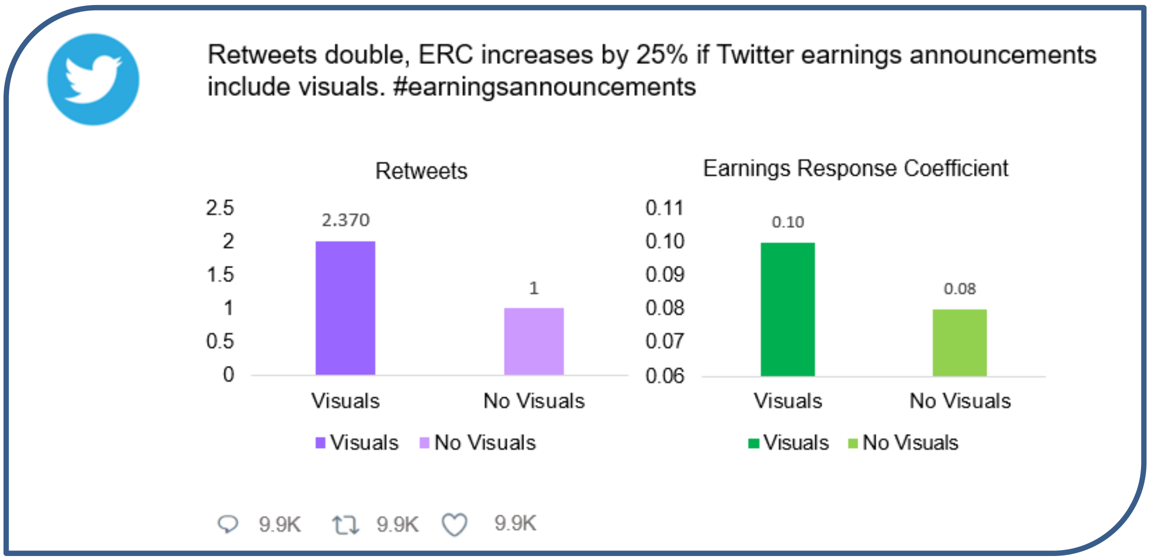
Visuals and Attention to Earnings News on Twitter*

Alex Nekrasov
University of Illinois at Chicago

Siew Hong Teoh
University of California, Irvine

Shijia Wu
University of California, Irvine



Abstract

We propose a *visual attention hypothesis* that visuals in firm earnings announcements increase attention to the firm. We find that visuals in firm Twitter earnings announcements increase follower engagement with the message via retweets and likes. Consistent with attention spillover, same day *other* tweets with visuals increase retweets and likes. Additionally, retweets increase at the firm level and decrease at the message level with the number of firm earnings tweets on the announcement day. Firms are more likely to use visuals in their earnings messages when earnings exceed analyst consensus expectations and are less persistent, consistent with managerial opportunism. Finally, consistent with visuals increasing investor attention, the initial return response to earnings news is stronger, and the post-announcement response is lower when visuals are used. Furthermore, the higher ERC from visuals is more pronounced on high investor distraction days when many other firms are also announcing earnings.

* We appreciate comments from workshop participants at Emory University, Georgia State University, University of California-Irvine, and Hong Kong Polytechnic University, and Karen Ton, Chuchu Liang, and Qin Li. We thank Ethan Chee, Ran Gu, Khanh Luu, Vrinda Jagad, and Tim Johnson for excellent research assistance.

A picture is worth a thousand words.

1. Introduction

The Securities and Exchange Commission acknowledges that in its capacity as a disclosure agency, it is committed to helping ensure that firm disclosures are understandable to the average investor.[1] As part of its plain writing initiative, the S.E.C.'s 1998 guide "A Plain English Handbook: How to Create Clear SEC Disclosure Documents" emphasized the importance of visuals, and not just word choice and sentence structure, to make disclosures understandable to the average investor.[2] Specifically, Chapter 7 of the handbook provides guidance on how a good visual design "serves the goal of communicating the information as clearly as possible" whereas a bad design "can make even a well-written document fail to communicate." According to the S.E.C., both what you say and *how* you say it are important for clear communication.[3]

---

[1] The S.E.C. has a division on plain writing. In addition to publishing the handbook on plain writing, the S.E.C. also mandated plain writing in certain sections of prospectuses in 1998. In 2008, the plain writing requirement was extended also to mutual fund summary prospectuses. All federal agencies are now required to write rules in plain English following the Federal Plain Language Guidelines after The Plain Writing Act of 2010.

[2] Chapter 7 of the S.E.C.'s plain writing guideline lists five elements possessed by a good visual design that aids understanding for a plain writing document: hierarchy or distinguishing levels of information, typography, layout, graphics, and color. We focus on the graphics element in this paper because it is relatively easier to identify whether a message contains visuals. The handbook identifies items as graphics that are tables, charts, figures, and graphs. We also include photos and videos, which automatically play in Twitter when the message is read. We use the word graphics interchangeably with visuals. We are currently unable to examine the other design elements (hierarchical structure, typography, layout and color) for their contribution to clarity. There is no widely accepted standard in the neuroscience, biology, or cognitive psychology literatures that suggest how to measure these elements that would map into a scale for clarity.

[3] Examples of some classic academic papers with famous visuals include Fama, Fisher, Jensen and Roll (1969), Ball and Brown (1968), Beaver (1968), Foster, Olsen, and Shevlin (1984), Bernard and Thomas (1989) and Burgstahler and Dichev (1997). The ability of the visuals to capture succinctly the key message of these studies very likely increase their impact on the literature. An example of a recent high impact study by Harvey, Liu, and Zhu (2016) included visuals in the abstract on ssrn.com, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2249314.

There is a large capital markets literature on disclosure readability based on textual analysis (see survey by Li 2011) and some research on speech analysis of financial communications (see Mayew and Venkatachalam 2012a), but there are few studies on the effect of visuals on investor understanding of public firm disclosures. The majority of these studies are laboratory experiments, and Ham, Seybert, and Wang (2017) is an archival data study examining CEO signature size with firm performance and investment choice.[4]

In this study, we propose as suggested in the S.E.C.'s handbook that investors are more likely to be attentive to, and be efficient at processing and impounding the information in financial disclosures that include visuals. We test a visual attention hypothesis that investor attention to earnings news is higher when the news disclosure is made using visuals.

Specifically, we study visuals in earnings messages disseminated by firms on Twitter on earnings announcement dates. First, we perform several tests on the effect of visuals on investor attention, which we measure using the firm followers' engagement with the message via retweets and likes. We test whether engagement is higher for messages with visuals than those without visuals. We also test whether visuals in *other* messages sent by the announcing firm on the earnings

[4] Asay, Libby, and Rennekamp's (2018) experiment shows that a CEO's photograph in earnings disclosure results in stronger reactions to both good and bad news. They suggest that the visual cue increases the perceived credibility of the disclosure. Elliott, Hodge, and Sedor (2012) find that experiment subjects believe explanations for restatements more when they are made via an online video than via text. Elliott, Grant, and Rennekamp (2017) find that visuals in a firm's CSR report significantly increases experiment subjects' willingness to invest in the firm. Cox, Goeij, and Campenhout (2018) find that mutual fund investors invest in a more optimal way when key fund information such as fees and past returns are summarized visually. Ham, Seybert, and Wang (2017) suggest that the size of a CEO's signature measures narcissism, and they find a negative correlation between CEO signature size and firm performance and investment choice.

announcement day generate spillover attention and increase retweets of the earnings message. Additionally, we test whether multiple messages on the earnings announcement date attract attention to the firm and increase retweets at the firm level but dilute attention to each earnings message, reducing retweets at the message level.

Second, we study the determinants of using visuals in Twitter disseminated earnings announcements. We test whether the use of visuals vary between good versus bad earnings news, and with the level of persistence of the earnings. Finally, we study the consequence of raising attention using visuals in the earnings message on the return reaction at the announcement and in the post-announcement period for earnings announcements. We also test whether visuals in the earnings announcement help a firm successfully compete for investor attention on high distraction days when many other firms are also announcing earnings on the same day as the test firm.

Visuals, including information presented using graphics, are fundamentally different from text. The evolutionary history of brain development in processing visual information began long before the invention of writing, so it is not surprising that the brain is superior at processing visuals over text. Neuroscience and psychology research finds that images are recognized, processed, and retrieved from memory much faster and more efficiently than text (e.g., Shepard 1967; Hockley 2008). The striking ability of the brain to extract conceptual information from visuals is highlighted by the fact that it can identify and remember images presented for even a tiny fraction of a second (Potter, Wyble, Hagmann, and McCourt 2014). Psychologists such as Fiske and Taylor (2016) contend that visuals are more salient and vivid than text and so attract greater attention.[5]

The S.E.C.'s perspective as expounded in the handbook guide on plain writing disclosures suggests that the agency subscribes to these advantages of visuals. For example, Chapter 7 states that "Graphics often illuminate information more clearly and quickly than text." In the same chapter, the S.E.C. recommends Tufte's (1983, 2007) guide on effective visual display of quantitative information, quoting the advantages as follows:

> "*At its best, graphics are instruments for reasoning about quantitative information. Often the most effective way to describe, explore, and summarize a set of numbers—even a very large set—is to look at pictures of those numbers. Furthermore, of all methods for analyzing and communicating statistical information, well-designed data graphics are usually the simplest and at the same time the most powerful"* (p.9)
>
> *"Graphical excellence is that which gives to the viewer the greatest number of ideas in the shortest time with the least ink in the smallest space*." (p.51).

In summary, the S.E.C. advocates for the use of visuals in disclosures to create more understandable disclosures, which is the agency's overriding goal for plain English communication between public firms and their investors.

Given that investor attention is a scarce cognitive resource, limited attention theory predicts that only a subset of investors attend to the release of public information and the equilibrium price is a weighted average of the beliefs of attentive and inattentive investors (Hirshleifer and Teoh 2003; Peng and Xiong 2006). Information can be disseminated through different channels and

[5] Salience is the extent to which a stimulus stands out relative to other stimuli in the environment, and vividness is the inherent attention-getting features of a stimulus regardless of environment (Fiske and Taylor 2016). Due to limitations of the data, and AI and cognitive psychology research tools and measures, we are currently unable to test which specific attribute or attributes of the visuals affect investor attention the most.

presented in different ways, all of which can affect whether the news is received and processed to affect investors' valuation. We do not attempt to distinguish the various steps in cognition, from becoming aware of the information, to encoding the messages in the brain and then cognitively processing and interpreting the information (see footnote 3). We expect collectively that when an earnings announcement message contains visuals, it will attract greater investor attention on the announcement date. The higher attention will lead to greater engagement with the message content, as indicated by the message recipients clicking 'like' to the message or sharing the message with others by retweeting. The higher engagement indicates greater attention to the message, which according to limited attention theory would lead to a sharper return reaction to the earnings news.

In 2013, the S.E.C. permitted companies to use social media outlets such as Facebook and Twitter to announce earnings news. Since then, Twitter has become a popular way for firms to directly communicate news to investors and, also for investors to engage with the firm and each other (Blankespoor, Miller, and White 2014). A key advantage of Twitter messages is that the messages are pushed to the receiver so the information is more likely to gain the receiver's attention unlike other dissemination channels such as news media outlets that require active effort on an investor to procure the information. Another potential advantage is that retweets by direct receivers of the firm message can expand the reach of the original message to more investors than would be reached via traditional dissemination channels. However, each recipient will still need to digest and process the information, which will still require attention effort.

The format of earnings dissemination on social media is currently unregulated. Therefore, visuals used to publicize earnings news vary widely across firms—see Appendix A for examples.

Some firms do not use visuals and only send simple text messages. Other firms use visuals that can contain performance measures, charts, quotes from the management, or an image that highlights the release of the earnings announcement. In some cases, the visual is a video message that plays automatically (the user does not have to click on the message) and explains the key results. Since all these visuals are more salient than a simple text message, we investigate whether the presence of visuals increases investor attention to the earnings news.

We obtain firms' Twitter messages sent on earnings announcement days and use a list of keywords (see Appendix B) to identify messages that are likely to relate to the dissemination of the earnings announcement news. Our main measure of visuals is an indicator variable of whether the firm sends at least one earnings-related message that contains visuals (image or video) on the earnings announcement date.

