The Feedback Effect of Social Media on Corporate Investment: Evidence from Twitter Presence and Follower Engagement

Abstract

Social media presence and follower engagement have a feedback effect on corporate investment through the learning channel and the disciplining effect. Utilizing 366 million posts for 2,065 firms on Twitter, we find that investment is less sensitive to stock prices for firms with Twitter presence and with more engaged followers. Managers forecast sales more accurately with Twitter presence and revise forecasts upwards (downwards) in response to improving (deteriorating) follower engagement, suggesting that managers learn *new* insights from social media. Interestingly, we find a greater responsiveness of investment to declining opportunities. The asymmetric effect suggests that social media disciplines managers.

Keywords: feedback effect; social media; investment; managerial learning; disciplining effect

Social media provides a centralized platform for a broad set of followers, including customers, investors, competitors, and other interested parties, to comment and express their opinions. Rather than the *dissemination* effect of social media emphasized in prior studies (e.g., Blankespoor, Miller, and White [2014]; Jung et al. [2018]; Lee, Hutton, and Shu [2015]), this study investigates the *real* effect of social media by examining whether and how social media presence and follower engagement have a *feedback* effect on corporate investment decisions.

Anecdotal evidence suggests that managers gain insights from social media presence and follower engagement and adjust investment decisions accordingly. According to Michael Sprague, vice president for marketing and communications of Kia Motors America, the automaker used business-intelligence software to monitor social media comments about its vehicles and noticed a groundswell of complaints about seat comfort from consumers and automotive writers. Accordingly, Kia modified the seat design and incorporated redesigned—and cushier—seats into the 2012 Optima, which represented a major shift in automotive research and development (R&D).[1] Aside from anecdotal evidence, there is no *systematic* evidence on the feedback effect of social media presence and follower engagement on corporate investment.

This study examines the feedback effect of social media by investigating whether and how social media interacts with stock prices in influencing corporate investment. In theory, it is ex ante uncertain whether social media presence and follower engagement increase or decrease the sensitivity of corporate investment to stock prices. Under the neo-classical theory, Tobin's q, which is closely related stock prices, determines investment. The literature of learning from stock prices suggest managers learn the private information in stock prices and incorporate the new information in investment decisions and that the more *private* information in stock prices, the higher sensitivity of investment to stock prices (e.g., Bond, Edmans, and Goldstein [2012]; Chen, Goldstein, and Jiang [2007]). Conceptually, social media presence and follower engagement could potentially provide *additional "wisdom of crowds"* of a *broader* set of outsiders about

[1] Josh Cable, "How Social Media is Fueling Automotive R&D." *Industry Week*, Sept. 8, 2011, https://www.industryweek.com/innovation/research-development/article/21957638/how-social-media-is-fueling-automotive-rd.

market trends, product demand shocks, and investment opportunities that are above and beyond stock prices.

While stock prices aggregate private information of investors that fall *within* the trading process, social media platforms aggregate "wisdom-of-crowds" of a broader set of followers, including consumers, investors, and competitors, *some* of whom fall *outside* of the trading process. Accordingly, social media provides a centralized platform for managers to learn additional insights from a bigger set of outsiders who fall either within or outside the trading process. Furthermore, as stock prices capture investors' *composite* information about all aspects of a given company, it is difficult to pinpoint exactly what specific information a stock price movement conveys. For instance, a stock price run-up (drop) could indicate investors' satisfaction (dissatisfaction) with the firm's operations, or with the management team, or with products or services, or all of the above. In contrast, followers communicate directly with the company on social media and thus it is easy for managers to identify *who* has communicated and *what* specific information a follower comment conveys. Using built-in tools on social media, managers can analyze follower engagement based on the locations where followers posted comments or based on the product lines about which followers commented. More specific follower comments, once aggregated at the location-by-location or product-by-product level, can reveal which product lines or geographic regions are over-performing and which are under-performing. Thus, follower engagement reveals into which business the firm should expand investment and into which business should contract investment. Accordingly, compared with stock prices, follower engagement on social media provides specific and granular signals that are useful for identifying investment opportunities.

In summary, social media provides an *alternative* information source for managers to learn *new* granular insights from a broader set of outsiders that are useful for identifying specific investment opportunities and evaluating industry trends. With social media presence and follower engagement, managers could rely less strongly on stock prices that aggregates private information of investor in the trading process in a composite manner for investment decisions. Thus, social media as an alternative information source could imply a *reduced* managerial reliance on stock prices to obtain new information about investment opportunities and investment profitability, implying a *lower* sensitivity of corporate investment to stock prices.

However, while managers obtain granular signals directly from social media, investors also have access to the same social media signals. Prior studies find that consumer opinions contain novel information about firms' fundamentals and thus make stock prices more informative with respect to future fundamentals (e.g., Fornell, Morgeson, and Hult [2016]; Huang [2018]). Thus, social media comments could at the same time improve the *overall* price informativeness with respect to firm fundamentals. One interpretation for the increased informativeness of stock prices with respect to fundamentals is a smaller measurement error in Tobin's q for capturing investment opportunities. Erickson and Whited [2000] and Gomes [2001] suggest that, in the absence of financing friction, a lower measurement error in Tobin's q in capturing investment opportunities results in a *higher* sensitivity of investment to stock prices.

Therefore, in theory, it is ex ante uncertain whether social media presence and follower engagement increase or decrease the sensitivity of corporate investment to stock prices. Empirically, as Twitter is arguably the social media platform most widely used by firms (Jung et al. [2018]), we use Twitter presence as a proxy for the overall social media presence and data from official Twitter accounts as a proxy for the overall feedback provided by followers on social media. Jung et al. [2018] find that 47 percent of S&P 1500 firms use Twitter whereas only 44 percent use Facebook and conclude that Twitter has become the preferred social media platform for companies. We hand collected the year and quarter in which a firm initiates its official Twitter account. The first variable of interest, social media presence (*PRESENCE*), is defined as 1 if the firm-quarter observation is after the initiation of its official Twitter account and 0 otherwise. Conditional on the initiation of corporate Twitter accounts, when a firm tweets, a follower may choose to provide feedback by liking, retweeting, or replying to the tweet. Follower engagement captures the follower *response rate* to a firm's given tweet. Follower engagement is measured as the total number of followers' responses (including retweets, likes, and replies) divided by the total number of firm-initiated tweets in a given quarter. In addition to the volume of follower engagement, we also capture the valence of follower engagement, which is measured as the ratio of the number of customer tweets that convey a positive assessment of products and brands over the number of customer tweets that convey a non-neutral (either positive or negative) assessment of products and brands in a given quarter. We use a comprehensive dataset of 366 million followers' responses (including replies, retweets, and likes) disseminated on the official corporate Twitter accounts of 2,065 firms during the period from 2006 to 2017. Utilizing the staggered adoption of official Twitter accounts, the baseline results suggest that corporate investment (as measured by capital expenditure) is less sensitive to stock prices after the initiation of Twitter presence.

We argue that the feedback effect of social media on corporate investment works through at least two channels. The first channel is that managers could learn *new* insights from social media presence and follower engagement that are useful for forecasting future demand and estimating returns to investment projects. We make three distinct predictions via the hypothesized managerial learning channel. First, the managerial learning channel implies that the feedback effect is greater when social media comments are more informative. Accordingly, we make the cross-sectional prediction that more informative social media signals are associated with a lower investment-to-stock price sensitivity. Comparatively, the more engaged the followers, the more *"wisdom of crowds"* of followers, the more likely managers are to learn *new* insights about potential investment opportunities. Furthermore, as Twitter is largely a social platform for leisure rather than business activities, individual consumers are more likely to share their product experience on Twitter than are business clients (e.g., Tang [2018]). Accordingly, follower engagement, especially customer comments, is more informative for investment decisions in consumer-facing companies than for non–consumer-facing companies. Empirically, we find evidence that the investment-stock price sensitivity is lower when social media signals are more informative, as in the case of more engaged followers and consumer-facing companies.

Second, the condition for the managerial learning channel is that managers learn *new* insights from social media that are above and beyond private information incorporated in stock prices. To substantiate the condition for managerial learning, we predict that managers could learn ***new*** insights about the demand for the firm's products and services from social media, which are useful for identifying specific investment opportunities. For instance, Tang [2018] suggests that comments from customers, one subset of followers on social media, is a leading indicator of revenue and unexpected revenue growth, suggesting that follower engagement, *aggregated* at the firm level, captures upcoming demand for a firm's products and services. Empirically, we find that, after the initiation of Twitter presence, management forecasts of sales, which reflects managers' forecasted demand for a company's products and services, is more accurate after controlling for stock returns and other information sources. The positive association between Twitter presence and management forecast accuracy provides *direct* evidence that social media provides some information that is not already known to managers and thus lends more support to the hypothesis that managers learn new insights from social media and improve their forecasts of future demand.

Third, the managerial learning channel also suggests that managers' forecasts of future demand are influenced not only by the informative-ness of social media signals and but also by the *valence* of follower engagement. For instance, one of the advantages of Twitter information is that managers could learn from customer engagement about future demand. Tang [2018] finds that customer comments on social media are more informative in predicting revenue growth and unexpected revenue growth for consumer-facing (business-to-consumer) companies than non–consumer-facing (business-to-business) companies. We make the *directional* prediction that managers revise sales forecasts upward (downward) in response to more positive (negative) follower engagement on social media, especially for consumer-facing companies. Empirically, we aggregate customer comments about a firm's products and services on Twitter at the firm level and find that managers in consumer-facing companies revise sales forecasts upwards (downwards) in response to improving (deteriorating) customer sentiments. However, there is largely no management forecast revision in response to the change in the valence of follower engagement for business-to-business companies possibly because the tweets are not representative of the broad customer response to the borrower's products and brands for non-consumer-facing companies.

The second channel underlying the feedback effect is that social media presence and follower engagement could potentially discipline managers against investments motivated by private benefits. Social media presence and follower engagement activate real-time and constant monitoring of managers from a broader set of followers (including investors) and constrain managers from agency-induced inefficiencies in investment decisions. While follower engagement can reveal information about both positive and negative investment prospects, there is an asymmetric misalignment of incentives between managers and investors when businesses are underperforming compared to when they are performing well. Agency problems, which result from the separation of ownership and control, induce empire building or overinvestment of free cash flow (Jensen [1986]; Harford [1999]; Bates [2005]; Richardson [2006]). Furthermore, concerns about reputation and reluctance to take action (i.e., the quiet life hypothesis) hinder the manager's discontinuation of underperforming businesses (Kanodia et al. [1989]; Boot [1992]; Bertrand and Mullainathan [2003]). Empire building tendencies and the reluctance to divest underperforming businesses are more problematic when those businesses are underperforming. This is because the optimal firm response is to curtail investment when investment opportunities are declining, but managers' incentives to empire building instead of closing businesses (i.e., reputation and the quiet life) are misaligned with shareholders' interest.

Following Wurgler [2000] and Zhu [2019], we define investment efficiency as the investment's responsiveness to investment opportunities. Firms increase investment when investment opportunities are expanding, and conversely decrease investment when investment opportunities are declining. Given that the misalignment of managerial incentives with those of shareholders is more severe when investment opportunities are deteriorating, the hypothesized governance channel yields the distinct prediction that investment is more responsive to deteriorating investment opportunities than to improving investment opportunities. Empirically, we find that social media presence and follower engagement are associated with a greater sensitivity of investment to deteriorating investment opportunities as measured by more negative follower engagement in the industry. The asymmetric effect of the valence of follower engagement on investment suggests that social media helps discipline corporate managers and mitigate agency-induced inefficiency in investment decisions.

In summary, the set of results collectively suggest that social media presence and follower engagement have a feedback effect on corporate investment through both the learning channel and the governance channel. This study contributes to multiple strands of literature. First, to the best of our knowledge, this is the first study to provide systematic evidence on the *feedback* effect of social media on corporate investment decisions. This study provides direct evidence that managers learn new insights from a broader set of followers on social media about future demand that are above and beyond private information incorporated in stock prices and thus rely less on stock prices for identifying potential investment opportunities. The feedback effect of social media presence and follower engagement on corporate investment is related to but distinct from that of stock prices on corporate investment decisions (e.g., Luo [2005]; Bond, Edmans, and Goldstein [2012]; Chen, Goldstein, and Jiang [2007]; Bakke and Whited [2010]). Accordingly, in terms of the scope of outsiders from whom managers can learn additional insights from, this study expands the scope from investors *in* the trading process to a broader set of followers on social media, some of whom fall *outside* of the trading process.

Second, this paper contributes to the literature on social media. There is virtually no evidence on whether social media presence benefits the firm itself beyond the dissemination of information in a timely manner (e.g., Blankespoor, Miller, and White [2014]; Jung et al. [2018]; Lee, Hutton, and Shu [2015]). Rather than emphasizing the dissemination effect of social media, this study examines the feedback effect of social media presence and engagement on *corporate* investment decisions. While prior studies provide evidence on the value of comments on social media and the internet for *financial* investment decisions (e.g., Huang [2018]; Bartov, Faurel, and Mohanram [2018]), there is virtually no evidence on the value of those comments with respect to *corporate* investment decisions. Accordingly, this study is the first to document the *real* effect of the wisdom of crowds on social media in terms of its value for corporate investment decisions.

