Social Media Discussion of Sell-Side Analyst Research: Evidence from Twitter

Andrew C. Call
**Corresponding Author*
University of Southern California
andycall@marshall.usc.edu

Mehmet Kara
University of Georgia
mehmet@uga.edu

Matt Peterson
University of Kansas
m.peterson@ku.edu

Eric Weisbrod
University of Kansas
eric.weisbrod@ku.edu

August 30, 2025

We thank Rachel Flam (discussant), Justin Hopkins, Michael Jung (discussant), Min Park, Jessie Watkins, workshop participants at Hong Kong Polytechnic University, University of Texas El Paso, INSEAD, Tulane University, University of Minnesota, the 2022 AAA Annual meeting, the 2023 FARS midyear meeting, and students in the accounting research seminar at the University of Kansas for helpful comments. Declarations of interest: None.

Social Media Discussion of Sell-Side Analyst Research: Evidence from Twitter

Abstract

We examine Twitter discussion of sell-side analysts' stock recommendation revisions. While many investors lack direct access to analyst research, we observe revision-related Twitter discussion associated with approximately 90% of the revisions in our sample, usually within three hours of their announcement. Revision-related Twitter discussion is more extensive for upgrades and for analysts from larger brokerages. Examining within-revision intraday price discovery, we also observe increased levels of price discovery during intraday windows with more revision-related tweets, especially for tweets with more user engagement, those posted by more influential authors, and for stocks with more intense retail trading volume. Finally, we find that revision-related retail trading is more intense and better predicts future returns for revisions with more revision-related Twitter discussion. However, we observe no such evidence for institutional investors who typically have direct access to sell-side research. Overall, our results suggest that Twitter is an important channel in facilitating price discovery following analyst revisions, particularly among retail investors.

Keywords: Sell-side analysts, analyst recommendations, social media, Twitter, retail investors.
JEL Classification: D62, D83, D84, G14, G24, M40, M41

1. Introduction

We examine the discussion of sell-side analysts' investment recommendations on Twitter.[1] Sell-side analysts are important information intermediaries in capital markets, and a large body of research finds that analysts' recommendations have investment value for their clients (Ramnath, Rock, and Shane 2008; Kothari, So, and Verdi 2016). However, analysts' recommendations are typically proprietary to the brokerage and only subscribers have direct access to this research in real time. Prior studies raise concerns that sophisticated institutional investors receive preferential access to analysts' research, putting retail investors at a disadvantage (e.g., Irvine, Lipson, and Puckett 2006; Mikhail, Walther, and Willis 2007). The value of sell-side analysts' research, along with its limited dissemination among brokerage clients, suggest that other information intermediaries such as data providers, the business press, and social media may be important in broadening analysts' market impact and expanding retail investors' access to analyst research.

Consequently, previous studies have examined the role of forecast data providers, or FDPs (e.g., Bloomberg and Thomson Reuters), and the business press in disseminating sell-side analyst research (e.g., Bonner, Hugon, and Walther 2007; Rees, Sharp, and Twedt 2015; Akbas, Markov, Subasi, and Weisbrod 2018; Ahn, Drake, Kyung, and Stice 2019; Bochkay, Markov, Subasi, and Weisbrod 2022). Akbas et al. (2018) and Ahn et al. (2019) conclude that the dissemination of analyst revisions by FDPs and the business press, respectively, is associated with a trading response from large institutional investors, consistent with these traditional intermediaries catering primarily to institutional investors.

In contrast, retail investors are increasingly gaining access to investment-related information through social media (Blankespoor, deHaan, and Marinovic 2020). Extant studies examining the role of social media in investment research have primarily examined user-generated investment research. These studies find that user-generated research posted on *Seeking Alpha* serves as a substitute for sell-side research, particularly among retail investors (Farrell, Green, Jame, and Markov

[1] Our sample period ends during 2020. Following our sample period, Twitter was subsequently acquired in 2022 and renamed to 𝕏 in 2023.

2022; Drake, Moon, Twedt, and Warren 2022). One likely reason that prior studies have focused on non-professional or crowd-sourced investment research is that most sell-side brokerages have policies barring sell-side analysts from disseminating their own reports via social media. However, Twitter is a unique medium for short-form content submission with minimal moderation, which is unlike *Seeking Alpha* and the traditional business press. The loosely-moderated "digital town square" nature of the Twitter platform potentially allows for user-driven discussion and dissemination of professional analysts' underlying research to a broader audience, including retail investors, on a timely basis.

Although Twitter has the potential to facilitate investors' use of sell-side analyst research, the prevalence and impact of Twitter discussion of sell-side analyst research remains unknown. In addition to brokerages barring analysts from disseminating their own research on social media, prior literature notes that brokerages go to "great lengths," including taking legal action, to try to prevent unauthorized dissemination of their research (Li, Ramesh, Shen, and Wu 2015). Therefore, Twitter discussion of sell-side research may be rare. Moreover, its impact on price discovery may not be distinct from that of FDPs and the traditional media, especially if Twitter is a redundant or less timely form of dissemination reaching the same set of institutional investors. We predict that, if Twitter does play a distinct role in facilitating price discovery of sell-side analysts' research, it is because of its unique ability to reach retail investors, unlike other intermediaries that have been shown to cater to large institutional investors. However, we acknowledge that in some cases prior studies find that social media-induced retail trading can actually distort or impede price discovery (Jia, Redigolo, Shu, and Zhao 2020; Cookson, Engelberg, and Mullins 2023; Campbell, Drake, Thornock, and Twedt 2023). Thus, the purpose of our study is to examine whether Twitter discussion of sell-side research is prevalent, whether it facilitates incremental price discovery of analysts' research, and, if so, whether it is associated with retail investor trading activity.

We analyze Twitter discussion of sell-side analysts' recommendation revisions using a text-based approach to identify revision-related tweets. We match analyst recommendation revision announcements with tweets that contain both the covered firm's cashtag (e.g., $AAPL) and any form of the word "upgrade" ("downgrade") within the [0,+1] day window around a recommendation upgrade (downgrade) announcement.[2] Throughout our analyses, we control for concurrent tweets that contain the firm's cashtag but that are unrelated to the recommendation revision (hereafter, "other tweets"). We also control for concurrent recommendation coverage in traditional media outlets using data from RavenPack, as well as concurrent dissemination of the recommendation revision by I/B/E/S, a prominent FDP.

Analyzing a sample of 50,286 recommendation revisions announced from 2013 to 2020, we find that Twitter discussion of analysts' recommendation revisions is prevalent. We observe at least one revision-related tweet during the two trading-day ([0,+1]) announcement window for 90.1% of all revisions in our sample. Revision-related tweets are also reasonably timely, with a median delay of 145 minutes (2 hours 25 minutes) from the revision announcement until the first revision-related tweet. We also find that the number of revision-related tweets increases sharply in the hours immediately following a revision announcement.

We model the determinants of this Twitter activity, and propose a number of revision-, analyst-, and firm-related characteristics that potentially determine the level of Twitter dissemination around a revision. One important revision-related characteristic is whether the revision is an upgrade or downgrade. Rees et al. (2015) find that analysts who issue sell recommendations are more likely to receive coverage in the financial press, consistent with the notion that "the best news story is someone else's disaster" (Wilkins and Patterson 1987; Shoemaker and Cohen 2012). In contrast, we find that revision-related Twitter discussion is significantly higher and more timely for upgrade revisions, consistent with Twitter users having incentives to share good news on social media. *Ceteris paribus*, our results indicate that upgrade revisions receive 8% more revision-related tweets than downgrade revisions, and upgrade revisions receive the first revision-related tweet about 27 minutes more quickly than downgrades.

In order to examine whether revision-related Twitter discussion facilitates price discovery of analysts' recommendation revisions, we focus on variation in price discovery at the intraday level.[3]

[2]Figure A.1 in the Appendix provides examples of revision-related tweets.

[3]In addition to intraday data providing more precise identification, we note that we do not observe evidence of

We conduct an intraday analysis that breaks the announcement window into distinct four-hour windows, and we examine the relation between revision-related tweets during a given four-hour period and the relative price discovery concentrated in the same four-hour period (e.g., Li et al. 2015; Akbas et al. 2018). We include revision, time-of-day, and event-time fixed effects, so our model focuses on the variation in price discovery between different four-hour windows *within* a given revision. Using data from Ravenpack, we also control for concurrent traditional media releases by or about the firm during the same four-hour window. We also control for concurrent dissemination by I/B/E/S using the I/B/E/S activation timestamp.

We find a robust positive association between revision-related tweets and intraday price discovery, with revision-related tweets within the first four trading hours following the revision announcement having the strongest impact on relative price discovery. Furthermore, we find a stronger association between the number of revision-related tweets and relative price discovery during a given four-hour window when the tweets during that window have higher levels of user engagement, contain URLs linking to more information, or are tweeted by more influential authors (i.e., authors with more followers or those who are "verified" by Twitter).[4]

We next examine whether more timely revision-related Twitter discussion is associated with a more timely market reaction. Following Bochkay et al. (2022), we estimate intraday market reaction timeliness (MRT) as an area-under-the-curve measure of the cumulative absolute return response to an event over the trading hours following the announcement time.[5] Higher (lower) values of intraday MRT indicate that earlier trading hours in the [0,1] trading-day announcement window account for a larger (smaller) portion of the overall buy-and-hold return. We find that recommendation revisions with more revision-related tweets during the first four hours, as well as revisions with a shorter delay until the first revision-related tweet, are associated with a more

long-window post-revision price drifts or reversals following recommendation revisions during our recent sample period.

[4]Figure A.2 provides background information for the top 25 authors of revision-related tweets in our sample. Anecdotally, the user accounts that generate revision-related tweets vary from investor portals and automated news feeds to individual traders and media personalities.

[5]Intraday MRT is an intraday equivalent to the daily "intraperiod timeliness" (IPT) efficiency measure used in a number of prior studies (e.g., Twedt 2015; Drake, Thornock, and Twedt 2017; Blankespoor, deHaan, and Zhu 2018; Campbell et al. 2023).

efficient market response. In terms of economic significance, a one standard deviation increase in the number of revision-related tweets in the first four hours following the revision announcement is associated with a 2% increase in MRT, relative to its mean. On the whole, our intraday analyses provide robust evidence that the dissemination on Twitter of analysts' stock recommendation revisions leads to improvements in price discovery.

Finally, we examine which type of investors respond to revision-related tweets. Prior studies generally view social media as a communication platform targeted towards retail investors (Farrell et al. 2022; Campbell et al. 2023). Thus, we expect revision-related Twitter discussion to be associated with retail investor trading activity. However, the manner in which retail traders will respond to revision-related Twitter discussion is unclear. In particular, Mikhail et al. (2007) find that small investors are net purchasers following analysts' recommendation revisions, regardless of the direction of the revision, suggesting that small investors' response to recommendation revisions is uninformed. In addition, Campbell et al. (2023) document a spike in abnormal retail volume around earnings that go "viral" on Twitter, but ultimately conclude that viral Twitter discussion of earnings announcements increases complexity for retail investors and exacerbates trading inefficiencies. In contrast, Farrell et al. (2022) find retail trading is actually more informed in the hours following the publication of investment research on Seeking Alpha.

Using the Barber, Huang, Jorion, Odean, and Schwarz (2024) algorithm to identify retail trades, we find that higher levels of revision-related Twitter discussion are associated with greater abnormal announcement-window retail trading volume. Moreover, revision-related Twitter discussion of upgrades (downgrades) is associated with a more positive (negative) announcement-window retail order imbalance.Importantly, we do not find any association between *institutional* order imbalance and revision-related Twitter discussion.

We also repeat our intraday analyses of relative price discovery and market reaction timeliness and compare our results across sub-samples of revisions with above vs. below median levels of abnormal announcement window retail trading. We find that our intraday results are largely concentrated in revisions with above-median abnormal retail trading intensity. Finally, following

Farrell et al. (2022), we examine whether post-revision order imbalance is more informed for revisions with greater revision-related Twitter discussion. We find an increased association between post-revision order imbalance and future market-adjusted returns for retail-initiated trades following revisions with greater revision-related Twitter discussion, but observe no evidence of a similar increase for institutional trades. Taken together, our findings suggest revision-related Twitter discussion promotes a stronger and more informed revision-related trading response among retail investors.

Our study extends prior research on investors' response to analyst recommendation revisions. Prior studies have examined the roles of the financial press and FDPs in publicizing analysts' research (Ahn et al. 2019; Bonner et al. 2007; Rees et al. 2015; Akbas et al. 2018). We document that in recent years analysts' recommendation revisions are frequently discussed on Twitter, consistent with social media becoming a significant channel for the dissemination of revision-related information. Importantly, we find that both the determinants and consequences of Twitter discussion of recommendation revisions differ from those of traditional media coverage of recommendation revisions, consistent with the differing incentives of journalists vs. social media users, as well as the differing audiences of traditional media vs. social media. For instance, while Ahn et al. (2019) find that the dissemination of recommendation revisions in traditional media outlets influences large-trade institutional investors, we find that Twitter discussion of analysts' recommendation revisions influences retail investors' trading behavior. Furthermore, while Mikhail et al. (2007) suggest that retail investors often traded in the opposite direction of analyst revisions prior to the rise of social media, we find that retail investors are more likely to trade in a manner consistent with the analyst revision and that their revision-related trading is better informed when this research is more broadly discussed on Twitter.

Our findings also speak to the role of social media in democratizing investors' access to investment research. Farrell et al. (2022) find that crowd-sourced investment research on Seeking Alpha provides value-relevant information to retail investors, and Drake et al. (2022) find that crowd-sourced social media research can preempt traditional sell-side research in the market. From the perspective of a user, one of the downsides of crowd-sourced research is that much of it is anonymous and of questionable value (Kadous, Mercer, and Zhou 2025; Dyer and Kim 2021). Our findings suggest that Twitter discussion of sell-side analyst research mitigates this concern by referencing the analysis of a professional capital market intermediary, leading to improved price discovery, especially when revision-related tweets are from trusted accounts or provide links to source material.

In this regard, our study contributes to research on the broader role of social media in capital markets. Extant literature offers mixed results as to whether social media discussion is beneficial or detrimental to investors. (e.g., Blankespoor, Miller, and White 2014; Curtis, Richardson, and Schmardebeck 2014; Heimer 2016; Bartov, Faurel, and Mohanram 2018; Nekrasov, Teoh, and Wu 2022; Jia et al. 2020; Han, Hirshleifer, and Walden 2021; Cookson et al. 2023). We find that Twitter discussion referencing professional sell-side analyst research yields benefits for retail investors, which underscores the idea that the role of social media in the capital markets is context-specific and based on the type and credibility of the information being disseminated (Kadous et al. 2025; Dyer and Kim 2021). Our findings are relevant to investors, as well as researchers and regulators interested in investors' access to investment-related information.

2. Background and Motivation

Traditionally, brokerages provide analyst research to their institutional clients as a proprietary service that is subsidized by soft-dollar trading commissions (e.g., Irvine et al. 2006; Li et al. 2015). Given its investment value, investor demand for sell-side research often extends beyond a given brokerage's direct clients. For example, Lawrence, Ryans, and Sun (2017) use Yahoo! Finance page view data to demonstrate that investor demand for analyst research "substantially trumps that of SEC filings and financial statement information." Furthermore, even institutional investors with direct access to analyst research face attention constraints in monitoring and integrating all available research in real-time. Accordingly, prior research finds that other information intermediaries serve important roles in broadening the impact of analyst research and helping investors integrate it into their trading decisions.

For example, FDPs play an important role in capital markets by aggregating, standardizing, and disseminating analyst research in machine readable form. Yet, most FDPs charge high subscription costs and cater to institutional investors. Consistent with this, Akbas et al. (2018) find that the intraday proportion of large trades increases around I/B/E/S dissemination of analyst revisions. The traditional financial press (e.g., Dow Jones Newswire) can also serve as an intermediary in broadening investors' access to and understanding of analyst research. However, similar to Akbas et al. (2018), Ahn et al. (2019) hypothesize that professional press coverage is primarily targeted at professional investors and find supporting evidence of an increase in the proportion of large trades around press coverage of analyst recommendations.

Therefore, it remains unknown whether and how retail investors access sell-side research. In recent years, retail investors are increasingly gaining access to investment-related information through social media (Blankespoor et al. 2020). However, most sell-side brokerages have policies barring sell-side analysts from disseminating their own reports via social media. As an alternative, social media platforms offering crowd-sourced investment research, such as Seeking Alpha (seekingalpha.com), have emerged to cater to retail investors. Drake et al. (2022, p. 1) note that "it is unclear how firm-specific research posted by individuals on social media...interrelates with information produced by professional sell-side analysts." They find that sell-side analyst reports are increasingly preempted by individuals posting their own investment research on Seeking Alpha, and that this phenomenon is more pronounced for firms with lower institutional ownership and higher retail trading volume. Farrell et al. (2022) also find that crowd-sourced investment research is more likely to be posted on Seeking Alpha for firms that are less likely to have sell-side research coverage. Overall, these results are consistent with social media platforms offering crowd-sourced investment research serving as a *substitute* for sell-side analyst research.

We propose that some social media platforms, such as Twitter, may instead *complement* sell-side analyst research and strengthen retail investors' response to analyst recommendations. In contrast to the business press and Seeking Alpha, Twitter limits posts to short-form messages with minimal content moderation, and is known for its broad user base and timely news dissemination.[6] Thus, Twitter has the potential to serve as a loosely-moderated "digital town square," fostering timely dissemination of short messages linking to underlying source content. These aspects of the Twitter platform enable user-driven discussion and dissemination of professional analysts' underlying research to a broader audience, including retail investors, on a timely basis.