Our first analysis examines the attention effects of visuals. Limited attention theory predicts that a salient signal attracts greater investor attention (Hirshleifer and Teoh 2003). Given the higher salience of visuals, we predict that the attention of a firm's followers to the earnings news is greater when the firm uses visuals. Usually, the researcher does not observe attention and instead uses indirect measures, such as returns and trading volume that reflect equilibrium predictions of investor attention theories.[6] A key feature of social media, including Twitter, is that it allows users to demonstrate their engagement with the message. Users can share the message with their own followers, that is 'retweet' it or show appreciation for the message, that is 'like' it.

[6] Several studies use internet search and download patterns to directly measure attention (e.g., Da, Engelberg, and Gao 2011; Loughran and Mcdonald 2017; Zhu 2018).

Since retweets and likes indicate that the firm's followers noticed the message and engaged with its content, they directly reveal active attention. Thus, our two measures of attention are indicators of whether followers retweeted or liked earnings-related messages.

We find that firm followers are more likely to retweet and more likely to like earnings-related messages when the firm uses visuals, consistent with our visual attention hypothesis that visuals attract attention to the earnings news. To corroborate the findings, we use a measure of attention based on Google search volume for the stock and find similar results.

We further examine two channels through which visuals can attract attention. First, we expect that a visual used in an earnings-related message will attract attention directly to that message—*the direct attention effect*. Second, visuals can draw attention to other messages sent by the firm. Research argues that attention to one firm can spillover to other firms (e.g., Roulstone and Wang 2016; Drake, Jennings, Roulstone, and Thornock 2017). Applying this to our context of *messages*, we predict that visual salience of one earnings-related message can attract followers' attention to other earnings-related messages sent by the firm on that day—*the attention spillover effect*. The results from our analysis at the individual message level provide strong evidence of both the direct and spillover effects. Followers are more likely to retweet and like an earnings-related message when that message contains visuals, *and* when other earnings-related messages sent on the same day by the firm contain visuals. Regarding the magnitude of the two effects, the direct (spillover) effect of visuals increases the odds of retweets 2.370 (1.280) times.

Our findings also reveal both an *attention focus* effect and an *attention dilution* effect. The attention focus effect is at the firm level; there is increased attention to a firm that sends a higher number of earnings-related messages on the earnings announcement date. On the other hand, the attention dilution effect is at the message level; the attention to an earnings-related message is lower when the firm sends a greater number of earnings-related messages on that day. Research shows that investor attention to a firm is distracted by a large number of same-day earnings announcements (Hirshleifer, Lim, and Teoh 2009). Our findings provide similar evidence of attention distraction at the level of individual messages sent by the same firm.

Next, we find considerable variability in the use of visuals, and we study determinants of firms' choice to use visuals to disseminate earnings news. First, we predict that the decision to use visuals is influenced by firms' desire to highlight news that portrays them favorably. Consistent with this prediction, we find that firms are more likely to use earnings-related messages with visuals when earnings exceed market expectations. Second, we examine if firms use the higher salience of visuals to signal more value relevant—i.e., more persistent—earnings, or if firms choose visuals when earnings are less persistent to take advantage of temporary good performance. Our findings point to the second alternative. The use of visuals is negatively associated with earnings persistence.

We also examine whether visuals influence investor reaction to earnings news. Limited attention theory predicts that salient news results in a stronger immediate price reaction and a lower post-announcement reaction. We measure immediate reaction using stock returns over the three-days around the earnings announcement, and we capture the delayed reaction using returns over the three-days around the *next* earnings announcement. Consistent with our predictions, we find that the immediate reaction to earnings news is higher and the delayed reaction is lower when firms use visuals. To mitigate endogeneity concerns, we use residual visuals from the regression of visuals on an expanded set of explanatory variables, and past visuals unrelated to earnings as an instrument for the firm's ex ante propensity to use of earnings-related visuals on the earnings announcement day. Further analysis suggests that the effect of visuals is concentrated on days with a large number of earnings announcements by other firms. Hirshleifer et al. (2009) show that investor attention is diluted by multiple same-day announcements. Our findings imply that visuals help the firm's announcement stand out from other concurrent announcements. Overall, while our results pertain to one communication channel (Twitter), they suggest visuals attract investor attention to earnings news.

Our study contributes to several strands of research. By examining the determinants of firms' choice to use visuals, we contribute to the growing literature on presentation attributes of disclosures, including readability, complexity, tone, and voice tone.[7] We also contribute to the literature by examining factors that influence investor attention.[8] Unlike most prior studies that use indirect measures of attention, we identify attention to individual earnings-related messages and study direct and spillover effects of visual salience. By examining the use of visuals on Twitter and their effects on followers' attention, our study also contributes to the emerging literature on the importance of the dissemination of earnings news on social media (Blankespoor et al. 2011;

[7] See, for example, Li (2008, 2011), Demers and Vega (2011), Huang, Teoh, and Zhang (2014), and Mayew and Venkatachalam (2012a, b), Huang, Nekrasov, and Teoh (2018), and Levi (2015).

[8] See, for example, Klibanoff, Lamont, and Wizman (1998), Hirshleifer and Teoh (2003), Barber and Odean (2008), Hou, Peng, and Xiong (2009), DellaVigna and Pollet (2009), Hirshleifer, Lim, and Teoh (2009), Da, Engelberg, and Gao (2011), Engelberg, Sasseville, and Williams (2012), Li and Yu (2012), and Lou (2014), Peress (2014), Yuan (2015), Loughran and Mcdonald (2017).

Lee at al. 2015; Bartov et al. 2018; Crowley et al. 2018; Jung et al. 2018; Teoh 2018). Finally, our results have potential policy applications for regulators concerned about clear communications by firms to investors.

2. Data and Variable Measurement

2.1 Sample Data

Twitter was created in October 2006 and initially only allowed users to send text messages that contain up to 140 characters. Beginning June 2011, Twitter allowed users to supplement text messages with visuals (still images and videos). Given our interest in firms' use of visuals, we begin the sample period in June 2011. The sample ends in December 2017, the last month for which we have necessary Twitter and financial data. We obtain analyst forecasts and actual earnings numbers from I/B/E/S. Company financial data are obtained from Compustat, and stock prices and returns are from CRSP.

Table 1 Panel A presents details of the sample selection. We begin with the sample of firms included in the S&P1500 index. We exclude 345 firms without an official Twitter account as of February 2018 when we began collecting Twitter handles for the firms. For the 1,155 firms with Twitter accounts, we collect all available messages that firms send to their followers on earnings announcement dates over the sample period. From this set, we identify messages as earnings announcement-related if they contain earnings-related keywords detailed in Appendix B. We drop 405 firms that did not send any earnings-announcement-related messages on the earnings announcement date during our sample period. Finally, we exclude observations that have missing stock returns or lack any of the necessary financial data or analyst forecasts. Our final sample contains 13,967 earnings-announcement-related messages sent over 4,928 firm–quarter earnings announcement days for 679 unique firms.

Panel B of Table 1 reports the distribution of the sample across industries, using the 12 Fama–French industry classification.[9] The industries with large numbers of firm-quarter observations are finance, business equipment, healthcare, medical equipment, and drugs. The telephone and television transmission industry has the smallest number of firm-quarter observations. While there is significant variation in the sample distribution across industries, no single industry dominates the sample.[10]

2.2 Twitter Measures

Our main measure of the firm's use of visuals when disseminating earnings news on Twitter is a firm level indicator $VISUALS_{jt}$, which equals 1 if firm j sends at least one earnings-announcement-related message that contains visuals (still images or videos) on the earnings announcement date for quarter t, and 0 otherwise.[11] At the level of individual messages, we use an indicator variable $VISUALS_{ijt,message.level}$, which equals 1 if earnings-announcement-related message i on the earnings announcement date for firm j quarter t contains visuals, and 0 otherwise.

[9] Available from Ken French at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[10] The finance industry is the largest, comprising 18.0% (887/4,928) of all firm-quarter sample observations.

[11] There is wide variation in the types of images and videos in our sample. With current machine learning AI tools and lack of good measures of visual attributes from the psychology and neuroscience research, it is impractical for us to analyze and classify the content of visuals to study cognition in greater depth. We use key words and the dates when the message was sent only to identify messages that are likely about the earnings announcement. The choices are then reviewed by human researchers.

To control for endogeneity of firm choice of visuals, we also use a residual visuals variable estimated from a first-stage regression and an instrumental variable based on past visuals unrelated to earnings, which we discuss in Sections 3.4 and 3.6, respectively.

Firms often disseminate earnings news by sending messages that contain quantitative items or web links to external websites. Quantitative items usually are about firm performance, and web links direct investors to the earnings press release on the firm's investor relation website, both of which may influence how investors process the news. To control for effects from these items, we use firm level indicator variables $QUANT.ITEMS_{jt}$ ($WEB.LINKS_{jt}$) which equals 1 if firm j's earnings announcement message for quarter t contains at least one quantitative item (web link), and 0 otherwise.[12] Equivalent indicators $QUANT.ITEMS_{message.level}$ and $WEB.LINKS_{message.level}$, are defined in a similar way for the use of quantitative items and web links at the individual message level.

A firm's followers can demonstrate their engagement with the received message on Twitter by retweeting the message to their own followers or by liking the message (i.e., showing appreciation for the message).[13] By retweeting the message, followers increase the dissemination beyond the original audience that received the message directly from the firm. The number of retweets and likes are displayed with the message and, therefore, can signal that other followers

[12] To increase the likelihood that quantitative items relate to performance, we require that the item is preceded or followed by one of the following characters or words: $, dollar, dollars, %, percent, cents, cent, c, thousand, k, million, m, mm, mn, mill, billion, b, bn, basis, bps.

[13] Twitter glossary says that likes "are used to show appreciation for a Tweet" (https://help.twitter.com/en/using-twitter/liking-tweets-and-moments). Other reasons people use likes include bookmarking useful tweets, showing that they saw the tweet, and attracting new followers (https://follows.com/blog/2016/01/tweet-likes-twitter).

found the message relevant. Thus, both retweets and likes potentially increase the reach of the message to attract greater attention to the message from people who traditionally do not follow firm news.

For our research, we are interested in retweets and likes as *direct* measures of firm followers' attention to visuals. We define a firm level indicator variable $RETWEETS_{jt}$ ($LIKES_{jt}$) that equals 1 if the firm's followers retweet (like) at least one earnings-related message on the earnings announcement date for firm j quarter t, and 0 otherwise. Indicators of retweets and likes at the individual message level, $RETWEETS_{message.level}$ and $LIKES_{message.level}$, equal 1 if there is a retweet or like at the message-level respectively, and are 0 otherwise

Finally, we include the following variables to further control for the volume of information on the same day as the earnings announcement. $EA.MESSAGES_{jt}$ is the number of earnings-announcement-related messages firm j sends on the earnings announcement date for quarter t. $LENGTH_{jt}$ is the natural logarithm of the average number of characters of the earnings-related messages on the earnings announcement date for quarter t. $FOLLOWERS_j$ is the natural logarithm of the number of Twitter users that follow firm j as of March 31, 2018, the month when we completed scraping the data on firm followers. The measure is calculated at a point in time because time-series data on the number of followers are not available.

2.3 Other Variables

In addition to Twitter measures, we use the following variables. Firm size, *SIZE*, is the natural logarithm of the market value of equity at the end of the previous fiscal quarter, to control for risk. *BTM* is the book-to-market ratio at the end of the previous fiscal quarter. An indicator of positive earnings news, *POS.SURP*, is defined as 1 if actual earnings for the quarter are greater than or equal to the consensus analyst forecast, and 0 otherwise. The consensus analyst forecast is the mean of the most recent forecasts made by individual analysts. Unexpected earnings, *SUE*, is actual quarterly earnings as reported by I/B/E/S minus the consensus analyst forecast, scaled by stock price at the end of the previous fiscal quarter. *RSUE*, is the decile rank of *SUE* scaled such that it varies from 0 (for the bottom decile) to 1 (for the top decile). Sales growth, *GROWTH*, calculated as the percentage change in quarterly sales from the same quarter last year. *EARN* is quarterly earnings before extraordinary items scaled by average total assets. $CAR(-1,+1)$ is the cumulative abnormal return over the 3-day window centered on the earnings announcement date, where daily abnormal returns are raw returns minus the market value-weighted return. $CAR(-1,+1)_{NEXT.QTR}$ is the cumulative abnormal return, $CAR(-1,+1)$, around the next-quarter earnings announcement. Analyst following, *ANA.FOLLOW*, is the natural logarithms of one plus the number of analysts that have outstanding earnings forecast for the firm for the quarter. Institutional ownership, *INST.OWN*, is the fraction of firm shares owned by institutional investors. *NRANK* is the quartile rank of the number of same-day earnings announcements by other firms. Time trend, *TIME*, is measured as the natural logarithm of the calendar year. *AB.SEARCH* is the abnormal Google search volume for the firm for the day, following Drake, Roulstone, Thornock (2012). *MEDIA.COVERAGE* is the natural logarithm of one plus the number of news articles for the firm for the day, where the number of articles is obtained from Bloomberg.