Third, this study contributes to the emerging literature on the governance role of alternative data. Alternative data are defined as data sets that are “not from a financial statement or report” (Quinlan and Associates 2017). Prior studies have examined the effect of financial reporting choices and regulation on investment efficiency (e.g., Biddle and Hilary [2006]; Hope and Thomas [2008]; Biddle et al. [2009]; Bushman et al. [2011]; Shroff et al. [2014]). In contrast, this study examines the effect of the volume and valence of follower engagement, which are distinct from financial reporting choices and regulatory changes, on the manager's actions. We find that social media presence and follower engagement are associated with a greater sensitivity of investment to deteriorating investment opportunities than to improving investment opportunities. The finding suggests that social media helps discipline corporate managers and mitigate agency-induced inefficiencies in capital expenditure and R&D decisions. Therefore, the findings from this study adds new empirical evidence to the governance role of alternative data as in Zhu [2019] and Ang, Hsu, Tang and Wu [2020].

Fourth, the findings that social media presence and engagement have a real effect on corporate investment has implications for policies on social media. For instance, on November 5, 2015, the SEC issued an updated investor alert to warn investors about false or misleading information on social media. The SEC also took enforcement actions against individuals for tweeting false and misleading information on social media[2] and for failing to disclose the compensation for touting stocks.[3] The feedback effect of social media presence and engagement on corporate investment decisions provides another rationale for regulators, such as the SEC, to tighten up the regulation of social media platforms to mitigate manipulation of information and ensure the reliability of information on social media.

1. Hypothesis development and related literature

Rather than the *dissemination* effect of social media emphasized in prior studies, this study examines the *feedback* effect of social media presence and engagement for corporate investment decisions. Social media provides a centralized platform for followers, including consumers, investors, competitors, and other interested parties, to comment and express their opinions. Given the literature on learning from market prices, we investigate whether the introduction of social media opens new dimensions into the real effect of information.

[2] Press Release, Securities and Exchange Commission, SEC Charges: False Tweets Sent Two Stocks Reeling in Market Manipulation (Nov. 5, 2015), https://www.sec.gov/news/pressrelease/2015-254.html.
[3] Securities and Exchange Commission, Litigation Release No. 21580, Securities and Exchange Commission v. McKeown (June 29, 2010), https://www.sec.gov/litigation/litreleases/2010/lr21580.htm.

First, we hypothesize that one channel through which social media presence and engagement could have a real effect on corporate investment decisions is *managerial learning*. While managers know best many aspects of their own firms, there are dimensions on which they could gain insights from *outsiders*. The condition for managerial learning is that followers on social media possess some *new* information that managers do not have. Social media provides a centralized platform for followers to comment and express their opinions. Many companies carry thousands and even millions of followers on social media. For instance, on Twitter, Google has over 19 million followers, Starbucks has over 11 million, and Target has over 1.9 million. Accordingly, social media presence and follower engagement could potentially provide *additional "wisdom of crowds"* of outsiders about market trends, product demand shocks, the competitive landscape, and investment opportunities.

The hypothesized managerial learning channel implies an interesting *interplay* between social media and other signals managers receive, such as stock prices, in influencing corporate investment. Prior literature suggest that managers learn *private* information from stock prices and incorporate such information in investment decisions (e.g., Bond, Edmans, and Goldstein [2012]; Chen et al. [2006]). We highlight two features of social media presence and follower engagement that could provide *additional* insights for investment decisions. First, social media presence and follower engagement could provide *more granular information* for investment decisions. For instance, a new trend in the lodging industry is that more capital expenditure decisions depend on social media comments about the condition, amenities, and services of a *particular* property and thus the needs of *individual* hotels rather than on brand standards (Hanson and Quadri-Felitti [2016]). Some executives in the lodging industry even suggested they have made additional investments in carpeting, high-speed Internet and remodeled lobbies in response to complaints and compliments on social media (*Los Angeles Times*, Oct. 4, 2015). Granular nature of social media signals underscore one of the differences between managerial learning from social media versus learning from stock prices. Stock prices communicate private information through the trading process and capture investors' *composite* information about all aspects of a given firm. It is difficult to pinpoint exactly what specific information a stock price movement conveys. For instance, a stock price run-up (drop) could indicate investors' satisfaction (dissatisfaction) with the firm's operations, or with the management team, or with products or services, or all of the above. Social media, on the other hand, provides a centralized platform for followers to communicate *directly* with the company and thus it is easy for managers to identify *who* has communicated and *what* specific information a follower comment conveys. Using built-in tools like Hootsuite Geo-Search on Twitter, managers can analyze follower engagement based on the locations where followers posted comments or based on the product lines about which followers commented. Accordingly, location-by-location or product-by-product follower feedback helps identifying over-performing versus underperforming product lines or geographic regions, which provides additional granular insights in picking up specific investment opportunities.

Second, social media presence and follower engagement could aggregate "wisdom-of-crowds" of a *broader* set of outsiders, including customers, investors, and competitors, for investment decisions. The feature that a subset of social media followers fall outside of the trading process underscores another difference between managerial learning from social media versus managerial learning from stock prices. The idea behind the theory of managerial learning from stock prices is that stock prices *aggregate* information from different market participants *in the trading process* who do not have channels for communication directly with the firm. While stock prices aggregate private information of investors that fall with*in* the trading process, social media platforms aggregate "wisdom-of-crowds" of a broader set of followers who have communicated directly with the firm. The broader set of social media followers include customers, investors, and competitors, some of whom fall within the trading process and others fall outside of the trading process. Accordingly, social media provides a centralized platform for managers to learn additional insights from a broader set of outsiders that communicate directly with the company but fall either within or outside the trading process.

In summary, social media provides an *alternative* information source for managers to learn new granular insights from a broader set of outsiders that are useful for identifying specific investment opportunities and evaluating industry trends. Accordingly, with the presence of social media, managers could rely less on stock prices, which aggregates private information of investors in the trading process, and rely somewhat on social media comments, which provides granular information from a broader set of followers, to obtain information about investment opportunities. The presence of social media as an alternative information source could imply a *reduced* managerial reliance on stock prices to obtain new information about investment profitability, implying a *lower* sensitivity of corporate investment to stock prices.

However, private information is incorporated in stock prices with a money stake, whereas follower engagement is largely voluntary and unverifiable without any skin in the game. As there is no money stake involved when followers of a social media platform provide their comments and feedback, there are serious concerns about the reliability and credibility of follower engagement. Followers of a firm's social media platform could lack either "the incentive to provide truthful information" or "the expertise to evaluate products" (e.g., Huang [2018]). Exacerbating the credibility issue further, followers' identities could be fabricated and the sentiments of tweets could be manipulated (Luca and Zervas [2016]). For instance, Twitter reportedly suspended more than 70 million accounts flagged as trolls and bots in 2018 (*Washington Post*, July 6, 2018). Thus, out of serious concerns about the quality and credibility of follower engagement, it is also possible that managers do *not* adjust investment decisions in response to follower engagement, implying *no change* in the sensitivity of corporate investment to stock prices.

A further complication is that while managers obtain granular signals *directly* from social media, investors *also* see the same information about the company on social media. Prior studies find that consumer opinions contain novel information about firms' fundamentals and thus make stock prices more informative with respect to future fundamentals (e.g., Fornell, Morgeson, and Hult [2016]; Huang [2018]). Thus, social media comments could potentially improve the *overall* informative-ness of stock prices about future fundamentals. One interpretation for the increased informative-ness of stock prices with respect to fundamentals is a smaller measurement error in Tobin's q for capturing investment opportunities. Erickson and Whited [2000] and Gomes [2001] suggest that, in the absence of financing friction, a lower measurement error in Tobin's q in capturing investment opportunities results in a *higher* sensitivity of investment to stock prices.

Accordingly, it is ex ante uncertain whether social media presence and follower engagement increase or decrease the sensitivity of corporate investment to stock prices.[4] We hypothesize that social media provides an alternative information source for managers to learn *granular* signals from a *broader* set of followers, and therefore, is likely to provide *new* insights useful for identifying specific investment opportunities that are above and beyond private information incorporated in stock prices. Accordingly, the sensitivity of investment to stock prices is likely to be lower once a firm initiates a presence on Twitter because social media provides a centralized platform for managers to learn *new* insights that are useful for investment decisions. This leads to the first hypothesis:

H1: Corporate investment is less sensitive to stock prices after the initiation of Twitter presence.

The condition for the managerial learning channel is that managers learn *new* insights from social media and use it in investment decisions. To substantiate the condition, we hypothesize that managers could learn ***new*** insights about the demand for the firm's products and market trends from social media, which are useful for identifying specific investment opportunities. Follower engagement on social media provide *granular and real-time* signals about the demand for the firm's products and market trends. For instance, customers, as one key constituent of followers on social media, could provide a wealth of insights beyond those of managers—including key market trends and demand for products and brands in real time. When discussing Kia's R&D shift to seat comfort in response to social media chats, Michael Sprague, vice president of Kia Motors America, explained that with social media, "you can have a focus group of a hundred or a thousand people versus 10 or 20" and "you can do it almost in real-time. And for an automotive company to do something that quickly is almost unheard of". Social media engagement provides information about future demand relating to assets in place or expected future investment opportunities. With respect to assets in place, social media engagement might reveal granular and timely information about which businesses are declining. With respect to investment opportunities, alternative data might

[4] This implies that social media presence and comments could increase the informative-ness of stock prices about future fundamentals (i.e., forecasting efficiency), but decrease the usefulness of stock prices for investment decisions (i.e., real efficiency).

reveal superior information about which businesses to expand. For instance, one of the advantages of Twitter information is that managers could learn more about demand on a location-by-location or on a product-by-product basis. Accordingly, after the initiation of Twitter presence, the availability of new insights from social media enables a more accurate forecast of sales that reflects managers' forecasted demand for a company's products and services. This leads to the second hypothesis:

H2: Management forecasts of future demand is more accurate after the initiation of Twitter presence.

If the feedback effect of social media on investment decisions works through the hypothesized managerial learning channel, learning models would also predict a more pronounced feedback effect when follower engagement is more informative. After the initiation of corporate Twitter accounts, firms use social media to disseminate information and to introduce and advertise their products and services. Followers on Twitter respond to firm-initiated tweets with likes, retweets, and replies. There is a significant cross-sectional variation in the extent of follower engagement on social media. First, many companies carry thousands and even millions of followers on social media, while others have rather limited number of followers. For instance, in sharp contrast to Google and Starbucks that have over 19 million and 14 million followers respectively, BWX Technologies and Penske have around 1,900 and 4,000 followers only. Second, conditional on the number of followers, followers in some companies respond actively to firm-initiated tweets and/or initiate their own tweets, but are less engaged in others. For instance, followers of Google and Starbucks respond 85 times and 63 times respectively per one company-initiated tweet, whereas one company-initiated tweet only triggers, on average, two responses from followers of Golden Enterprises. The more engaged the followers, the more *"wisdom of crowds"* of outsiders about investment opportunities, the more likely managers are to learn *new* insights from follower engagement, the lower sensitivity of investment to stock prices.

Furthermore, as Twitter is largely a social platform for leisure rather than business activities, individual consumers are more likely to share their product experience on Twitter than are business clients (e.g., Tang [2018]). Accordingly, follower engagement, especially customer comments, is more informative for investment decisions in consumer-facing companies than for non–consumer-facing companies. As follower engagement is more informative for consumer-facing companies, the reduction in investment-stock price sensitivity is likely to be greater for consumer-facing companies than for non–consumer-facing companies. In summary, this leads to the third hypothesis on the cross-sectional variation in the managerial learning effect:

H3a: The more engaged the followers, the lower the investment-stock price sensitivity.
H3b: Social media presence and follower engagement are associated with a greater reduction in investment-stock price sensitivity for consumer-facing companies.

Moreover, the hypothesized managerial learning channel suggests that, in addition to the availability and informative-ness of social media signals, the *valence* of follower engagement also affect managers' forecasts of future demand. In particular, if managers learn new insights from follower engagement, managers will update their beliefs about demand for the company's products and services in the *direction* that the valence of follower engagement indicates. Tang [2018] finds that the valence of customer comments, a substantial subset of followers on social media, is a leading indicator of revenue and unexpected revenue growth. The finding suggests that customer engagement, *aggregated* at the firm level, captures upcoming demand for a firm's products and services. The predicative power of the valence of customer comments with respect to revenue comes from two sources: first, it is a broad indicator of customer satisfactions, which provides new insights about future demand; second, firms use social media to introduce and advertise their new products and to strengthen customer loyalty. Therefore, in addition to learning about future demand, customer engagement may have a *direct* influence on consumers' demand for their products. More positive customer comments could generate additional demand for the company's products and services due to "word-of-mouth" effect (Tang [2018]). Accordingly, more positive customer sentiment implies a higher demand for a company's products and services. Therefore, the managerial learning channel yields the *directional* prediction that managers revise sales forecasts upwards (downwards) in response to more positive (negative) customer engagement on social media.

Furthermore, Tang [2018] finds that customer comments on social media are more informative in predicting revenue growth and unexpected revenue growth for consumer-facing (business-to-consumer) companies than non–consumer-facing (business-to-business) companies. This is largely because the ability of customer engagement on Twitter to reflect future demand depends on whether the customer tweets are representative of the broad customer response to the company's products and brands. As the customer base of a consumer-facing company consists predominantly of individual consumers, its representative customer is an individual consumer, who are likely to comment on products and services on Twitter. In contrast, as the customer base of a non-consumer facing company consists predominantly of business clients, its representative customer is another business entity, who is less likely to comment on products and services on Twitter. Therefore, we expect that the revision of management forecast of future demand in response to customer engagement is largely concentrated in consuming-facing companies. This leads to the directional hypothesis that managers revise forecasts of future demand in response to the *valence* of customer engagement:

H4: Managers in consumer-facing companies revise sales forecasts upward (downward) in response to more positive (negative) customer engagement.