To the extent that revision-related Twitter discussion occurs, we also examine whether the determinants of revision-related Twitter discussion are more similar to the determinants of traditional revision-related coverage, or to those of broader investment-related social media discussion.[7] Accordingly, we examine the prevalence and determinants of revision-related Twitter discussion:

Research Question 1 (RQ1): *To what degree are sell-side analyst recommendation revisions discussed on Twitter?*

To the extent that revision-related Twitter discussion improves investors' access to (or understanding of) analyst research, it may, in turn, affect their trading response to revision announcements. It is important to understand whether revision-related Twitter discussion affects the strength and speed of price discovery following analyst recommendation revisions because Womack (1996) documents substantial post-revision drift following analysts' recommendation revisions, suggesting an incomplete response to recommendation revisions during the announcement window. In this regard, Akbas et al. (2018) and Ahn et al. (2019) find that FDP and business press coverage of analysts' recommendation revisions, respectively, increase the market reaction to the revision and decrease post-revision price drift, consistent with improved price discovery of the news contained in analysts' revisions.

The role of Twitter discussion in facilitating investors' response to sell-side analysts' recommendation revisions is less clear ex-ante. To the extent that revision-related discussion on Twitter

[6] Twitter's Q4 2020 letter to shareholders reports over 192 million active daily users as of the end of our sample period https://ppc.world/uploads/article_images/2021/09/twitter/final-q4-20-twtr-shareholder-letter.pdf.

[7] For example, Rees et al. (2015) find that analysts with outstanding sell recommendations are more likely to be cited in the media than those with outstanding buy recommendations, consistent with the traditional media's incentives to cover bad news. However, prior research suggests behavioral biases may lead investor interactions over social networks to instead promote 'good' news (e.g., Hirshleifer 2020; Han et al. 2021).

is redundant to FDP and traditional media coverage it may not have an incremental impact on price discovery. This is especially true if institutional investors largely drive revision-related price discovery but do not attend to social media, although revision-related Twitter discussion may foster price discovery among retail investors.[8]

In this regard, prior research in other capital market settings provides mixed evidence on the capital market consequences of Twitter discussion among retail investors. Consistent with Twitter discussion leading to more efficient capital market outcomes, Curtis et al. (2014) find that tweets about earnings news are associated with a stronger and more timely investor response to earnings news, and Bartov et al. (2018) find that the tone of firm-related tweets in the days prior to an earnings announcement predict the earnings surprise and its market response.[9] However, several other studies find that peer interactions over social media can instead exacerbate behavioral biases and spread stale news or unsubstantiated rumors (e.g., Heimer 2016; Han et al. 2021; Jia et al. 2020; Cookson et al. 2023). In the context of earnings news, Drake et al. (2017) and Campbell et al. (2023) find that "non-professional" internet articles about earnings announcements, and earnings announcements that "go viral" on Twitter are associated with less efficient market responses, respectively. Similarly, Cookson et al. (2023) demonstrate that social media platforms can create "echo chambers." Such echo chamber effects can either exacerbate disagreement around analyst revisions or lead to return overreactions if investors anchor on revision-related discussion that confirms their existing views. Therefore, it is also possible that Twitter discussion could hinder the price response to analyst revisions. Accordingly, we examine whether revision-related Twitter discussion affects the market response to analysts' recommendation revisions:

Research Question 2 (RQ2): *Ceteris paribus, is Twitter discussion of analysts' recommendation revisions associated with the strength and speed of revision-related price discovery?*

To the extent that revision-related Twitter discussion affects the market response to analyst rec-

[8]Furthermore, capital markets have become more efficient since the advent of Twitter (e.g., Martineau et al. 2022), such that material variation in price discovery across recommendation revisions may no longer pose a concern during our sample period.

[9]We note that prior studies also examine managers' use of Twitter to disclose information to investors via the firm's official Twitter account (e.g., Blankespoor et al. 2014; Nekrasov et al. 2022).

ommendation revisions, we expect its impact is primarily driven by retail investors. Prior research generally views social media as a communication platform targeted towards retail investors (e.g., Farrell et al. 2022). However, it is unclear whether and how retail traders trade in response to analyst recommendation revisions. Using small trade size as a proxy for retail investor trading, Mikhail et al. (2007) find that, on average, small investors are net purchasers following recommendation revisions, regardless of the direction of the revision, and lose money on these trades, suggesting that retail investors' response to recommendation revisions is uninformed. In contrast, Mikhail et al. (2007) find that large investors trade in the direction of analysts' recommendation revisions, and appear to trade profitably.

However, more recent studies have questioned the use of trade size as a proxy for retail investor trading activity because of the widespread adoption of order-splitting algorithms by institutional investors, leading to the adoption of new retail trading measures based on sub-penny price improvement (Boehmer, Jones, Zhang, and Zhang 2021; Barber et al. 2024). Using Boehmer et al. (2021)'s price-improvement-based measure of retail trading activity, Farrell et al. (2022) find retail trading is more informed in the hours following the publication of investment research on Seeking Alpha. Alternately, using the same measure of retail trading, Campbell et al. (2023) find evidence suggesting that viral Twitter discussion of earnings announcements increases complexity for retail investors and exacerbates trading inefficiences. Accordingly, we examine whether revision-related Twitter discussion is associated with revision-related retail trading activity:

Research Question 3 (RQ3): *Ceteris paribus, is Twitter discussion of analysts' recommendation revisions associated with retail investors' trading response to recommendation revisions?*

3. Research Design

3.1 Determinants

To examine our first research question (RQ1) regarding the determinants of Twitter discussion (and its timeliness) around analysts' recommendation revisions, we estimate variations of the following model:

$$\begin{aligned} Tweet\ Measure = \alpha + \beta_1 Revision\ Characteristics + \beta_2 Analyst\ Characteristics \\ + \beta_3 Firm\ Characteristics + A \times AnnHr\ FE\ + \epsilon, \end{aligned} \tag{1}$$

where $Tweet\ Measure$ is one of three measures. Our primary measure is $Ln(Rev\ Tweets)$, the natural logarithm of one plus the number of revision-related tweets observed during the [0,+1] trading-day window relative to the forecast revision announcement date. Revision-related tweets ($Rev\ Tweets$) are defined as tweets that contain both the firm's cashtag and any form of the word "upgrad*" or "downgrad*" matching the direction of the forecast revision.[10] Figure A.1 provides examples of revision-related tweets.

For comparison, we also examine $Ln(Other\ Tweets)$, the natural logarithm of one plus the number of total tweets observed during the [0,+1] trading-day window relative to the forecast revision announcement date less the number of revision-related tweets observed over the same period. Because $Other\ Tweets$ includes any tweets that contain the firm's cashtag but excludes revision-related tweets, this variable proxies for announcement-window Twitter discussion about the firm that is unrelated to the recommendation revision.[11]

Finally, given that prior studies find that the timeliness of third-party dissemination of analyst research is associated with the speed of price discovery (e.g., Akbas et al. 2018), we examine the timeliness of the Twitter response to analysts' recommendation revisions using $Ln(Tweet\ Delay)$, the natural logarithm of one plus the number of minutes from the I/B/E/S revision announcement timestamp to the first $Rev\ Tweet$ timestamp within one trading day of the revision.[12] Using these tweet measures, we examine whether the magnitude and timeliness of Twitter discussion varies with a number of revision-, analyst-, and firm- related characteristics, represented in Eq. (1) by the vectors $Revision\ Characteristics$, $Analyst\ Characteristics$, and $Firm\ Characteristics$, respectively. To control for effects of the timing of the revision announcement that may influence

[10] To validate our identification strategy, we randomly sampled 500 revision-related tweets and examined the subject matter of each tweet. 97.4% of the tweets pertained to the recommendation revision of the covered firm.

[11] For example, Altınkılıç and Hansen (2009) demonstrate that recommendation revisions often occur shortly after other material corporate events.

[12] This measure assumes that the I/B/E/S announcement timestamp is more timely than Twitter dissemination of the revision, and that the first revision-related tweet following a revision announcement relates to the current announcement rather than a previous revision of the same sign.

the level and timing of revision-related Twitter discussion, we include announcement-hour fixed effects ($AnnHR\ FE$), which is the hour of day of the announcement timestamp from I/B/E/S.

$Revision\ Characteristics$ include the direction ($Upgrade$) and magnitude ($Magnitude$) of the revision.[13] We also examine FDP and traditional media coverage of the revision, by including $Activation\ Delay$ and $Ln(Rev\ Stories)$, respectively. As noted above, Rees et al. (2015) find that sell recommendations are more likely to be cited by the financial press than buy recommendations. However, to the extent that a Twitter user holds a long position in the covered stock, they may have stronger incentives to promote good news about the stock (e.g., upgrades). Consistent with this, prior research on investors' social transmission bias predicts that investors are more likely to share good news rather than bad news on social media (Hirshleifer 2020).

$Analyst\ Characteristics$ includes analyst-related characteristics that may be relevant in determining the magnitude and timing of Twitter discussion. We include $Ln(Broker\ Size)$, $Ln(Experience)$, $Prior\ Profitability$, $Prior\ Bullishness$, and $Prior\ Accuracy$.[14] $Firm\ Characteristics$ includes a broad set of characteristics of the underlying firm or stock at the time of the announcement that may be relevant in determining revision-related Twitter discussion. Specifically, we include $Ln(Past\ Tweets)$, $Ln(Following)$, $Prior\ Retail\ Volume$, $Inst\ Own$, $Ln(MVE)$, $Accruals$, MTB, $Intangibles$, $R\&D$, $Advertising$, $Cap\ Ex$, $Sales\ Growth$, and $Leverage$. Formal variable definitions for all variables are provided in Appendix A.1.

3.2 Relative Price Discovery

To examine our second research question (RQ2) and better understand the relation between revision-related Twitter discussion and the market response to revision announcements, we conduct two types of intraday trading analyses. To examine whether revision-related Twitter discussion facilitates revision-related price discovery, we break the 32 trading-hour return (i.e., two trading days including extended-hours trading) following the revision announcement into eight four-hour in-

[13] All recommendation revisions in our sample are either upgrades or downgrades. We do not consider recommendation reiterations to be "revisions" and do not include reiteration announcements in our sample.

[14] Inferences are similar if we replace analysts' general experience ($Ln(Experience)$) with their firm-specific experience.

tervals (as in Figure 1).[15] We then measure the relative price discovery (RPD) that occurs in a given four-hour window ($RPD_{[4hr]}$) as $\frac{Ret_{[4hr]}}{Ret_{[32hr]}}$, where $Ret_{[4hr]}$ is the return over a given four-hour trading window (e.g. hours [0,3] or hours [8,11]) and $Ret_{[32hr]}$ is the total return over the entire thirty-two hour trading window (Li et al. 2015; Akbas et al. 2018). Intuitively, higher values of $RPD_{[4hr]}$ indicate that a larger portion of total announcement-window price discovery is concentrated in a specific four-hour period.[16] Please see Figure 4 Panel A for a detailed illustration of our RPD research design.

We then examine whether $RPD_{[4hr]}$ is associated with the number of revision-related tweets in the same four-hour interval by estimating the following model:

$$\begin{aligned} RPD_{[4hr]t+x} = {} & \beta_1 Ln(Rev\ Tweets_{[4hr]})_{t+x} + \beta_2 Ln(Other\ Tweets_{[4hr]})_{t+x} \\ & + \beta_3 Ln(Rev\ Stories_{[4hr]})_{t+x} + \beta_4 Ln(Other\ Stories_{[4hr]})_{t+x} + \beta_5 Activated_{t+x} \\ & + \beta_{[6-12]} Event\ Window_{t+x} + \beta_{[13-19]} Ln(Rev\ Tweets_{[4hr]})_{t+x} \times Event\ Window_{t+x} \\ & + A \times Revision\ FE + B \times Time\text{-}of\text{-}Day\ FE + \epsilon, \end{aligned} \tag{2}$$

where $RPD_{[4hr]t+x}$ is the value of $RPD_{[4hr]}$ for the four-hour window beginning at time $t + x$ relative to the revision announcement. Our variable of interest is $Ln(Rev\ Tweets_{[4hr]})_{t+x}$, the natural logarithm of one plus the number of revision-related tweets observed during the same four-hour window. To hold constant differences across revisions that may determine both the level of revision-related tweets and the overall market reaction to the revision, we include $Revision\ FE$ which enables us to focus on the variation in $RPD_{[4hr]t+x}$ and $Ln(Rev\ Tweets_{[4hr]})_{t+x}$ ***between*** four-hour windows *within* a given revision.

Given our focus on within-revision variation, we include control variables that vary between four-hour windows following a recommendation revision announcement. We first control for traditional media coverage of the recommendation revision during the four-hour window by including $Ln(Rev\ Stories_{[4hr]})_{t+x}$, which is the natural logarithm of one plus the number of revision-related stories from RavenPack observed during the same four-hour window (Ahn et al. 2019). We also

[15]Sixteen trading hours capture one full extended hours trading day (e.g., 4AM to 8PM) (Li et al. 2015), such that our [0,1] two-day announcement window covers 32 intraday trading hours.

[16]We avoid splitting the intraday trading periods into overly granular windows as we do not expect the causal link between revision-related tweets and investor's trading activity to occur instantaneously. For example, retail investors may notice revision-related tweets when checking their Twitter feeds at random intervals, and then manually place trades afterwards.

control for the activation of the recommendation revision in I/B/E/S by including an indicator variable, $Activated_{t+x}$, which is equal to one if the revision was activated in a given four-hour window (Akbas et al. 2018). Additionally, we include $Ln(Other\ Tweets_{[4hr]})_{t+x}$, which is the natural logarithm of one plus the number of $Other\ Tweets$ observed during the four-hour window, and $Ln(Other\ Stories_{[4hr]})_{t+x}$, which is the natural logarithm of one plus the number of other stories from RavenPack observed during the four-hour window. These variables control for the extent of other news about the firm that is discussed on Twitter or published by news sources during the same four-hour window. In addition, to capture how many trading hours (*x*) have passed between the revision announcement and the current observation, we include $Event\ Window_{t+x}$, which is a series of indicator variables set equal to one if the current four-hour observation is from time $t + x$ relative to the revision announcement, and zero otherwise. Finally, to control for time-of-day variation in intraday trading patterns (e.g., market open and close), we include $Time\text{-}of\text{-}Day\ FE$, which are a set of fixed effects for the time of day of the four-hour window.

If greater Twitter discussion of recommendation revisions is associated with intraday price discovery, we expect a positive coefficient on $Ln(Rev\ Tweets_{[4hr]})_{t+x}$. We also interact $Ln(Rev\ Tweets_{[4hr]})_{t+x}$ with event-time indicators ($Event\ Window_{t+x}$) to examine whether more timely revision-related tweets have a greater impact on price discovery. The baseline four-hour window in the regression is for trading hours [0,3] relative to the revision announcement. Therefore, the main effect on $Ln(Rev\ Tweets_{[4hr]})_{t+x}$ captures the effect of $Ln(Rev\ Tweets_{[4hr]})_{t+x}$ on relative price discovery during the first four hours after a revision announcement, while the interaction terms capture variation in the effect of $Ln(Rev\ Tweets_{[4hr]})_{t+x}$ on price discovery as the four-hour windows become more delayed relative to the announcement time. To the extent that more timely tweets have a larger impact on price discovery, we expect to observe negative coefficients on the interactions between $Ln(Rev\ Tweets_{[4hr]})_{t+x}$ and the $Event\ Window_{t+x}$ indicators. Finally, as discussed more fully below, we perform several cross-sectional tests to examine whether the association between revision-related tweets and relative price discovery varies with characteristics of the tweets posted during the four hour window.

3.3 Market Reaction Timeliness

Eq. (2) allows us to examine whether revision-related Twitter discussion in a specific window is associated with the intensity of trading in that same window. We also examine whether more timely revision-related Twitter discussion is associated with a more timely overall response to the revision announcement. To test whether revision-related Twitter discussion is associated with the timeliness of the announcement-window market reaction to analysts' recommendation revisions, we calculate intraday market reaction timeliness, ($MRT_{[32hr]}$), as $\frac{RET_{[0,3]}}{RET_{[0,31]}} + \frac{RET_{[0,7]}}{RET_{[0,31]}} + \frac{RET_{[0,11]}}{RET_{[0,31]}} + \frac{RET_{[0,15]}}{RET_{[0,31]}} + \frac{RET_{[0,19]}}{RET_{[0,31]}} + \frac{RET_{[0,23]}}{RET_{[0,31]}} + \frac{RET_{[0,27]}}{RET_{[0,31]}} + 0.5$, where $RET_{[0,t]}$ is the buy-and-hold return up to and including hour t following the revision announcement (Bochkay et al. 2022).[17] Intuitively, $MRT_{[32hr]}$ approximates the area-under-the-curve of the cumulative absolute return response to an event over the following trading day, such that price discovery is more (less) efficient if earlier four-hour windows in the return window account for a larger (smaller) portion of the overall buy-and-hold return, leading to larger (smaller) values of $MRT_{[32hr]}$. To examine the effect of Twitter discussion of recommendation revisions on the efficiency of the market reaction, we estimate the model below:

$$\begin{aligned} MRT_{[32hr]} = {} & \beta_1 Tweet\ Measure\ + \beta_2 Ln(Other\ Tweets)\ + \beta_3 Ln(Rev\ Stories) + \\ & \beta_4 Ln(Other\ Stories) + \beta_5 Ln(Activation\ Delay) + A \times Controls + \\ & B \times Firm\ FE + C \times Analyst\ FE + D \times CalQtr\ FE + E \times AnnHr\ FE + \epsilon, \end{aligned} \tag{3}$$

where *Tweet Measure* is either $Ln(Rev\ Tweets_{[0,3]})$ or $Ln(Tweet\ Delay)$. *Controls* is a vector of variables listed as "Control Variables" in Appendix A.1. We also include firm (*Firm FE*), analyst (*Analyst FE*), and calendar-quarter fixed effects (*CalQtr FE*) to further isolate the effects of Twitter discussion from potential correlated omitted variables. Finally, we control for the time of day of the revision announcement by including announcement hour fixed effects (*AnnHr FE*). A positive (negative) coefficient when *Tweet Measure* is $Ln(Rev\ Tweets_{[0,3]})$ ($Ln(Tweet\ Delay)$) indicates that more timely Twitter discussion is associated with a more timely intraday market reaction to recommendation revisions, with timely discussion measured as either the number of tweets in the

[17] To reduce the influence of small denominators and extreme return overreactions, each return fraction is winsorized at -1 and 1.

first four hours after the revision announcement or the time until the first revision-related tweet, respectively. Please see Figure 4 Panel B for an illustration of our MRT research design.