3. Empirical Results

3.1 Descriptive Statistics

Table 2 Panel A reports descriptive statistics for variables related to Twitter activity at the firm-quarter level. The mean of 0.233 for the visual indicator variable, *VISUALS*, indicates that 23.3% of firm-quarter earnings announcements contains with visuals. On average, 31.0% of firm-quarter earnings announcements contain dollar-value or percent magnitudes of quantitative items and 94.4% include a web link. Firm followers retweet (like) at least one earnings-related message for 65.8% (61.3%) of the firm-quarter observations. The mean number of retweets (likes) of earnings-related messages in a given firm-quarter is 31.35 (66.80) when firms use visuals and 7.00 (7.62) when firms do not use visuals (untabulated).

Panel B of Table 2 provides descriptive statistics for variables related to Twitter activity at the message level. The statistics indicate that 16.2% of earnings-announcement-related messages contain visuals, 27.4% contain quantitative items, and 70.4% contain web links. On average, firm followers retweet (like) 54.7% (54.3%) of earnings-announcement-related messages.

Panel C of Table 2 reports descriptive statistics for financial variables. The mean *POS.SURP* is 0.672, indicating that earnings exceed the consensus forecast in 67.2% of earnings announcements. Given our use of S&P1500 firms with active Twitter activity, firms in our sample are relatively large, with a mean (median) market capitalization of $25,845.5 ($8,594.6) million. The mean (median) number of analysts following the firm is 13.52 (13). The mean (median) number of same-day earnings announcements is 73.25 (70).

3.2 Attention to Visuals

Limited attention theory predicts that salient information attracts greater investor attention (Hirshleifer and Teoh 2003). Applying this to the context of earnings news disseminated on Twitter and the higher salience of visuals than text-only messages, we predict the following at the firm level:

Visual Attention Hypothesis, H1a: Attention of firm followers is higher when earnings news is disseminated on Twitter with visuals than without visuals.

As explained earlier, we measure followers' attention using the number of retweets and likes at the firm and message levels. When a firm's followers retweet or like an earnings-related message, it means that the followers have noticed and engaged with the message. Thus, compared to other indirect measures of attention, such as returns and trading volume, retweets and likes directly reveal the attention of the firm's followers.

Visuals can attract followers' attention in two ways. First, visuals used in an earnings-related message can attract attention directly to that message. We refer to this channel as the *direct attention effect* of visuals. Second, visuals can draw attention to all messages sent by the firm. Prior research argues that attention to one firm can spillover to other firms in the industry or economy (e.g., Roulstone and Wang 2016; Drake, Jennings, Roulstone, and Thornock 2017). In our context, we propose that visual salience of one earnings-related message can draw followers' attention to the firm and prompt them to read *other* earnings-related messages sent by the firm. We refer to this channel as an *attention spillover effect* of visuals. These two channels are complementary, as both increase the followers' attention to the firm as a whole. In sum, we have the following two hypotheses at the message level:

Direct Attention Effect, H1b: The attention of firm followers to an earnings-related message is greater when that message contains visuals.

Attention Spillover Effect, H1c: The attention of firm followers to an earnings-related message is greater when other earnings-related messages sent by the firm contain visuals.

We measure followers' attention to individual earnings-related messages using message-level retweets and likes. We test for the spillover effect using the variable, *VISUALS.OTHER*, which reflects the use of visuals in other earnings-related messages sent by the firm on the earnings announcement day.

To test how followers' attention to the earnings news is influenced by visuals (H1a), we estimate the following regressions at the firm-quarter level:

$$\begin{aligned} RETWEETS_{jt} \text{ or } LIKES_{jt} = \alpha + \beta_1\, VISUALS_{jt} + \beta_2\, QUANT.ITEMS_{jt} + \beta_3\, WEB.LINKS_{jt} \\ + \beta_4\, SIZE_{jt} + \beta_5\, ANA.FOLLOW_{jt} + \beta_6\, POS.SURP_{jt} + \beta_7\, GROWTH_{jt} + \beta_8\, BTM_{jt} \\ + \beta_9\, INST.OWN_{jt} + \beta_{10}\, FOLLOWERS_{jt} + \beta_{11}\, EA.MESSAGES_{jt} + \beta_{12}\, LENGTH_{jt} \\ + \beta_{13}\, MEDIA.COVERAGE_{jt} + \beta_{14}\, TIME_{jt} + \varepsilon_{jt}, \end{aligned} \tag{1a}$$

where subscripts *jt* denote firm *j* quarter *t*, the indicators of retweets and likes by the firm's followers of earnings-announcement-related messages (*RETWEETS* and *LIKES*, respectively) are used to proxy for the followers' attention to the earnings news, and *VISUALS* is the indicator of the firm's use of visuals to disseminate the earnings news. If visuals increase followers' attention to the earnings news, the coefficient β_1 should be positive. Given the directional prediction, the significance test for β_1 is one-tailed. All variables are as defined in Section 2.

We use firm size (*SIZE*) and analyst following (*ANA.FOLLOW*) to control for information environment. We include the positive earnings surprise indicator (*POS.SURP*) to proxy for good earnings news, sales growth (*GROWTH*) to proxy for current growth, and the book-to-market ratio (*BTM*) to control for future growth opportunities. We include institutional ownership (*INST.OWN*) to control for investor base, the number of the firm's followers (*FOLLOWERS*) to control for the size of the firm's Twitter audience, the number of earnings-announcement-related messages (*EA.MESSAGES*) and the average length of the earnings-announcement-related messages (*LENGTH*) to control for the volume of the dissemination of earnings news on Twitter, the number of articles about the firm (*MEDIA.COVERAGE*) to control for the media coverage, and time trend (*TIME*) to control for the time trend in the use of Twitter.[14]

We also include the indicator of the firm's use of quantitative items in earnings-announcement-related messages (*QUANT.ITEM*) since findings in prior research suggest that quantitative items attract investor attention (Huang, Nekrasov, and Teoh 2018). Finally, we include the indicator of the firm's use of web links (*WEB.LINK*). Whether web links attract investor attention is of interest because Blankespoor, Miller, and White (2014) find that the dissemination of web links to earnings press releases can reduce information asymmetry.

[14] The results are similar when we use year fixed effects instead of time trend.

To test for the direct attention effect (H1b) and the attention spillover effect (H1c), we estimate the following regressions at the individual message level:

$$
\begin{aligned}
&RETWEETS_{ijt,message.level} \text{ or } LIKES_{ijt,message.level} = \alpha + \beta_1\, VISUALS_{ijt,message.level} \\
&+ \beta_2\, VISUALS.OTHER_{ijt,message.level} + \beta_3\, QUANT.ITEMS_{ijt,message.level} \\
&+ \beta_4\, WEB.LINKS_{ijt,message.level} + \beta_5\, SIZE_{jt} + \beta_6\, ANA.FOLLOW_{jt} + \beta_7\, POS.SURP_{jt} \\
&+ \beta_8\, GROWTH_{jt} + \beta_9\, BTM_{jt} + \beta_{10}\, INST.OWN_{jt} + \beta_{11}\, FOLLOWERS_{jt} \\
&+ \beta_{12}\, EA.MESSAGES_{jt} + \beta_{13}\, LENGTH_{ijt,message.level} + \beta_{14}\, MEDIA.COVERAGE_{jt} \\
&+ \beta_{15}\, TIME_{jt} + \varepsilon_{jt}, \qquad (1b)
\end{aligned}
$$

where *VISUALS.OTHER* reflects the presence of visuals in other earnings-related messages sent by the firm on that day. The subscripts *ijt* denote message *i* firm *j* quarter *t*. The subscript *message.level* denotes variables measured at the level of the individual message, and the remaining variables are measured at the firm level. All variables are as defined in Section 2.

Table 3 Panel A reports the results of estimating the firm-quarter model (1a). The first two columns show the results for *RETWEETS* and the last two columns for *LIKES*. Consistent with the hypothesis that visuals attract followers' attention to the earnings news (H1a), the coefficient on *VISUALS* is positive and significant for both retweets and likes. Regarding the economic significance of the result, the magnitude of the coefficients on *VISUALS* indicates that the odds of retweets and likes increase 1.923 and 2.028 times, respectively, when the firm uses visuals (exp(0.654*1) = 1.923 and exp(0.707*1) = 2.028 respectively).[15]

[15] We use industry rather than firm fixed effects in this test to avoid losing firms with no variation in the dependent variable, i.e., firms that either always or never had retweets (likes) of earnings-related messages during our relatively short time series. As a robustness check, we include firm fixed effects and find similar results.

With regards to the control variables, the results show that the coefficient on the use of quantitative items, *QUANT.ITEMS*, is positive and significant, suggesting that followers pay greater attention to earnings news when the firm uses quantitative items, consistent with Huang, Nekrasov, and Teoh's (2018) findings that quantification of headlines leads to stronger investor reaction to earnings news. In contrast, the use of web links, *WEB.LINKS,* is not significantly associated with retweets and is negatively associated with likes, suggesting that web links do not draw greater attention of firm followers. The positive and significant coefficients on *SIZE* and *FOLLOWERS* suggest that the dissemination of earnings news on Twitter receives greater attention for large firms and firms with more followers. We defer discussion of the results for *EA.MESSAGES* until after we discuss Panel B results.

Panel B of Table 3 reports the results of estimating model (1b). Consistent with the direct attention effect of visuals for individual earnings-related messages (H1b), the coefficient on $VISUALS_{message.level}$ is positive and significant for both retweets and likes. The results also reveal an attention spillover effect of visuals (H1c). The coefficient on visuals in other earnings-related messages, $VISUALS.OTHER_{message.level}$, is positive and significant for both retweets and likes. The coefficient on $VISUALS_{message.level}$ is larger than the coefficient on $VISUALS.OTHER_{message.level}$, which is consistent with the intuition that, all else equal, the direct effect should be stronger than the spillover effect. For example, for the model of retweets, the direct and spillover effects of visuals increase the odds of retweets 2.370 and 1.280 times, respectively (exp(0.863*1) = 2.370 and exp(0.247*1) = 1.280, respectively). The results for *QUANT.ITEMS*, *WEB.LINKS*, *SIZE*, and *FOLLOWERS*, are generally similar to the findings from the firm-level analysis in Panel A.

Turning to the interpretation of the coefficients on *EA.MESSAGES* in Panels A and B, we see that the coefficient is significantly positive in Panel A firm-level regressions and significantly negative at the message level regression. Panel A results show an *attention focus* effect where a large number of messages sent by the announcing firm on the day of the announcement attracts attention to the firm itself. The cumulative attention to all earnings-related messages increases with the number of messages, which draws attention to the firm. In contrast, Panel B results show an opposite effect where there is an *attention dilution effect.* When attention is finite, attention to any individual earnings-related message is diluted when there is a large number of earnings-related messages sent by the firm on that day. In other words, the volume of other messages on the same day distracts attention from a specific message. This is similar to the distraction effect of Hirshleifer et al. (2009) who show that investor attention to a specific firm is distracted by a large number of same-day earnings announcements by other firms.

3.3 Visuals and Google Search Volume

We next corroborate our findings on investor attention from retweets and likes using a measure of attention based on Google search volume. Studies use Google search volume around the earnings announcement for the firm's ticker symbol to capture investor attention (Da, Engelberg, and Gao 2011; Drake, Roulstone, Thornock 2012). The idea behind this measure is that market participants are paying attention to the firm when they search for information on the firm's stock. If visuals attract investor attention and prompt their search for additional information on the stock, we expect a positive association between visuals and Google search volume.