Next, we hypothesize the disciplining effect of social media presence and follower engagement on investment decisions as the second channel underlying the feedback effect of social media. Social media presence and follower engagement could potentially discipline corporate managers and mitigate agency-driven investment distortions. Social media presence and follower engagement activate real-time and constant monitoring of managers from a broader set of followers (including investors) and discipline managers against investment that are motivated by private benefits. Follower engagement provides granular and timely information relating to assets in place or expected future investment opportunities. With respect to assets in place, follower engagement might reveal information about which businesses are declining. With respect to investment opportunities, follower engagement might reveal granular information about which businesses to expand. For instance, one of the advantages of Twitter information is that managers could learn more about future demand on a location-by-location or on a product-by-product basis. Therefore, granular signals on social media can reveal which product lines or geographic regions are performing better and which are performing worse. Thus, follower engagement reveals into which business the firm should expand investment and into which business should contract investment.

While social media engagement can reveal information about both positive and negative performance, there is an asymmetric misalignment of incentives between managers and investors when businesses are underperforming compared to when they are performing well. Agency problems, which result from the separation of ownership and control, induce empire building or overinvestment of free cash flow (Jensen [1986]; Harford [1999]; Bates [2005]; Richardson [2006]). Furthermore, concerns about reputation and reluctance to take action (i.e., the quiet life hypothesis) hinder the manager's discontinuation of underperforming businesses (Kanodia et al. [1989]; Boot [1992]; Bertrand and Mullainathan [2003]). Empire building tendencies and the reluctance to divest underperforming businesses are more problematic when those businesses are underperforming. This is because the optimal firm response is to curtail investment when investment opportunities are declining, but managers' incentives to empire building instead of closing businesses (i.e., reputation and the quiet life) are misaligned with shareholders' interest.

Following Wurgler [2000] and Zhu [2019], we define investment efficiency as the investment's responsiveness to investment opportunities. Firms increase investment when investment opportunities are expanding, and conversely decrease investment when investment opportunities are declining. Given that the misalignment of managerial incentives with those of shareholders is more severe when investment opportunities are deteriorating, we focus on whether social media presence and follower engagement curb investment in areas with declining investment opportunities. In a cross-country study, Wurgler [2000] finds that strong investor rights allow minority investors to exert pressure on managers to keep investment out of declining industries and invest free cash flow efficiently, consistent with Jensen's [1986] free cash flow theory. Similarly, Zhu [2019] finds that the introduction of big data is associated with a greater sensitivity to deteriorating investment opportunities. In the context of M&As, Ang et al. [2020] find that social media comments could discipline managers from taking value-destructive mergers. If social media presence and follower engagement helps discipline corporate managers, the governance channel yields the distinct prediction that investment is more responsive to deteriorating investment opportunities than to improving investment opportunities for firms with social media presence and for firms with more engaged followers. This leads to the hypothesis on the asymmetric effect of the valence of follower engagement on investment:

H5: Social media presence and follower engagement discipline corporate managers, and thus, are associated with a greater sensitivity of investment to deteriorating investment opportunities.

2. Sample, Data, and Baseline Results

2.1 Sample, data, and social media measures

We first explain the sample formation and the data collection process. Firms use various social media platforms such as Twitter, Facebook, Instagram, and YouTube. However, Twitter is arguably the social media platform most widely used by firms (Jung et al. [2018]). We hand collected the year and quarter in which a firm initiates its official Twitter account. The first variable of interest, social media presence (*PRESENCE*), is defined as 1 if the firm-quarter observation is after the initiation of its official Twitter account and 0 otherwise. Conditional on the initiation of corporate Twitter accounts, we use data from official Twitter accounts as a proxy for the overall feedback provided by followers on social media. When a firm tweets, a follower may choose to provide feedback by liking, retweeting, or replying to the tweet. Many firms carry thousands and even millions of followers on Twitter and, therefore, follower feedback, in aggregate, may provide some new insights to managers that are useful for investment decisions. We use a comprehensive dataset of firm-initiated tweets and the likes, retweets, and replies associated with these tweets collected from the official Twitter accounts of all U.S. firms listed on the New York Stock Exchange, the American Stock Exchange, and NASDAQ.[5] The second variable of interest, *ENGAGEMENT*, captures the follower *response rate* to a firm's given tweet. To account for the fact that the number of followers' responses increases in the number of firm-initiated tweets, *ENGAGEMENT* is measured as the total number of followers' responses divided by the total number of firm-initiated tweets in a given quarter. The total number of followers' responses sums up the number of followers' retweets, the number of followers' likes, and the number of followers' replies.

[5] We employ the same dataset of firm-initiated tweets and the associated follower responses as the one used by Hosseini et al. [2020]. They collect firm-initiated tweets and the corresponding responses using a combination of "Stream API 2.0" and direct purchase from GNIP (the official Twitter vendor). We are thankful to them for sharing the data with us.

We collect financial data, including capital expenditure and R&D expense, from Compustat and stock returns data from CRSP. We remove financial service firms from the sample because their investment decisions are distinct from non-financial firms. As the empirical test compares a firm's investment decisions before and after it initiates an official Twitter account, the sample excludes firms that have no official Twitter accounts during the entire sample period from 2006 to 2017. As shown in table 1A, the final sample comprises 75,484 firm-quarter observations for 2,065 unique Tweeting publicly traded firms from 2006 to 2017. The sample covers 366 million Twitter responses from followers—202 million likes, 131 million retweets, and 33 million replies—in response to 17.1 million firm-initiated tweets. As illustrated by figure 1, there is an increasing trend of Twitter presence over the sample period for all firms and for firms included in the sample as well. Conditional on the initiation of an official Twitter account, panel B of table 1 provides descriptive statistics on follower engagement. On average, a firm tweets 365 times and followers engage 7,819 times with firm-initiated tweets in a given quarter.[6] The mean follower response rate (*ENGAGEMENT*) is 11.3 and the median follower response rate is 4. The standard deviation in *ENGAGEMENT* is 97.70, which is about eight and half times the mean value. As illustrated in figure 2, we take the natural log of *ENGAGEMENT* in the regression analysis to accommodate the power law distribution. Table 2 provides descriptive statistics of key variables and panels A and B of table 3 present the correlation between the dependent and explanatory variables. To mitigate the influence of outliers, we winsorize all continuous variables at the 1 percent and 99 percent levels. All variables are defined in appendix A.

The third variable, *VALENCE_ENGAGEMENT*, captures the valence of follower engagement. We make use of comments that *customers* make on Twitter about products and brands to proxy for the valence of follower engagement for two major reasons. First, in addition to disseminating information on social media, firms also use social media to introduce and advertise their products and services. Therefore,

[6] In aggregate, we also find an increasing trend for both the number of firm-initiated tweets and the number of follower responses —from 722 (2,945) firm-initiated tweets (follower responses) in 2007 to 3.09 million (123 million) firm-initiated tweets (follower responses) in 2017.

customers are an integral part of followers on social media. Second, this study hypothesizes that managers could learn ***new*** insights about the demand for the firm's products and market trends from social media, which are useful for identifying specific investment opportunities. Customers are the origin and source of demand for a firm's products and services (e.g., Petusevsky [2010]; Tang [2018]; Walker [1990]; Webster [1994]).

Customer engagement data comes from LikeFolio.com, a professional data analytics outfit that sells data and insights to professional investors, corporate research teams, and software providers.[7] We are able to achieve a significant level of product information aggregation[8] via the data provider's use of proprietary information to map several products and brands to companies that offer them—a process that is challenging if applied to alternative social media platforms (e.g., Google+, Amazon, Yelp). Twitter user accounts have unique, comprehensive features that data scientists, including LikeFolio.com (our data provider), can exploit in developing bot detection algorithms that purge 'fake' tweets, consequently making the valence of customer engagement more credible. Following Tang (2018), *VALENCE_ENGAGEMENT* is measured as the ratio of the number of customer tweets that convey a positive assessment of products and brands over the number of customer tweets that convey a non-neutral (either positive or negative) assessment of products and brands. The dataset on the valence of customer engagement covers 1,391 firms with 10,668 firm- quarter observations over the 2012–2015 period and 796 of these firms have official twitter accounts. After merging with the final sample, the subsample with available data on the valence of customer engagement comprises 5,593 firm-quarters for 610 unique Tweeting publicly traded firms from 2012 to 2015.

2.2. Research design on the relation between social media presence and corporate investment

The study investigates the feedback effect of social media on investment by first investigating whether and how social media interacts with other signals managers receive, such as stock prices, in influencing

[7] Some of LikeFolio's activities have been covered by popular finance news media (see, e.g., articles in CNN Money, NBC News, Yahoo Finance) and they run an app in their name on the Apple App Store and Google Play.
[8] For regressions using firm-period observations, product- or brand-level comments should be aggregated at the firm level, as individual firms are likely to have multiple products or brands.

corporate investment. Following Malmendier and Tate [2005], we use the equation to estimate the association between social media presence and the sensitivity of investment to stock prices:

$$CAPEX_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 TWEET\_VARIABLE}_{\,i,t+1} + \boldsymbol{\beta_2 TWEET\_VARIABLE}_{\,i,t+1} \boldsymbol{* \; TOBIN'SQ_{i,t+1}} + \beta_3 \mathrm{TOBIN'SQ}_{i,t+1} + \sum \beta_n CONTROL\ VARIABLES_{i,t+1} + \sum FIRM_i + \sum TIME_{t+1} + \varepsilon_{i,t+1} \quad (1)$$

where *CAPEX* is the capital expenditure scaled by the previous quarter end's property plant and equipment. Following Malmendier and Tate [2005], Tobin's q, cash flow, and size are included as the explanatory variables. *TOBIN'SQ* is defined as the ratio of market value of assets over book value of assets, which capture stock prices.[9] Additionally, as suggested by prior literature, we also include tangibility, firm age, and advertising expense as additional control variables (Chen et al. [2011]; Tang [2018])[10]. We use firm and time (year-quarter) fixed-effects. The tweet variables are Twitter presence (*PRESENCE*) and follower engagement (*ENGAGEMENT*). The variables of interest are the interaction between the tweet variables and Tobin's q. The first hypothesis predicts that the slope coefficient on the interaction between *PRESENCE* and *TOBIN'SQ* (β_2) is negative if corporate investment becomes less sensitive to stock prices after the initiation of Twitter presence.

2.3. Baseline results on the relation between social media presence and corporate investment

Table 4 presents the results for the sample of all Twitter firms. As shown in column 1, the variable of interest, the slope coefficient on the interaction between *PRESENCE* with *TOBIN'SQ*, is negative and statistically significant at the 1% level. The lower sensitivity of investment to stock prices is consistent with the first hypothesis. In economic magnitude, the sensitivity of investment to stock prices is lower by 43.2% when a firm has a presence on Twitter compared to that when it does not. The baseline result suggests that while social media information may have been incorporated into stock prices and improve the overall informative-ness of stock prices with respect to fundamentals, managers could learn *new* insights useful for

[9] We follow Chen, Goldstein, and Jiang [2007] and calculate the market value of assets as the sum of market value of equity plus book value of assets minus the book value of equity.
[10] Compustat reports only the annual advertising expenses of firms. We assume that the advertising expenses are incurred uniformly across all four quarters and, therefore, calculate the quarterly advertising expenses by dividing the annual advertising expenses by four.

investment decisions directly from social media presence that are above and beyond private information incorporated in stock prices. This results in a lower sensitivity of investment to stock prices. It is noteworthy that the slope coefficient on *PRESENCE* is positive and statistically significant at the 1% level, suggesting that firms with social media presence tend to invest more on average. When we include other information sources, including press releases, media coverage, and analyst coverage, as additional control variables, the results are quantitatively and qualitatively similar as shown in column 2.

By the same logic, it is also possible that managers learn new insights from social media and incorporate the new information in making research and development expense decisions. Therefore, we use the sum of capital expenditure and R&D expenses scaled by last quarter end's property plant and equipment as the dependent variable in columns 3. We again find that the slope coefficient on interaction between *PRESENCE* and *TOBIN'SQ* is negative and significant at the 1% level. The results are robust to the inclusion of other information sources as shown in column 4.

2.4. Cross-sectional variation on the relation between social media and investment

As presented in column 1 of panel A of table 5, the slope coefficient on the interaction between *LOG (ENGAGEMENT)* and *TOBIN'SQ* is also negative and statistically significant at the 1% level. In terms of economic significance, a one-standard-deviation increase in *LOG (ENGAGEMENT)* is associated with 86.3% (3.373*(-0.256) = -0.863) decrease in the sensitivity of capital expenditure to stock prices.[11] Similarly, as shown in column 2, when the dependent variable is the sum of capital expenditure and R&D expenses, the slope coefficient on the interaction between *LOG (ENGAGEMENT)* and *TOBIN'SQ* is also negative and statistically significant at the 1% level. The results from panel A of table 5 suggest that the more engaged the followers are, the lower is the investment-stock price sensitivity.

As follower engagement, especially customer engagement, is more informative for consumer-facing companies, the reduction in the sensitivity of investment to stock is hypothesized to be greater for consumer-facing (business-to-consumer) companies. As presented in panel B of table 5, we include an

[11] The standard deviation of *LOG(ENGAGEMENT)* is 3.373.

indicator variable, B2C, for business-to-consumer companies, and the interaction term *TWEET_VARIABLE * TOBIN'SQ*B2C* in equation (1).[12] As shown in the first column, the slope coefficient on *PRESENCE * TOBIN'SQ * B2C* is -0.467 and statistically significant at the 1% level, which suggests that B2C firms with social media presence have a significantly lower sensitivity of investment to stock prices than non-B2C firms. Similarly, in column 2, the slope coefficient on *LOG (ENGAGEMENT)* TOBIN'SQ * B2C* is -0.268 and statistically significant at the 1% level. These results provide evidence in support of the hypothesis that social media presence and follower engagement are associated with a greater reduction in investment-stock price sensitivity for business-to-consumer firms.