3.4 Trading Behavior by Investor Type

Finally, we conduct several tests examining whether the response to revision-related Twitter discussion varies by investor type (RQ3). The key element of these tests is identifying retail-initiated order flow using the Barber et al. (2024) algorithm.[18] This algorithm relies on the fact that most retail-facing discount brokerages (e.g., Charles Schwab, Robinhood, etc.) offer sub-penny price improvement to retail investors when executing their order flow off-exchange.[19]

Our first set of tests examines the association between revision-related Twitter discussion and abnormal retail trading intensity, as well as abnormal retail and institutional order imbalances. Specifically, we estimate the following model for each type of order imbalance:

$$\begin{aligned} Ab\ Retail\ Vol\ or\ Ab\ OIB = {} & \beta_1 Ln(Rev\ Tweets) + \beta_2 Ln(Other\ Tweets) + \beta_3 Ln(Rev\ Stories) \\ & + \beta_4 Ln(Other\ Stories) + \beta_5 Ln(Activation\ Delay) + A \times Controls \\ & + B \times Firm\ FE + C \times Analyst\ FE + D \times CalQtr\ FE + \epsilon, \end{aligned} \tag{4}$$

where $Ab\ Retail\ Vol$ is calculated as the retail share of total trading volume during the [0,+1] trading-day window minus the average retail share over the [-41,-11] trading-day window prior to the revision announcement. $Ab\ OIB$ is the order imbalance during the [0,+1] trading-day window minus its average over the [-41,-11] trading-day window prior to the revision announcement. We calculate order imbalance for retail (institutional) investors by scaling the total dollar value of retail (institutional) buys less the total dollar value of retail (institutional) sells by total retail (institutional) dollar volume over the [0,+1] trading window. We use the Barber et al. (2024) method to identify and sign retail-initiated trades and also test whether our results are robust to using the original Boehmer et al. (2021) method. Following Farrell et al. (2022), we classify all trades not identified as retail-initiated as institutional trades.

[18]The Barber et al. (2024) algorithm is an extension of a similar algorithm developed by Boehmer et al. (2021). We also confirm the robustness of our results using the original Boehmer et al. (2021) algorithm.

[19]See Boehmer et al. (2021) and Barber et al. (2024) for a detailed description of the algorithm.

For each order imbalance measure, we estimate Eq. (4) separately for downgrades and upgrades. If revision-related Twitter discussion primarily increases retail investors' trading activity relative to total trading in the stock, then we should observe a positive coefficient on $Ln(Rev\,Tweets)$ when the dependent measure is $Ab\ Retail\ Vol$. Furthermore, if revision-related Twitter discussion increases the degree to which investors incorporate the revision news in their trading decisions, the coefficient on $Ln(Rev\,Tweets)$ should be the same sign as the revision news (i.e., negative (positive) for downgrades (upgrades)). However, if Twitter discussion leads to uninformed attention-induced buying, we may observe positive coefficients for both downgrade and upgrade revisions (e.g., Mikhail et al. 2007). In addition to these direct tests of changes in retail-identified trading behavior, we also examine whether our RPD and MRT results are stronger among revisions with larger increases in retail trading intensity during the [0,+1] announcement window (i.e., those with higher values of $Ab\ Retail\ Vol$).

3.5 Post-Revision Trading Informativeness

Our final set of tests examine whether retail investor's trading becomes more informed when observing revision-related Twitter discussion, similar to the effect observed in Farrell et al. (2022) following posts on Seeking Alpha. Specifically, we test whether post-revision retail order imbalance is more strongly associated with future returns when there are more revision-related tweets across all intervals within the revision. Based on the analyses in Farrell et al. (2022), we estimate the following model:

$$\begin{aligned} BHAR_{[t,t+5d]} = {} & \beta_1 Retail\ OIB_{[4hr]} + \beta_2 Inst\ OIB_{[4hr]} + \beta_3 Post + \beta_4 Retail\ OIB_{[4hr]} \times Post + \\ & \beta_5 Inst\ OIB_{[4hr]} \times Post + A \times Controls + B \times Time\text{-}of\text{-}Day\ FE + \epsilon, \end{aligned} \tag{5}$$

Where $BHAR_{[t,t+5d]}$ is the buy-and-hold abnormal return starting after the end of a given four-hour window and ending at the close of the fifth trading after the revision announcement. We multiply the returns by 100 for ease of interpretation. $Controls$ includes the same vector of control variables as in Eq. (2) with the addition of $High\ Prior\ Volume$, $Low\ Prior\ Volume$, $Prior\ Return$, and $Abs(Prior\ Return)$ to proxy for new information and extreme trading activity from the prior four-hour window that may affect retail investor trading in the current interval (Farrell et al. 2022).

If the informativeness of retail order imbalance increases in the hours following an analyst recommendation revision, we expect a positive coefficient on $Retail\ OIB_{[4hr]} \times Post$. To examine whether this effect varies with revision tweets, we also introduce an indicator variable ($High$) that equals one if the number of revision tweets across all intervals within a revision is higher than the annual median, and then fully interact all variables in Eq. (4) with the $High$ indicator. To facilitate the presentation of the fully interacted model, we present the results separately for low- and high-revision tweet samples and test for a difference in the coefficient estimate on $Retail\ OIB_{[4hr]} \times Post$ based on the coefficient from $Retail\ OIB_{[4hr]} \times Post \times High$. If greater revision-related Twitter discussion increases the informativeness of retail trading, we expect a stronger increase in the association between post-revision retail order imbalance and future returns for intervals belonging to revisions with more revision tweets. Finally, we also estimate an alternate, reduced-form specification, similar to Eq. (2), where we restrict our sample to post-revision trading windows and replace $Retail\ OIB_{[4hr]} \times Post$ with $Retail\ OIB_{[4hr]} \times Ln(Rev\ Tweets_{[4hr]}$. In this post-only specification, we expect to observe a positive coefficient on $Retail\ OIB_{[4hr]} \times Ln(Rev\ Tweets_{[4hr]}$ if revision-related tweets increase the informativeness of post-revision retail order imbalance.

4. Data and Results

4.0.1 Sample Selection

Table 1 outlines our sample selection procedure. We obtain analyst recommendation revisions from the I/B/E/S recommendation detail file accessed through Wharton Research Database Services (WRDS). We limit our sample to upgrade and downgrade revisions for U.S. firms issued between January 1st, 2013, and December 31st, 2020. Our sample period begins in 2013 as it is the first full year following the official adoption of the "cashtag" by Twitter in mid-2012.[20] Our initial recommendation revision sample includes 82,340 observations covering 5,671 unique firms. We then merge our initial revision sample with data from other WRDS sources such as CRSP, NYSE TAQ, and Compustat fundamentals to collect relevant variables listed in Appendix A.1, which

[20] https://www.theverge.com/2012/7/30/3205284/twitter-stock-ticker-cashtag-links-official

reduces our sample to 50,315 revisions covering 3,555 unique firms.

Next, we merge the WRDS data with data collected from the Twitter API. We collect tweets using Twitter's academic historical API endpoint by first identifying relevant tweets through use of the "cashtag."[21] Using a broad list of 7,871 unique stock tickers, we download all English-language tweets from January 1st, 2013, to December 31st, 2020 that identify these tickers using a cashtag. Our total cashtag tweet database has over 175 million tweets. We limit our sample to companies that have at least one tweet about their cashtag at any point during the sample period. We then match our I/B/E/S revision sample to our Twitter data for these companies, giving a final sample of 50,286 recommendation revisions with 8,962,328 announcement-window cashtag tweets.

We identify 589,960 of the 8,962,328 announcement-window cashtag tweets as revision-related tweets. These revision-related tweets are tweeted by a total of 20,296 unique Twitter users ("authors"). Figure A.2 provides background information for the top 25 authors of revision tweets in our sample. The top 25 authors account for 38.62% of the revision tweets in our sample. For each of the top 25 authors, we excerpt the text of the description in the author's user profile and list the total number of revision-related tweets in our sample by that author, as well as the author's total number of followers as of the time we pulled the information from the API. We also manually check whether each author offers a link promoting a paid subscription service, which provides insight into the potential incentives for tweeting out information about analysts' stock recommendation revisions. Anecdotally, the user accounts that generate revision tweets vary from automated news feeds and investor portals such as Benzinga or "MarketBeat.com" to individual traders (e.g., @paynej247 and @silverjet2) and media personalities (e.g., Jim Cramer). We further examine characteristics of the authors in our sample in Section 4.2.2.

4.0.2 Descriptive Statistics

Descriptively, revision-related Twitter discussion is prevalent for the revision announcements in our sample, with 90.1% of revisions in our sample exhibiting at least one revision-related tweet in

[21] Similar to hashtags, the cashtag enables users to tag a company in a tweet by using the U.S. dollar sign followed by the company ticker symbol (i.e. "$AAPL" is the cashtag for Apple Inc.) https://help.twitter.com/en/resources/glossary.

the [0,+1] announcement window (untabulated).[22] Figures 1 to 3 further illustrate the timing and prevalence of Twitter discussion of analysts' recommendation revisions. Figure 1 plots the frequency of tweets in intraday event time around analyst recommendation revision announcements. The top (bottom) panel plots the average number of $Rev\ Tweets$ ($Other\ Tweets$) observed during the sixteen trading hours before and the thirty-two trading hours after the I/B/E/S announcement timestamp. Each column plots the average number of tweets observed during the four trading-hour window beginning at the specified hour $t + n$ relative to the revision announcement.

Prior to the revision announcement, the average frequency of $Rev\ Tweets$ is close to zero, but spikes sharply to an average of 3.6 revision-related tweets during the first four trading-hour window following the time of the announcement, and then gradually trails off over the remainder of the trading day. In contrast, while there are an average of around 10 - 24 $Other\ Tweets$ in any given four-hour window in the day before and after the announcement, the spike in volume around time zero is much more gradual and peaks before the revision announcement, consistent with $Other\ Tweets$ capturing discussion of other concurrent events.

Figure 2 plots the mean number of [0,+1] announcement-day $Rev\ Tweets$ by Fama-French 49 industry classification. Intuitively, revisions for companies in growth industries and industries salient to retail investors exhibit higher mean revision-related tweets. Figure 3 plots the frequency of analyst revisions (Panel a) and median $Tweet\ Delay$ (Panel b), by the hour-of-day of the I/B/E/S recommendation announcement timestamp. Consistent with Li et al. (2015), we observe that the majority of analyst recommendation revisions are announced outside of regular trading hours, most commonly around 6:00AM to 8:00AM during the morning pre-market extended hours trading session. Twitter users also seem to be attentive during this time, with median tweet delays of less than two hours for revisions announced from 6:00AM to noon. Consistent with more timely Twitter discussion during regular trading hours, Tweet delays are longest (over 12 hrs) for revisions announced just after market close (i.e., 4:00PM - 6:00PM). Accordingly, we control for the time of day of the revision announcement in all of our intraday analyses.

[22] In untabulated tests, we also checked for time-series variation in the prevalence of revision-related tweets over the sample period and found the prevalence of of revision-related Twitter discussion to be fairly stable over time.

Table 2 reports additional descriptive statistics for our sample. Roughly 45% of the revisions in our sample are upgrades. The average revision receives 12 revision-related tweets during the announcement window, with a mean (median) time delay of 362 (145) minutes from the revision announcement to the first revision tweet. During this same announcement window, firms are covered by an average of 167 other tweets. On average, the brokerages for the recommending analysts in our sample employ 108 analysts, and their mean $Experience$ is 6.1 years. In terms of firm characteristics, the average observation in our sample has 18 analysts following the firm and institutional ownership of 76%. The average $Ln(MVE)$ is 8.27, implying a market capitalization of about $3.9 billion.

4.1 Determinants

Columns (1)-(3) of Table 3 report the results of estimating our determinants model from Eq. (1) using OLS regression with standard errors clustered by firm and announcement date. All continuous variables are standardized to have a mean of zero and standard deviation of one to facilitate interpretation. Notably, the coefficient on *Upgrade* is 0.084 (t-stat = 5.445) in column (1) and -0.084 in column (2) (t-stat = -9.215) , implying that upgrade revisions are associated with higher levels of $Ln(Rev\ Tweets)$ than downgrades, which differs from $Ln(Other\ Tweets)$, which are more prevalent around downgrades. Several other revision-related characteristics are also significant determinants of revision-related Twitter discussion.

Turning to analyst-related characteristics, revision-related Twitter discussion is greater for analysts from larger brokerages and for analysts whose prior recommendations are more profitable. In column (1), the coefficient of 0.166 on $Ln(Broker\ Size)$ and the coefficient of 0.025 on $Profitability$ are both highly significant (t-stat = 18.848 and t-stat = 6.430, respectively). Not surprisingly, one of the most significant firm-related determinants of $Ln(Rev\ Tweets)$ and $Ln(Other\ Tweets)$ is $Ln(Past\ Tweets)$. Other important firm-related characteristics include $Ln(Following)$, $Ln(MVE)$, $R\&D$, and $Intangibles$ which are all statistically significant at the 1% level.

Overall, the results in this section indicate that revision-related Twitter discussion is a prevalent phenomenon with characteristics that sometimes differ from other social media discussion and from traditional media coverage of analyst revisions. Whereas traditional media is more likely to cover unfavorable recommendations, revision-related Twitter discussion is more prevalent and timely for upgrades and for stocks with higher retail trading volume, consistent with social transmission bias playing a role in investors' sharing of analyst research on Twitter. In addition, unlike investment research posted on Seeking Alpha, revision-related Twitter discussion is prevalent for revisions from larger brokers and for stocks with higher institutional ownership, consistent with revision-related Twitter discussion serving as a complement to sell-side research.

4.2 Relative Price Discovery

4.2.1 Main Results

We next turn to our second research question (RQ2) examining the association between revision-related Twitter discussion and revision-related price discovery. Table 4 reports the results from estimating Eq. (2) using OLS regression with standard errors clustered by firm and announcement date. For ease of interpretation, all continuous variables are standardized to have a mean of zero and standard deviation of one. In column (1) we limit the sample to include only observations from the first four trading hours following the revision announcement (i.e. hours 0 through 3). The coefficient of 0.025 on $Ln(Rev\ Tweets_{[4hr]})$ (t-stat = 7.080) indicates a positive and significant association between the number of revision-related tweets and price discovery in the first four trading hours following the revision announcement. The positive coefficient on $Ln(Rev\ Stories_{[4hr]})$ reflects the relation between price discovery and traditional media coverage of recommendation revisions in the same interval, while the coefficients on $Ln(Other\ Tweets_{[4hr]})$ and $Ln(Other\ Stories_{[4hr]})$ capture trading activity associated with other firm news discussed on Twitter or other news coverage in the same interval but unrelated to $Ln(Rev\ Tweets_{[4hr]})$.

In columns (2) - (4) we expand the sample to examine price discovery during the entire thirty-two hours following the revision announcement. Importantly, we also include revision fixed effects which allow us to better hold constant differences across revisions and focus on variation in price discovery and revision-related tweets between four-hour windows for a given revision. In column (2) we omit the event-window indicators to show the average association between Twitter discussion and relative-price discovery without considering the amount of time that has passed since the revision announcement. These results are similar to those presented in column (1) and suggest that *ceteris paribus* there is greater price discovery in any four-hour window when there are greater levels of revision-related discussion on Twitter. This on-average result also holds in column (3) when we control for the event-window indicators. While untabulated, the coefficients on the $Event\ Window_{t+x}$ indicators from column (3) are negative indicating there is less price discovery on average for a given trading window as more time passes from the initial revision announcement.