To test the relation between visuals and Google search volume on the earnings announcement day, we estimate the following regression at the firm-quarter level:

$$
\begin{aligned}
AB.SEARCH_{jt} = \alpha + \beta_1\, VISUALS_{jt} + \beta_2\, QUANT.ITEMS_{jt} + \beta_3\, WEB.LINKS_{jt} + \beta_4\, SIZE_{jt} \\
+ \beta_5\, ANA.FOLLOW_{jt} + \beta_6\, POS.SURP_{jt} + \beta_7\, GROWTH_{jt} + \beta_8\, BTM_{jt} + \beta_9\, INST.OWN_{jt} \\
+ \beta_{10}\, FOLLOWERS_{jt} + \beta_{11}\, EA.MESSAGES_{jt} + \beta_{12}\, LENGTH_{jt} \\
+ \beta_{13}\, MEDIA.COVERAGE_{jt} + \beta_{14}\, TIME_{jt} + \beta_{15}\, NRANK_{jt} \\
+ \beta_{16}\, Lagged\ AB.SEARCH_{jt} + \varepsilon_{jt},
\end{aligned}
\tag{2}
$$

where *AB.SEARCH* is the abnormal Google search volume for the firm's stock symbol on the earnings announcement day, following Drake et al. (2012). All variables are defined in Section 2.

The results presented in Table 4 are consistent with the positive relation between Google search volume and visuals. The coefficient on *VISUALS* is positive (0.054) and significant at the p = 0.042 one-sided level. The magnitude of the coefficient indicates that an increase in *VISUALS* from 0 to 1 corresponds to an increase in *AB.SEARCH* by 21.7% relative to the average search volume on earnings announcement days (0.054/0.249=21.7%). With respect to the control variables, the results suggest that investors pay greater attention to earning announcements of large firms (*SIZE*) and firm with greater growth (*GROWTH*). The negative association between the Google search volume and the number of earnings announcement (*NRANK*) is consistent with investor distraction when more firms announce earnings on that day (Hirshleifer, Lim, and Teoh 2009; Drake, Roulstone, and Thornock 2012).

3.4 Determinants of Firms' Choice to Use Visuals

Firms use a range of presentation formats to disclose information to outsiders, including text, tables, and figures, as well as locations of different prominence within the document. The array of presentation formats expanded over the years beyond traditional financial statements and press releases to new formats such as PowerPoint presentations, podcasts, and visuals transmitted directly to the firm's followers. Firms' use of these formats is not universal. In fact, firms do not use visuals to disseminate earnings news in 76.7% of firm-quarter observations in our sample. This raises the question of what determines firms' choice to use visuals. Several studies examine the determinants of firms' decision to present information more saliently by placing it in the headline or an earlier part of the document (e.g., Bowen, Davis, and Matsumoto 2005; Files, Swanson, and Tse 2009; Huang et al. 2018). The determinants examined in this research relate to firms' desire to emphasize information that makes the firm look more positive or information that the management believes is more value relevant.

We follow this literature as we identify the determinants of firms' choice to use visuals. Since good earnings news portrays the firm more favorably to outsiders than bad earnings news, we expect that firms will be more likely to use visuals when earnings exceed market expectations. Regarding the value relevance of current performance, we examine how the choice of visuals relates to earnings persistence.

To examine whether firms have stronger incentives to attract followers' attention with visuals when earnings news is good, we estimate the following regression at the firm-quarter level:

$$VISUALS_{jt} = \alpha + \beta_1\, POS.SURP_{jt} + \beta_2\, QUANT.ITEMS_{jt} + \beta_3\, WEB.LINKS_{jt} + \beta_4\, SIZE_{jt}$$
$$+ \beta_5\, ANA.FOLLOW_{jt} + \beta_6\, GROWTH_{jt} + \beta_7\, BTM_{jt} + \beta_8\, INST.OWN_{jt} + \beta_9\, FOLLOWERS_{jt}$$
$$+ \beta_{10}\, EA.MESSAGES_{jt} + \beta_{11}\, LENGTH_{jt} + \beta_{12}\, NRANK_{jt} + \beta_{13}\, MEDIA.COVERAGE_{jt}$$
$$+ \beta_{14}\, TIME_{jt} + \varepsilon_{jt}, \qquad (3)$$

If firms are more likely to use visuals when earnings news is good, we expect a significant positive coefficient on the indicator of positive earnings surprise, *POS.SURP*. In addition to the variables used in equation (1a), we also include the time trend variable, *TIME*, since firms are likely to incorporate the new technology and use visuals more frequently in later years. All variables are defined in Section 2.

The results are presented in Table 5. The first two columns show the results of the logistic regression. We also estimate the OLS regression and report the results in the last two columns. The purpose of the OLS regression is to obtain the residual visuals variable, *VISUALS.RES*, which we define as the residuals from the OLS regression. We use *VISUALS.RES* in our market tests as a way to control for the predicted determinants of firms' choice of visuals.

Consistent with our intuition, we find evidence that firms with good earnings news are more likely to use visuals. The coefficient on *POS.SURP* in the logistic regression is positive (0.252) and significant at the $p = 0.018$ one-sided level. The magnitude of the coefficient indicates that the odds of a firm using visuals to disseminate earnings news increase 1.287 times when earnings news are good ($\exp(0.252*1) = 1.287$). We do not find that firm size, analyst following, institutional ownership, or the number of same-day earnings announcements have a significant effect on firms' choice to use visuals.

The negative and significant coefficients on *QUANT.ITEMS* and *WEB.LINKS* suggest that, on average, firms tend to use visuals as substitutes to quantitative items and web links. The results also show that firms with more followers, *FOLLOWERS*, and firms that send a larger number of earnings-related messages, *EA.MESSAGES*, are more likely to use visuals. Finally, the positive coefficient on the time trend variable, *TIME*, is consistent with the growing use of visuals to disseminate earnings news over time.[16]

We next examine the relation between the use of visuals and persistence of earnings. Research shows that earnings are more value relevant when they are more persistent (Kormendi and Lipe 1987; Collins and Kothari 1989). If managers use visual salience to signal more persistent earnings, visuals would be positively related to earnings persistence. On the other hand, managers may have incentives to take advantage of the current temporary good earnings news by making it more salient to outsiders. In this case, we should expect a negative relationship between visuals and earnings persistence.

To test the association between visuals and earnings persistence, we estimate the following regressions:

$$\begin{aligned} EARN_{jt+1} = \alpha &+ \beta_1\, VIS.VAR_{jt}{*}EARN_{jt} + \beta_2\, SIZE_{jt}{*}EARN_{jt} + \beta_3\, BTM_{jt}{*}EARN_{jt} \\ &+ \beta_4\, STD.EARN_{jt}{*}EARN_{jt} + \beta_5\, LOSS_{jt}{*}EARN_{jt} + \beta_6\, EARN_{jt} + \beta_7\, EARN_{jt-3} + \beta_8\, VIS.VAR_{jt} \\ &+ \beta_9\, SIZE_{jt} + \beta_{10}\, BTM_{jt} + \beta_{11}\, STD.EARN_{jt} + \beta_{12}\, LOSS_{jt} + \varepsilon_{jt}, \end{aligned} \tag{4a}$$

[16] In this test, we use industry rather than firm fixed effects to avoid losing firms with no variation in the dependent variable, i.e., firms that either always or never used visuals in earnings-related messages during our relatively short time series. The results are similar when we include firm fixed effects.

where *VIS.VAR* is either the visuals indicator, *VISUALS*, or the residuals from the first-stage OLS regression (3), *VISUALS.RES*. The interaction of *VIS.VAR* and $EARN_t$ captures the effect of *VIS.VAR* on the earnings persistence. In addition to size and book-to-market, we control for earnings volatility, *STD.EARN*, and the indicator of losses, *LOSS*, since volatile earnings and negative earnings are less persistent (e.g., Hayn 1995; Dichev and Tang 2009). We also include earnings for the same quarter last year, $EARN_{t-3}$, to control for seasonality. If firms use visuals when earnings are more (less) persistent, the coefficient on the interaction between visuals and earnings should be positive (negative).

To corroborate the evidence from earnings persistence, we also test the relation between visuals and persistence of sales growth using the following regressions:

$$\begin{aligned} GROWTH_{jt+1} = \alpha &+ \beta_1\, VIS.VAR_{jt}{*}GROWTH_{jt} + \beta_2\, SIZE_{jt}{*}GROWTH_{jt} \\ &+ \beta_3\, BTM_{jt}{*}GROWTH_{jt} + \beta_4\, STD.GROWTH_{jt}{*}GROWTH_{jt} \\ &+ \beta_5\, NEG.GROWTH_{jt}{*}GROWTH_{jt} + \beta_6\, GROWTH_{jt} + \beta_7\, GROWTH_{jt-3} + \beta_8\, VIS.VAR_{jt} \\ &+ \beta_9\, SIZE_{jt} + \beta_{10}\, BTM_{jt} + \beta_{11}\, STD.GROWTH_{jt} + \beta_{12}\, NEG.GROWTH_{jt} + \varepsilon_{jt}, \end{aligned} \tag{4b}$$

where we include controls for volatility of sales growth, *STD.GROWTH*, and the indicator of negative sales growth, *NEG.GROWTH*, since we expect volatile growth and negative growth to be less persistent. Similar to equation (4a), we also include sales growth for the same quarter last year, $GROWTH_{t-3}$, to control for seasonality.

Table 6 Panel A presents the results of estimating the earnings persistence equation (4a). The first two columns present the results for the visual indicator, *VISUALS*, and the last two columns report the results for the residual visuals, *VISUALS.RES*. The coefficients on both

*VISUALS*EARN* and *VISUALS.RES*EARN* are negative and significant. The results suggest that, rather than using visuals to signal more persistent earnings, firms use visuals when earnings are less persistent. This is similar to the findings in Huang et al. (2018) on the use of salient headlines to attract attention to temporary good earnings news, consistent with strategic behavior by managers to 'make hay while the sun shines.' The results of estimating equation (4b) show a similar negative relation between the use of visuals and persistence of sales growth (Table 6 Panel B). The coefficients on *VISUALS*GROWTH* and *VISUALS.RES*GROWTH* are negative and significant.

3.5 Visuals and Market Reaction to Earnings News

Our next analysis provides evidence on the relationship between visuals and investor reaction to earnings news. Limited attention theory predicts that greater salience of news results in a stronger immediate price reaction and either a smaller drift in the same direction or a stronger post-announcement reversal (Hirshleifer and Teoh 2003; Hirshleifer, Lim and Teoh 2011). Our findings in Table 3 suggest that visuals increase the salience of earnings news. Thus, we expect a higher (lower) association between announcement (post-announcement) returns and earnings news when firms use visuals to disseminate earnings news.[17]

---

[17] We do not have an exogenous shock for visuals in the regression design to permit us to make a definitive causal inference that visuals increase investor attention to the earnings news, resulting in a sharper ERC. However, we note that visuals are positively associated with a *lower* earnings persistence, which would suggest that endogeneity of visuals would bias against our finding a sharper ERC for visuals.

To test for the immediate reaction to earnings news, we estimate the following regressions of cumulative abnormal return around earnings announcements, *CAR(−1,+1)*, at the firm-quarter level:

$$\begin{aligned} CAR(-1,+1)_{jt} &= \alpha + \beta_1\, VIS.VAR_{jt}{*}RSUE_{jt} + \beta_2\, QUANT.ITEMS_{jt}{*}RSUE_{jt} \\ &+ \beta_3\, WEB.LINKS_{jt}{*}RSUE_{jt} + \beta_4\, SIZE_{jt}{*}RSUE_{jt} + \beta_5\, ANA.FOLLOW_{jt}{*}RSUE_{jt} \\ &+ \beta_6\, GROWTH_{jt}{*}RSUE_{jt} + \beta_7\, BTM_{jt}{*}RSUE_{jt} + \beta_8\, INST.OWN_{jt}{*}RSUE_{jt} \\ &+ \beta_9\, EA.MESSAGES_{jt}{*}RSUE_{jt} + \beta_{10}\, LENGTH_{jt}{*}RSUE_{jt} \\ &+ \beta_{11}\, MEDIA.COVERAGE_{jt}{*}RSUE_{jt} + Main\ Effects_{jt} + \varepsilon_{jt}, \end{aligned} \tag{5a}$$

where *VIS.VAR* is either the visuals indicator, *VISUALS*, or the residuals from the first-stage OLS regression (3), *VISUALS.RES*. The benefit of using the residual visuals is that it controls for the predicted determinants of firms' choice of visuals. If visuals positively influence the response to earnings news, then we expect a positive coefficient on the interaction between visuals and earnings surprise ($\beta_1 > 0$).[18]

The results are presented in Table 7 Panel A. The coefficients on both *VISUALS***RSUE* and *VISUALS.RES***RSUE* are positive and significant. The results are consistent with the prediction that investor response to earnings news is stronger when firms use visuals to disseminate earnings news. Both *RSUE* and *VISUALS* range from 0 to 1, so an increase in *VISUALS* from 0 to 1 corresponds to an increase in the differential CAR between the top and bottom deciles of 2.0% (0.020). The average earnings response coefficient (ERC) estimated from a regression of

[18] We do not include *RETWEETS*, *LIKES*, and *AB.SEARCH* since we view them as outcomes of visual salience, equations (1) and (2). The results are robust when we include these variables and their interactions with earnings surprise.