Column 3 and column 4 of panel B of table 5 report the results for the subsample analysis of business-to-consumer (B2C) firms and column 5 and column 6 report the results for the subsample analysis of business-to-business (B2B) firms. The subsample results are largely consistent with the results for the entire sample. For instance, while the slope coefficient on the interaction term between social media presence (follower engagement) and *TOBIN'SQ* is negative for both subsamples, the slope coefficient on the interaction term is *more negative* for B2C firms than for B2B firms. For instance, the slope coefficient on *PRESENCE*TOBIN'SQ* is -1.837 for the B2C subsample but -0.361 for the B2B subsample. Similarly, the slope coefficient on *LOG (ENGAGEMENT)*TOBINS'Q* is -0.431 for the B2C subsample but -0.219 for the B2B subsample.

3. Substantiate managerial learning as one underlying channel for the feedback effect

This section substantiates managerial learning as one underlying channel for the feedback effect of social media by examining whether social media presence is associated with the ability of managers to forecast future demand more accurately and examining whether managers revise the forecast of future demand in the direction in which the valence of follower engagement indicates.

3.1. Social media presence and accuracy of management forecasts of sales

[12] We do not use firm fixed-effects for the empirical analysis for the first two columns in Table 5B because otherwise the variable B2C will be perfectly collinear with the firm fixed-effects.

We use the following equation to estimate whether social media presence enables managers to learn additional insights about future demand and thus make more accurate forecasts of future sales:

$$|MFE|_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 PRESENCE_{i,t+1}} + \sum\beta_n CONTROL\ VARIABLES_{i,t+1} + \sum INDUSTRY_j + \sum TIME_{t+1} + \varepsilon_{i,t+1} \quad (2a)$$

where |*MFE*| is the absolute difference between the most recent quarterly management sales forecast and the actual sales scaled by previous quarter end's total assets. We require that the sales forecast be issued at least seven days before the earnings announcement date.[13] The number of observations used for estimating equation2a is drastically lower than that used in equation1because only 19% of the sample firms provide management forecast of future sales. Following Goodman et al. [2014], we use sales forecast precision, Tobin's q, size, return on assets, leverage, stock return, stock return volatility, cash flow volatility, and sales growth as control variables[14]. All the explanatory variables, including the variables of interest, are contemporaneous variables. We use Fama-French 48 industry and time (year-quarter) fixed-effects and cluster standard errors by firm. The variable of interest is the slope coefficient on Twitter presence. We predict that β_1, the slope coefficient on *PRESENCE*, is negative if managers learn new insights about future demand from social media and follower comments improve the accuracy of management sales forecast.

Table 6 presents the results on social media presence and managerial learning as proxied by the absolute value of the sales forecast error. If managers gain additional insights about future demand by paying attention to the followers' responses on the firms' social media platforms, they should be able to make more accurate estimates of future demand, as proxied by managers' forecast of sales. The first column presents the results of social media presence on sales forecast accuracy without controls. We exploit the staggered adoption of corporate Twitter accounts by different firms at different times and find that Twitter presence is associated with improved sales forecast accuracy by the managers. Specifically, we find that, after controlling for industry and time fixed-effects, the sales forecast is more accurate, as evident from a

[13] Goodman et al. [2014] use annual management forecasts and require that the forecasts be issued at least three weeks before the earnings announcement date. Our empirical analysis uses quarterly management sales forecasts and, therefore, we require that the forecasts be issued at least one week before the earnings announcement date.

[14] The missing control variables data further reduces the number of observations used in columns 2 and 3 of Table 6.

lower forecast error, *after* the initiation of corporate Twitter accounts compared with that before initiation. The results in column 2 are similar after including control variables that could also affect the management forecast accuracy, such as stock prices. As shown in columns 1 and 2, the slope coefficients on *PRESENCE* are –0.005 and –0.004 and statistically significant at the 1 percent and 5 percent level respectively. To account for the fact that management forecast accuracy could be different for the last quarter of the fiscal year, we include Q4, an indicator variable for the fourth quarter, as an additional control variable. We find that the slope coefficient on *PRESENCE* continues to negative and significant, whereas the slope coefficient on the interaction between *PRESENCE* and *Q4* is negative but not statistically significant. This suggests that the managerial learning from social media does not differ significantly across quarters. It is worth noting that the lower management sales forecast error is robust to control for stock returns.

The effect of social media presence on the accuracy of management forecast is also economically significant. We measure the absolute sales forecast error scaled by lagged total assets. The result in column 1 implies that having presence on Twitter is associated with an improvement of 0.5% of lagged total assets in quarterly sales forecast accuracy compared to when the firm does not have a presence on Twitter. Similarly, the result in column 2 implies that having presence on Twitter is associated with an improvement of 0.4% of lagged total assets in quarterly sales forecast accuracy compared to when the firm does not have a presence on Twitter. The positive association between Twitter presence and management forecast accuracy provides *direct* evidence that social media provides some information that is not already known to managers and thus lends more support to the hypothesis that managers learn new insights from social media and improve their forecasts of future demand that are above and beyond information incorporated in stock prices.

3.2. The valence of follower engagement and management revision of sales forecasts

If managers learn new insights about future demand for the company's products and services from follower engagement, especially customer engagement, managers will update their beliefs about demand for the company's products and services in the direction the valence of follower engagement indicates. Managers may revise upwards (downwards) sales forecasts in response to more positive (negative) customer engagement on social media. Such revision is expected to be more pronounced for consumer-facing firms because customer comments on social media are more informative in predicting sales growth and unexpected sales growth for consumer-facing (business-to-consumer) companies than business-to-business (non–consumer-facing) companies (Tang [2018]). We use the following equation to estimate the association between the change in the valence of customer engagement and management revision of sales forecasts:

$$MF\_SALES\_REVISION_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 CHG\_VALENCE\_ENGAGEMENT_{i,t+1}} + \boldsymbol{\beta_2 CHG\_VALENCE\_ENGAGEMENT_{i,t+1} * B2C} + \beta_3 B2C + \sum \beta_n CONTROL\ VARIABLES_{i,t+1} + \sum INDUSTRY_j + \sum TIME_{t+1} + \varepsilon_{i,t+1} \qquad 2(b)$$

where *MF_SALES_REVISION* is the signed difference between the most recent sales forecast and the previous sales forecast scaled by previous quarter end's total assets . *CHG_VALENCE_ENGAGEMENT* is the change in customer sentiment in the current quarter relative to that in the previous quarter. We use Fama-French 48 industry and time (year-quarter) fixed-effects and cluster standard errors by firm. The variable of interest is the sum of the slope coefficient on *CHG_VALENCE_ENGAGEMENT* ($\beta 1$) and the slope coefficient on *CHG_VALENCE_ENGAGMENT*B2C* (β_2). We predict that the sum of β_1 and β_2 is positive if managers in consumer-facing companies revise upwards (downwards) sales forecasts in response to more positive (negative) customer engagement.

Table 7 presents the results on the valence of follower engagement and managerial learning as proxied by the revision of management forecasts of sales. The dependent variable is the signed difference between the most recent sales forecast and the previous sales forecast, with both sales forecasts made for the current quarter. Notice that the number of observations in column 1 is only 734. This is because there are only 769 firm-quarters for which both sales forecast revisions and the valence of customer engagement are available. Missing control variables data further reduces the number of observations. The first column displays the results for all Twitter firms. As shown in column 1, while the slope coefficients on both *CHG_VALENCE_ENGAGEMENT* and *CHG_VALENCE_ENGAGEMENT* B2C* are positive but statistically insignificant, the sum of the two coefficients is 0.018 and statistically significant with a p-value of 0.059. The positive sum of the two coefficients suggests that managers in B2C firms revise upwards (downwards) in response to more positive (negative) customer sentiment. We perform the same analysis for two subsamples of B2C firms and non-B2C firms respectively. As shown in column 2, the slope coefficient of *CHG_VALENCE_ENGAGEMENT* is 0.019 and statistically significant at the 10% level for the subsample of B2C firms. As shown in column 3, the slope coefficient of *CHG_VALENCE_ENGAGEMENT* is positive but not significant for non-B2C firms. These results imply that the revision of management forecast of future demand in response to customer engagement is largely concentrated in business-to-consumer companies.

4. The disciplining role of social media as the second underlying channel for the feedback effect

Social media presence and follower engagement could potentially serve as an additional monitoring and governance tool, which mitigates agency-driven investment distortions. The valence of follower engagement has an asymmetric effect in curbing investment inefficiencies. Given that the misalignment of managerial incentives with those of shareholders is more severe when investment opportunities are deteriorating, we examine whether social media presence and follower engagement are associated with a greater sensitivity of investment to declining investment opportunities compared with that to improving investment opportunities (Wurgler [2000]; Zhu [2019]). Following Wurgler [2000] and Zhu [2019], we use the following equation to estimate the sensitivity of the change in investment to the change in the valence of follower engagement:

$$LOG(CHANGE\_CAPEX)_{i,t+1}=\beta_0+\beta_1 TWEET\_VARIABLE_{i,t+1}+\beta_2 TWEET\_VARIABLE_{i,t+1}* IND\_CHANGE\_CUSTOMERVALENCE_{i,t+1}+\boldsymbol{\beta_3 TWEET\_VARIABLE_{i,t+1}*IND\_CHANGE\_\_CUSTOMERVALENCE_{i,t+1}*DECLINE_{i,t+1}}+\beta_4\, IND\_CHANGE\_CUSTOMERVALENCE_{i\ i,t+1} +\beta_5\, DECLINE_{i,t+1} + \sum \beta_n CONTROL\ VARIABLES_{i,t+1} + \sum INDUSTRY_j + \varepsilon_{i,t+1} \qquad (3)$$

where *LOG(CHANGE_CAPEX)* is the natural log of the ratio of current *CAPEX* over the previous quarter' *CAPEX*. *CAPEX* is measured as the capital expenditure scaled by previous quarter end's property plant and equipment. The assumption is that the baseline level of investment, which is required to maintaining existing operations and assets, is capital expenditure or capital expenditure plus R&D from the prior quarter.

IND_CHANGE_CUSTOMERVALENCE is the quarterly change in the industry-level customer sentiment, which is calculated as the average quarterly changes in the valence of customer engagement across all firms in a given Fama-French industry. More negative customer sentiment *indicates* deteriorating investment opportunities in the industry, whereas more positive customer sentiment indicates improving investment opportunities in the industry. *DECLINE* is an indicator variable equal to 1 when the change in the valence of customer engagement in the industry is negative and 0 otherwise. As suggested by prior literature, we also use Tobin's q, cash flow, size, tangibility, firm age, and advertising expense as additional controls (Chen et al. [2011]; Tang [2018]; Zhu [2019]). We use Fama-French 48 industry fixed-effects and cluster standard errors by firm. The variable of interest is the slope coefficient on *TWEET_VARIABLE*IND_CHANGE_CUSTOMERVALENCE*DECLINE*. We predict that $\beta_{3,}$ is positive if social media presence and follower engagement are associated with a greater sensitivity of investment in response to declining investment opportunities.

Table 8 presents the results on the governance role of social media. As shown in column 1 and column 2, the dependent variable is the percentage change in capital expenditure. The slope coefficient of *PRESENCE* IND_CHANGE_CUSTOMERVALENCE*DECLINE* is 3.422 and statistically significant at the 1% level. Similarly, the slope coefficient on *LOG(ENGAGEMENT)* IND_CHANGE_CUSTOMERVALENCE *DECLINE is* 2.160 and statistically significant. As shown in column 3 and column 4, the dependent variable is the percentage change in the sum of capital and R&D expenditures and the slope coefficients on the triple interaction term are positive and significant at the 1% level. The results from table 8 suggest that social media presence and follower engagement are associated with a greater sensitivity of investment to deteriorating investment opportunities as measured by more negative customer sentiment in the industry. The asymmetric effect of the valence of follower engagement on investment suggests that social media helps discipline corporate managers and mitigate agency-induced inefficiency in investment decisions.

5. Supplementary analyses

5.1. The usefulness of the components of follower engagement for investment decisions

The followers can respond to firm-initiated tweets by liking, retweeting or replying to them. We examine whether each component of follower engagement contains new information that are useful for managers' investment decisions. We present the results in table 9. As shown in the first three columns, when *CAPEX* is the dependent variable, the slope coefficient on *LOG(REPLIES) *TOBIN'SQ* is -0.103, the slope coefficient on *LOG(LIKES) *TOBIN'SQ* is -0.099, and the slope coefficient on *LOG(RETWEETS)* **TOBIN'SQ* is -0.099. All of the three slope coefficients are statistically significant at the 1% level. Similarly, as shown from column 4 to column 6, when the dependent variable is capital expenditure plus R&D expenses, the slope coefficient on the interaction term between each component of follower engagement (likes, retweets, and replies) and *TOBIN'SQ* is negative and statistically significant. The result from table 10 indicates that managers can learn additional new insights from *each* component of follower engagement and rely less strongly on stock prices for investment decisions.

5.2. Social media, external equity financing, and investment

We interpret the main results as managers learn additional new insights from social media presence and follower engagement, and thus, rely less strongly on stock prices for investment decisions and that social media presence and follower engagement discipline managers against investment motivated by private benefits. In this section, to explore the possibility that social media presence and follower engagement could have implications beyond the learning effect and the disciplining effect, we relate our findings to an alternative explanation for the link between social media and investment.