In column (4), we present the results from estimating the fully specified model outlined in Eq. (2). The main effect of $Ln(Rev\ Tweets_{[4hr]})$ captures the effect of revision tweets in the first four hours and remains significantly positive (coef. = 0.042, t-stat = 14.727). For brevity, we only display the interactions of $Ln(Rev\ Tweets_{[4hr]})$ and the trading window indicators for the first full trading day. As expected, the negative and significant coefficients on $Ln(Rev\ Tweets_{[4hr]}) \times [4,7]\ Window$, $Ln(Rev\ Tweets_{[4hr]}) \times [8,11]\ Window$, and $Ln(Rev\ Tweets_{[4hr]}) \times [12,15]\ Window$ of -0.013 (t-stat = -3.695), -0.035 (t-stat = -8.516), and -0.036 (t-stat = -9.751), respectively, indicate that the positive effect of $Ln(Rev\ Tweets_{[4hr]})$ decreases with the amount of time that passes between the revision announcement and the revision-related tweets. Taken together, the results in Table 4 provide strong evidence that revision-related tweets facilitate the market response to analysts' recommendation revisions and that more timely revision tweets have a greater impact on price discovery.[23]

[23] While our research design accounts for many potentially confounding factors, we recognize it cannot rule out the possibility that other news may be correlated with the amount of revision-related discussion on Twitter and greater price discovery in the same four-hour window. Because revisions often coincide with earnings announcements, in untabulated tests, we re-estimated Eq. (2) using subsamples of observations with and without a concurrent earnings announcement in the [-5,+1] day window around a revision announcement. We find the coefficient estimates for $Ln(Rev\ Tweets_{[4hr]})$ are positive and statistically significant in both sub-samples and the magnitude of the coefficient is higher in the sample of revisions without a concurrent earnings announcement. Therefore, other sources of potential firm-level news do not appear to be significantly driving our results.

4.2.2 Cross-Sectional Tests Across Characteristics of Revision-Related Tweets and Authors

If the relation we observe between revision-related tweets and price discovery is due to investors responding to the information in revision-related tweets, we expect the association to vary with the characteristics of the tweets during a given four-hour window. Accordingly, we examine four properties of revision tweets (or their authors) to examine whether certain attributes of Twitter dissemination are more informative for investors. First, we focus on two properties of revision-related tweets that may be associated with differential responses by investors: $Engagement$ and $URLs$. We expect the effect of Twitter discussion on relative price discovery to be greater for tweets with more engagement by Twitter users. We use measures of public tweet engagement available from the Twitter API. For every tweet, Twitter provides information about four types of publicly observable metrics: likes, retweets, replies, and quotes (i.e., replies that include quotes from the original tweets).[24] We count all types of engagement equally, and create an indicator variable equal to one if the amount of engagement with revision tweets in a given four-hour window is higher than the median for that year ($Engagement$). Additionally, we expect the effect of Twitter discussion on relative price discovery to be greater for tweets that include a URL linking to an external information source within the revision tweet. We count the number of URLs included in revision tweets in each window, and create an indicator variable equal to one if the number of URLs included in revision tweets in a given four-hour window is higher than the median for that year ($URLs$).

We also identify influential authors whose revision tweets arguably have greater credibility, and thus, may be associated with greater price discovery. In order to measure author characteristics, we leverage data on Twitter users' profiles, available from the Twitter API, to identify the number of followers for the author of each revision tweet, and to determine whether the author is "verified."[25] We create an indicator variable equal to one if the cumulative number of followers for the authors of

[24]For example, the icons below Jim Cramer's March 2, 2015 tweet presented in Figure A.1 show that it has 2 replies (speech bubble), 5 retweets (cycling arrows), and 10 likes (heart), for a total engagement score of 17.

[25]The author information sourced from the Twitter API is measured for each account as of the time it was retrieved during 2023. To achieve verified status during our sample period, users submitted an application which required evidence of the users' notability.

revision tweets in a given four-hour window is higher than the median for that year ($Followers$). Finally, we examine whether the verification status of the revision tweet authors conveys more meaningful information to Twitter users. Accordingly, we create an indicator variable equal to one if the number of revision tweets with verified authors in a given four-hour window is higher than the median for that year ($Verified$).

To investigate whether the association between $RPD_{[4hr]}$ and $Ln(Rev\ Tweets_{[4hr]})$ is associated with meaningful properties of the revision-related tweets and authors, we use the specification from column (3) in Table 4 and interact each of the aforementioned indicator variables with $Ln(Rev\ Tweets_{[4hr]})$. Table 5 reports the results of these additional analyses. The variable $HIGH$ represents the cross-sectional variable of interest corresponding to the variables across the top of the table. Specifically, columns (1), (2), (3), and (4) report the results when the cross-sectional variable of interest is $Engagement$, $URLs$, $Followers$, and $Verified$, respectively.

Consistent with our predictions, we find the interaction term of $Ln(Rev\ Tweets_{[4hr]})xHIGH$ is positive and statistically significant at 1% across all four models. The coefficients (t-statistics) for the interaction of $Engagement$, $URLs$, $Followers$, and $Verified$ with $Ln(Rev\ Tweets_{[4hr]})$ are 0.016 (t-stat = 3.932), 0.027 (t-stat = 4.597), 0.027 (t-stat = 6.838), and 0.014 (t-stat = 2.708), respectively. These findings suggest that when revision tweets in a given four-hour window receive more engagement, link to additional information, or come from more influential authors, they exhibit a stronger association with relative price discovery. Overall, the results of this analysis help corroborate our primary inference that discussion of recommendation revisions on Twitter results in a stronger market reaction to the revision itself.

4.3 Market Reaction Timeliness

The results in Section 4.2 provide evidence that more extensive revision-related Twitter discussion is associated with concurrent price discovery. However, concurrent price discovery does not speak to the efficiency of the response to the recommendation revision. Accordingly, we examine the association between timely revision-related Twitter discussion and the timeliness of the announcement-window market reaction following a recommendation revision.

Before formally estimating Eq. (3), in Figure 5 we plot the mean cumulative intraday market reaction timeliness (MRT) over the announcement day following revisions with fast vs. slow $Tweet\ Delay$. For each point t, we plot the average $MRT_{[0,t]}$, calculated as $\frac{RET_{[0,t]}}{RET_{[0,31hr]}}$, where $RET_{[0,t]}$ is the four-hour return up to and including hour t following the revision announcement. The solid red (blue dashed) line plots the mean cumulative $MRT_{[0,t]}$ for revisions in the lowest (highest) decile of $Tweet\ Delay$. Consistent with a positive association between intraday MRT and the timeliness of revision-related Twitter discussion, the $MRT_{[0,t]}$ for revisions with faster (i.e., shorter) $Tweet\ Delay$ is consistently higher than the $MRT_{[0,t]}$ for revisions with slower (i.e., longer) $Tweet\ Delay$. For example, as of the end of the first four trading hours ([0,+3]), an average of 36.8% of the overall two-day announcement return is incorporated in price for observations with faster $Tweet\ Delay$ compared to only 13.0% for observations with slow $Tweet\ Delay$.

Table 6 reports the results of estimating Eq. (3) using OLS regressions with standard errors clustered by firm and announcement date. The coefficient on $Ln(Rev\ Tweets_{[0,3]})$ of 0.040 in column (1) (t-stat = 5.658) provides evidence of a positive association between the number of revision-related tweets in the first four hours after the revision announcement and intraday market reaction timeliness. Similarly, the coefficient on $Ln(Tweet\ Delay)$ of -0.020 (t-stat = -2.932) in column (3) is consistent with a less timely market response for revisions with longer tweet delays. Stated differently, as the speed of Twitter dissemination increases, the market is more efficient and the speed of price formation also increases. We also do not observe evidence of systematic return drifts or reversals, regardless of the level of revision-related discussion on Twitter, across a number of untabulated regression tests, supporting our focus on intraday market reaction timeliness as our measure of market efficiency.[26] Taken together, the results in this section are consistent with more prevalent and timely revision-related Twitter discussion leading to improved intraday market reaction timeliness incremental to discussion of other firm-related news, business press coverage

[26] We tested for evidence of post-recommendation revision drift over the month (trading days [+2,+23]) following the revision announcement, as well as over shorter (e.g., [+2,+5] trading days) or longer post-announcement return horizons. We repeated our tests using alternate measures of revision news, as well as with/without control variables and a variety of fixed effects. We did not observe evidence of significant drift or reversal over any of the specifications examined.

of revisions, and the timeliness of I/B/E/S dissemination of sell-side research.

4.4 Trading Behavior by Investor Type

4.4.1 Abnormal Volume and Order Imbalance

Our final set of analyses examine whether the associations we document between revision-related Twitter discussion and the market reaction to analysts' recommendation revisions are driven by retail investors. Table 7 reports the results of estimating Eq. (4) using OLS regressions with standard errors clustered by firm and announcement date. Panel A reports the results using the Barber et al. (2024) methodology to construct our investor trading measures, and Panel B reports the results using the Boehmer et al. (2021) methodology. In both Panels, column (1) presents the results when the dependent variable is $Ab\ Retail\ Vol$. The coefficient estimate for $Ln(Rev\ Tweets)$ is positive and statistically significant at 5% or better in both panels. Thus, the results are consistent with retail investors exhibiting increases in their trading intensity around revisions with more revision-related Twitter discussion.

The dependent variable is abnormal retail order imbalance ($Ab\ OIB_{Retail}$) in columns (2) and (3) and abnormal institutional order imbalance ($Ab\ OIB_{Institutional}$) in columns (4) and (5). In Panel A, the coefficients on $Ln(Rev\ Tweets)$ of -0.009 (t-stat = -2.552) for downgrades and 0.008 (t-stat = 2.224) for upgrades are consistent with retail investors trading more strongly in the direction of the revision news for revisions with more revision-related tweets. Our inferences are unchanged in Panel B when we use the Boehmer et al. (2021) methodology. These results suggest retail investors trade more strongly in the direction of the analyst revision around revisions with greater levels of revision-related Twitter discussion. This result is notable given than Mikhail et al. (2007) suggest that small traders trade in an uninformed matter in response to recommendation revisions, and trade in the opposite direction around recommendation downgrades.

In columns (4) and (5) we do not observe evidence of an association between $Ln(Rev\ Tweets)$ and institutional investor order imbalance, regardless of the direction of the revision. This is not surprising, given that institutional investors are more likely to learn of analyst revisions from their brokers or through FDP subscriptions (Akbas et al. 2018). In contrast, the coefficients of 0.011

(t-stat = 6.912) and 0.006 (t-stat = 3.546) for $Ln(Other\ Tweets)$ in columns (4) and (5) of Panel A, respectively indicate a positive association between the number of other tweets and institutional investor order imbalance for both downgrade and upgrade revisions.[27]

4.4.2 Cross-Sectional Tests of RPD and MRT by Retail Trading Activity

If our RPD and MRT results are primarily driven by retail trading, we also expect these results to be stronger among revisions with relatively higher levels of retail trading activity. Accordingly, we re-estimate Eq. (2) and (3) using subsamples of revisions with above- and below-median $Ab\ Retail\ Vol$ and compare the coefficient estimates of the independent variables of interest across the two samples.

Panel A of Table 8 presents the Relative Price Discovery results comparing samples of revisions with high and low levels of retail trading activity. In columns (1) and (2), the coefficient on $Ln(Rev\ Tweets_{[4hr]})$ is 0.018 (t-stat = 3.873) and 0.032 (t-stat = 6.996) in the first four-hourly intervals of revisions with low and high abnormal retail trading volume, respectively. The difference of 0.014 is statistically significant at 5% (t-stat = 2.425) suggesting that price discovery associated with the level of revision-related Twitter discussion is greater for revisions with increased retail trading. In columns (3) and (4), we expand each sample to include all the four-hour intervals after the revision announcement. Across all intervals, we continue to find that the relation between price discovery and revision-related tweets is greater for revisions with above-median levels of abnormal retail trading volume.

Similarly, Panel B of Table 8 presents the Market Reaction Timeliness results comparing samples of revisions with high and low levels of retail trading activity. In columns (1) and (2), the coefficient estimate on $Ln(Rev\ Tweets_{[0,3]})$ is 0.021 (t-stat = 2.159) and 0.044 (t-stat = 4.149) for revisions with low and high abnormal retail trading volume, respectively. However, the difference of 0.023 is not statistically significant at conventional levels using a two-tailed t-test.

[27]The coefficient on $Ln(Other\ Tweets)$ captures the component of trading that is associated with $Ln(Other\ Tweets)$ but unrelated to $Ln(Rev\ Tweets)$. Accordingly, these results may be consistent with $Ln(Other\ Tweets)$ capturing concurrent news that is relevant to institutional investors, or with institutional investors trading algorithmically based on overall Twitter sentiment. This would be consistent with prior studies documenting that overall social media tone is generally bullish (e.g., Cookson et al. 2023).

Likewise in columns (3) and (4), when we examine the difference in the relation of $MRT_{[32hr]}$ and $Ln(Tweet\ Delay)$ between revisions with high and low abnormal retail trading activity, we observe the difference of -0.015 between the coefficient estimates of $Ln(Tweet\ Delay)$ is not statistically significant.

Taken together, the results from our tests examining retail-initiated trading activity suggest that the associations we document between revision-related Twitter discussion and the market reaction to analysts' recommendation revisions are primarily driven by retail investors.

4.5 Retail Trading Informativeness and Revision-Related Twitter Discussion

The results thus far indicate that revision-related discussion is associated with more efficient price discovery driven, in part, by retail investors' trading activity. Our final set of results explore whether post-revision retail order imbalance is more informed when there is more revision-related Twitter discussion. Table 9 reports the results of estimating Eq. (5) using OLS regressions with standard errors clustered by firm and announcement date. To facilitate interpretation, we multiply $BHAR_{[t,t+5d]}$ by 100 and standardize all continuous variables to have a mean equal to zero and a standard deviation equal to one.

In Panel A, we report the results from estimating a reduced-form of Eq. (5) in which we only examine post-revision event windows and separately interact $Retail\ OIB_{[4hr]}$ and $Inst\ OIB_{[4hr]}$ with $Ln(Rev\ Tweets_{[4hr]})$. In column (1), we use only the first four-hour window after the revision, and in column (2), we use all post-revision windows. In column (1), the interaction term of $Retail\ OIB_{[4hr]}\ \times Ln(Rev\ Tweets_{[4hr]})$ is 0.069 and significant at 10% (t-stat = 1.646). Similarly, in column (2), the coefficient estimate of 0.053 on the interaction term of $Retail\ OIB_{[4hr]}\ \times$ $Ln(Rev\ Tweets_{[4hr]})$ is also positive and statistically significant at 1% (t-stat = 2.745), indicating that a one-standard deviation increase in both $Retail\ OIB_{[4hr]}$ and $Ln(Rev\ Tweets_{[4hr]})$ from their means is associated with a 0.053% future return. In both columns, we do not observe a positive association on the interaction term $Inst\ OIB_{[4hr]}\ \times Ln(Rev\ Tweets_{[4hr]})$, suggesting institutional trading does not become more informed conditional on more revision-related Twitter discussion.

In Panel B, we report the results of estimating Eq. (5). In columns (1) and (2), we use only the event windows immediately preceding and following the revision announcement ([-4,+3] windows), and in columns (3) and (4) we use the [-16,+31] windows around the revision announcement. We estimate the model separately for intervals with Low and $High$ numbers of $Rev\ Tweets$ observed across the intervals within a given revision relative to the annual median. In column (1), the coefficient estimate on $Retail\ OIB_{[4hr]}\ \times Post$ is statistically insignificant, but in column (2) the coefficient estimate on $Retail\ OIB_{[4hr]}\ \times Post$ is 0.405 and statistically significant at 1% (t-stat = 4.441). The difference of 0.293% in estimated future returns is significant at 5% indicating retail trading in the first four-hours is more informed when there are more revision tweets. In columns (3) and (4), we repeat the previous analysis using an expanded set of intervals around the revision announcement. The coefficient estimates on $Retail\ OIB_{[4hr]}\ \times Post$ are both positive and statistically significant at 5% or better (t-stat = 2.321 and t-stat = 3.930, respectively). However, the magnitude of the coefficient estimate in column (4) (coef. = 0.280) is greater than the same estimate in column (3) (coef. = 0.100) with the difference in estimated future returns of 0.180% being statistically significant at 5%. Taken together, these results indicate that retail trading becomes more informed after the revision announcement, and this association is greater when there are more revision tweets.

5. Conclusion

We examine the discussion of analysts' recommendation revisions on Twitter, which is important given the barriers retail investors face in accessing analysts' stock recommendation revisions in a timely fashion. Our results indicate that more extensive and timely revision-related Twitter discussion improves the efficiency of the initial market reaction to analysts' research. However, unlike coverage in the financial press, which is biased towards pessimistic recommendations, revision-related Twitter discussion is more prevalent for upgrade revisions, consistent with recent theories of social transmission bias among investors (Han et al. 2021).

Our examination of within-revision, intraday price discovery demonstrates that increases in price discovery occur during four-hour windows that include more revision-related Twitter discussion, especially for more influential tweets, which helps rule out alternative explanations for our findings. We also find evidence that the market response to revision-related Twitter discussion is driven by retail investors, and that retail investor's trading behavior becomes more informed following revisions accompanied by more revision-related Twitter discussion. Overall, our results are consistent with revision-related Twitter discussion complementing analysts' research by improving retail investors' trading response to analysts' recommendation revisions.

While our results suggest that revision-related Twitter discussion is beneficial for price discovery and potentially improves retail investors' trading response to analysts' recommendation revisions, we note that we cannot directly observe the profitability (or lack thereof) of retail trading in response to revision-related Twitter discussion. Moreover, our study cannot speak to the implications of revision-related Twitter discussion for sell-side brokerages and their institutional clients.[28] Informed by our results, regulators and future researchers may wish to further examine whether revision-related Twitter discussion is associated with more profitable retail trading or generates additional trading opportunities for investors with preferential access to brokerage research.

[28]We observe a reasonable but economically meaningful delay from the time that an analyst transmits their research to their brokerage clients and the first mention of the analyst's research on Twitter. Therefore, it is possible that institutional investors with early access to revisions could take a position to profit from the trades of investors who subsequently learn of the revision through social media.