CAR(−1,+1) on *RSUE* and commonly used controls for size and book-to-market is 0.080 (untabulated). When compared to the average ERC, the effect of visuals represents an economically significant increase in immediate investor reaction by one-quarter (0.020/0.080=25%).

Visual salience is likely to be most important when investors face high information load. Because cognitive resources are finite, attention must be allocated selectively. When investors have to process a large number of information signals, the attention to each signal suffers. In the context of earnings announcements, research shows that investor attention to a firm's earnings announcement is distracted by a large number of same-day earnings announcements by other firms (Hirshleifer, Lim, and Teoh 2009). At a time when investor attention is distracted by many competing announcements, visuals can make the firm's announcement stand out from the rest and lead to a stronger reaction to earnings news. Thus, we test whether the effect of visuals is more pronounced on days when the firm is competing for scarce investor attention when there is a large number of earnings announcements by other firms.

We rank the number of same-day earnings announcements by other firms and allocate observations in the top (bottom) quartile of the distribution into High (Low) subsamples. We then estimate the investor reaction model (5a) within High and Low subsamples, separately. Table 7 Panel B presents the results. The first (last) four columns report the results for days with a high (low) number of same-day announcements. Consistent with our prediction, the results show that the effect of visuals is concentrated on days when investors face many competing announcements. The coefficients on both *VISUALS*RSUE* and *VISUALS.RES*RSUE* are positive and significant when the number of same-day announcements is high (0.042, p = 0.022 and 0.050, p = 0.009, respectively) and insignificant when the number of same-day announcements is low.

Our next test examines the relationship between visuals and post-announcement reaction to earnings news. If higher visual salience leads to a stronger reaction to earnings news, we expect a lower underreaction and therefore a less positive or more negative post-announcement reaction. Past research finds that a disproportionate fraction of the post-announcement reaction is concentrated in the short-window around the next earnings announcement (Bernard and Thomas 1990). Therefore, we use a 3-day window around the next earnings announcement to increase the test power to detect the post-announcement reaction. Specifically, we estimate the following regressions of cumulative abnormal return around next-quarter earnings announcements, $CAR(-1,+1)_{NEXT.QTR}$, at the firm-quarter level:

$$
\begin{gathered}
CAR(-1,+1)_{NEXT.QTR,jt} = \alpha + \beta_1\ VIS.VAR_{jt}{*}RSUE_{jt} + \beta_2\ QUANT.ITEMS_{jt}{*}RSUE_{jt} \\
+ \beta_3\ WEB.LINKS_{jt}{*}RSUE_{jt} + \beta_4\ SIZE_{jt}{*}RSUE_{jt} + \beta_5\ ANA.FOLLOW_{jt}{*}RSUE_{jt} \\
+ \beta_6\ GROWTH_{jt}{*}RSUE_{jt} + \beta_7\ BTM_{jt}{*}RSUE_{jt} + \beta_8\ INST.OWN_{jt}{*}RSUE_{jt} \\
+ \beta_9\ EA.MESSAGES_{jt}{*}RSUE_{jt} + \beta_{10}\ LENGTH_{jt}{*}RSUE_{jt} \\
+ \beta_{11}\ MEDIA.COVERAGE_{jt}{*}RSUE_{jt} + Main\ Effects_{jt} + \varepsilon_{jt}.
\end{gathered} \tag{5b}
$$

If visuals attract investor attention and lead to a stronger immediate reaction, then we expect the association between earnings news and returns around the next earnings announcement to be lower when firms use visuals. That is, the coefficient on the interaction of earnings news and visuals should be negative ($\beta_1 < 0$).

The results are presented in Table 8. Consistent with our prediction, we find some evidence that the post-announcement reaction to earnings news is lower when visuals are used to disseminate earnings news. The coefficients on both *VISUALS*RSUE* and *VISUALS.RES*RSUE* are negative and significant at the p = 0.033 and 0.023 one-sided levels, respectively. When we keep all other variables constant and equal to their sample means, an increase in *VISUALS* from 0 to 1 corresponds to a decrease in $CAR(-1,+1)_{NEXT.QTR}$ between the top and bottom deciles of 1.9% (0.019). The 1.9% decrease is almost as large as the 2.0% increase in the initial reaction in Table 7 Panel A. Thus, it appears that investors largely undo their initial reaction due to visuals.

3.6 Instrumental Variable Approach

We use an instrumental variable approach to further mitigate the concern that the choice of visuals may be influenced by omitted correlated variables. As an instrument for *VISUALS*, we use the firm propensity to use visuals in messages *unrelated* to earnings in the week prior to the earnings announcement date. The measure is likely to be a reasonable instrument because past use of non-earnings-related visuals is unlikely to be driven by the firm's desire to attract investor attention to the earnings announcement but is likely to be a predictor of the firm's use of visuals in earnings-related messages on the earnings announcement day. Since the instrument reflects ex ante propensity to use visuals, it also helps rule out the possibility that firms use visuals in response to higher announcement returns.

The results are presented in Table 9. The instrument for *VISUALS*, *Past non-earnings-related visuals*, is calculated as the quartile rank of the total number of visuals across all non-earnings-related messages over trading days (-15,-8), where day 0 is the earnings announcement date. The instrument for *VISUALS*RSUE* is the interactive variable, *Past non-earnings-related visuals*RSUE*. Panel A shows the results of the first-stage estimation, where *VISUALS* and *VISUALS*RSUE* are regressed on their instruments and control variables. Consistent with the past non-earnings related visuals predicting the firm's tendency to use visuals in earnings-related messages on the earnings announcement date, *VISUALS* and *VISUALS*RSUE* are significantly associated with their instruments. The (weak) under-identification test reported at the bottom of Panel A rejects the null that there is no correlation (only a weak correlation) between the instrument and the endogenous variable ($p<0.001$).

Panel B reports the results of the second-stage estimation results of the market reaction tests, where we use the predicted values from the first-stage estimation. The results are consistent with the findings in Tables 7 and 8. The coefficient on the instrumented *VISUAL*RSUE* is positive and significant in the regression of the immediate market reaction and negative and significant in the regression of the market reaction around the next earnings announcement. The significant statistic for the endogeneity test reported in the bottom row of Panel B indicates that the two-stage instrumental variable approach estimation corrects a significant amount of the endogeneity present in the ordinary least square estimation.

4. Conclusion

We propose that the use of visuals in the dissemination of the earnings news increases investor attention to the earnings news. We examine firm choice to use visuals to disseminate earnings news on Twitter, and how this choice affects the attention of firm followers to the news. We use firm followers' direct engagement with these earnings-related messages using retweets and likes to measure attention.

Consistent with the prediction of limited attention theory that salient information attracts greater investor attention, we find that followers' attention to the earnings news is significantly higher when the firm uses visuals. We further find that visuals attract attention through two channels. First, the results show the direct attention effect of visuals, where attention to an earnings-related message is greater when that message contains visuals. Second, the results reveal the attention spillover effect of visuals, where visual salience of one earnings-related message attracts followers' attention to other earnings-related messages sent by the firm. Additionally, we find both an attention focus effect and an attention dilution effect by firms issuing multiple messages on the earnings announcement date. The multiple messages on the same day focus investor attention on the firm, but dilute attention to each message.

We also find evidence suggesting that firms' use of visuals is influenced by a desire to emphasize news that makes them look more favorable to outsiders. Firms are more likely to use visuals when earnings exceed market expectations. We do not find that firms use visuals to signal more value relevant (i.e., more persistent) earnings. On the contrary, our results indicate that visuals are negatively related to earnings persistence, suggesting that managers take advantage of temporary good earnings news by making it more salient.

We also examine the effect of visuals on market prices. Consistent with the predictions of limited attention theories, we find that the initial investor reaction to earnings news is stronger, and the post-announcement reaction is lower when visuals are used to disseminate earnings news. The results also suggest that the effect of visuals is concentrated on days with many earnings announcements by other firms when visuals are likely to help the firm's announcement stand out from other announcements. Overall, our evidence that using visuals increases investor attention to earnings news supports the S.E.C.'s contention that visuals encourage higher investor engagement and improve investor understanding of financial performance in firm communication with investors.

References

Asay, H. S., Libby, R., and Rennekamp, K. M. 2018. Do features that associate managers with a message magnify investors' reactions to narrative disclosures? *Accounting, Organization, and Society*. Vol 68-69, pp 1-14.

Ball, R., and Brown, P. 1968. An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research*. 6: 159-178.

Barber, B., and T. Odean. 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies* 21: 785–818.

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

Bernard, V., and J. Thomas. 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics* 13: 305 – 340.

Beaver, W. H. 1968. The Information Content of Annual Earnings Announcement. *Journal of Accounting Research*. 6: 67-92.

Blankespoor, E., G. Miller, and H. White. 2014. The role of dissemination in market liquidity: evidence from firms' use of Twitter™. *The Accounting Review* 89: 79–112.

Bowen, R. M., A. K. Davis, and D. A. Matsumoto. 2005. Emphasis on pro forma versus GAAP earnings in quarterly press releases: Determinants, SEC intervention, and market reactions. *The Accounting Review* 80: 1011–1038.

Burgstahler,D and Dichev, I. 1997. Earnings Management to Avoid Earnings Decreases and Losses. *Journal of Accounting and Economics*. 24: 99-126.

Collins, D., and S. Kothari. 1989. An analysis of inter-temporal and cross-sectional determinants of earnings response coefficients. *Journal of Accounting and Economics* 11: 143 – 181.

Cox, R., Goeij, P., and Campenhout, G. V. 2018. Are Pictures Worth a Thousand Words? Infographics and Investment Decision Making. Working paper, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3277502

Crowley, R. M., W. Huang, and H. Lu. 2018. Discretionary Dissemination on Twitter. Working Paper. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3105847.

Curtis, A., V. Richardson, and R. Schmardebeck. 2014. Investor attention and the pricing of earnings news. Working paper, University of Washington. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2467243.

Da, Z., J. Engelberg, and P. Gao. 2011. In search of attention. *Journal of Finance* 66: 1461–99.

DellaVigna, S., and J. Pollet. 2009. Investor inattention and Friday earnings announcements. *Journal of Finance* 64: 709–49.

Demers, E., and C. Vega. 2011. Linguistic tone in earnings announcements: News or noise? Working paper, INSEAD.

Dichev, I., and V. Tang. 2009. Earnings volatility and earnings persistence. *Journal of Accounting and Economics* 47: 160–181.

Drake, M., J. Jennings, D. Roulstone, and J. Thornock. 2016. The comovement of investor attention. *Management Science* 63: 2847–2867.

Elliott, W. B., Grant, S. M., and Rennekamp, K. M. 2017. How Disclosure Features of Corporate Social Responsibility Reports Interact with Investor Numeracy to Influence Investor Judgement. *Contemporary Accounting Research*. Vol 34 (3), pp. 1596-1621

Elliott, W. B., Hodge, F. D., and Sedor, L. M. 2012. Using Online Video to Announce a Restatement: Influences on Investment Decisions and the Mediating Role of Trust. *The Accounting Review* Vol 87 (2), pp. 513-535.

Engelberg, J., C. Sasseville, and J. Williams. 2012. Market madness: The case of Mad Money. *Management Science* 58: 351–64.

Files, R., E. Swanson, and S. Tse. 2009. Stealth disclosure of accounting restatements. *The Accounting Review* 84: 1495–1520.

Fiske, S., and S.Taylor. 2016. *Social Cognition, from Brains to Culture*. New York: McGraw-Hill.

Foster, G., Olsen, C., and Shevlin., T. 1984. Earnings Releases, Anomalies, and the Behavior of Security Returns. *The Accounting Review*. 59: 574-603.

Jung, M., J. Naughton, A. Tahoun, and C. Wang. 2018. Do firms strategically disseminate? Evidence from Corporate Use of Social Media. *The Accounting Review* 93: 225–252.

Klibanoff, P., O. Lamont, and T. A. Wizman. 1998. Investor reaction to salient news in closed-end country funds. *Journal of Finance* 53: 673–699.