Baker, Stein, and Wurgler [2003] have shown that financing constraints prevent firms from pursuing their optimal investment plans and that better access to external financing increases investment. We expect that firms with Twitter presence and greater follower engagement could have a better access to external equity financing. To test whether social media could influence corporate investment through alternative channels beyond the documented learning effect and the disciplining effect, we use the following specification:

$$NEW\_EQUITY_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 TWEET\_VARIABLE_{i,t+1} + \beta_2 TWEET\_VARIABLE_{i,t+1} * MEDIAN\_CASH\_FLOW_{i,t+1}} + \boldsymbol{\beta_3\, MEDIAN\_CASH\_FLOW_{i,t+1}} + \sum \beta_n\, CONTROL\ VARIABLES_{\,i,t+1} + \sum INDUSTRY_j + \sum TIME_{t+1} + \varepsilon_{i,t+1} \quad (4a)$$

The dependent variable in equation 4a is the amount of new external equity financing ($NEW\_EQUITY_{i,t+1}$). *MEDIAN_CASH_FLOW* is an indicator variable equal to 1 if the cash flow is greater than the Fama-French 48 industry median. We expect β_1 to be positive as it represents the slope coefficient of firms that are more likely to face cash flow constraints. Panel A of Table 10 presents the results. As shown in column 1 and column 2 respectively, we find a positive and statistically significant β_1 and a negative and statistically significant slope in β_2. The positive slope coefficient on *PRESENCE (ENGAGEMENT)* suggests that social media presence and follower engagement are associated with a greater access to external equity financing for firms that are more likely to be financially constrained. The result indicates that social media presence and follower engagement enable better access to external equity financing for cash-constrained firms. The slope coefficient on PRESENCE(ENGAGEMENT)*MEDIAN_CASHFLOW (β_2) is negative, suggesting that social media presence and follower engagement are associated with a lower level of external equity financing for firms that are less likely to face cash constraints (with above-median cash flows) than firms that are more likely to face cash constraints (with below-median cash flows).

If firms that have social media presence and greater follower engagement have a better access to external equity financing, we expect a lower sensitivity of investment to cash flows. We use the following equation to test whether social media presence and follower engagement are associated with a lower sensitivity of investment to cash flows:

$$CAPEX_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 TWEET\_VARIABLE_{\,i,t+1} + \beta_2 TWEET\_VARIABLE_{\,i,t+1} * \ CASH\_FLOW_{i,t+1}} + \boldsymbol{\beta_3 NEW\_EQUITY_{i,t+1}} + \sum \beta_n CONTROL\ VARIABLES_{i,t+1} + \sum INDUSTRY_j + \sum TIME_{t+1} + \varepsilon_{i,t+1} \quad (4b)$$

Panel B of table 10 presents the results from equation 4b. As shown in column 1, the slope coefficient on *PRESENCE* CASH_FLOW* is -5.075 and statistically significant at the 1% level. Similarly, as shown in column 2, the slope coefficient on *LOG (ENGAGEMENT)* CASH_FLOW* is -5.204 and statistically significant at the 1% level. The results indicate that social media presence and follower engagement are associated with a lower sensitivity of investment to cash flows possibly because social media presence and more engaged followers imply a greater visibility of the company and thus a better access to external equity financing to fund their investment projects. Accordingly, there could also be an external financing channel through which social media presence and follower engagement influence corporate investment.

7. Conclusion

Utilizing 352 million posts for 2,062 firms on Twitter, the paper finds that social media presence and follower engagement have a feedback effect on corporate investment. By taking advantage of the staggered adoption of official Twitter accounts, the baseline result suggests that investment is less sensitive to stock prices after the initiation of Twitter presence. The paper provides further evidence that the feedback effect of social media on investment works through both the managerial learning channel and the disciplining channel.

The hypothesized managerial learning channel yields three distinct predictions. First, managerial learning yield the cross-sectional prediction that the feedback effect of social media is greater when follower engagement is more informative. Comparatively, we find that the sensitivity of investment to stock prices is lower when the firm has more engaged followers and is a consumer-facing company. Second, the condition for managerial learning is that managers learn *new* insights from social media that are above and beyond information incorporated in stock prices. To substantiate the condition, we find that, after controlling for stock returns and other information sources, management forecasts of sales, which reflects managers' forecasted demand for a company's products and services, is more accurate after the initiation of Twitter presence. Third, managerial learning yields the *directional* prediction that managers' forecasts of future demand are in the same direction as the valence of follower engagement indicates. Empirically, we find that managers revise sales forecasts upward (downward) in response to more positive (negative) customer sentiment on social media, especially for consumer-facing companies.

The hypothesized governance channel yields the distinct prediction that investment is more responsive to deteriorating investment opportunities than to improving investment opportunities. Empirically, we find that social media presence and follower engagement are associated with a greater sensitivity of investment to deteriorating investment opportunities. The asymmetric effect of the valence of follower engagement on investment suggests that social media helps discipline corporate managers against agency-induced inefficiency in investment decisions.

To the best of our knowledge, this is the first study to provide systematic evidence on the *feedback* effect of social media on corporate investment decisions. In addition to the feedback effect of social media on investment, future studies could investigate the implications of social media presence and follower engagement for other corporate decisions.

References

ANG, J., C. HSU, D. TANG, and C. WU. 'The Role of Social Media Corporate Governance.' The Accounting Review 96 (2021): 1–32.

BAI, J., T. PHILIPPON, and A. SAVOV. 'Have Financial Markets Become More Informative?' Journal of Financial Economics 122 (2016): 625–54.

BAKER, M., J. STEIN, and J. WURGLER. 'When Does the Market Matter? Stock Prices and the Investment of Equity-Dependent Firms.' Quarterly Journal of Economics 118 (2003): 969–1005.

BAKKE, T., and T. WHITED. 'Which Firms Follow the Market? An Analysis of Corporate Investment Decisions.' Review of Financial Studies 23 (2010): 1941–80.

BARTOV, E., L. FAUREL, and P. MOHANRAM. 'Can Twitter Help Predict Firm-Level Earnings and Stock Returns?' Accounting Review 93 (2018): 25–57.

BATES. T. 'Asset sales, investment opportunities, and the use of proceeds.' Journal of Finance 60 (2005): 105–35.

BERTRAND, M., and S. Mullainathan. 'Enjoying the Quiet Life? Corporate Governance and Managerial Preferences.' Journal of Political Economy 111 (2003): 1043–75.

BIDDLE, G., and G. HILARY. 'Accounting Quality and Firm-Level Capital Investment.' Accounting Review 81 (2006): 963–82.

BIDDLE, G., G. HILARY, and R. VERDI. 'How Does Financial Reporting Quality Relate to Investment Efficiency?' Journal of Accounting and Economics 48 (2009): 112–31.

BLANCHARD, O., F. LOPEZ-DE-SILANEZ, and A. SHLEIFER. 'What Do Firms Do with Cash Windfalls?' Journal of Financial Economics 36 (1994): 337–60.

BLANKESPOOR, E., G. S. MILLER, and H. D. WHITE. 'The Role of Dissemination in Market Liquidity: Evidence from Firms' Use of Twitter.' Accounting Review 89 (2014): 79–112.

BOND, P., A. EDMANS, and I. GOLDSTEIN. 'The Real Effects of Financial Markets.' Annual Review of Financial Economics (2012): 339–60.

BOOT, A. 'Why hang on to losers? Divestitures and takeovers.' Journal of Finance 47 (1992): 1401–23.

BUSHEE, B. J., J. E. CORE, W. GUAY, and S. J. W. HAMM. ‘The Role of the Business Press as an Information Intermediary.’ Journal of Accounting Research 48 (2010): 1-19.

CHEN, F., O. HOPE, Q. LI, and X. WANG. ‘Financial Reporting Quality and Investment Efficiency of Private Firms in Emerging Markets.’ Accounting Review 86 (2011): 1255–88.

CHEN, Q., I. GOLDSTEIN, and W. JIANG. ‘Price Informativeness and Investment Sensitivity to Stock Price.’ Review of Financial Studies 20 (2007): 619–50.

DECHOW, P., and I. DICHEV. ‘The quality of accruals and earnings: the role of accrual estimation errors.’ The Accounting Review 77 (2002): 35–59.

DELOITTE. Corporate Development 2013: Pushing boundaries in M&A. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/finance/us-fas-corporate-development-survey-report-2013-10312014.pdf

DOW, J., and G. GORTON. ‘Stock Market Efficiency and Economic Efficiency: Is There a Connection?’ Journal of Finance 52 (1997): 1087–1129.

EBERLY, J. ‘International Evidence on Investment and Fundamentals.’ European Economic Review 41 (1997): 1055–78.

EASLEY, D., and M. O’HARA. ‘Price, Trade Size, and Information in Security Markets.’ Journal of Financial Economics 19 (1987): 69–90.

EDMANS, A., S. JAYARAMAN, and J. SCHNEEMEIER. ‘The Source of Information in Prices and Investment-Price Sensitivity.’ Journal of Financial Economics 122 (2017): 74–96.

ERICKSON, T., and T. WHITED. ‘Measurement Error and the Relationship between Investment and q.’ Journal of Political Economy 108 (2000): 1027–57.

PETERSEN, M. “Estimating standard errors in finance panel data sets: comparing approaches.” Review of Financial Studies 22 (2009): 435–80.

FORNELL, C., F. MORGESON, and G. HULT. ‘Stock Returns on Customer Satisfaction Do Beat the Market: Gauging the Effect of a Marketing Intangible.’ Journal of Marketing 80 (2016): 92–107.

FOUCAULT, T., and L. FRESARD. ‘Learning from Peers’ Stock Prices and Corporate Investment.’ Journal of Financial Economics 111 (2014): 554–77.

FRANKEL, R., and X. LI. 'Characteristics of a Firm's Information Environment and the Information Asymmetry between Outsiders and Insiders.' Journal of Accounting and Economics 37 (2004): 229–59.

GAO, P., and P. LIANG. 'Informational Feedback, Adverse Selection, and Optimal Disclosure Policy.' Journal of Accounting Research 51 (2013): 1133–58.

GLOSTEN, L., and P. MILGROM. 'Bid, Ask, and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders.' Journal of Financial Economics (1985): 71–100.

GOLDSTEIN, I., and L. YANG. 'Good Disclosure, Bad Disclosure.' Journal of Financial Economics 131 (2019): 118–38.

GOLDSTEIN, I., S. YANG, and L. ZUO. 'The Real Effects of Modern Information Technologies.' NBER Working Paper No. w27529, 2020. Available at https://ssrn.com/abstract=3649893.

GOMES, J. 'Financing Investment.' American Economic Review 91 (2001): 1263–85.

GOODMAN, T., M. NEAMTIU, N. SHROFF, and H. WHITE. 'Management Forecast Quality and Capital Investment Decisions.' The Accounting Review 89 (2014): 331–65.

GROSSMAN, S., and J. STIGLITZ. 'On the Impossibility of Informationally Efficient Markets.' American Economic Review 70 (1980): 393–408.

HANSON, B., and D. QUADRI-FELITTI. 'U.S. Hotels and Social Media: Objectives, Reporting, Measurement and Results.' Penn State School of Hospitality Management, 2016. Available at https://hhd.psu.edu/shm/u-s-hotels-and-social-media-objectives-reporting-measurement-and-results.

HARFORD, J. 'Corporate Cash Reserves and Acquisitions.' Journal of Finance 54 (1999): 1969–97.

HOSSEINI, A., S. KANG, R. SAVICKAS, and A. SINGH. 'Technology Diffusion and Who's On and Who's Not on Social Media An Empirical Study of Twitter Adoptions.' Working Paper, George Washington University School of Business, 2020.

HUBBARD, R. 'Capital-Market Imperfections and Investment.' Journal of Economic Literature 36 (1998): 193–225.

HUANG, J. 'The Customer Knows Best: The Investment Value of Consumer Opinions.' Journal of Financial Economics 128 (2018): 164–82.

JAYARAMAN, S., and J. WU. 'Should I Stay or Should I Grow? Using Voluntary Disclosure to Elicit Market Feedback.' Review of Financial Studies 33 (2020): 3854–88.

JENSEN, M. 'Agency Cost of Free Cash Flow, Corporate Finance, and Takeovers.' American Economic Review 76 (1986): 323–29.

JENSEN, M. 'Agency Costs of Overvalued Equity.' Financial Management (Spring 2005): 5–19.

JENSEN, M., and W. MECKLING. 'Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure.' Journal of Financial Economics 3 (1976): 305–60.

JUNG, M., J. NAUGHTON, A. TAHOUN, and C. WANG. 'Do Firms Strategically Disseminate? Evidence from Corporate Use of Social Media.' Accounting Review 93 (2018): 225–52.

KANODIA, C., R. BUSHMAN, and J. DICKHAUT. 'Escalation Errors and the Sunk Cost Effect: An Explanation Based on Reputation and Information Asymmetries.' Journal of Accounting Research 27 (1989): 59–77.

KROSS, W., B. RO, and D. SCHROEDER. 'Earnings Expectations: The Analysts' Information Advantage.' Accounting Review 65 (1990): 461–77.

KYLE, S. 'Continuous Auctions and Insider Trading.' *Econometrica* 53 (1985): 1315–36.

LEE, D., K. HOSANAGAR, and H. NAIR. 'Advertising Content and Consumer Engagement on Social Media: Evidence from Facebook.' Management Science 64 (2018): 5105–31.

LEE, L.F., A.P. HUTTON, and S. SHU. 'The Role of Social Media in the Capital Market: Evidence from Consumer Product Recalls.' Journal of Accounting Research 53 (2015): 367–404.