REFERENCES

Ahn, M., M. Drake, H. Kyung, and H. Stice. 2019. "The role of the business press in the pricing of analysts' recommendation revisions." *Review of Accounting Studies* 24:341–392.

Akbas, F., S. Markov, M. Subasi, and E. Weisbrod. 2018. "Determinants and consequences of information processing delay: Evidence from the Thomson Reuters Institutional Brokers' Estimate System." *Journal of Financial Economics* 127 (2): 366–388.

Altınkılıç, O., and R. S. Hansen. 2009. "On the information role of stock recommendation revisions." *Journal of Accounting and Economics* 48 (1): 17–36.

Barber, B. M., X. Huang, P. Jorion, T. Odean, and C. Schwarz. 2024. "A (sub) penny for your thoughts: Tracking retail investor activity in TAQ." *The Journal of Finance* 79 (4): 2403–2427.

Bartov, E., L. Faurel, and P. S. Mohanram. 2018. "Can Twitter help predict firm-level earnings and stock returns?" *The Accounting Review* 93 (3): 25–57.

Blankespoor, E., E. deHaan, and I. Marinovic. 2020. "Disclosure processing costs, investors' information choice, and equity market outcomes: A review." *Journal of Accounting and Economics* 70 (2-3): 101–344.

Blankespoor, E., E. deHaan, and C. Zhu. 2018. "Capital market effects of media synthesis and dissemination: Evidence from robo-journalism." *Review of Accounting Studies* 23 (1): 1–36.

Blankespoor, E., G. S. Miller, and H. D. White. 2014. "The role of dissemination in market liquidity: Evidence from firms' use of Twitter™." *The accounting review* 89 (1): 79–112.

Bochkay, K., S. Markov, M. Subasi, and E. Weisbrod. 2022. "The roles of data providers and analysts in the production, dissemination, and pricing of street earnings." *Journal of accounting research* 60 (5): 1695–1740.

Boehmer, E., C. M. Jones, X. Zhang, and X. Zhang. 2021. "Tracking retail investor activity." *The Journal of Finance* 76 (5): 2249–2305.

Bonner, S. E., A. Hugon, and B. R. Walther. 2007. "Investor reaction to celebrity analysts: The case of earnings forecast revisions." *Journal of Accounting Research* 45 (3): 481–513.

Campbell, B., M. Drake, J. Thornock, and B. Twedt. 2023. "Earnings virality." *Journal of Accounting and Economics* 75 (1): 101517.

Cookson, J. A., J. E. Engelberg, and W. Mullins. 2023. "Echo chambers." *The Review of Financial Studies* 36 (2): 450–500.

Curtis, A., V. J. Richardson, and R. Schmardebeck. 2014. "Investor attention and the pricing of earnings news." *Handbook of Sentiment Analysis in Finance, Forthcoming*.

Drake, M. S., J. R. Moon, B. J. Twedt, and J. D. Warren. 2022. "Social media analysts and sell-side analyst research." *Review of Accounting Studies,* 1–36.

Drake, M. S., J. R. Thornock, and B. J. Twedt. 2017. "The internet as an information intermediary." *Review of Accounting Studies* 22 (2): 543–576.

Dyer, T., and E. Kim. 2021. "Anonymous equity research." *Journal of Accounting Research* 59 (2): 575–611.

Farrell, M., T. C. Green, R. Jame, and S. Markov. 2022. "The democratization of investment research and the informativeness of retail investor trading." *Journal of Financial Economics* 145 (2): 616–641.

Han, B., D. Hirshleifer, and J. Walden. 2021. "Social transmission bias and investor behavior." *Journal of Financial and Quantitative Analysis,* 1–42.

Heimer, R. Z. 2016. "Peer pressure: Social interaction and the disposition effect." *The Review of Financial Studies* 29 (11): 3177–3209.

Hirshleifer, D. 2020. "Presidential address: Social transmission bias in economics and finance." *The Journal of Finance* 75 (4): 1779–1831.

Irvine, P., M. Lipson, and A. Puckett. 2006. "Tipping." *The Review of Financial Studies* 20 (3): 741–768.

Jia, W., G. Redigolo, S. Shu, and J. Zhao. 2020. "Can social media distort price discovery? Evidence from merger rumors." *Journal of Accounting and Economics* 70 (1): 101334.

Kadous, K., M. Mercer, and Y. Zhou. 2025. "Why do investors rely on low-quality investment advice? Experimental evidence from social media platforms." *Behavioral Research in Accounting* 37 (1): 97–115.

Kothari, S. P., E. So, and R. Verdi. 2016. "Analysts' forecasts and asset pricing: A survey." *Annual Review of Financial Economics* 8:197–219.

Lawrence, A., J. P. Ryans, and E. Y. Sun. 2017. "Investor demand for sell-side research." *The Accounting Review* 92 (2): 123–149.

Li, E. X., K. Ramesh, M. Shen, and J. S. Wu. 2015. "Do Analyst Stock Recommendations Piggyback on Recent Corporate News? An Analysis of Regular-Hour and After-Hours Revisions." *Journal of Accounting Research* 53 (4): 821–861.

Martineau, C., et al. 2022. "Rest in Peace Post-Earnings Announcement Drift." *Critical Finance Review* 11 (3-4): 613–646.

Mikhail, M. B., B. R. Walther, and R. H. Willis. 2007. "When security analysts talk, who listens?" *The Accounting Review* 82 (5): 1227–1253.

Nekrasov, A., S. H. Teoh, and S. Wu. 2022. "Visuals and attention to earnings news on Twitter." *Review of Accounting Studies* 27 (4): 1233–1275.

Ramnath, S., S. Rock, and P. Shane. 2008. "The financial analyst forecasting literature: A taxonomy with suggestions for further research." *International Journal of Forecasting* 24 (1): 34–75.

Rees, L., N. Sharp, and B. Twedt. 2015. "Who's heard on the Street? Determinants and consequences of financial analyst coverage in the business press." *Review of Accounting Studies* 20 (1): 173–209.

Shoemaker, P. J., and A. A. Cohen. 2012. *News around the world: Content, practitioners, and the public.* Routledge.

Twedt, B. 2015. "Spreading the word: Price discovery and newswire dissemination of management earnings guidance." *The Accounting Review* 91 (1): 317–346.

Wilkins, L., and P. Patterson. 1987. "Risk analysis and the construction of news." *Journal of communication.*

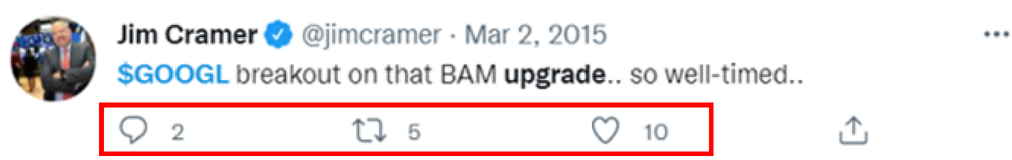
Womack, K. L. 1996. "Do brokerage analysts' recommendations have investment value?" *The journal of finance* 51 (1): 137–167.

Appendix

FIGURE A.1
Examples of revision-related tweets

Panel A: Basic examples

Panel B: A revision-related tweet with *Engagement* by a *Verified* author



Panel C: A revision-related tweet with *URL*

This figure provides examples of revision-related tweets ($Rev\ Tweets$). Panel A provides examples of downgrade and upgrade revision-related tweets. $Rev\ Tweets$ are identified by matching the text of the tweet to the covered firm's cashtag ($PFG and $JEC in the example above) and any form of the words "upgrade" or "downgrade" matching the sign of the revision within [0,+1] window around the revision announcement. Panel B provides an example of a revision-related tweet with public engagement ($Engagement$) by a verified user ($Verified$). This tweet by Jim Cramer had 2 replies, 5 retweets, and 10 likes, and the blue check mark next to his name indicates this particular account is verified. Panel C provides an example of a revision tweet with a URL included in the tweet. Formal definitions for all variables are provided in Table A.1.

FIGURE A.2
Top-25 Most Frequent Authors of Revision-Related Tweets

Rank	Username	Description	Rev Tweets	Followers	Subscription
1	MarketBeatCom	Stock Market News and Research Tools	25,456	13,299	Yes
2	firsttomarkets	N/A	21,028	1,152	No
3	AmericanBanking	Banks, Credit Unions & Financial Institutions	19,978	8,540	Yes
4	usratings	Latest US stock rating information.	19,589	786	No
5	AnalystWire	A sampling of our research news coverage. For the full, real-time feed upgrade to StreetInsider Premium	17,433	4,781	Yes
6	theflynews	First in stock news. Tweets small sample of real-time reporting. Access all stories with free trial. APIs available. Institutional investors call 888-633-3330.	15,024	27,777	Yes
7	TickerReport	Market moving news	10,048	3,819	Yes
8	OpenOutcrier	Real-time stock & option trading headlines, breaking news, rumors and strategy. Nothing we post constitutes investment advice; we may have positions in markets	9,708	78,601	Yes
9	WKRBNews	WKRB News - News and Analysis.	8,623	1,371	Yes
10	CFinancialNews	Community Financial News	7,856	580	No
11	jonogg	Investor with 30 years stock/bond/market/econ coverage. Collectibles as an alternative asset class! Join @CollectorsDash1	7,657	1,242	No
12	AlertTrade	Day trade alerts, swing trade alerts, trade-ideas and crypto. All alerts are delayed. Best Stock Screener via	6,943	229,360	Yes
13	Benzinga	Twitter delayed Real-time newsfeed (2-weeks FREE): Newsletters: Shows: CEO: @JasonRaznick	6,100	261,744	Yes
14	MarketCurrents	Real-time stock market news from Seeking Alpha.	5,854	87,794	Yes
15	intercooleronli	N/A	5,619	840	Yes
16	247WallSt	Daily tweets from editors @jonogg & @dougmcintyre and updates from 24/7 Wall St.	5,565	216,941	No
17	dakotafinancial	N/A	4,947	1,512	Yes
18	stockhoot	Get winning Stock, Option and Cryptocurrency trade ideas from pro-traders. Follow their strategies, see how they perform. All the info you need in one place.	4,619	3,074	No
19	dailypoliticaln	Daily Political is an independent news agency that specializes in bringing a fresh perspective to news and politics from around the world	4,496	1,361	Yes
20	paynej247	CHRISTIAN, STOCK TRADER. MY TWEETS ARE OPINIONS ONLY, NOT A RECOMMENDATION TO BUY OR SELL. see section 27A SEC act of 1933 / forward statements & risks.	4,058	3,454	No
21	WatchlistN	Watchlist News brings you the latest news in the world of business and finance	3,695	3,327	Yes
22	reurope_stock	REurope brings only trustable news on value analysis, research of the market, finances and steady growth.	3,645	261	No
23	midetimes	MidEast Times reports the business news of the day along with relevant finance news	3,619	664	Yes
24	silverjet2	Man About Town; Raconteur; Adventurer; Candidate for Prime Minister of Canada!	3,159	920	No
25	The_CasualSmart	The Casual Smart carries only important financial news for investors who want to be in top 10 richest people in the world.	3,125	214	No

This figure provides the Top 25 most frequent authors of revision-related tweets ($Rev\ Tweets$) during our sample period. This figure includes authors' usernames, account descriptions, revision tweet count, percentage of overall sample, and whether the account promoted a premium subscription service. The author information in the table is sourced from the Twitter API and represents the available information for each account as of the time it was retrieved during 2023. The cumulative percentage of revision-related tweets from the Top 25 most frequent authors comprises approximately 38.1% of revision-tweets in our sample.

TABLE A.1
Variable Definitions and Data Sources

Main Dependent and Independent Variables	
Variable	Definition
$Ln(Rev\ Tweets)$	The natural logarithm of one plus the number of revision-related tweets observed during the [0,+1] trading-day window relative to the forecast revision announcement date. Revision-related tweets ($Rev\ Tweets$) are defined as tweets that contain both the firm's cashtag and any form of the word "upgrad*" or "downgrad*" matching the direction of the forecast revision.
$Ln(Other\ Tweets)$	The natural logarithm of one plus the number of other tweets observed during the [0,+1] trading-day window relative to the forecast revision announcement date. Other tweets are defined as any tweets that contain the firm's cashtag not including revision-related tweets.
$Ln(Tweet\ Delay)$	The natural logarithm of one plus the number of minutes from the I/B/E/S revision announcement timestamp to the first $Rev\ Tweet$ timestamp within five days of the revision.
$RPD_{[4hr]}$	Relative price discovery, calculated as $\frac{Ret_{[4hr]}}{Ret_{[32hr]}}$ where $Ret_{[4hr]}$ is the return over a four-hour trading window (e.g. hours [0,3] or hours [8,11]) and $Ret_{[32hr]}$ is the total return over the thirty-two hour trading window following the revision announcement.
$Engagement$	An indicator variable equal to one if the amount of user engagement for the revision tweets in a given four-hour window was greater than the annual median amount of revision tweet engagement. Engagement is defined as either a like, retweet, reply, or quote (see public_metrics from the Twitter API at https://developer.twitter.com/en/docs/twitter-api/metrics).
$URLs$	An indicator variable equal to one if the number of URLs included in the revision tweets in a given four-hour window was greater than the annual median number of revision tweet URLs.
$Followers$	An indicator variable equal to one if the number of followers of revision tweet authors for the revision tweets in a given four-hour window was greater than the annual median number of followers.
$Verified$	An indicator variable equal to one if the number of verified authors of revision tweet authors for the revision tweets in a given four-hour window is greater than the annual median. During our sample period, users could apply for verification which required users to be authentic, notable, and active. Details can be found at https://help.twitter.com/en/managing-your-account/legacy-verification-policy.
$MRT_{[32Hour]}$	Market reaction timeliness, calculated as $\frac{RET_{[0,3]}}{RET_{[0,31]}} + \frac{RET_{[0,7]}}{RET_{[0,31]}} + \frac{RET_{[0,11]}}{RET_{[0,31]}} + \frac{RET_{[0,15]}}{RET_{[0,31]}} + \frac{RET_{[0,19]}}{RET_{[0,31]}} + \frac{RET_{[0,23]}}{RET_{[0,31]}} + \frac{RET_{[0,27]}}{RET_{[0,31]}} + 0.5$, where $RET_{[0,t]}$ is the buy-and-hold return up to and including hour t following the revision announcement. Each return fraction is winsorized at -1 and 1.
$Ab\ Retail\ Vol$	The difference between the retail share of trading volume during the [0,+1] trading-day window around the revision announcement date and the average retail share of trading volume during the [-41,-11] trading-day window prior to the announcement date. Retail trades are identified following the Barber, Huang, Jorion, Odean, and Schwarz (2024) algorithm.

Table A.1, continued

$Ab\,OIB_{Retail}$	The difference between retail order imbalance during the [0,+1] trading-day window around the forecast revision announcement date and the average two-day retail order imbalance during the [-41-,11] trading-day window prior to the revision announcement date. Retail order imbalance is calculated as the total dollar value of retail buys less the total dollar value of retail sells scaled by the total retail dollar value over the [0, +1] trading window.
$Ab\,OIB_{Institional}$	The difference between institutional order imbalance during the [0,+1] trading-day window around the forecast revision announcement date and the average two-day institutional order imbalance during the [-41,-11] trading-day window prior to the revision announcement date. Institutional order imbalance is calculated as the total dollar value of institutional buys less the total dollar value of institutional sells scaled by the total institutional dollar value over each trading window. The total dollar value of institutional buys (sells) are calculated as the total dollar value of buys (sells) less the total dollar value of retail buys (sells).
$BHAR_{[t,t+5d]}$	The buy-and-hold return beginning after the four-hour window until the end of the fifth trading day after the revision announcement minus the buy-and-hold return for the CRSP value-weighted index for the five trading days after the revision.
$High\ Prior\ Volume$	An indicator variable equal to one if the dollar volume in the prior four-hour window was higher than the volume of the same time-of-day interval on each of the previous 9 trading days, following Farrell, Green, Jame, and Markov (2022).
$Low\ Prior\ Volume$	An indicator variable equal to one if the dollar volume of the prior four-hour window was lower than the volume of the same time-of-day interval on each of the previous 9 trading days, following Farrell, Green, Jame, and Markov (2022).
$Prior\ Return$	The return from the prior four-hour trading window, following Farrell, Green, Jame, and Markov (2022).