Ham, C., Seybert, N., and Wang, S. 2018. Narcissism is a bad sign: CEO signature size, investment, and performance. *Review of Accounting Studies* Vol 23 (1), pp. 234-264.

Harvey, C. Liu, Y. and Zhu, H. 2016. …and the Cross-Section of Expected Returns. *The Review of Financial Studies*. 29: 5-68.

Hayn, C., 1995. The information content of losses. *Journal of Accounting and Economics* 20: 125–153.

Hirshleifer, D., S. S. Lim, and S. H. Teoh. 2009. Driven to distraction: Extraneous events and underreaction to earnings news. *Journal of Finance* 64: 2287 – 323.

Hirshleifer, D., S. S. Lim, and S. H. Teoh. 2011. Limited investor attention and stock market misreactions to accounting information. *Review of Asset Pricing Studies* 1: 35 – 73.

Hirshleifer, D., and S. H. Teoh. 2003. Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics* 36: 337 – 386.

Hockley, W. 2008. The picture superiority effect in associative recognition. *Memory & Cognition*, *36*: 1351 – 1359.

Hou, K., L. Peng, and W. Xiong. 2009. A tale of two anomalies: The implication of investor attention for price and earnings momentum. Working paper. Ohio State University.

Huang, X., A. Nekrasov, and S. H. Teoh. 2018. Headline salience, managerial opportunism, and over- and underreactions to earnings. *The Accounting Review, 93(6),* pp.231-255.

Huang, X., S. H. Teoh, and Y. L. Zhang. 2014. Tone management. *The Accounting Review* 89, 3: 1083–1113.

Kormendi, R., and R. Lipe. 1987. Earnings innovations, earnings persistence and stock returns. *Journal of Business* 60: 323 – 345.

Lee, L., A. Hutton, and S. Shu. 2015. The role of social media in the capital market: Evidence from consumer product recalls. *Journal of Accounting Research* 53: 367–404.

Levi, Y. 2015. Information Architecture and Intertemporal Choice: A Randomized Field Experiment in the United States. *Working paper.*

Li, F. 2008. Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics* 45: 221–247.

Li, F. 2011. Textual analysis of corporate disclosures: A survey of the literature. *Journal of Accounting Literature* 29: 143–165.

Li, J., and J. Yu. 2012. Investor attention, psychological anchors, and stock return predictability. *Journal of Financial Economics* 104: 401–419.

Loughran, T., and B. Mcdonald. 2017. The use of EDGAR filings by investors. *Journal of Behavioral Finance* 18: 231–248.

Lou, D. 2014. Attracting investor attention through advertising. *Review of Financial Studies* 27: 1797–1829.

Mayew, W., and M. Venkatachalam. 2012a. Speech Analysis in Financial Markets. *Foundations and Trends in Accounting* Vol 7, no. 2: 73-130.

Mayew, W., and M. Venkatachalam. 2012b. The power of voice: Managerial affective states and future firm performance. *Journal of Finance* 67: 1–44.

Peng, L., and W. Xiong. 2006, Investor attention, overconfidence and category learning. *Journal of Financial Economics* 80: 563–602.

Peress, J. 2014. The media and the diffusion of information in financial markets: Evidence from newspaper strikes. *Journal of Finance* 69: 2007–43.

Potter, M., B. Wyble, C. Hagmann, and E. McCourt. 2014. Detecting meaning in RSVP at 13 ms per picture. *Attention, Perception, & Psychophysics 76*: 270–279.

Rennekamp, K. 2012. Processing fluency and investors’ reactions to disclosure readability. *Journal of Accounting Research* 50: 1319–1354.

Roulstone, D., and X. Wang. 2016. Investor attention spill-over effect: Evidence from DJIA record days. Working paper, Ohio State University.

Shepard, R. 1967. Recognition memory for words, sentences, and pictures. *Journal of Memory and Language 6:* 156–163.

Tang, V. 2018. Wisdom of crowds: Cross-sectional variation in the informativeness of third-party-generated product information on Twitter. *Journal of Accounting Research* 56: 989–1034.

Teoh, S., 2018. The promise and challenges of new datasets for accounting research. *Accounting, Organizations and Society* 68–69: 109–117.

Tufte, E., 1983, 2006. The Visual Display of Quantitative Information. Graphics Press.

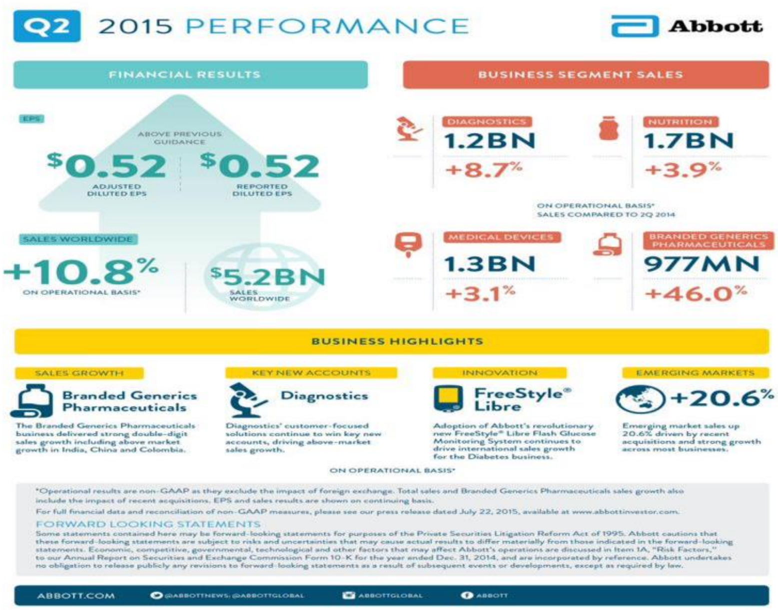
U.S. Securities and Exchange Commission. 1998. A Plain English Handbook How to Create Clear SEC Disclosure Documents. Office of Investor Education and Assistance, S.E.C., Washington, DC 20549, available at https://www.sec.gov/pdf/handbook.pdf

Yuan, Y. 2015. Market-wide attention, trading, and stock returns. *Journal of Financial Economics* 116: 548–64

Zhu, C. 2018. Investor Demand for Contextual Information: Evidence from Wikipedia. *Working paper.*

Appendix A
Examples of Earnings-Announcement-Related Messages with Visuals

Example 1 (Abbott Laboratories' message about its earnings announcement on 07/22/2015):
$ABT reports Q2 results; adjusted earnings per share of 52 cents, exceeding analyst estimates.



Example 2 (Newport Corp.'s message about its earnings announcement on 07/30/2014):
$NEWP Q2 Earnings Call Highlights #NEWPQ2

Example 3 (WPX Energy's message about its earnings announcement on 08/05/2015):
$WPX reports 2Q 2015 results. Read more:

Appendix B
Keywords

The appendix provides the list of the keywords that we use to identify, among all messages sent on earnings announcement dates, those messages that are likely to be related to the earnings announcement.

earnings	beats	Q1
earning	dividend	Q2
income	cash dividend	Q3
revenue	transcript	Q4
results	transcripts	EPS
quarter	forward-looking statement	profit
quarterly	forward-looking statements	profits
press release	net income	sales
financial results	common share	strong performance
earnings results	earnings forecast	stock repurchases
earnings guidance	earnings forecasts	GAAP
conference call	1Q	non-GAAP
conf call	2Q	profitability
webcast	3Q	shareholder value
beat	4Q	exceeds expectations

Appendix C
Variable Definitions

Variable	Description
Twitter Variables at the Firm-Quarter Level	
VISUALS	An indicator variable that equals 1 if the firm sent at least one earnings-announcement-related message with visuals on the earnings announcement date, and 0 otherwise
VISUALS.RES	The residual visuals, calculated as the residuals from the first-stage OLS regression (3), where *VISUALS* is regressed on a set of its predicted determinants.
QUANT.ITEMS	An indicator variable that equals 1 if the firm sent at least one earnings-announcement-related message on the earnings announcement date that contains quantitative information, and 0 otherwise.
WEB.LINKS	An indicator variable that equals 1 if the firm sent at least one earnings-announcement-related message on the earnings announcement date that contains a hyperlink that directs to an external website, and 0 otherwise.
RETWEETS	An indicator variable that equals 1 if the firm's followers retweeted at least one earnings-announcement-related message on the earnings announcement date, and 0 otherwise.
LIKES	An indicator variable that equals 1 if the firm's followers liked at least one earnings-announcement-related message on the earnings announcement date, and 0 otherwise.
FOLLOWERS	The natural logarithm of a firm's total number of the firm's Twitter followers as of March 2018, the day we completed the data scraping of followers information.
EA.MESSAGES	The number of earnings-announcement-related messages on the earnings announcement date for the firm for the quarter.
LENGTH	The natural logarithm of the average number of characters of the earnings-related messages on the earnings announcement date for the firm for the quarter.

Twitter Variables at the Message Level

$VISUALS_{message.level}$	An indicator variable that equals 1 if the earnings-announcement-related message contains visuals (still images or videos), and 0 otherwise.
$VISUALS.OTHER_{message.level}$	An indicator variable that equals 1 if there is at least one other earnings-announcement-related message that is sent by the firm on the earnings announcement date and that contains visuals, and 0 otherwise.
$QUANT.ITEMS_{message.level}$	An indicator variable that equals 1 if the earnings-announcement-related message contains quantitative information, and 0 otherwise.
$WEB.LINKS_{message.level}$	An indicator variable that equals 1 if the earnings-announcement-related message contains a hyperlink, and 0 otherwise.
$RETWEETS_{message.level}$	An indicator variable that equals 1 if the earnings-announcement-related message was retweeted on the earnings announcement date, and 0 otherwise.
$LIKES_{message.level}$	An indicator variable that equals 1 if the earnings-announcement-related message was liked on the earnings announcement date, and 0 otherwise.
$LENGTH_{message.level}$	The natural logarithm of the number of characters of the earnings-related message.

Other Variables

POS.SURP	An indicator of positive earnings surprise that equals to 1 if actual earnings for the quarter are greater than or equal to the consensus analyst forecast, and 0 otherwise. The consensus analyst forecast is the mean of the most recent forecasts made by individual analysts.
SUE	Unexpected earnings, calculated as actual quarterly earnings as reported by I/B/E/S minus the consensus analyst forecast, scaled by stock price at the end of the previous fiscal quarter. The consensus analyst forecast is the mean of the most recent forecasts made by individual analysts.
RSUE	The decile rank of unexpected earnings, *SUE*, scaled such that it varies from 0 (for the bottom decile) to 1 (for the top decile).

SIZE	The natural logarithm of the market value of equity at the end of the previous fiscal quarter.
GROWTH	Sales growth, calculated as the percentage change in quarterly sales from the same quarter last year.
STD.GROWTH	The standard deviation of sales growth, *GROWTH*, over the last eight quarters.
NEG.GROWTH	An indicator variable that equals to 1 if the quarterly sales growth from the same quarter last year is negative, and 0 otherwise.
BTM	The book-to-market ratio at the end of the previous fiscal quarter.
ANA.FOLLOW	Analyst following, calculated as the natural logarithms of one plus the number of analysts that have outstanding earnings forecast for the firm for the quarter.
EARN	Quarterly earnings before extraordinary items scaled by the average total assets.
STD.EARN	The standard deviation of *EARN* measured over the last eight quarters.
LOSS	An indicator variable that equals to 1 if the quarterly earnings before extraordinary items are negative, and 0 otherwise.
INST.OWN	Institutional ownership, calculated as the fraction of firm shares owned by institutional investors.
#EA	The number of same-day earnings announcements by other firms.
NRANK	The quartile rank of the number of the same-day earnings announcements by other firms.
TIME	Time trend, measured as the natural logarithm of the calendar year.
$CAR(-1,+1)$	The cumulative abnormal return over the 3-day window centered on the earnings announcement date, where daily abnormal returns are raw stock returns minus the market value-weighted return.
$CAR(-1,+1)_{NEXT.QTR}$	The cumulative abnormal return, $CAR(-1,+1)$, around the next earnings announcement day.

AB.SEARCH	Abnormal Google search volume for the firm for the day, calculated as the difference between the Google search volume for the firm for the day and the average Google search volume for the same firm and weekday over the previous 10 weeks, scaled by the average Google search volume for the same firm and weekday over the previous 10 weeks (Drake, Roulstone, Thornock 2012).
Lagged AB.SEARCH	Abnormal Google search volume, *AB.SEARCH*, for the firm for the previous day.
MEDIA.COVERAGE	Media coverage, calculated as the natural logarithm of one plus the number of news articles for the firm for the day, where the number of articles is obtained from Bloomberg.