LUCA, M., and S. ZERVAS. 'Fake It Till You Make It: Reputation, Competition, and Yelp Review Fraud.' Management Science 62 (2016): 3412–27.

LUO, Y. 'How Does Globalization Affect Corporate Governance and Accountability? A Perspective from MNEs.' Journal of International Management 11 (2005): 19–41.

MALMENDIER, U., and G. TATE. 'CEO Overconfidence and Corporate Investment.' Journal of Finance 60 (2005): 2661–2700.

MCNICHOLS, M. 2002. 'Discussion of the quality of accruals and earnings: the role of accrual estimation errors.' The Accounting Review 77 (2002): 61–69.

MCNICHOLS, M., and S. STUBBEN. ‘Does Earnings Management Affect Firms’ Investment Decisions?’ Accounting Review 83 (2008): 1571–1603.

MILLER, G. S. ‘The Press as a Watchdog for Accounting Fraud.’ Journal of Accounting Research 44 (2006): 1001–33.

MODIGLIANI, F., and M. MILLER. ‘The Cost of Capital, Corporation Finance and the Theory of Investment.’ American Economic Review 48 (1958): 261–97.

MYERS, S. ‘Determinants of Corporate Borrowing.’ Journal of Financial Economics 5 (1977): 147–75.

MYERS, S., and N. MAJLUF. ‘Corporate Financing and Investment Decisions When Firms Have Information that Investors Do Not Have.’ Journal of Financial Economics 13 (1984): 187–221.

OPLER, T., L. PINKOWITZ, R. STULZ, and R. WILLIAMSON. ‘The Determinants and Implications of Corporate Cash Holdings.’ Journal of Financial Economics 52 (1999): 3–46.

RICHARDSON, S. ‘Over-investment of free cash flow.’ Review of Accounting Studies (2006): 159–89.

SUBRAHMANYAM, A., and S. TITMAN. ‘The Going-Public Decision and the Development of Financial Markets.’ Journal of Finance 54 (1999): 1045–82.

TANG, V. W. ‘Wisdom of Crowds: Cross-Sectional Variation in the Informativeness of Third-Party-Generated Product Information on Twitter.’ Journal of Accounting Research 56 (2018): 989–1034.

WRUGLER, J. ‘Financial markets and the allocation of capital.’ Journal of Financial Economics 58 (2000): 187–214.

ZHU, C. ‘Big Data as a Governance Mechanism.’ Review of Financial Studies 32 (2019): 2021–61.

ZUO, L. ‘The Informational Feedback Effect of Stock Prices on Management Forecasts.’ Journal of Accounting and Economics 61 (2016): 391–413.

Appendix A
Variables Description

Variables of Interest: Social Media	
PRESENCE	An indicator variable that takes the value of one if the firm has a Twitter account, and zero otherwise
TWEETS	The number of tweets initiated by a firm on its official Twitter account
RESPONSES	The sum of total retweets, total likes and total replies by followers of a firm's Twitter account
ENGAGEMENT	RESPONSES/TWEETS
VALENCE_ENGAGEMENT	Ratio of the number of customer-initiated tweets that convey a positive assessment of products and brands over the number of tweets that convey a non-neutral (either positive or negative) assessment of products and brands
CHG_VALENCE_ENGAGEMENT	Signed difference between the current and previous quarters' VALENCE_ENGAGEMENT
LOG(LIKES)	LOG(1 plus total likes by followers of a firm's Twitter account)
LOG(REPLIES)	LOG (1 plus total replies by followers of a firm's Twitter account)
LOG(RETWEETS)	LOG (1 plus total retweets by followers of a firm's Twitter account)
IND_CHANGE_CUSTOMERVALENCE	The quarterly change in the industry-level customer sentiment, which is calculated as the average quarterly changes in the valence of customer engagement (VALENCE_ENGAGEMENT) across all firms in a given Fama-French industry.
DECLINE	An indicator variable that takes the value of one when the change in the industry's customer sentiment is negative and 0, otherwise.
Dependent Variables:	
CAPEX	Capital expenditure scaled by previous quarter's PP&E multiplied by 100.
CAPEX+R&D	Sum of capital expenditure and research and development expenditure and scaled by previous quarter's PP&E multiplied by 100.
/MFE_SALES/	Absolute value of the difference between the quarterly management sales forecast and the actual sales scaled by previous quarter end's total assets.
MF_SALES_REVISION	Signed difference between the most recent sales forecast and the previous sales forecast scaled by previous quarter end's total assets.
LOG(CHANGE_CAPEX)	Log of ratio of current and previous quarters' *CAPEX*.

LOG(CHANGE_(CAPEX+R&D))	Log of ratio of current quarter and previous quarters' (*CAPEX+R&D)*.
NEW_EQUITY	New equity issued by the firm scaled by previous quarter's total assets
Explanatory Variables	
TOBIN'SQ	(Book value of assets - book value of equity + market value of equity)/ book value of assets.
B2C	An indicator variable that takes the value of 1 if the firm belongs to a consumer facing industry, and 0 otherwise.
CASH_FLOW	Sum of income before extraordinary items and depreciation divided by total assets.
MEDIAN_CASH_FLOW	An indicator variable that takes the value of 1 if the firm's cash flow is greater than the median cash flow of the industry (Fama French-48), and 0 otherwise.
FIRM_AGE	Age of the firm in *months* measured from the time it first appears in Compustat.
ADV_EXPENSE	Annual advertising expense divided by four to calculate the quarterly advertising expenses.
LOG(ANALYST)	Log (1 plus the number of analysts following a firm)
LOG(PRESS_RELEASES)	Log (1 plus the number of press releases issued by the firm and distributed via a news provider)
LOG(MEDIA_COVERAGE)	Log (1 plus the number of news articles written about a firm)
LEVERAGE	Ratio of long-term debt to total assets.
LOG(ASSET)	Log of total assets.
σ (CFO)	Standard deviation of cash flows from operations deflated by average assets from t-5 to t-1.
σ (STOCK_RETURN)	Standard deviation of daily stock returns of the quarter.
SALES_GROWTH	Percentage change in sales during the quarter.
SALES_FORECAST_PRECISION	Difference between upper and lower bounds of management sales forecast divided by previous quarter's total assets.
Q4	Indicator variable equal to 1 if it is the fourth quarter and 0, otherwise.
MTB	Ratio of the market value of equity to book value of equity.
ROA	Income before extraordinary items divided by the average total assets.
STOCK_RETURN	Quarterly stock returns of the firm.
TANGIBILITY	Ratio of PPE to total assets.

Table 1: Descriptive Statistics of Twitter Posting

Panel A: All firm-year observations, descriptive statistics on key social media variables

Variables	**Observations**	**Mean**	**Median**	**Std. Dev.**	**Min**	**P25**	**P75**	**Max**
$PRESENCE_{i,t+1}$	75,484	0.620	1	0.485	0	0	1	1
$TWEETS_{i,t+1}$	75,484	226.54	3	2062.66	0	0	92	126,845
$RESPONSE_{i,t+1}$	75,484	4848.71	11	112867.70	0	0	462	13,200,000
$LIKES_{i,t+1}$	75,484	2676.06	4	71920.90	0	0	166	9,364,155
$RETWEETS_{i,t+1}$	75,484	1735.47	4	41893.16	0	0	174	3,764,600
$REPLIES_{i,t+1}$	75,484	434.53	3	4447.31	0	0	104	242,098
$ENGAGEMENT_{i,t+1}$	75,484	7.02	3	77.14	0	0	4.588	7,917.657

Panel B: Conditional on having Twitter presence, descriptive statistics of Twitter posting

Variables	**Observations**	**Sum**	**Mean**	**Median**	**P25**	**P75**	**Std. Dev.**
$TWEETS_{i,t+1}$	46,809	17,100,000	365.31	54	7	206	2609.24
$RESPONSE_{i,t+1}$	46,809	366,000,000	7819.01	256	30	1192	143242.10
$LIKES_{i,t+1}$	46,809	202,000,000	4315.41	91	10	433	91289.11
$RETWEETS_{i,t+1}$	46,809	131,000,000	2798.61	95	11	456	53168.98
$REPLIES_{i,t+1}$	46,809	32,800,000	700.72	60	8	249	5630.17
$ENGAGEMENT_{i,t+1}$	46,809	530,117	11.33	4	3.14	6.20	97.70

Panel C: Conditional on having data on customer sentiment from 2012 to 2015, descriptive statistics

Variables	**Observations**	**Sum**	**Mean**	**Median**	**P25**	**P75**	**Std. Dev.**
$VALENCE\_ENGAGEMTN_{i,t+1}$	5,593	4893.32	0.87	0.90	0.81	0.98	0.12
$CHG\_VALENCE\_ENGAGEMENT_{i,t+1}$	4,639	-15.90	-0.003	0.000	-0.033	0.026	0.086

All variables are as defined in Appendix A

Table 2: Descriptive Statistics of Key Variables

Variables	Observations	Mean	Median	P25	P75	Std. Dev.
$CAPEX_{i,t+1}$	75,484	18.07	12.14	5.76	23.54	18.56
$(CAPEX + R\&D)_{i,t+1}$	75,484	72.45	18.83	7.79	48.53	220.44
$ASSET_{i,t+1}$	75,484	7739.41	840.56	183.14	3963.10	28897.56
$TOBIN'SQ_{i,t+1}$	75,484	2.28	1.67	1.24	2.57	1.88
$TANGIBILITY_{i,t+1}$	75,484	0.22	0.14	0.06	0.31	0.22
$FIRM\_AGE_{i,t+1}$	75,484	263.69	228	129	363	171.20
B2C	75,484	0.12	0	0	0	0.32
$LEVERAGE_{i,t+1}$	75,484	0.17	0.13	0	0.28	0.19
$CASH\_FLOW_{i,t+1}$	75,484	0.002	0.020	0.001	0.030	0.080
$ADV\_EXPENSE_{i,t+1}$	75,484	8.03	0	0	1.82	21.75
$LOG(MEDIA\_COVERAGE)_{i,t+1}$	75,484	1.70	1.39	0	2.77	1.67
$LOG(PRESS\_RELEASES)_{i,t+1}$	75,484	0.95	0	0	1.79	1.28
$LOG(ANALYST)_{i,t+1}$	75,484	1.71	1.95	0.69	2.56	1.09
$MTB_{i,t+1}$	75,484	3.41	2.33	1.39	4.04	5.33
$ROA_{i,t+1}$	75,484	-0.01	0.01	-0.01	0.02	0.08
$NEW\_EQUITY_{i,t+1}$	75,484	0.045	0.002	0.000	0.009	0.162
$SLACK_{i,t+1}$	75,458	6.99	0.86	0.20	3.80	25.56
$\sigma(CFO)_{i,t+1}$	75,332	0.08	0.05	0.03	0.07	0.16
$SALES\_GROWTH_{i,t+1}$	73,932	0.05	0.02	-0.05	0.10	0.30
$LOG(CHANGE\_CAPEX)_{i,t+1}$	73,695	0.00	0.34	-0.21	0.58	1.02
$STOCK\_RETURN_{i,t+1}$	70,316	0.03	0.02	-0.10	0.14	0.23
$\sigma(STOCK\_RETURN)_{i,t+1}$	69,638	0.03	0.02	0.02	0.03	0.02
$\lvert MFE\_SALES_{i,t+1}\rvert$	13,916	0.012	0.005	0.002	0.012	0.022
$MF\_SALES\_REVISION_{i,t+1}$	13,916	-0.0004	0.000	0.000	0.000	0.010
$SALES\_FORECAST\_PRECISION_{i,t+1}$	13,916	0.0093	0.006	0.002	0.012	0.010

All variables are as defined in Appendix A.