Determinants of Revision-Related Tweets / Revision-Level Control Variables

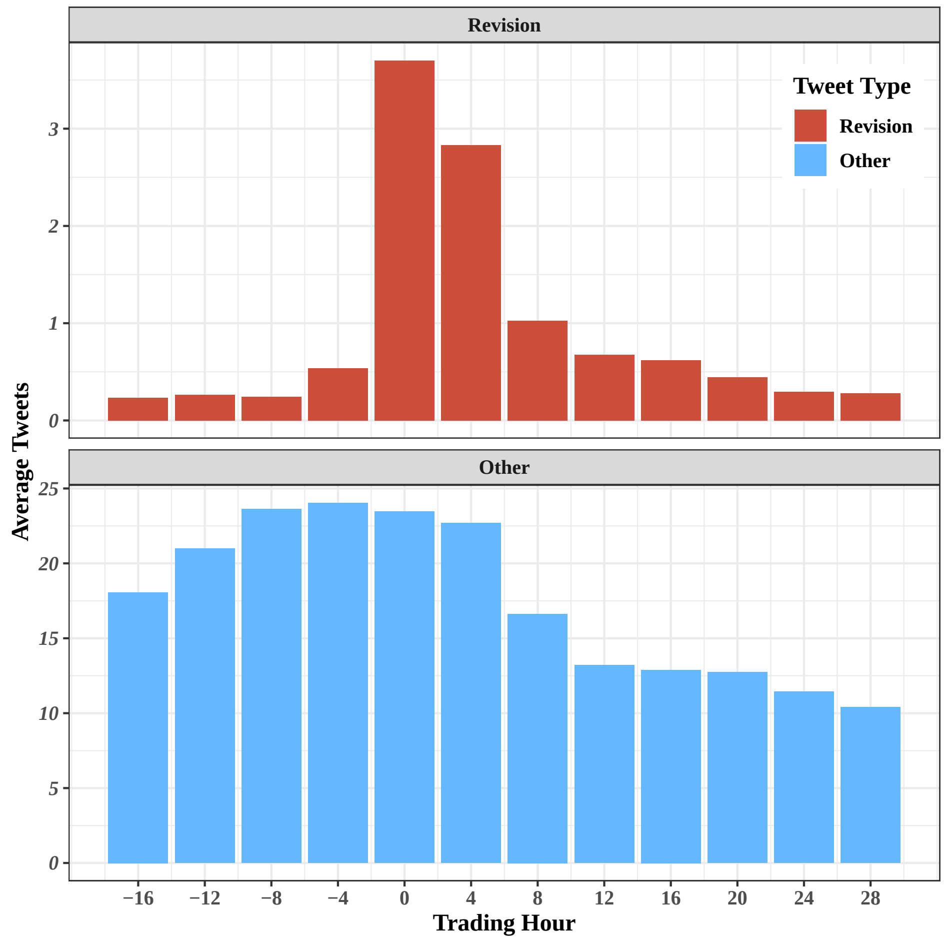
Variable	Definition
$Upgrade$	An indicator variable equal to one if the revision is an upgrade.
$Magnitude$	The absolute value of the change in the I/B/E/S recommendation number.
$Ln(Activation\ Delay)$	The natural logarithm of one plus the time (in minutes) from the revision announcement timestamp and the activation timestamp in I/B/E/S.
$Activated$	An indicator variable equal to one if the recommendation revision was activated by I/B/E/S during the four-hour window, and zero otherwise.
$Ln(Rev\ Stories)$	The natural logarithm of one plus the number of revision-related stories observed during the [0,+1] trading-day window relative to the forecast revision announcement date. Revision-related stories ($Rev\ Stories$) are defined as stories from the Full Edition of RavenPack with the category field of the story (e.g. "analyst-ratings-change-positive") matching the direction of the forecast revision.
$Ln(Other\ Stories)$	The natural logarithm of one plus the number of other stories observed during the [0,+1] trading-day window relative to the forecast revision announcement date. Other stories are defined as total stories from the Full Edition of RavenPack that are tagged by RavenPack as mentioning the covered firm less the number of $Rev\ Stories$ during the same window.
$Ln(Broker\ Size)$	The natural logarithm of one plus the number of analysts employed at the recommending analysts' brokerage, measured over the previous year.

Table A.1, continued

$Ln(Experience)$	The natural logarithm of one plus the total number of years the analyst has appeared in I/B/E/S prior to the revision.
$Prior\ Profitability$	The mean 5-day buy-and-hold abnormal return to the analysts' recommendation revisions during the prior year, multiplied by -1 for downgrades. Profitability is quintile-ranked by year with missing values assigned to the middle quintile.
$Prior\ Bullishness$	The mean for the analysts' level of recommendation for all firms (I/B/E/S variable = 'IRECCD') in their portfolio during the year prior to the recommendation revision of the covered firm. Bullishness is quintile-ranked by year with missing values assigned to the middle quintile.
$Prior\ Accuracy$	The mean absolute EPS forecast error for each analyst during the year prior to the recommendation revision, multiplied by -1. Accuracy is quintile-ranked by year with missing values assigned to the middle quintile.
$Ln(Past\ Tweets)$	The natural logarithm of one plus the number of total tweets observed during the [-2,-31] trading-day window relative to the recommendation revision announcement date. Total tweets are defined as any tweets that contain the firm's cashtag.
$Ln(Following)$	The natural logarithm of one plus the number of analysts covering the firm over the year prior to the revision.
$Prior\ Retail\ Volume$	The average daily retail trading volume as a proportion of total trading volume over the prior [-41, -11] trading-day window prior to the recommendation revision announcement date.
$Inst\ Own$	Percentage of shares held by 13F institutions as of the end of the most 13F report date prior to the revision.
$Accruals$	Income before extraordinary items less cash flow from operations scaled by total assets from the previous fiscal year-end.
MTB	The ratio of market value to book value of common shareholders' equity from the previous fiscal year-end.
$Ln(MVE)$	The natural logarithm of one plus the market value of equity from the previous fiscal year-end.
$Intangibles$	Intangible assets scaled by total assets from the previous fiscal year-end.
$Cap\ Exp$	Capital expenditures scaled by total assets from the previous fiscal year-end.
$R\&D$	Research and development expenditures scaled by total assets from the previous fiscal year-end.
$Advertising$	Advertising expenditures scaled by total assets from the previous fiscal year-end.
$Sales\ Growth$	The percentage growth in annual sales revenue as of the previous fiscal year-end.
$Leverage$	Long-term debt scaled by total assets from the previous fiscal year-end .

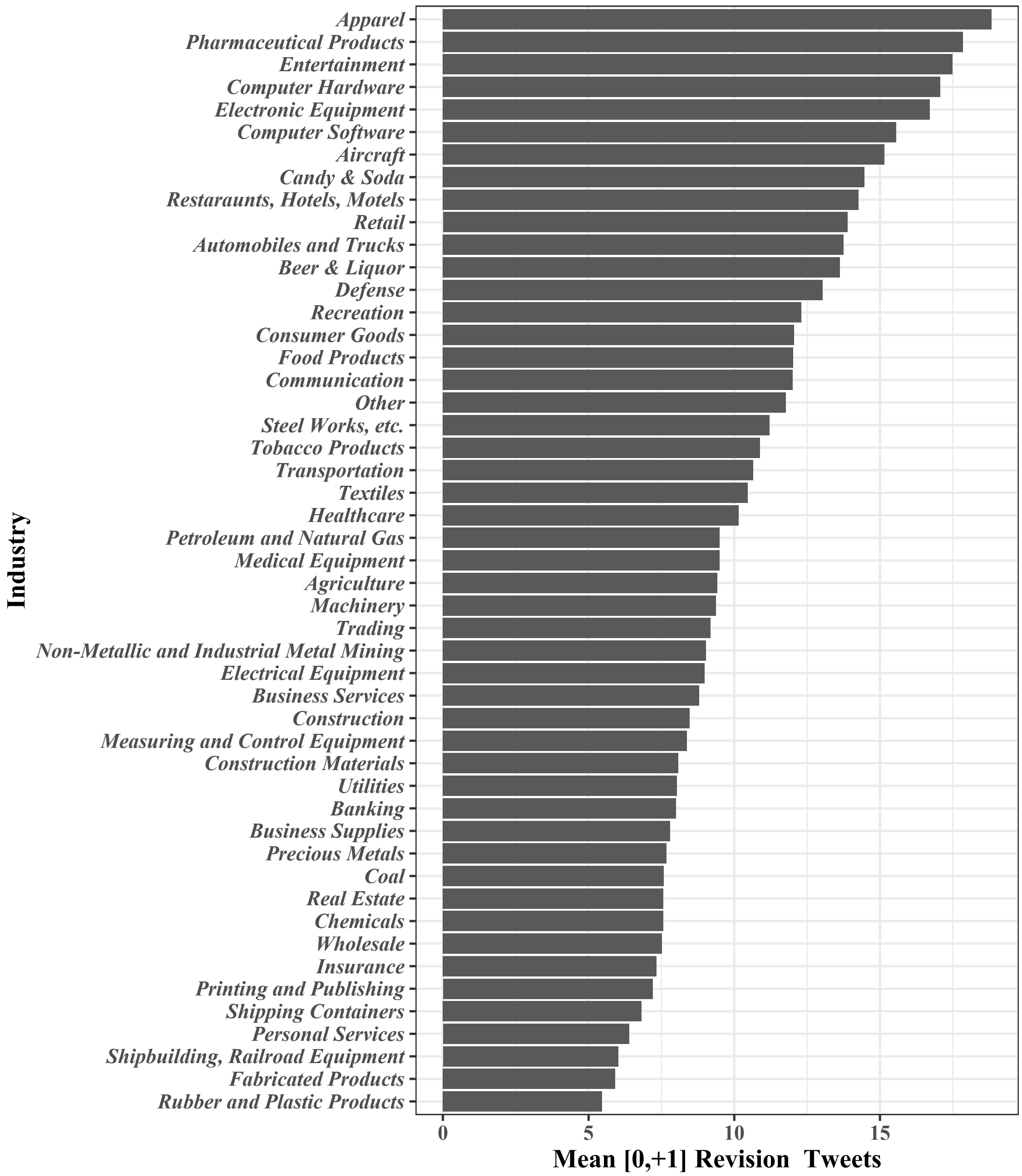
Figures and Tables

FIGURE 1
Average Intra-day Frequency of Tweets Around Analyst Recommendation Revisions



This figure plots the frequency of tweets in intra-day event time around analyst recommendation revision announcements. The top (bottom) panel plots the average number of $Rev\ Tweets$ ($Other\ Tweets$) observed during the sixteen trading hours before and the thirty-two trading hours after the I/B/E/S announcement timestamp. Each column plots the average number of tweets observed during the four trading-hour window beginning at the specified hour $t + n$ relative to the revision announcement, such that the first (last) column plots average tweets observed during the [-16,-13] ([+28,+31]) interval. We include pre-open and post-close extended hours trading sessions, such that a full trading day covers 16 trading hours from 4AM to 8PM. Thus, the figure covers one trading day before and two days after the revision announcement. $Rev\ Tweets$ are tweets that contain both the firm's cashtag and any form of the word "upgrad*" or "downgrad*" matching the direction of the forecast revision, and $Other\ Tweets$ are all tweets that contain the firm's cashtag excluding revision-related tweets. Formal definitions for all variables are provided in Appendix A.1.

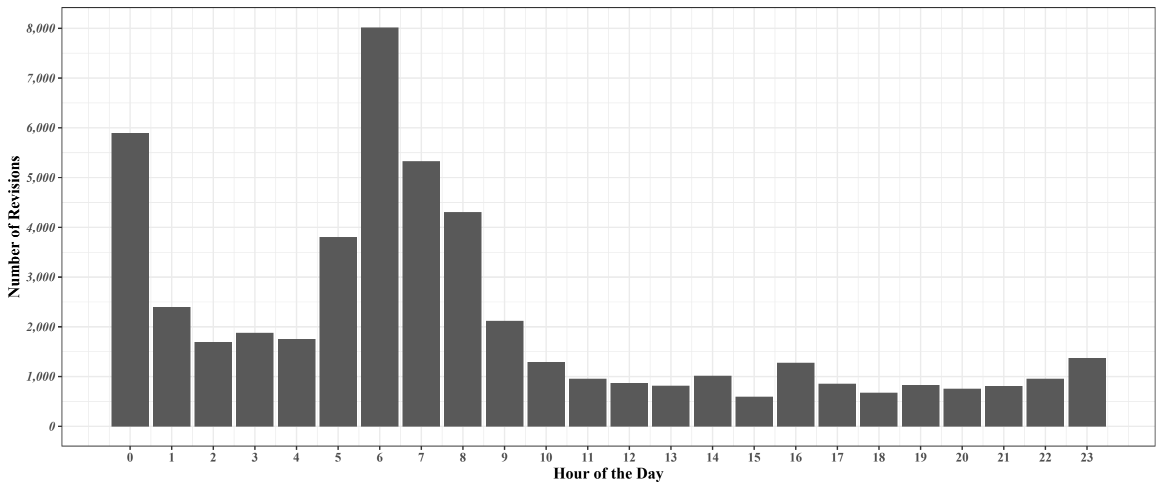
FIGURE 2
Mean Revision Tweets by Industry



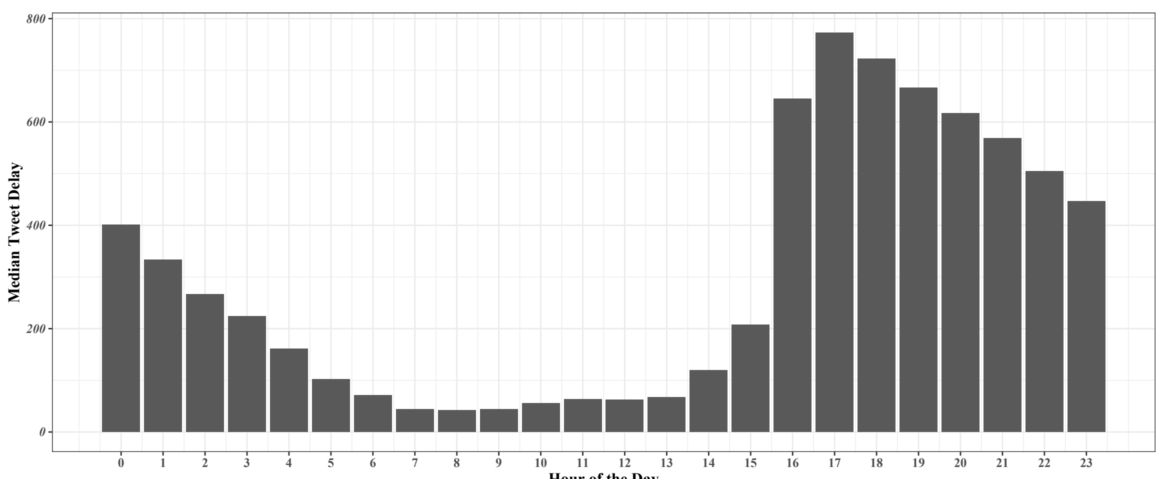
This figure plots the mean number of revision-related tweets ($Rev\ Tweets$) observed during the [0,+1] trading day window around analysts' recommendation revisions, by industry. Industries are classified using the Fama-French 49 industry classification. $Rev\ Tweets$ are tweets that contain both the firm's cashtag and any form of the word "upgrad*" or "downgrad*" matching the direction of the forecast revision. Formal definitions for all variables are provided in Appendix A.1.

FIGURE 3
Revision Frequency and Tweet Delay, by Announcement Hour

(a) Number of Revision Announcements



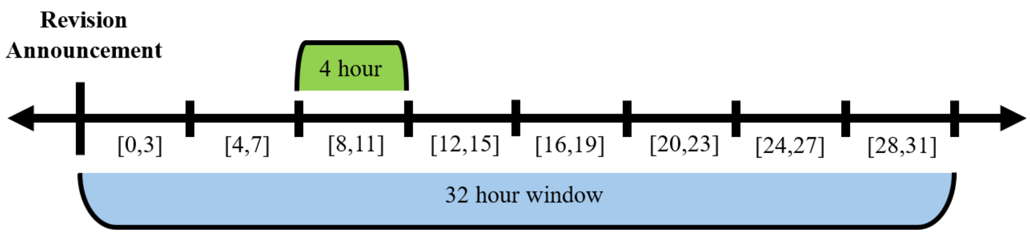
(b) Median Tweet Delay (minutes)



This figure plots the frequency of analyst revisions (Panel a) and median $Tweet\ Delay$ (Panel b), by the hour-of-day of the I/B/E/S recommendation announcement timestamp. $Tweet\ Delay$ is defined as the number of minutes from the I/B/E/S revision announcement timestamp to the first $Rev\ Tweet$ timestamp within five days after the revision. $Rev\ Tweets$ are tweets that contain both the firm's cashtag and any form of the word "upgrad*" or "downgrad*" matching the direction of the forecast revision. Formal definitions for all variables are provided in Appendix A.1.

FIGURE 4
Relative Price Discovery and Market Reaction Timeliness Research Designs

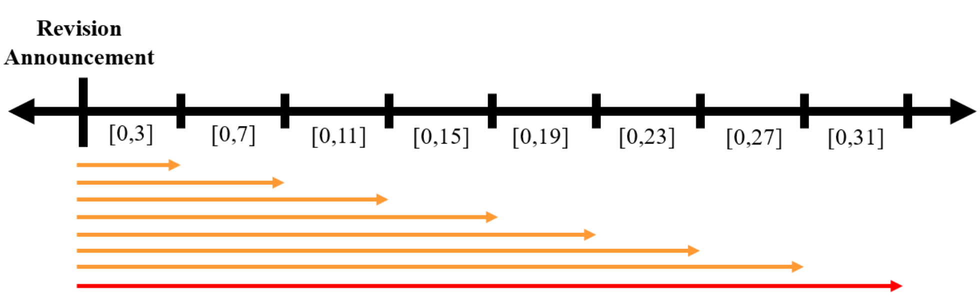
Panel A: Research Design for Eq. (2)



$$RPD_{[4hr]} = \frac{RET_{[4\ hour]}}{RET_{[32\ hour]}}$$

The figure above graphically demonstrates the research design used for our relative price discovery test (Eq.(2)). $RPD_{[4hr]}$ is calculated as $\frac{Ret_{[4hr]}}{Ret_{[32hr]}}$ where $Ret_{[4hr]}$ is the return over a given four-hour trading window (green shading) and $Ret_{[32hr]}$ is the total return over the thirty-two hour trading window after the revision announcement (blue shading). Our independent variable of interest, $Ln(Rev\ Tweets_{[4hr]})$, and other control variables are also measured over each four-hour trading window (green shading). Our primary model includes Revision Fixed Effects which are defined as the unique combination of firm, analyst, and announcement timestamp associated with each revision. This allows us to hold constant the news of the revision, characteristics of the firm, and characteristics of the analyst and focus on variation in $RPD_{[4hr]}$ and $Ln(Rev\ Tweets_{[4hr]})$ between four-hour windows within a recommendation revision announcement.