Table 1
Sample Description

	# firms	# firm–quarters	# earnings announcement messages
Panel A: Sample Selection			
# S&P 1500 Index Firms as of 2/2018	1,500		
Less:			
Firms without Twitter account as of 2/2018	(345)		
Firms without earnings announcement messages during our sample period	(405)		
Earnings announcement messages during our sample period	750	5,276	15,113
Less:			
Missing stock returns	(27)	(53)	(159)
Missing analyst forecasts or necessary financial data	(44)	(295)	(987)
Final sample	679	4,928	13,967
Panel B: Sample Distribution by Industry			
Consumer Non-Durables	35	251	885
Consumer Durables	13	110	304
Manufacturing	68	498	1,042
Energy	27	275	773
Chemicals and Allied Products	22	248	760
Business Equipment	141	836	3,064
Telephone and Television Transmission	9	78	414
Utilities	33	352	739
Wholesales, Retails, and Some Services	53	349	1,262
Healthcare, Medical Equipment, and Drugs	50	507	1,358
Finance	137	887	2,067
Other	91	537	1,299
Total	679	4,928	13,967

The table reports the sample selection and industry distribution. Earnings announcement messages are Twitter messages sent on the earnings announcement date and containing at least one of the earnings-related keywords listed in Appendix B. Panel A reports the criteria for inclusion in the sample selection. Panel B reports the distribution of the sample over the 12 Fama-French industries. The sample period spans from June 2011 to December 2017.

Table 2
Summary Statistics

Panel A: Twitter Variables at the Firm-Quarter Level

Variable	Mean	StdDev	P10	P25	Median	P75	P90
VISUALS	0.233	0.423	0	0	0	0	1
VISUALS.RES	0.000	0.358	-0.387	-0.254	-0.079	0.164	0.591
QUANT.ITEMS	0.310	0.463	0	0	0	1	1
WEB.LINKS	0.944	0.230	1	1	1	1	1
RETWEETS	0.658	0.474	0	0	1	1	1
LIKES	0.613	0.487	0	0	1	1	1
FOLLOWERS	8.888	1.779	6.645	7.575	8.821	9.995	11.402
EA.MESSAGES	2.868	5.848	1	1	1	2	6
LENGTH	4.400	0.336	3.932	4.174	4.443	4.654	4.762

Panel B: Twitter Variables at the Message Level

Variable	Mean	StdDev	P10	P25	Median	P75	P90
$VISUALS_{message.level}$	0.162	0.368	0	0	0	0	1
$VISUALS.OTHER_{message.level}$	0.225	0.418	0	0	0	0	1
$QUANT.ITEMS_{message.level}$	0.274	0.446	0	0	0	1	1
$WEB.LINKS_{message.level}$	0.704	0.456	0	0	1	1	1
$RETWEETS_{message.level}$	0.547	0.497	0	0	1	1	1
$LIKES_{message.level}$	0.543	0.498	0	0	1	1	1
$LENGTH_{message.level}$	4.483	0.392	3.951	4.234	4.533	4.745	4.920

Panel C: Other Variables

Variable	Mean	StdDev	P10	P25	Median	P75	P90
POS.SURP	0.672	0.469	0	0	1	1	1
SUE	0.001	0.005	-0.002	0	0.000	0.002	0.004
SIZE	8.983	1.637	5.217	7.807	9.059	10.152	12.382
Mkt Cap	25,845.5	46,661.6	900.6	2,458.2	8,594.6	25,645.5	69,109.8
GROWTH	0.061	0.197	-0.115	-0.024	0.042	0.121	0.248
STD.GROWTH	0.113	0.129	0.024	0.038	0.069	0.133	0.260
NEG.GROWTH	0.327	0.469	0	0	0	1	1
BTM	0.446	0.329	0.098	0.211	0.375	0.617	0.864
ANA.FOLLOW	2.513	0.613	0.693	2.079	2.639	2.996	3.526
#ANALYSTS	13.52	7.51	4	7	13	19	24
EARN	0.014	0.021	-0.003	0.004	0.012	0.023	0.036
STD.EARN	0.011	0.015	0.002	0.003	0.006	0.012	0.025
LOSS	0.128	0.334	0	0	0	0	1
INST.OWN	0.780	0.202	0.601	0.709	0.817	0.914	0.982
#EA	73.250	48.173	10	30	70	113	134
$CAR(-1,+1)$	0.001	0.067	-0.069	-0.029	0.001	0.034	0.073
$CAR(-1,+1)_{NEXT.QTR}$	0.001	0.068	-0.069	-0.031	-0.000	0.032	0.071
AB.SEARCH	0.249	0.823	-0.286	-0.083	0.031	0.275	1.116
MEDIA.COVERAGE	5.175	1.510	5.375	4.263	4.836	5.916	6.522

The table provides descriptive statistics. Panel A reports descriptive statistics for Twitter variables at the firm-quarter level. Panel B reports descriptive statistics for Twitter variables at the message level. Descriptive statistics for other variables are reported in Panel C. *Mkt Cap* is the market value of equity and *SIZE* is ln(mkt cap). *#ANALYSTS* is the number of analysts following the firm. *#EA* is the number of same-day earnings announcements. All other variables are as defined in Appendix C.

Table 3
Attention to Visuals

Panel A: Follower Retweets and Likes – Firm-Level Analysis

	Dependent Variable			
	RETWEETS	*p-value*	*LIKES*	*p-value*
VISUALS	0.654***	<0.001	0.707***	<0.001
QUANT.ITEMS	0.484***	<0.001	0.323**	0.011
WEB.LINKS	0.068	0.744	-0.540**	0.036
SIZE	0.260***	0.006	0.298***	<0.001
ANA.FOLLOW	0.164	0.317	0.074	0.617
POS.SURP	0.078	0.356	0.176**	0.042
GROWTH	0.263	0.236	0.408*	0.071
BTM	0.231	0.270	0.300	0.120
INST.OWN	-0.638*	0.070	-0.154	0.508
FOLLOWERS	0.454***	<0.001	0.394***	<0.001
EA.MESSAGES	0.843***	<0.001	0.768***	<0.001
LENGTH	0.059	0.709	0.211	0.182
MEDIA.COVERAGE	0.063	0.176	-0.014	0.716
TIME	0.134***	<0.001	0.620***	<0.001
Observations	4,753		4,779	
Pseudo-R^2	25.69%		36.11%	

Panel B: Direct and Spillover Attention Effects – Message-Level Analysis

	Dependent Variable			
	$RETWEETS_{message.level}$	*p-value*	$LIKES_{message.level}$	*p-value*
$VISUALS_{message.level}$	0.863***	<0.001	0.862***	<0.001
$VISUALS.OTHER_{message.level}$	0.247***	<0.001	0.360***	<0.001
$QUANT.ITEMS_{message.level}$	0.278***	<0.001	0.170***	0.006
$WEB.LINKS_{message.level}$	-0.210***	<0.001	-0.567***	<0.001
SIZE	0.218**	<0.001	0.355***	<0.001
ANA.FOLLOW	0.046	0.479	-0.209***	0.005
POS.SURP	0.028	0.580	0.038	0.503
GROWTH	-0.084	0.502	0.322**	0.027
BTM	0.178*	0.074	0.348***	0.003
INST.OWN	-0.649***	<0.001	-0.540***	0.003
FOLLOWERS	0.365***	<0.001	0.396***	<0.001
EA.MESSAGES	-0.454***	<0.001	-0.583***	<0.001
$LENGTH_{message.level}$	0.092	0.174	0.323***	<0.001
MEDIA.COVERAGE	0.061***	0.003	-0.009	0.689
TIME	0.075***	<0.001	0.635***	<0.001
Observations	11,247		11,317	
Pseudo-R^2	22.86%		37.90%	

Panel A reports the results of estimating the logistic regression (1a) at the firm-quarter level. The dependent variable is *RETWEETS* (first two columns) or *LIKES* (last two columns). *VISUALS* (*QUANT.ITEMS*, *WEB.LINKS*) is the indicator of the firm's use of visuals (quantitative items, web links) in earnings-announcement-related messages. Panel B reports the results of estimating the logistic regression (1b) at the level of individual messages. *VISUALS.OTHER* is the indicator of the firm's use of visuals in *other* earnings-related messages. All other variables are as defined in Appendix C. The regressions are estimated with industry and quarter fixed effects. Standard errors are clustered by firm. All *p*-values are based on two-sided tests except for *VISUALS* and *VISUALS.OTHER*, which are one-sided. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4
Visuals and Abnormal Google Search Volume

	Dependent Variable	
	AB.SEARCH	*p-value*
VISUALS	0.054**	0.042
QUANT.ITEMS	-0.027*	0.096
WEB.LINKS	0.022*	0.053
SIZE	0.009**	0.013
ANA.FOLLOW	0.096	0.685
POS.SURP	-0.035	0.484
GROWTH	0.207**	0.036
BTM	-0.001	0.724
INST.OWN	-0.253*	0.060
FOLLOWERS	0.011	0.222
EA.MESSAGES	-0.041*	0.062
LENGTH	-0.040	0.262
MEDIA.COVERAGE	0.019*	0.075
TIME	0.001	0.935
NRANK	-0.034***	<0.001
Lagged AB.SEARCH	0.289***	<0.001
Observations	4,608	
Adjusted-R^2	35.58%	

The table reports the results of estimating equation (2). Abnormal Google search volume for the firm's stock ticker for the earnings announcement day, *AB.SEARCH*, is regressed on the visuals indicator, *VISUALS*, and control variables. All variables are as defined in Appendix C. The regressions are estimated with firm and quarter fixed effects. Standard errors are clustered by firm. All *p*-values are based on two-sided tests except for *VIS.VAR*, which are one-sided. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Firms' Use of Visuals

	Logistic Regression		OLS Regression	
	VISUALS	*p-value*	*VISUALS*	*p-value*
POS.SURP	0.252**	0.018	0.026**	0.020
QUANT.ITEMS	-0.464***	0.016	-0.067***	0.003
WEB.LINKS	-1.733***	<0.001	-0.267***	<0.001
SIZE	-0.116	0.420	-0.017	0.257
ANA.FOLLOW	-0.046	0.867	0.001	0.960
GROWTH	0.306	0.279	0.061*	0.085
BTM	0.180	0.594	0.026	0.514
INST.OWN	0.450	0.414	-0.019	0.672
FOLLOWERS	0.388***	<0.001	0.053***	<0.001
EA.MESSAGES	0.842***	<0.001	0.119***	<0.001
LENGTH	0.207	0.332	0.051**	0.050
NRANK	0.019	0.742	0.001	0.968
MEDIA.COVERAGE	-0.026	0.770	-0.001	0.989
TIME	0.871***	<0.001	0.084***	<0.001
Observations	4,719		4,719	
Pseudo-R^2 / Adjusted-R^2	33.31%		30.19%	

The table reports the results of estimating equation (3). The indicator of the firm's use of visuals in earnings-announcement-related messages, *VISUALS*, is regressed on a set of predicted determinants. The first (last) two columns show the results of the logistic (OLS) regression. All other variables are as defined in Appendix C. The regressions are estimated with industry and quarter fixed effects. Standard errors are clustered by firm. All *p*-values are based on two-sided tests except for *POS.SURP*, which are one-sided. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Earnings Persistence and Sales Growth Persistence

Panel A: Earnings Persistence

	VIS.VAR = VISUALS		*VIS.VAR = VISUALS.RES*	
	$EARN_{t+1}$	*p-value*	$EARN_{t+1}$	*p-value*
$VIS.VAR*EARN_t$	-0.162***	<0.001	-0.128***	0.003
$SIZE*EARN_t$	-0.011	0.242	-0.017*	0.063
$BTM*EARN_t$	0.028	0.544	0.037	0.436
$STD.EARN*EARN_t$	0.607	0.239	0.617	0.232
$LOSS*EARN_t$	0.023	0.630	0.021	0.662
$EARN_t$	0.229**	0.015	0.244***	0.010
$EARN_{t-3}$	0.152***	<0.001	0.153***	<0.001
VIS.VAR	0.002**	0.043	0.001	0.437
SIZE	0.002*	0.083	0.001	0.222
BTM	-0.018***	<0.001	-0.020***	<0.001
STD.EARN	-0.094***	<0.001	-0.090***	0.001
LOSS	0.001	0.357	0.001	0.698
Observations	4,612		4,612	
Adjusted R^2	50.01%		50.63%	