Table 3: Correlation

Panel A: Correlations between Capex and Explanatory Variables

Pearson/Spearman	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)CAPEX$_{i,t+1}$	1	0.71***	0.03***	0.05***	0.04***	0.23***	-0.16***
(2)(CAPEX+R&D)$_{i,t+1}$	0.32***	1	0.04***	0.04***	-0.17***	0.36***	-0.37***
(3)PRESENCE$_{i,t+1}$	0.02***	0.01	1	0.741**	-0.03***	0.08***	0.10***
(4)LOG(ENGAGEMENT)$_{i,t+1}$	0.02***	-0.04***	0.67***	1	0.03***	0.13***	0.20***
(5)CASH_FLOW$_{i,t+1}$	-0.10***	-0.43***	0.01	0.05***	1	0.20***	0.29***
(6)TOBINSQ$_{i,t+1}$	0.24***	0.35***	0.05***	0.08***	-0.35***	1	-0.15***
(7)LOG(ASSET)$_{i,t+1}$	-0.24***	-0.31***	0.11***	0.24***	0.39***	-0.29***	1
(8)TANGIBILITY$_{i,t+1}$	-0.29***	-0.24***	-0.04***	0.02	0.14***	-0.18***	0.29***
(9)FIRM_AGE$_{i,t+1}$	-0.27***	-0.22***	0.02***	0.05***	0.25***	-0.27***	0.41***
(10)ADV_EXPENSE$_{i,t+1}$	-0.07***	-0.08***	0.05***	0.23***	0.11***	-0.01	0.43***

Pearson/Spearman	(8)	(9)	(10)
(8)TANGIBILITY$_{i,t+1}$	1	0.24***	0.01***
(9)FIRM_AGE$_{i,t+1}$	0.16***	1	0.03***
(10)ADV_EXPENSE$_{i,t+1}$	0.04***	0.18***	1

Table 3 (continued)

Panel B: Correlations between Management Forecast error and Explanatory Variables

Pearson/Spearman	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)|$MFE\_SALES_{i,t+1}$|	1	0.08**	-0.13***	0.10***	0.27***	-0.09**	-0.07*
(2)$MF\_SALES\_REVISION_{i,t+1}$	0.002	1	0.01	-0.02	0.01	0.01	0.08**
(3)$PRESENCE_{i,t+1}$	-0.06***	0.02**	1	-0.03	0.10***	-0.18***	0.18***
(4)$CHG\_VALENCE\_ENGAGEMENT_{i,t+1}$	-0.01	0.06*	-0.05	1	0.03	0.023	0.01
(5)$SALES\_FORECAST\_PRECISION_{i,t+1}$	0.24***	-0.00	-0.01*	0.03	1	-0.17***	-0.02
(6)$LOG(ASSET)_{i,t+1}$	-0.03***	0.01	0.11***	0.01	-0.18***	1	0.05
(7)$TOBINSQ_{i,t+1}$	-0.01	0.03***	0.07***	0.03	-0.06***	-0.16***	1
(8)$ROA_{i,t+1}$	0.00	0.07***	-0.01*	-0.03	-0.02*	0.31***	-0.11***
(9)$LEVERAGE_{i,t+1}$	-0.03***	0.02***	0.08***	-0.03	-0.13***	0.38***	-0.13***
(10)$STOCK\_RETURN_{i,t+1}$	0.04***	0.10***	0.05***	0.06*	0.02***	0.01**	0.15***
(11)$\sigma(STOCK\_RETURN)_{i,t+1}$	0.07***	-0.03***	-0.13***	0.06*	0.15***	-0.45***	-0.02***
(12)$\sigma(CFO)_{i,t+1}$	0.06***	0.01	-0.01***	0.06*	0.07***	-0.22***	0.28***
(13)$SALES\_GROWTH_{i,t+1}$	0.11***	0.12***	-0.00	-0.03	0.07***	-0.05***	0.07***

Pearson/Spearman	(8)	(9)	(10)	(11)	(12)	(13)
(8)$ROA_{i,t+1}$	1	0.05	0.09***	-0.32***	0.31***	0.13***
(9)$LEVERAGE_{i,t+1}$	0.00	1	0.06	-0.24***	-0.04	-0.01
(10)$STOCK\_RETURN_{i,t+1}$	0.08***	-0.00	1	-0.00	0.10***	0.04
(11)$\sigma(STOCK\_RETURN)_{i,t+1}$	-0.34***	-0.09***	0.04***	1	0.10***	-0.01
(12)$\sigma(CFO)_{i,t+1}$	-0.26***	-0.11***	-0.03***	0.17***	1	0.04
(13)$SALES\_GROWTH_{i,t+1}$	0.04***	-0.01***	0.02***	0.01***	0.09***	1

The lower diagonal shows Pearson's correlation coefficients and the upper diagonal shows the Spearman's correlation coefficients.

All variables are as defined in Appendix A. *** represents p-value <1%, ** represents p-value <5%, * represents p-value <10%

Table 4: Investment and Social Media Presence

VARIABLES	*Predicted Sign*	*CAPEX$_{i,t+1}$* (1)	(2)	*(CAPEX + R&D)$_{i,t+1}$* (3)	(4)
PRESENCE$_{i,t+1}$		1.274***	1.217***	1.431	1.535
		(5.102)	(4.882)	(0.783)	(0.840)
PRESENCE$_{i,t}$*TOBIN'SQ$_{i,t+1}$	*(-)*	***-0.432****	***-0.430****	***-3.753****	***-3.757****
		(-6.280)	***(-6.259)***	***(-7.453)***	***(-7.461)***
CASH_FLOW$_{i,t+1}$		14.556***	14.779***	-102.993***	-103.068***
		(14.289)	(14.525)	(-13.808)	(-13.817)
TOBINS'Q$_{i,t+1}$		1.709***	1.681***	9.059***	9.095***
		(26.278)	(25.766)	(19.029)	(19.020)
LOG(ASSET)$_{i,t+1}$		1.417***	0.918***	-12.786***	-12.608***
		(9.849)	(6.116)	(-12.136)	(-11.461)
TANGIBILITY$_{i,t+1}$		-17.941***	-17.746***	-214.331***	-214.742***
		(-18.217)	(-18.037)	(-29.722)	(-29.772)
FIRM_AGE$_{i,t+1}$		0.061***	0.064***	0.049	0.031
		(3.500)	(3.673)	(0.385)	(0.242)
ADV_EXPENSE$_{i,t+1}$		-0.011	-0.014	0.146**	0.156**
		(-1.172)	(-1.497)	(2.128)	(2.274)
LOG(PRESS_RELEASES)$_{i,t+1}$			-0.339***		-2.064***
			(-4.381)		(-3.636)
LOG(MEDIA_COVERAGE)$_{i,t+1}$			0.167*		1.173*
			(1.891)		(1.815)
LOG(ANALYST)$_{i,t+1}$			1.563***		-0.562
			(13.309)		(-0.653)
INTERCEPT		-6.984**	-6.848**	157.130***	157.925***
		(-2.030)	(-1.992)	(6.238)	(6.267)
Observations		75,484	75,484	75,484	75,484
R-squared		0.437	0.439	0.786	0.786
Fixed Effects		Time and Firm	Time and Firm	Time and Firm	Time and Firm
Clustering of Errors		No	No	No	No

The table shows the results of OLS regression using equation 1: $CAPEX_{i,t+1} = \beta_0 + \beta_1 TWEET\_VARIABLE_{i,t+1} + \boldsymbol{\beta_2 TWEET\_VARIABLE_{i,t+1} * TOBIN'SQ_{i,t+1}} + \beta_3 \mathrm{TOBIN'SQ}_{i,t+1} + \sum \beta_n\, CONTROL\ VARIABLES_{i,t+1} + \sum FIRM_i + \sum TIME_{t+1} + \varepsilon_{i,t+1}$

The sample is all Twitter firms (excluding firms that never created a Twitter account during the sample period 2006-2017).

t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All variables are defined in Appendix A.

Table 5: Cross-sectional Analysis on Social Media and Investment

Panel A: Follower Engagement and Investment

VARIABLES	***Predicted Sign***	***CAPEX$_{i,t+1}$*** (1)	***(CAPEX + R&D)$_{i,t+1}$*** (2)
LOG(ENGAGEMENT)$_{i,t+1}$		0.730***	0.280
		(5.901)	(0.309)
LOG(ENGAGEMENT)$_{i,t+1}$*TOBIN'SQ$_{i,t+1}$	***(-)***	***-0.256****	***-1.713****
		(-7.608)	***(-6.961)***
CASH_FLOW$_{i,t+1}$		14.648***	-102.993***
		(14.378)	(-13.808)
TOBINSQ$_{i,t+1}$		1.675***	9.059***
		(28.856)	(19.029)
LOG(ASSET)$_{i,t+1}$		1.457***	-12.786***
		(10.112)	(-12.136)
TANGIBILITY$_{i,t+1}$		-17.946***	-214.331***
		(-18.219)	(-29.722)
FIRM_AGE$_{i,t+1}$		0.068***	0.049
		(3.899)	(0.385)
ADV_EXPENSE$_{i,t+1}$		-0.011	0.146**
		(-1.132)	(2.128)
INTERCEPT		-8.507**	157.130***
		(-2.464)	(6.238)
Observations		75,484	75,484
R-squared		0.437	0.786
Fixed Effects		Time and Firm	Time and Firm
Clustering of Errors		No	No

Table 5 (continued)

Panel B: Comparative Analysis between B2C Firms and B2B Firms

		$CAPEX_{i,t+1}$					
		All Firms		**B2C Firms**		**Non B2C Firms**	
VARIABLES	***Predicted Sign***	(1)	(2)	(3)	(4)	(5)	(6)
$PRESENCE_{i,t+1}$		1.073***		2.534***		1.230***	
		(4.522)		(4.498)		(4.518)	
*$PRESENCE_{i,t+1}$*B2C*		*-0.197*					
		(-0.385)					
$PRESENCE_{i,t+1}$*TOBIN'S$Q_{i,t+1}$		*0.129**		***-1.387****		***-0.361****	
		(1.940)		***(-7.636)***		***(-4.894)***	
$PRESENCE_{i,t+1}$*TOBIN'S$Q_{i,t+1}$*B2C	*(-)*	***-0.467****					
		(-3.110)					
$LOG(ENGAGEMENT)_{i,t+1}$			0.660***		1.270***		0.657***
			(5.872)		(5.142)		(4.769)
$LOG(ENGAGEMENT)_{i,t+1}$*B2C			0.241				
			(1.049)				
$LOG(ENGAGEMENT)_{i,t+1}$*TOBIN'S$Q_{i,t+1}$			*0.048*		***-0.431****		***-0.219****
			(1.526)		***(-6.457)***		***(-5.860)***
$LOG(ENGAGEMENT)_{i,t+1}$*TOBIN'S$Q_{i,t+1}$*B2C	*(-)*		***-0.268****				
			(-4.076)				
Controls		Included	Included	Included	Included	Included	Included
Intercept		Included	Included	Included	Included	Included	Included
Observations		75,484	75,484	8,889	8,889	66,595	66,595
R-squared		0.234	0.235	0.500	0.499	0.431	0.431
Fixed Effects		Time	Time	Time and Firm	Time and Firm	Time and Firm	Time and Firm
Clustering of Errors		No	No	No	No	No	No

Table 5 (continued)

Panel A shows the results of OLS regression using equation 1: $CAPEX_{i,t+1} = \beta_0 + \beta_1 TWEET\_VARIABLE_{i,t+1} + \boldsymbol{\beta_2 TWEET\_VARIABLE_{i,t+1} * TOBIN'SQ_{i,t+1}}$

$+ \beta_3 \mathrm{TOBIN'SQ}_{i,t+1} + \sum \beta_n\, CONTROL\ VARIABLES_{i,t+1} + \sum FIRM_i + \sum TIME_{t+1} + \varepsilon_{i,t+1}$

Panel B shows the results of OLS regression using a modification of equation 1: $CAPEX_{i,t+1} = \beta_0 + \beta_1 TWEET\_VARIABLE_{i,t+1} + \beta_2 TWEET\_VARIABLE_{i,t+1} * B2C$
$+ \beta_3 TWEET\_VARIABLE_{i,t+1} * TOBIN'SQ_{i,t+1} + \boldsymbol{\beta_4 TWEET\_VARIABLE_{i,t+1} * TOBIN'SQ_{i,t+1} * B2C} + \beta_5 TOBIN'SQ_{i,t+1} + \sum \beta_n CONTROL\ VARIABLES_{i,t+1}$
$+ \sum TIME_{t+1} + \varepsilon_{i,t+1}$

Both panels show the results for all Twitter firms (excluding firms that never created a Twitter account during the sample period 2006-2017).

t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All variables are defined in Appendix A.

Table 6: Management Sales Forecast Error and Presence on Twitter

		$\lvert MFE\_SALES_{i,t+1}\rvert$		
VARIABLES	***Predicted Sign***	(1)	(2)	(3)
PRESENCE $_{i,t+1}$	***(-)***	***-0.005******	***-0.004*****	***-0.003*****
		(-3.082)	***(-2.497)***	***(-2.258)***
PRESENCE $_{i,t+1}$ *Q4 $_{i,t+1}$				-0.001
				(-1.204)
SALES_FORECAST_PRECISION $_{i,t+1}$			0.506***	0.506***
			(6.627)	(6.625)
LOG(ASSET) $_{i,t+1}$			0.001	0.001
			(1.098)	(1.097)
TOBIN'SQ $_{i,t+1}$			-0.000	-0.000
			(-0.974)	(-0.974)
ROA $_{i,t+1}$			-0.005	-0.005
			(-0.659)	(-0.666)
LEVERAGE $_{i,t+1}$			-0.001	-0.001
			(-0.399)	(-0.401)
STOCK_RETURN $_{i,t+1}$			0.004***	0.004***
			(3.660)	(3.661)
σ(STOCK_RETURN) $_{i,t+1}$			0.099**	0.099**
			(2.440)	(2.441)
σ(CFO) $_{i,t+1}$			0.013**	0.013**
			(2.093)	(2.093)
SALES_GROWTH $_{i,t+1}$			0.009***	0.009***
			(4.791)	(4.804)
Q4 $_{i,t+1}$				0.004
				(1.628)
INTERCEPT		0.013***	0.003	0.003
		(9.155)	(0.837)	(0.837)
Observations		14,213	13,855	13,855
R-squared		0.035	0.105	0.106
Fixed Effects		Time and Industry	Time and Industry	Time and Industry
Clustering of Errors		Firm	Firm	Firm

The table shows the results of OLS regression using equation 2a: $|MFE|_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 PRESENCE_{i,t+1}} + \sum \beta_n CONTROL\ VARIABLES_{i,t+1} + \sum INDUSTRY_j + \sum TIME_{t+1} + \varepsilon_{i,t+1}$
The sample is all Twitter firms (excluding firms that never created a Twitter account during the sample period 2006-2017).

t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All variables are defined in Appendix A.