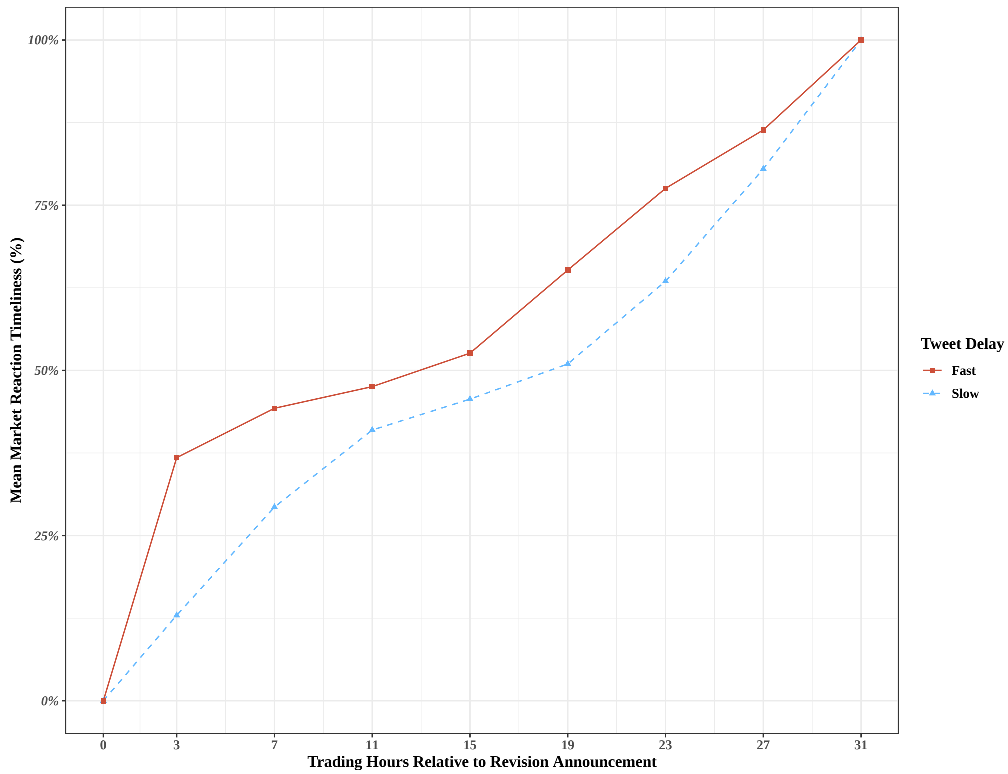
Panel B: Research Design for Eq. (3)



$$MRT_{[32hr]} = \sum \frac{RET_{[0,t]}}{RET_{[0,31]}} + 0.5$$

The figure above graphically demonstrates the research design used for our market reaction timeliness test (Eq.(3)). $MRT_{[16hr]}$ is calculated as $\frac{RET_{[0,3]}}{RET_{[0,31]}} + \frac{RET_{[0,7]}}{RET_{[0,31]}} + \frac{RET_{[0,11]}}{RET_{[0,31]}} + \cdots + \frac{RET_{[0,27]}}{RET_{[0,31]}} + 0.5$. $RET_{[0,t]}$ is the buy-and-hold return up to and including hour t following the revision announcement and is represented by the orange lines in the above figure for each interval. $RET_{[0,31]}$ is the buy-and-hold return for the 32-trading hours after the revision announcement and is represented by the red line. Each return fraction is winsorized at -1 and 1. Our independent variables of interest are $Ln(Rev\ Tweets_{[0,3]})$ and $Ln(TweetDelay)$. $Ln(Rev\ Tweets_{[0,3]})$ corresponds to the revision-related tweets identified in the first trading window after the revision announcement (the smallest orange line). $Ln(TweetDelay)$ represents the time, in minutes, since the recommendation revision announcement and the first identified revision-related tweet, irrespective of each four-hour window.

FIGURE 5
Intra-period Market Reaction Timeliness of Recommendation Revision Market Reaction, by Tweet Delay



This figure plots the mean cumulative market reaction timeliness (MRT) of the market reaction to analyst recommendation revisions, by $Tweet\ Delay$. $MRT_{[0,t]}$ is calculated as $\frac{RET_{[0,t]}}{RET_{[0,31]}}$, where $RET_{[0,t]}$ is the return up to and including hour t following the revision announcement. Each return fraction is winsorized at -1 and 1. $Tweet\ Delay$ is defined as the number of minutes from the I/B/E/S revision announcement timestamp to the first $Rev\ Tweet$ timestamp within five days after the revision. The solid red (blue dashed) line plots the mean cumulative $MRT_{[0,t]}$ for revisions with fast (slow) $Tweet\ Delay$. Fast (slow) $Tweet\ Delay$ observations are defined as observations with $Tweet\ Delay$ in the lowest (highest) annual $Tweet\ Delay$ decile. Formal definitions for all variables are provided in Appendix A.1.

TABLE 1
Sample Selection

Step	Description	Observations	Unique Firms	Total Tweets
1	Revisions in IBES recommendation detail file (US Firms) from 2013 - 2020	82,340	5,671	
2	Revisions from Step 1 with available data for all required variables from I/B/E/S, CRSP, and Compustat.	51,809	3,663	
3	Revisions from Step 2 with an I/B/E/S activation delay less than 10 days.	51,250	3,656	
4	Revisions from Step 3 with available data for all required variables from TAQ used in Eq. (1) and Eq. (2).	50,315	3,555	
	Total firms and tweets in our 2013 - 2020 cashtag tweet database		7,871	175,237,214
5	Revisions with available financial and Twitter data for our revision-level analyses. Total cashtag tweets for this row is the total number of tweets observed in the [0,+1] window around each revision.	50,286	3,551	8,962,328
6	Number of 4-hour trading windows in the [0,+1] days around each revision for our intraday-level analyses.	402,288	3,551	6,751,319

This table outlines our sample selection procedure. We obtain analyst recommendation revisions from the I/B/E/S recommendation detail file. We limit our sample to upgrade and downgrade revisions for U.S. firms issued between January 1st, 2013, and December 31st, 2020. We then merge our initial revision sample with data from other WRDS sources such as CRSP, NYSE TAQ, and Compustat fundamentals to collect relevant variables listed in Appendix A.1. Next, we merge the WRDS data with data collected from the Twitter API. We limit our sample to companies that have at least one tweet about their cashtag at any point during the sample period. We then match our I/B/E/S revision sample to our Twitter data for these companies, giving a final sample of 50,286 recommendation revisions with 8,962,328 announcement-window cashtag tweets.

TABLE 2
Descriptive Statistics

	N	Mean	SD	Min	P25	Median	P75	Max
Variables of Interest								
$Rev\ Tweets$	50,286	11.73	15.38	0.00	3.00	7.00	14.00	97.00
$Other\ Tweets$	50,286	166.50	433.85	0.00	16.00	37.00	106.00	3,204.00
$Tweet\ Delay$	45,654	362.43	712.65	1.14	46.40	145.22	390.36	4,794.04
$MRT_{[0,+31]}$	50,083	4.37	2.90	-6.50	3.18	5.25	6.50	7.50
$Ab\ Retail\ Vol$	50,286	0.00	0.03	-0.07	-0.02	-0.00	0.01	0.13
$Ab\ OIB_{Retail}$	50,163	-0.00	0.30	-0.89	-0.14	0.00	0.14	0.91
$Ab\ OIB_{Institutional}$	50,163	0.01	0.12	-0.35	-0.05	0.01	0.07	0.36
Revision Characteristics								
$Upgrade$	50,286	0.45	0.50	0.00	0.00	0.00	1.00	1.00
$Magnitude$	50,286	1.36	0.51	1.00	1.00	1.00	2.00	4.00
$Activation\ Delay$	50,286	474.28	1,419.69	0.67	7.83	23.65	201.28	9,039.16
$Rev\ Stories$	50,286	4.98	6.58	0.00	0.00	3.00	8.00	34.00
$Other\ Stories$	50,286	104.87	307.87	0.00	0.00	14.00	60.00	2,161.45
Analyst Characteristics								
$Broker\ Size$	50,286	108.19	106.36	1.00	30.00	72.00	155.00	528.00
$Experience$	50,286	6.11	4.96	0.16	2.18	4.75	8.83	20.91
$Prior\ Profitability$	42,410	0.04	0.09	-3.61	0.01	0.03	0.06	1.24
$Prior\ Bullishness$	42,410	2.58	0.52	1.00	2.31	2.60	3.00	5.00
$Prior\ Accuracy$	42,410	0.23	0.12	0.00	0.13	0.20	0.30	1.00
Firm Characteristics								
$Past\ Tweets$	50,286	678.70	1,482.98	10.00	103.00	230.00	535.00	10,632.55
$Following$	50,286	17.74	9.98	2.00	10.00	17.00	24.00	44.00
$Prior\ Retail\ Vol$	50,286	0.06	0.04	0.00	0.04	0.05	0.07	0.46
$Ln(MVE)$	50,286	8.27	1.70	4.33	7.10	8.20	9.43	12.36
$Inst\ Own$	50,286	0.76	0.24	0.01	0.68	0.83	0.93	1.00
MTB	50,286	4.46	6.49	0.53	1.53	2.54	4.57	49.40
$Accruals$	50,286	-0.07	0.08	-0.41	-0.10	-0.05	-0.02	0.16
$Intangibles$	50,286	0.21	0.25	0.00	0.02	0.12	0.34	1.18
$Cap\ Exp$	50,286	0.06	0.07	0.00	0.01	0.03	0.07	0.40
$R\&D$	50,286	0.04	0.09	0.00	0.00	0.00	0.05	0.53
$Advertising$	50,286	0.01	0.03	0.00	0.00	0.00	0.01	0.20
$Sales\ Growth$	50,286	0.11	0.27	-0.50	-0.01	0.06	0.17	1.56
$Leverage$	50,286	0.27	0.23	0.00	0.09	0.24	0.40	1.11

This table provides descriptive statistics for the variables of interest used in our revision-level analyses. All variables are defined in Appendix A.1.

TABLE 3
Determinants of Twitter Activity Around Analyst Recommendation Announcements

	(1) $Ln(Rev\ Tweets)$	(2) $Ln(Other\ Tweets)$	(3) $Ln(Tweet\ Delay)$
Revision Characteristics			
$Upgrade$	0.084***	−0.084***	−0.047***
	(5.445)	(−9.215)	(−5.091)
$Magnitude$	0.060***	0.031***	0.026**
	(3.646)	(3.472)	(2.403)
$Ln(Activation\ Delay)$	−0.117***	−0.025***	0.048***
	(−17.962)	(−5.513)	(9.157)
$Ln(Rev\ Stories)$	0.282***	0.061***	−0.114***
	(16.900)	(6.912)	(−13.862)
Analyst Characteristics			
$Ln(Broker\ Size)$	0.166***	0.022***	−0.089***
	(18.848)	(4.526)	(−13.179)
$Ln(Experience)$	0.011**	−0.001	0.002
	(1.992)	(−0.209)	(0.544)
$Profitability$	0.025***	0.028***	−0.014***
	(6.430)	(9.684)	(−4.327)
$Bullish$	0.008	0.003	0.002
	(1.525)	(0.851)	(0.507)
$Accuracy$	−0.011**	−0.012***	0.014***
	(−2.153)	(−3.198)	(3.458)
Firm Characteristics			
$Ln(Past\ Tweets)$	0.290***	0.598***	−0.042***
	(20.506)	(49.167)	(−4.724)
$Ln(Following)$	0.131***	0.109***	−0.056***
	(8.828)	(10.507)	(−5.895)
$Prior\ Retail\ Vol$	−0.004	0.024***	−0.006
	(−0.502)	(3.944)	(−1.201)
$Ln(MVE)$	−0.150***	0.000	0.072***
	(−8.962)	(−0.022)	(6.997)
$Inst\ Own$	−0.006	−0.005	0.017***
	(−0.671)	(−0.833)	(2.754)
MTB	0.017*	0.008	−0.008
	(1.951)	(1.097)	(−1.475)
$Accruals$	−0.019*	−0.012	0.001
	(−1.940)	(−1.579)	(0.210)
$Intangibles$	0.028***	0.019***	−0.024***
	(3.114)	(2.783)	(−4.094)
$Cap\ Exp$	−0.008	−0.017**	−0.006
	(−0.880)	(−2.177)	(−0.857)
$R\&D$	0.091***	0.133***	−0.076***
	(9.050)	(15.585)	(−11.091)
$Advertising$	0.021***	0.044***	−0.024***
	(2.732)	(6.203)	(−4.367)
$Sales\ Growth$	0.001	0.005	0.001
	(0.113)	(0.766)	(0.197)
$Leverage$	−0.016*	−0.015**	0.014**
	(−1.823)	(−2.191)	(2.453)
Ann. Hr. FE	Included	Included	Included
N	50,286	50,286	45,654
R^2	0.309	0.532	0.344
R^2 Within	0.284	0.525	0.055

This table reports the estimated coefficients from regressions of Eq. (1). Ann. Hr. FE is a vector of fixed effect indicators identifying the hour of day of the revision announcement based on its I/B/E/S announcement timestamp. All variables are defined in Appendix A.1. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the two-tailed t-test. Standard errors are clustered by firm and announcement date.

TABLE 4
Intraday Relative Price Discovery

	(1)	(2)	(3)	(4)
	$RPD_{[4hr]}$	$RPD_{[4hr]}$	$RPD_{[4hr]}$	$RPD_{[4hr]}$
	[0,+3] Only	[0,+31] Windows	[0,+31] Windows	[0,+31] Windows
$Ln(Rev\ Tweets_{[4hr]})$	0.025^{***}	0.028^{***}	0.019^{***}	0.042^{***}
	(7.080)	(19.836)	(13.083)	(14.727)
$Ln(Other\ Tweets_{[4hr]})$	0.022^{***}	0.037^{***}	0.033^{***}	0.032^{***}
	(6.354)	(20.641)	(18.546)	(17.858)
$Ln(Rev\ Stories_{[4hr]})$	0.015^{***}	0.020^{***}	0.013^{***}	0.010^{***}
	(4.111)	(13.062)	(8.313)	(6.642)
$Ln(Other\ Stories_{[4hr]})$	-0.015^{***}	0.008^{***}	0.007^{***}	0.007^{***}
	(-4.044)	(3.633)	(3.210)	(3.246)
$Activated$	0.012^{*}	0.065^{***}	0.012^{***}	0.008^{*}
	(1.846)	(18.278)	(2.718)	(1.859)
$Ln(Rev\ Tweets_{[4hr]})x[4,7]Window$				-0.013^{***}
				(-3.695)
$Ln(Rev\ Tweets_{[4hr]})x[8,11]Window$				-0.035^{***}
				(-8.516)
$Ln(Rev\ Tweets_{[4hr]})x[12,15]Window$				-0.036^{***}
				(-9.751)
Revision Fixed Effects	Excluded	Included	Included	Included
Time-of-Day Fixed Effects	Included	Included	Included	Included
Event Window Fixed Effects	Excluded	Excluded	Included	Included
N	50,286	402,288	402,288	402,288
R^2	0.091	0.085	0.088	0.089
R^2 Within	0.006	0.015	0.003	0.004

This table reports the estimated coefficients from regressions of Eq. (2). $RPD_{[4hr]}$ is calculated as $\frac{Ret_{[4hr]}}{Ret_{[32hr]}}$ where $Ret_{[4hr]}$ is the return over a given four-hour trading window and $Ret_{[32hr]}$ is the total return over the thirty-two hour trading window following the revision announcement. Revision Fixed Effects are defined as the unique combination of firm, analyst, and announcement timestamp associated with each revision. Time-of-Day Fixed Effects are defined as the hour of day of the first hour in each trading window. Event Window Fixed Effects are defined as a series of indicator variables set equal to one if the current four-hour observation occurs at time $t + x$ relative to the I/B/E/S announcement time (e.g., event window [0,3],[4,7],...[28,31]). In column (1), we limit the sample to the first four trading hours following the revision announcement. In column (2), we use the full sample to provide the average association between Twitter discussion and relative price discovery. In column (3), we add Event Window Fixed Effects to control for the length of time between the revision announcement and a given four-hour window. Column (4) reports the results of the fully specified model in Eq. (2). ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the two-tailed t-test. Standard errors are clustered by firm and announcement date. Full variable definitions are provided in Appendix A.1.