Panel B: Persistence of Sales Growth

	VIS.VAR = VISUALS		*VIS.VAR = VISUALS.RES*	
	$GROWTH_{t+1}$	*p-value*	$GROWTH_{t+1}$	*p-value*
$VIS.VAR*GROWTH_t$	-0.163***	<0.001	-0.170***	<0.001
$SIZE*GROWTH_t$	-0.015*	0.081	-0.027***	0.002
$BTM*GROWTH_t$	-0.173***	<0.001	-0.181***	<0.001
$STD.GROWTH*GROWTH_t$	0.019	0.450	0.011	0.669
$NEG.GROWTH*GROWTH_t$	0.035	0.335	0.073**	0.049
$GROWTH_t$	0.824***	<0.001	0.890***	<0.001
$GROWTH_{t-3}$	-0.261***	<0.001	-0.264***	<0.001
VIS.VAR	0.012*	0.096	0.017**	0.024
SIZE	0.036***	<0.001	0.040***	<0.001
BTM	-0.067***	0.001	-0.063***	0.002
STD.GROWTH	0.027	0.376	0.054*	0.091
NEG.GROWTH	-0.013**	0.045	-0.012*	0.079
Observations	4,600		4,600	
Adjusted R^2	56.87%		55.68%	

The table reports the results of estimating equations (4a) and (4b), where the dependent variable $EARN_{t+1}$ is earnings for quarter *t+1*. In the first two columns, the visual variable, *VIS.VAR*, is the indicator of the firm's use of visuals in earnings-announcement-related messages, *VISUALS*. In the last two columns, the visual variable, *VIS.VAR*, is the residual visuals, *VISUALS.RES*, calculated as the residuals from the first-stage regression (3). All other variables are as defined in Appendix C. The regressions are estimated with firm and quarter fixed effects. Standard errors are clustered by firm. All *p*-values are based on two-sided tests. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Reaction to Earnings News

Panel A: Full Sample

	VIS.VAR = VISUALS		*VIS.VAR = VISUALS.RES*	
	CAR(−1,+1)	*p-value*	*CAR(−1,+1)*	*p-value*
*VIS.VAR*RSUE*	0.020**	0.016	0.026***	0.003
*QUANT.ITEMS*RSUE*	0.004	0.660	0.005	0.598
*WEB.LINKS*RSUE*	-0.014	0.404	-0.020	0.224
*SIZE*RSUE*	-0.027***	<0.001	-0.027***	<0.001
*ANA.FOLLOW*RSUE*	0.031***	<0.001	0.032***	<0.001
*GROWTH*RSUE*	-0.001	0.977	0.001	0.983
*BTM*RSUE*	-0.041***	<0.001	-0.043***	<0.001
*INST.OWN*RSUE*	-0.017	0.310	-0.016	0.326
*EA.MESSAGES*RSUE*	-0.006	0.426	-0.006	0.397
*LENGTH*RSUE*	-0.035***	0.002	-0.034***	0.004
*MEDIA.COVERAGE*RSUE*	0.006**	0.017	0.006**	0.019
RSUE	0.418***	<0.001	0.411***	<0.001
VIS.VAR	-0.004	0.513	-0.007	0.263
QUANT.ITEMS	-0.003	0.662	-0.003	0.615
WEB.LINKS	0.005	0.623	0.006	0.548
SIZE	-0.011**	0.019	-0.011**	0.026
ANA.FOLLOW	-0.028***	<0.001	-0.028***	<0.001
GROWTH	0.010	0.370	0.009	0.411
BTM	0.047***	<0.001	0.050***	<0.001
INST.OWN	0.025	0.107	0.026*	0.097
EA.MESSAGES	0.005	0.378	0.005	0.345
LENGTH	0.024***	0.001	0.023***	0.001
MEDIA.COVERAGE	-0.002	0.410	-0.002	0.293
Observations	4,606		4.606	
Adjusted R^2	16.19%		16.23%	

The table reports the results of estimating regressions (5a), where the dependent variable, *CAR(−1,+1)*, is a cumulative abnormal return around the earnings announcement date. In the first two columns, the visual variable, *VIS.VAR*, is the indicator of the firm's use of visuals in earnings-announcement-related messages, *VISUALS*. In the last two columns, the visual variable, *VIS.VAR*, is the residual visuals, *VISUALS.RES*, calculated as the residuals from the first-stage regression (3). All other variables are as defined in Appendix C. The regressions are estimated with firm, year, and quarter fixed effects. Standard errors are clustered by firm. All *p*-values are based on two-sided tests except for *VIS.VAR*RSUE*, which are one-sided. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel B: Subsamples of High- and Low-Distraction Days

	High Number of Same-Day Earnings Announcements				*Low Number of Same-Day Earnings Announcements*			
	VIS.VAR = VISUALS		*VIS.VAR = VISUALS.RES*		*VIS.VAR = VISUALS*		*VIS.VAR = VISUALS.RES*	
	CAR(−1,+1)	*p-value*	*CAR(−1,+1)*	*p-value*	*CAR(−1,+1)*	*p-value*	*CAR(−1,+1)*	*p-value*
*VIS.VAR*RSUE*	0.042**	0.022	0.050***	0.009	0.012	0.316	0.020	0.208
Controls	Yes		Yes		Yes		Yes	
*Controls*RSUE*	Yes		Yes		Yes		Yes	
Observations	1,028		1,028		1,042		1,042	
Adjusted R^2	18.17%		18.52%		18.36%		18.37%	

The table reports the results of estimating regressions (5a), where the dependent variable, *CAR(−1,+1)*, is a cumulative abnormal return around the earnings announcement date. Panel A reports the results for the full sample. In the first two columns, the visual variable, *VIS.VAR*, is the indicator of the firm's use of visuals in earnings-announcement-related messages, *VISUALS*. In the third and fourth columns, the visual variable, *VIS.VAR*, is the residual visuals, *VISUALS.RES*, calculated as the residuals from the first-stage OLS regression (3). Panel B reports the results for subsamples of high- and low-distraction days. The first (last) four columns report the results for days in the top (bottom) quartile of the distribution of the number of same-day announcements (#EA). All other variables are as defined in Appendix C. The regressions are estimated with firm, year, and quarter fixed effects. Standard errors are clustered by firm. All *p*-values are based on two-sided tests except for *VIS.VAR*RSUE*, which are one-sided. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Returns around Next Earnings Announcement

	VIS.VAR = VISUALS		*VIS.VAR = VISUALS.RES*	
	$CAR(-1,+1)_{NEXT.QTR}$	*p-value*	$CAR(-1,+1)_{NEXT.QTR}$	*p-value*
*VIS.VAR*RSUE*	-0.019**	0.033	-0.021**	0.023
*QUANT.ITEMS*RSUE*	0.011	0.281	0.009	0.358
*WEB.LINKS*RSUE*	-0.006	0.760	0.0002	0.992
*SIZE*RSUE*	0.012***	0.001	0.011***	0.002
*ANA.FOLLOW*RSUE*	-0.018**	0.020	-0.018**	0.023
*GROWTH*RSUE*	0.037**	0.041	0.036**	0.045
*BTM*RSUE*	0.029**	0.011	0.030***	0.010
*INST.OWN*RSUE*	0.017	0.351	-0.015	0.409
*EA.MESSAGES*RSUE*	0.014*	0.075	0.015*	0.066
*LENGTH*RSUE*	-0.018	0.148	-0.018	0.147
*MEDIA.COVERAGE*RSUE*	-0.008***	0.006	-0.008***	0.008
RSUE	-0.008	0.898	-0.008	0.902
VIS.VAR	0.008	0.219	0.010	0.161
QUANT.ITEMS	-0.001	0.931	0.001	0.964
WEB.LINKS	0.010	0.387	0.007	0.522
SIZE	-0.048***	<0.001	-0.048***	<0.001
ANA.FOLLOW	-0.009	0.254	-0.009	0.243
GROWTH	-0.015	0.217	-0.015	0.226
BTM	-0.022*	0.051	-0.023**	0.045
INST.OWN	-0.025	0.145	-0.024	0.166
EA.MESSAGES	-0.020***	<0.001	-0.021***	<0.001
LENGTH	0.010	0.245	0.010	0.244
MEDIA.COVERAGE	0.003	0.256	0.002	0.278
Observations	4,619		4,619	
Adjusted R^2	6.51%		6.52%	

The table reports the results of estimating regressions (5b), where the dependent variable, $CAR(-1,+1)_{NEXT.QTR}$, is a cumulative abnormal return around the next-quarter earnings announcement date. In the first two columns, the visual variable, *VIS.VAR*, is the indicator of the firm's use of visuals in earnings-announcement-related messages, *VISUALS*. In the last two columns, the visual variable, *VIS.VAR*, is the residual visuals, *VISUALS.RES*, calculated as the residuals from the first-stage OLS regression (3). All other variables are as defined in Appendix C. The regressions are estimated with firm, year, and quarter fixed effects. Standard errors are clustered by firm. All *p*-values are based on two-sided tests except for *VIS.VAR*RSUE*, which are one-sided. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9
Additional Analysis: 2SLS Estimation with Instrumental Variables

Panel A: First-Stage Estimation

$$VISUALS_{jt} = \alpha_1\ Past\ non\text{-}earnings\text{-}related\ visuals_{jt} + \alpha_2\ Past\ non\text{-}earnings\text{-}related\ visuals_{jt} * RSUE_{jt} + \alpha_3\ RSUE_{jt} + Controls + \varepsilon_{jt} \quad (5a)$$

$$VISUALS_{jt} * RSUE_{jt} = \beta_1\ Past\ non\text{-}earnings\text{-}related\ visuals_{jt} + \beta_2\ Past\ non\text{-}earnings\text{-}related\ visuals_{jt} * RSUE_{jt} + \beta_3\ RSUE_{jt} + Controls + \delta_{jt} \quad (5b)$$

	VISUALS		*VISUALS*RSUE*	
	Coeff	*p-value*	*Coeff*	*p-value*
Past non-earnings-related visuals	0.104***	<0.001	-0.111***	<0.001
*Past non-earnings-related visuals*RSUE*	0.023	0.591	0.323***	<0.001
Controls	Yes		Yes	
#obs	4,863		4,863	
Adj. R^2	27.93%		18.96%	
Partial R^2 of Instrument	2.86%		8.35%	
Under-identification Test (Sanderson-Windmeijer multivariate chi-squared):	78.72***	<0.001	397.38***	<0.001
Weak identification Test (Sanderson-Windmeijer multivariate F statistic):	67.31***	<0.001	339.77***	<0.001

Panel B: Second-Stage Estimation

$$CAR[window] = \gamma_1 + \gamma_2\ RSUE_{jt} + \gamma_3\ \overline{VISUALS_{jt}} + \gamma_4\ \overline{VISUALS * RSUE_{jt}} + Controls + Controls * RSUE_{jt} + \nu_{jt} \quad (5c)$$

	CAR(-1,+1)		*CAR(-1,+1)$_{NEXT.QTR}$*	
	Coeff	*p-value*	*Coeff*	*p-value*
$\overline{VISUALS}$	-0.051*	0.126	0.038*	0.128
$\overline{VISUALS * RSUE}$	0.107***	<0.001	-0.048**	0.015
RSUE	0.414***	<0.001	-0.089***	<0.001
Controls	Yes		Yes	
Controls*RSUE	Yes		Yes	
#obs	4,606		4,619	
Adj. R^2	5.64%		6.03%	
Endogeneity Test (Chi2)	9.918***	0.007	10.362***	0.006

This table reports the results of the two-stage instrument variable analysis. Panel A reports the results of first stage estimation of equations (5a) and (5b). The instrument for *VISUALS*, *Past non-earnings-related* *visuals*, is the quartile rank of the total number of visuals across all non-earnings-related messages over trading days (-15,-8), where day 0 is the earnings announcement date. In Panel B, $\overline{VISUALS}$ is the predicted *VISUALS* from equation (5a) and $\overline{VISUALS * RSUE}$ is the predicted *VISUALS**RSUE* from equation (5b). All other variables are defined in Appendix C. The regressions are estimated with firm, year, and quarter fixed effects. Standard errors are clustered by firm. All *p*-values are based on two-sided tests except for $\overline{VISUALS * RSUE}$, which are one-sided. *, **, *** denote significant at the 10%, 5%, and 1% levels, respectively.