^2$ | 0.14 | 0.20 | 0.19 | 0.05 | 0.12 |

This table presents summary statistics for the matched sample analysis. Panel A presents distributional statistics for two samples, the full sample, and a sub sample of firms that were selected using a matching process based on observable firm characteristics. Panel B presents regression summary statistics from estimating equations (1) through (4) using the matched sample. Industry fixed effects are based on the Fama and French (1997) 48-industry classification. Standard errors clustered by firm and year-quarter appear in parentheses. *, **, *** indicate significance at 10%, 5%, and 1%. The sample comprises of 26,902 observations from 1,665 U.S. firms from 2008 to 2021. See the Appendix A for definitions of all variables.

# Appendix A: Variable definitions

| Variable | Description |
|---|---|
| $Analyst$ | Natural logarithm of 1 plus the number of analysts providing an earnings forecast calculated at the firm-quarter level. |
| $AFE$ | Decile ranking of the absolute analyst forecast error, calculated as the decile ranking of earnings per share for the quarter minus the median analyst estimate scaled by stock price at the end of the quarter. |
| $ARVol$ | Abnormal retail volume calculated as the natural logarithm of one plus the proportion of retail trading volume over the $[-1, 1]$ day period relative to the quarterly earnings announcement and the proportion of retail trading volume over the $[-54, -5]$ day period. |
| $ATVol$ | Abnormal trading volume calculated as the natural logarithm of one plus the share turnover ratio across days $[-1, 1]$, scaled by the average daily turnover ratio across days $[-54, -5]$ relative to the quarterly earnings announcement. Defined as $ATVol = ln(1 + \frac{\frac{1}{3}\sum_{j=-1}^{1} TR_{i,t+j}}{\frac{1}{50}\sum_{j=5}^{54} TR_{i,t-j}})$. $TR$ is the ratio between the number of shares traded and the number of shares outstanding, $j$ represents the trading day relative to the quarterly earnings announcement. |
| $BTM$ | Natural logarithm of the equity book-to-market ratio at the end of the fiscal quarter. |
| $CAR[a, b]$ | Cumulative abnormal equity return during days $[a, b]$ relative to the quarter's earnings announcement. Calculated as Raw return minus the value-weighted return for a portfolio of firms matched on $5 \times 5$ sorts of equity market value and market-to-book ratio Daniel et al. (1997). |
| $Dissem$ | Natural logarithm of 1 plus the number of firm initiated tweets that disseminate existing information in the [-1,+1] window surrounding a firm's quarterly earnings announcement. |
| $Fund$ | Natural logarithm of 1 plus the number of firm initiated tweets that contain fundamental information in the [-1,+1] window surrounding a firm's quarterly earnings announcement. |
| $InstOwn$ | Percentage of shares owned by institutions at the most recent quarter-end relative to fiscal quarter. |
| $IPE$ | Intraperiod efficiency of reported earnings, defined as: $IPE = 1 - \sum_{j=0}^{5} \frac{\lvert CAR[0,5] - CAR[0,j] \rvert}{\lvert CAR[0,5] \rvert}$, where $j$ represents the trading day from 0 to 5 relative to the quarterly earnings announcement. |
| $IPT$ | Intraperiod timeliness of reported earnings, defined as: $IPT = \sum_{j=0}^{4} \frac{CAR[0,j]}{CAR[0,5]} + 0.5$, where $j$ represents the trading day from 0 to 5 relative to the quarterly earnings announcement. |
| $Loss$ | An indicator variable equal to 1 if the firm reports a loss for the quarter. |
| $IV$ | Implied volatility, measured by averaging the implied volatilities of put and call options with durations of 30 days measured over the $[-1, 1]$ period relative to a firm's quarterly earnings announcement date Sridharan (2015). |
| $IV\_Base$ | Baseline implied volatility, measured on day $-2$ relative to a firm's quarterly earnings announcement date. |
| $VIX$ | A change in market volatility index (CBOE Volatility index) measured over the $[-1, 1]$ period relative to a firm's quarterly earnings announcement. |
| $Mom$ | Six-month cumulative stock return ending one month prior to the period quarter end date. |
| $OAcc$ | Operating accruals, calculated as the difference between income before extraordinary items and cash flows from operating activities, divided by average total assets at the end of the quarter. |
| $ROE$ | Return on book value of equity during the fiscal quarter, measured as the ratio between net income before extraordinary items and average total assets. |
| $Size$ | Natural logarithm of market value of equity at the end of a firm's fiscal quarter. |
| $SUV$ | The ratio between total trading volume during days $[-1, 1]$ that cannot be explained by positive or negative stock returns during the measurement window, and the standard deviation of residuals from a regression of trading volume on positive and negative stock returns during days $[-54, -5]$ relative to the earnings announcement date (Lerman et al., 2010; Israeli et al., 2022b). |
| $Tweets$ | Natural logarithm of 1 plus the number of firm initiated tweets in the $[-1, 1]$ window surrounding a firm's quarterly earnings announcement. |

# Appendix B: Classification of tweets

To characterize firms' use of Twitter, we classify tweets according to their content. We follow prior research and implement two classification schemes: (1) whether or not the tweet disseminates information, and (2) whether or not the tweet contains fundamental information. We classify tweets as dissemination tweets according to the methodology in Bartov et al. (2018) i.e., a retweet of an existing tweet or a tweet containing a hyperlink leading to an external website. We classify tweets as fundamental tweets following Bartov et al. (2018) and Nerkasov et al. (2022), i.e., firm generated tweets that focus on fundamental information that is likely related to firm or market performance. Panel A presents the vocabularies we use to classify the tweets in our sample and Panel B provides examples of tweets and their classifications.