TABLE 5
Intraday Relative Price Discovery, by Tweet Characteristic

	(1) $RPD_{[4hr]}$	(2) $RPD_{[4hr]}$	(3) $RPD_{[4hr]}$	(4) $RPD_{[4hr]}$
	$Engagement$	$URLs$	$Followers$	$Verified$
$HIGH$	-0.005	-0.045^{***}	-0.016^{**}	-0.023^{**}
	(-0.700)	(-4.080)	(-2.569)	(-2.384)
$Ln(Rev\ Tweets_{[4hr]})$	0.013^{***}	0.015^{***}	0.008^{***}	0.018^{***}
	(8.065)	(7.895)	(4.356)	(11.505)
$Ln(Rev\ Tweets_{[4hr]})xHIGH$	0.016^{***}	0.027^{***}	0.027^{***}	0.014^{***}
	(3.932)	(4.597)	(6.838)	(2.708)
$Ln(Other\ Tweets_{[4hr]})$	0.033^{***}	0.033^{***}	0.032^{***}	0.033^{***}
	(18.486)	(18.370)	(18.191)	(18.489)
$Ln(Rev\ Stories_{[4hr]})$	0.012^{***}	0.012^{***}	0.011^{***}	0.012^{***}
	(7.754)	(7.822)	(7.503)	(8.078)
$Ln(Other\ Stories_{[4hr]})$	0.007^{***}	0.007^{***}	0.007^{***}	0.007^{***}
	(3.081)	(3.114)	(3.186)	(3.191)
$Activated$	0.012^{***}	0.012^{***}	0.011^{**}	0.012^{***}
	(2.587)	(2.601)	(2.510)	(2.687)
Revision Fixed Effects	Included	Included	Included	Included
Time-of-Day Fixed Effects	Included	Included	Included	Included
Event Window Fixed Effects	Included	Included	Included	Included
N	402,288	402,288	402,288	402,288
R^2	0.088	0.088	0.088	0.088
R^2 Within	0.004	0.004	0.004	0.004

This table reports the estimated coefficients from regressions of Eq. (2) including interactions of four cross-sectional variables and $Ln(Rev\ Tweets_{[4hr]})$. $RPD_{[4hr]}$ is calculated as $\frac{Ret_{[4hr]}}{Ret_{[32hr]}}$ where $Ret_{[4hr]}$ is the return over a given four-hour trading window and $Ret_{[32hr]}$ is the total return over the thirty-two hour trading window following the revision announcement. Columns (1), (2), (3), and (4) report the results when the cross-sectional variable of interest is $Engagement$, $URLs$, $Followers$, and $Verified$, respectively. $Engagement$ is an indicator variable equal to one if the amount of engagement with revision tweets in a given four-hour window is greater than the median for that year and zero otherwise. $URLs$ is an indicator variable equal to one if the number of URLs included in revision tweets in a given four-hour window is greater than the median for that year and zero otherwise. $Followers$ is an indicator variable equal to one if the number of followers associated with authors of revision tweets in a given four-hour window is greater than the median for that year and zero otherwise. $Verified$ is an indicator variable equal to one if the number of revision tweets with verified authors in a given four-hour window is greater than the median for that year and zero otherwise. The variable $HIGH$ represents the cross-sectional variable of interest corresponding to the variables across the top of the table. Revision Fixed Effects are defined as the unique combination of firm, analyst, and announcement timestamp associated with each revision. Time-of-Day Fixed Effects are defined as the hour of day of the first hour in each trading window. Event Window Fixed Effects are defined as a series of indicator variables set equal to one if the current four-hour observation occurs at time $t + x$ relative to the I/B/E/S announcement time (e.g., event window [0,3],[4,7],...[28,31]). ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the two-tailed t-test. Standard errors are clustered by firm and announcement date. Full variable definitions are provided in Appendix A.1.

TABLE 6
Regressions of Intraday Market Reaction Timeliness on Revision-Related Tweets

	(1) $MRT_{[32hr]}$	(2) $MRT_{[32hr]}$
$Ln(Rev\ Tweets_{[0,3]})$	0.040^{***}	
	(5.658)	
$Ln(Tweet\ Delay)$		-0.020^{***}
		(-2.932)
$Ln(Other\ Tweets)$	0.074^{***}	0.072^{***}
	(8.063)	(7.545)
$Ln(Rev\ Stories)$	0.083^{***}	0.074^{***}
	(7.311)	(5.985)
$Ln(Other\ Stories)$	0.044^{**}	0.050^{***}
	(2.577)	(2.718)
$Ln(Activation\ Delay)$	-0.010	-0.015^{**}
	(-1.484)	(-2.139)
$CONTROLS$	Included	Included
Firm Fixed Effects	Included	Included
Analyst Fixed Effects	Included	Included
Quarter Fixed Effects	Included	Included
Ann. Hr.Fixed Effects	Included	Included
N	49,203	44,584
R^2	0.191	0.194
R^2 Within	0.010	0.007

This table reports the estimated coefficients from regressions of Eq. (3). Column (1) reports the results when $Tweet\ Measure$ is $Ln(Rev\ Tweets_{[0,3]})$, and columns (2) reports the results when $Tweet\ Measure$ is $Ln(Tweet\ Delay)$. $MRT_{[32hr]}$ is calculated as $\frac{RET_{[0,3]}}{RET_{[0,31]}} + \frac{RET_{[0,7]}}{RET_{[0,31]}} + \frac{RET_{[0,11]}}{RET_{[0,31]}} + \frac{RET_{[0,15]}}{RET_{[0,31]}} + \frac{RET_{[0,19]}}{RET_{[0,31]}} + \frac{RET_{[0,23]}}{RET_{[0,31]}} + \frac{RET_{[0,27]}}{RET_{[0,31]}} + 0.5$, where $RET_{[0,t]}$ is the buy-and-hold return up to and including hour t following the revision announcement. 'Control Variables' are as defined in Appendix A.1. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the two-tailed t-test. Standard errors are clustered by firm and announcement date. Full variable definitions are provided in Appendix A.1.

TABLE 7

Regressions of Abnormal Retail Volume and Order Imbalance on Revision-Related Tweets

Panel A: Using Barber, Huang, Jorion, Odean, and Schwarz (2024) Algorithm to Identify Retail Trades

	(1)	(2)	(3)	(4)	(5)
	$Ab\ Retail\ Vol$	$Ab\ OIB_{Retail}$		$Ab\ OIB_{Institutional}$	
		$Downgrade$	$Upgrade$	$Downgrade$	$Upgrade$
$Ln(Rev\ Tweets)$	0.020**	−0.009**	0.008**	−0.001	−0.001
	(2.375)	(−2.552)	(2.224)	(−0.922)	(−0.579)
$Ln(Other\ Tweets)$	0.156***	−0.005	−0.014***	0.011***	0.006***
	(11.072)	(−1.109)	(−2.923)	(6.912)	(3.546)
$Ln(Rev\ Stories)$	0.034***	0.009**	−0.002	0.002	−0.001
	(3.010)	(2.035)	(−0.457)	(1.051)	(−0.518)
$Ln(Other\ Stories)$	0.133***	0.013*	−0.014*	0.014***	−0.007**
	(6.181)	(1.837)	(−1.858)	(5.077)	(−2.177)
$Ln(Activation\ Delay)$	−0.008	0.003	0.000	−0.001	0.001
	(−1.237)	(1.050)	(−0.133)	(−1.166)	(0.614)
$CONTROLS$	Included	Included	Included	Included	Included
Analyst Fixed Effects	Included	Included	Included	Included	Included
Firm Fixed Effects	Included	Included	Included	Included	Included
Calendar Qtr Fixed Effects	Included	Included	Included	Included	Included
N	49,409	26,423	21,397	26,423	21,397
R^2	0.248	0.278	0.263	0.307	0.264
R^2 Within	0.034	0.003	0.003	0.009	0.002

Panel B: Using Boehmer, Jones, Zhang, and Zhang (2021) Algorithm to Identify Retail Trades

	(1)	(2)	(3)	(4)	(5)
	$Ab\ Retail\ Vol$	$Ab\ OIB_{Retail}$		$Ab\ OIB_{Institutional}$	
		$Downgrade$	$Upgrade$	$Downgrade$	$Upgrade$
$Ln(Rev\ Tweets)$	0.035***	−0.010***	0.006***	0.000	0.000
	(4.153)	(−4.493)	(2.730)	(−0.202)	(−0.047)
$Ln(Other\ Tweets)$	0.388***	−0.008***	−0.004	0.010***	0.003*
	(26.017)	(−3.122)	(−1.446)	(6.545)	(1.850)
$Ln(Rev\ Stories)$	0.045***	0.004	0.000	0.002	−0.001
	(4.455)	(1.494)	(0.127)	(1.137)	(−0.525)
$Ln(Other\ Stories)$	0.276***	−0.004	−0.004	0.017***	−0.007**
	(13.266)	(−0.843)	(−0.759)	(5.960)	(−2.391)
$Ln(Activation\ Delay)$	0.011*	0.001	0.000	0.001	0.000
	(1.859)	(0.558)	(0.231)	(0.755)	(−0.218)
$CONTROLS$	Included	Included	Included	Included	Included
Analyst Fixed Effects	Included	Included	Included	Included	Included
Firm Fixed Effects	Included	Included	Included	Included	Included
Calendar Qtr Fixed Effects	Included	Included	Included	Included	Included
N	49,317	26,440	21,395	26,440	21,395
R^2	0.368	0.306	0.271	0.288	0.257
R^2 Within	0.122	0.006	0.002	0.010	0.001

This table reports the estimated coefficients from regressions of Eq. (4). Panel A uses the recent methodology of Barber, Huang, Jorion, Odean, and Schwarz (2024) to identify retail trades, and Panel B uses the methodology of Boehmer, Jones, Zhang, and Zhang (2021) to identify retail trades. In both panels, column (1) reports the results when the dependent variable is $Ab\ Retail\ Vol$ which is the abnormal retail volume during the [0,+1] trading-day window. Columns (2) and (3) report the results of $Ab\ OIB_{Retail}$ for downgrades and upgrades, respectively. Columns (3) and (4) report the results of $Ab\ OIB_{Institutional}$ for downgrades and upgrades, respectively. $Ab\ OIB$ is the abnormal order imbalance during the [0,+1] trading-day window. Following Farrell, Green, Jame, and Markov (2022), we identify institutional trades as total trades minus retail trades. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the two-tailed t-test. Standard errors are clustered by firm and announcement date. Full variable definitions are provided in Appendix A.1.

TABLE 8
Intraday Relative Price Discovery and Market Reaction Timeliness, by Retail Trading Volume

Panel A: Intraday Relative Price Discovery, by Retail Trading Volume

	(1) $RPD_{[4hr]}$	(2) $RPD_{[4hr]}$	(3) $RPD_{[4hr]}$	(4) $RPD_{[4hr]}$
	[0,+3] Only	[0,+3] Only	[0,+31] Windows	[0,+31] Windows
	$Low\ Ab\ Retail\ Vol$	$High\ Ab\ Retail\ Vol$	$Low\ Ab\ Retail\ Vol$	$High\ Ab\ Retail\ Vol$
$Ln(Rev\ Tweets_{[4hr]})$	0.018***	0.032***	0.016***	0.022***
	(3.873)	(6.996)	(8.155)	(11.003)
High - Low		0.014**		0.005*
		(2.425)		(1.941)
$CONTROLS$	Included	Included	Included	Included
Revision Fixed Effects	Excluded	Excluded	Included	Included
Time-of-Day Fixed Effects	Included	Included	Included	Included
Event Window Fixed Effects	Excluded	Excluded	Included	Included
N	25,145	25,141	201,160	201,128
R^2	0.087	0.096	0.083	0.093
R^2 Within	0.005	0.008	0.003	0.004

Panel B: Market Reaction Timeliness, by Retail Trading Volume

	(1) $MRT_{[32hr]}$	(2) $MRT_{[32hr]}$	(3) $MRT_{[32hr]}$	(4) $MRT_{[32hr]}$
	$Low\ Ab\ Retail\ Vol$	$High\ Ab\ Retail\ Vol$	$Low\ Ab\ Retail\ Vol$	$High\ Ab\ Retail\ Vol$
$Ln(Rev\ Tweets_{[0,3]})$	0.021**	0.044***		
	(2.159)	(4.149)		
$Ln(Tweet\ Delay)$			−0.003	−0.018*
			(−0.312)	(−1.796)
High - Low		0.023		−0.015
		(1.576)		(−1.030)
$CONTROLS$	Included	Included	Included	Included
Firm Fixed Effects	Included	Included	Included	Included
Analyst Fixed Effects	Included	Included	Included	Included
Quarter Fixed Effects	Included	Included	Included	Included
Ann. Hr.Fixed Effects	Included	Included	Included	Included
N	23,913	23,860	21,478	21,677
R^2	0.275	0.272	0.286	0.280
R^2 Within	0.008	0.013	0.005	0.010

This table reports the estimated coefficients from regressions of Eq. (2) and Eq. (3) by estimating each model separately for recommendation revisions with high and low levels of yearly abnormal retail trading volume ($Ab\ Retail\ Vol$) during the [0,+1] announcement window. Panel A presents the results from estimating Eq. (2). Columns (1) and (2) use the specification from column (1) of Table 4 estimated separately for low and high $Ab\ Retail\ Vol$, respectively. Columns (3) and (4) use the specification from column (4) of Table 4 estimated separately for low and high $Ab\ Retail\ Vol$, respectively. Panel B reports the results from estimating Eq. (3). Columns (1) and (2) use the specification from column (1) of Table 6 estimated separately for low and high $Ab\ Retail\ Vol$, respectively. Columns (3) and (4) use the specification from column (2) of Table 4 estimated separately for low and high $Ab\ Retail\ Vol$, respectively. For each independent variable displayed, we report the difference in coefficient estimates between the high and low specifications and the associated t-statistic for the difference. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the two-tailed t-test. Standard errors are clustered by firm and announcement date. Full variable definitions are provided in Appendix A.1.

TABLE 9
Retail Trading Informativeness and Revision Tweets

Panel A: Future Returns Regressed on Order Imbalance Interacted with a Continuous Measure of $Rev\ Tweets$

	(1) $BHAR_{[t,t+5d]}$	(2) $BHAR_{[t,t+5d]}$
	[0,+3] Windows	[0,+31] Windows
$Retail\ OIB_{[4hr]}$	0.035	0.024
	(0.878)	(1.279)
$Inst\ OIB_{[4hr]}$	-0.081^{*}	-0.027
	(-1.701)	(-1.379)
$Ln(Rev\ Tweets_{[4hr]})$	-0.053	0.029
	(-0.745)	(0.875)
$Retail\ OIB_{[4hr]}\ xLn(Rev\ Tweets_{[4hr]})$	0.069^{*}	0.053^{***}
	(1.646)	(2.745)
$Inst\ OIB_{[4hr]}\ xLn(Rev\ Tweets_{[4hr]})$	-0.038	-0.014
	(-0.876)	(-0.585)
Time-of-Day Fixed Effects	Included	Included
N	27,315	269,331
R^2	0.003	0.001
R^2 Within	0.002	0.001

Panel B: Future Returns Regressed On Order Imbalance Before and After Announcement by High vs Low $Rev\ Tweets$

	(1) $BHAR_{[t,t+5d]}$	(2) $BHAR_{[t,t+5d]}$	(3) $BHAR_{[t,t+5d]}$	(4) $BHAR_{[t,t+5d]}$
	[-4,+3] Windows	[-4,+3] Windows	[-16,+31] Windows	[-16,+31] Windows
	$Low\ Rev\ Tweets$	$High\ Rev\ Tweets$	$Low\ Rev\ Tweets$	$High\ Rev\ Tweets$
$Retail\ OIB_{[4hr]}$	-0.131^{**}	-0.293^{***}	-0.089^{**}	-0.236^{***}
	(-2.361)	(-4.578)	(-2.232)	(-3.561)
$Inst\ OIB_{[4hr]}$	-0.034	0.024	0.018	0.103
	(-0.638)	(0.409)	(0.333)	(1.400)
$Post$	0.237^{*}	0.227	0.756^{***}	0.610^{***}
	(1.799)	(1.151)	(9.465)	(5.162)
$Retail\ OIB_{[4hr]}\ xPost$	0.112	0.405^{***}	0.100^{**}	0.280^{***}
	(1.377)	(4.441)	(2.321)	(3.930)
$Inst\ OIB_{[4hr]}\ xPost$	-0.063	-0.152	-0.041	-0.142^{*}
	(-0.523)	(-1.012)	(-0.726)	(-1.721)
$Retail\ OIB_{[4hr]}\ xPost$: High - Low		0.293^{**}		0.180^{**}
		(2.369)		(2.199)
Time-of-Day Fixed Effects	Included	Included	Included	Included
N	24,170	24,796	201,919	201,915
R^2	0.004	0.017	0.004	0.008
R^2 Within	0.003	0.014	0.003	0.007

This table presents the estimated coefficients from regressions of Eq. (5). In both panels, the dependent variable is the buy-and-hold abnormal return beginning after the intraday window until the end of the fifth trading day after the revision ($BHAR_{[t,t+5d]}$). In Panel A, we estimate the reduced form of Eq. (5) during the [0,+31] period and interact $Retail\ OIB_{[4hr]}$ and $Inst\ OIB_{[4hr]}$ with $Ln(Rev\ Tweets_{[4hr]})$ instead of $Post$. In column (1) of Panel A, we examine the first four-hour event window after the revision, and in column (2), we include all post-revision event windows. In Panel B, we use the full model of Eq. (5) and present the results separately for intervals with low versus high numbers of revision-related tweets, determined by the total revision tweets observed across the intervals within a revision relative to the annual median. Columns (1) and (2) examine the [-4,+3] windows around the revision announcement, and columns (3) and (4) examine the [-16,+31] windows around the revision announcement. We also report the differences in the coefficient estimates on the interaction terms of $Retail\ OIB_{[4hr]}\ x\ Post$ between the high and low specifications and the associated t-statistics for the differences. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using the two-tailed t-test. Standard errors are clustered by firm and announcement date.