### Panel A: Fundamental words lists

| Source | List of words |
|---|---|
| Bartov et al. (2018) | adjusted, earning, ebit, ebitda, eps, expense, fiscal, gaap, gain, in the black, in the green, in the red, income, loss, noi, nopat, normalized, oibda, operating, per share, pro forma, profit, proforma, pro-forma, results, revenue,sales, yearend, year-end, accounting, acquir,aggressive, asset, balance sheet, boosted, business model, capacity, capital, cash, CDS, charge, compete, competit, conservative, consumer, contract, corporat, covenant, customer, debt, decline, demand, dividend, effective, equity, executive, financial statement, forecast, fraud, gain, goodwill, growth, income statement, industry, inflate, innovati, internal control, inventory, investigat, lawsuit, legal, lever, liquidity, m&a, margin, miss, obfuscate, overstat, patent, peer, ponzi, produc, profit, pyramid, rating, red flag, reserv, resource, restructur, risk, roll-up, solven, supplier, surprise, takeover, technolog, whisper, writedown, write-down, writeoff, write-off, after hour, analyst, bear, bought, break, bull, buy, call, climb, close, cover, downgrade, downside, halt, high, invest, long, low, market, move, moving, open, play, position, price, put, quote, rally, resistance, sell, share, short, sold, spike, stock, stop, support, target, trade, trading, tumble, upgrade, upside, valuation, value, volume |
| Nekrasov et al. (2022) | earnings, earning, income, revenue, results, quarter, quarterly, press release, financial results, earnings results, beats, dividend, cash dividend, forward-looking statement, forward-looking statements, net income, common share, earnings forecast, earnings forecasts, 1Q, Q1, Q2, 2Q, Q3, 3Q, Q4, 4Q, EPS, profit, profits, sales, strong performance, stock repurchases, earnings guidance, conference call, conf call, webcast, beat, GAAP, non-GAAP, profitability, shareholder value, exceeds expectations |
| Additional words | ceo, chief, investment, operating margin, revenue, performance |

This panel provides the list of words we use in our textual analysis to identify tweets that contain fundamental information. Nekrasov et al. (2022) offers a list of words that are related to firm earnings announcements. Bartov et al. (2018) provide a list of words related to trading and fundamental information. To these lists we add several key words that appear in firm initiated tweets and relate to fundamental information.

## Panel B: Examples of tweets

| Twitter account | Tweet date | Tweet text | *Dissem* | *Fund* |
|---|---|---|---|---|
| *(1) MarshMcLennan* | 10/22/2021 | "150 years of Marsh McLennan and the celebrations continue! Our colleagues in Poland came together to mark the occasion. https://t.co/Rsp206iknh #MM150 https://t.co/FzrT3OuKJ0" | Yes | No |
| *(2) Kodak* | 03/17/2021 | "Our NEXFINITY Digital Press gives printers the versatility to create high-quality, customized direct mail, photobooks, brochures, catalogs and more https://t.co/i385KS07dD https://t.co/Bt9GOvtkWJ" | Yes | No |
| *(3) PulteGroupNews* | 04/27/2021 | "Net new orders for Q1 2021 increased 31% to 9,852 homes, while the order value increased 42% to $4.6 billion $PHM #earnings" | No | Yes |
| *(4) CACIIntl* | 08/12/2021 | "CEO John Mengucci: For FY21, we delivered revenue growth of 6%, adjusted EBITDA margins of 11.1%, and robust cash flow. Our organic revenue growth of 5% was ahead of our underlying addressable market, and we delivered healthy margin expansion" | No | Yes |
| *(5) GoldmanSachs* | 10/14/2021 | "Watch David Kostin, $GS' chief US equity strategist, discuss supply chain disruption and his forecast on next year's earnings growth on @SquawkStreet. https://t.co/PehMPm9rT6" | Yes | Yes |
| *(6) AbbottNews* | 04/20/2021 | "We're off to a great start in 2021, with growth across all four businesses and new products adding momentum to our already strong portfolio of life-changing technologies. Learn more about $ABT Q1 #earnings: https://t.co/kjlJrFviSH https://t.co/jqA8CPIsSg" | Yes | Yes |
| *(7) ATT* | 01/26/2021 | "Closing the homework gap is a group project. Let's do it together" | No | No |
| *(8) Nike* | 12/17/2021 | "For classic campus style, HBCU alumni ground their look with the OG hoops sneaker" | No | No |

This panel presents examples of tweets from our sample and their classification. Tweets (1)-(2) and (5)-(6) are classified as *Dissem* and tweets (3)-(4) and (5)-(6) are classified as *Fund*. Tweets (7)-(8) belong to the group of tweets that are neither classified as *Dissem* nor *Fund*.