Table 7: Management Sales Forecast Revision and the Valence of Follower Engagement

			MF_SALES_REVISION$_{i,t+1}$	
	Predicted Sign	**All Firms**	**B2C Firms**	**Non B2C Firms**
VARIABLES		(1)	(2)	(3)
CHG_VALENCE_ENGAGEMENT$_{i,t+1}$		***0.003***	***0.019****	***0.003***
		(0.756)	***(2.073)***	***(0.746)***
CHG_VALENCE_ENGAGEMENT$_{i,t+1}$*B2C		***0.015***		
		(1.487)		
$\beta_1 + \beta_2$	*(+)*	***0.018****		
Joint Significance ($\beta_1 + \beta_2$ =0) p-value		***0.059***		
B2C		-0.012		
		(-1.285)		
SALES_FORECAST_PRECISION$_{i,t+1}$		-0.023	0.059	-0.019
		(-0.751)	(0.422)	(-0.528)
LOG(ASSET)$_{i,t+1}$		-0.000	0.002	-0.000
		(-0.018)	(1.237)	(-0.467)
TOBIN'SQ$_{i,t+1}$		-0.000	0.003***	-0.000
		(-0.059)	(5.015)	(-0.357)
ROA$_{i,t+1}$		-0.014	-0.089	-0.014
		(-1.224)	(-1.238)	(-1.118)
LEVERAGE$_{i,t+1}$		-0.001	0.039*	-0.001
		(-0.588)	(1.904)	(-0.841)
STOCK_RETURN$_{i,t+1}$		0.001	-0.007	0.001
		(0.663)	(-1.415)	(0.573)
σ(STOCK_RETURN)$_{i,t+1}$		0.036	-0.015	0.033
		(0.998)	(-0.069)	(0.900)
σ(CFO)$_{i,t+1}$		0.000	-0.005	0.001
		(0.045)	(-0.341)	(0.151)
SALES_GROWTH$_{i,t+1}$		0.001	-0.004	0.001
		(0.527)	(-0.991)	(0.900)
ADV_EXPENSE$_{i,t+1}$		0.000	-0.000	0.000
		(0.212)	(-1.410)	(0.307)
INTERCEPT		-0.003	-0.029*	-0.002
		(-1.004)	(-1.996)	(-0.682)
Observations		734	57	677
R-squared		0.084	0.658	0.068
Fixed Effects		Time and Industry	Time and Industry	Time and Industry
Clustering of Errors		Firm	Firm	Firm

Table 7 (continued)

The table shows the results of OLS regression using equation 2b: $MF\_SALES\_REVISION_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 CHG\_VALENCE\_ENGAGEMENT_{i,t+1}} + \boldsymbol{\beta_2 CHG\_VALENCE\_ENGAGEMENT_{i,t+1} * B2C} + \beta_3 B2C + \sum\beta_n CONTROL\ VARIABLES_{i,t+1} + \sum INDUSTRY_j + \sum TIME_{t+1} + \varepsilon_{i,t+1}$

The sample is all Twitter firms (excluding firms that never created a Twitter account during the sample period 2006-2017).

t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All variables are defined in Appendix A.

Table 8: The Governance Role of Social Media

VARIABLES	*Predicted Sign*	*LOG(CHANGE_CAPEX)$_{i,t+1}$* (1)	(2)	*LOG(CHANGE_(CAPEX+R&D))$_{i,t+1}$* (3)	(4)
PRESENCE$_{i,t+1}$*IND_CHANGE_CUSTOMERVALENCE$_{i,t+1}$		-2.015***		-2.717***	
		(-2.700)		(-4.274)	
PRESENCE$_{i,t+1}$*IND_CHANGE_CUSTOMERVALENCE$_{i,t+1}$*DECLINE$_{i,t+1}$	*(+)*	***3.422****		***3.757****	
		(3.897)		***(4.849)***	
PRESENCE$_{i,t+1}$		0.037**		0.048***	
		(2.320)		(3.506)	
LOG(ENGAGEMENT)$_{i,t+1}$* IND_CHANGE_CUSTOMERVALENCE$_{i,t+1}$			-1.034***		-1.311***
			(-3.508)		(-5.258)
LOG(ENGAGEMENT)$_{i,t+1}$*IND_CHANGE_CUSTOMERVALENCE$_{i,t+1}$*DECLINE$_{i,t+1}$	*(+)*		***2.160****		***2.292****
			(5.632)		***(6.938)***
LOG(ENGAGEMENT)$_{i,t+1}$			0.016***		0.020***
			(3.386)		(4.745)
IND_CHANGE_CUSTOMERVALENCE$_{i,t+1}$		-3.489***	-4.067***	-0.578	-1.448***
		(-4.989)	(-9.201)	(-0.956)	(-3.930)
IND_CHANGE_CUSTOMERVALENCE$_{i,t+1}$*DECLINE$_{i,t+1}$		3.822***	4.394***	0.755	1.471***
		(4.649)	(8.035)	(1.027)	(3.168)
DECLINE$_{i,t+1}$		0.049***	0.050***	0.045***	0.046***
		(3.575)	(3.645)	(3.798)	(3.816)
Controls		Included	Included	Included	Included
Intercept		Included	Included	Included	Included
Observations		23,093	23,093	23,093	23,094
R-squared		0.026	0.027	0.015	0.017
Fixed Effects		Industry	Industry	Industry	Industry
Clustering of Errors		Firm	Firm	Firm	Firm

The table shows the results of OLS regression using equation 3: $LOG(CHANGE\_CAPEX)_{i,t+1}=\beta_0+\beta_1 TWEET\_VARIABLE_{i,t+1}+\beta_2 TWEET\_VARIABLE_{i,t+1}*IND\_CHANGE\_CUSTOMERVALENCE_{i,t+1}+\boldsymbol{\beta_3 TWEET\_VARIABLE_{i,t+1}*IND\_CHANGE\_CUSTOMERVALENCE_{i,t+1}*DECLINE_{i,t+1}}+\beta_4 IND\_CHANGE\_CUSTOMERVALENCE_{i\ i,t+1}+\beta_5 DECLINE_{i,t+1}+\sum \beta_n CONTROL\ VARIABLES_{i,t+1}+\sum INDUSTRY_j+\varepsilon_{i,t+1}$

The sample is all Twitter firms (excluding firms that never created a Twitter account during the sample period 2006-2017).

t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All variables are defined in Appendix A.

Table 9: Supplemental Analysis on Social Media and Components of Follower Engagement

		$CAPEX_{i,t+1}$			$(CAPEX + R\&D)_{i,t+1}$		
VARIABLES	***Predicted Sign***	(1)	(2)	(3)	(4)	(5)	(6)
$LOG(LIKES)_{i,t+1}$		0.287***			0.304		
		(6.167)			(0.893)		
$LOG(LIKES)_{i,t+1}$*$TOBIN'SQ_{i,t+1}$	*(-)*	***-0.099******			***-1.010******		
		(-7.493)			***(-10.442)***		
$LOG(RETWEETS)_{i,t+1}$			0.272***			0.182	
			(5.905)			(0.540)	
$LOG(RETWEETS)_{i,t+1}$*$TOBIN'SQ_{i,t+1}$	*(-)*		***-0.099******			***-0.900******	
			(-7.429)			***(-9.260)***	
$LOG(REPLIES)_{i,t+1}$				0.297***			0.264
				(5.890)			(0.714)
$LOG(REPLIES)_{i,t+1}$*$TOBIN'SQ_{i,t+1}$	*(-)*			***-0.103******			***-0.963******
				(-6.959)			***(-8.903)***
$CASH\_FLOW_{i,t+1}$		14.689***	14.687***	14.661***	-101.723***	-102.017***	-102.042***
		(14.417)	(14.415)	(14.389)	(-13.643)	(-13.679)	(-13.682)
$TOBIN'SQ_{i,t+1}$		1.680***	1.680***	1.663***	9.221***	8.962***	8.852***
		(28.617)	(28.544)	(28.326)	(21.468)	(20.799)	(20.596)
$LOG(ASSET)_{i,t+1}$		1.444***	1.439***	1.421***	-12.028***	-12.267***	-12.447***
		(10.021)	(9.995)	(9.881)	(-11.406)	(-11.638)	(-11.822)
$TANGIBILITY_{i,t+1}$		-17.903***	-17.928***	-17.936***	-215.324***	-215.536***	-215.600***
		(-18.173)	(-18.199)	(-18.206)	(-29.868)	(-29.891)	(-29.898)
$FIRM\_AGE_{i,t+1}$		0.066***	0.065***	0.065***	0.006	0.007	0.011
		(3.813)	(3.754)	(3.731)	(0.044)	(0.053)	(0.090)
$ADV\_EXPENSE_{i,t+1}$		-0.011	-0.011	-0.011	0.172**	0.168**	0.164**
		(-1.192)	(-1.188)	(-1.207)	(2.509)	(2.453)	(2.395)
Constant		-8.124**	-7.890**	-7.649**	160.277***	162.302***	162.872***
		(-2.359)	(-2.293)	(-2.224)	(6.361)	(6.445)	(6.470)
Observations		75,484	75,484	75,484	75,484	75,484	75,484
R-squared		0.437	0.437	0.437	0.786	0.786	0.786
Fixed Effects		Time and Firm	Time and Firm	Time and Firm	Time and Firm	Time and Firm	Time and Firm
Clustering of Errors		No	No	No	No	No	No

Table 9 (continued)

Table 9 shows the results of OLS regression using a modification of equation 1: $CAPEX_{i,t+1} = \beta_0 + \beta_1 ENGAGEMENT\_COMPONENT_{i,t+1} + \boldsymbol{\beta_2\ ENGAGEMENT\_COMPONENT_{i,t+1} * TOBIN'SQ_{i,t+1}} + \beta_3 \mathrm{TOBIN'SQ}_{i,t+1} + \sum \beta_n CONTROL\ VARIABLES_{i,t+1} + \sum FIRM_i + \sum TIME_{t+1} + \varepsilon_{i,t+1}$

The sample is all Twitter firms (excluding firms that never created a Twitter account during the sample period 2006-2017).

t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All variables are defined in Appendix A.

Table 10: Supplemental Analysis on Social Media, External Financing and Investment

Panel A: External Equity Financing and Social Media

		$NEW\_EQUITY_{i,t+1}$	
VARIABLES	***Predicted Sign***	(1)	(2)
PRESENCE$_{i,t+1}$	*(+)*	***0.007****	
		(3.923)	
PRESENCE$_{i,t+1}$*MEDIAN_CASH_FLOW$_{i,t+1}$	*(-)*	***-0.008****	
		(-4.211)	
LOG(ENGAGEMENT)$_{i,t+1}$	*(+)*		***0.006****
			(7.688)
LOG(ENGAGEMENT)$_{i,t+1}$*MEDIAN_CASH_FLOW$_{i,t+1}$	*(-)*		***-0.004****
			(-4.333)
MEDIAN_CASH_FLOW$_{i,t+1}$		-0.020***	-0.022***
		(-12.885)	(-17.010)
LOG(ASSET)$_{i,t+1}$		-0.012***	-0.012***
		(-45.267)	(-45.504)
MTB$_{i,t+1}$		0.002***	0.002***
		(21.207)	(20.586)
STOCK_RETURN$_{i,t+1}$		0.005**	0.005**
		(2.258)	(2.276)
INTERCEPT		0.109***	0.113***
		(26.805)	(27.821)
Observations		72,021	72,021
R-squared		0.188	0.188
Fixed Effects		Time and Industry	Time and Industry
Clustering of Errors		No	No

Table 10 (continued)

Panel B: Social Media and the Investment Sensitivity to Cash Flows

		$CAPEX_{i,t+1}$	
VARIABLES	***Predicted Sign***	(1)	(2)
$PRESENCE_{i,t+1}$		0.998***	
		(5.367)	
$PRESENCE_{i,t+1}$*CASH_FLOW$_{i,t+1}$	***(-)***	***-5.075****	
		(-3.416)	
$LOG(ENGAGEMENT)_{i,t+1}$			0.714***
			(9.256)
$LOG(ENGAGEMENT)_{i,t+1}$*CASH_FLOW$_{i,t+1}$	***(-)***		***-3.872****
			(-4.716)
$NEW\_EQUITY_{i,t+1}$		18.863***	18.838***
		(44.369)	(44.349)
$TOBIN'SQ_{i,t+1}$		1.240***	1.213***
		(31.450)	(30.589)
$CASH\_FLOW_{i,t+1}$		21.222***	21.216***
		(17.101)	(19.569)
$LOG(ASSET)_{i,t+1}$		-1.105***	-1.166***
		(-34.615)	(-35.247)
$MTB_{i,t+1}$		0.083***	0.079***
		(6.757)	(6.422)
Constant		15.509***	15.995***
		(30.972)	(31.651)
Observations		75,484	75,484
R-squared		0.246	0.246
Fixed Effects		Time and Industry	Time and Industry
Clustering of Errors		No	No

Panel A shows the results of OLS regression using equation 4a: $NEW\_EQUITY_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 TWEET\_VARIABLE_{i,t+1} + \beta_2 TWEET\_VARIABLE_{i,t+1} * MEDIAN\_CASH\_FLOW_{i,t+1}} + \beta_3 MEDIAN\_CASH\_FLOW_{i,t+1} + \sum\beta_n CONTROL\ VARIABLES_{i,t+1} + \sum INDUSTRY_j + \sum TIME_{t+1} + \varepsilon_{i,t+1}$

Panel B shows the results of OLS regression using equation 4b: $CAPEX_{i,t+1} = \beta_0 + \beta_1 TWEET\_VARIABLE_{i,t+1} + \boldsymbol{\beta_2 TWEET\_VARIABLE_{i,t+1} * CASH\_FLOW_{i,t+1}} + \beta_3 NEW\_EQUITY_{i,t+1} + \sum\beta_n CONTROL\ VARIABLES_{i,t+1} + \sum INDUSTRY_j + \sum TIME_{t+1} + \varepsilon_{i,t+1}$

Both panels show the results for Twitter firms (excluding firms that never created a Twitter account during the sample period 2006-2017).

t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All variables are defined in Appendix A.

Figure 1A: Trend in Twitter Presence over Time – All Firms

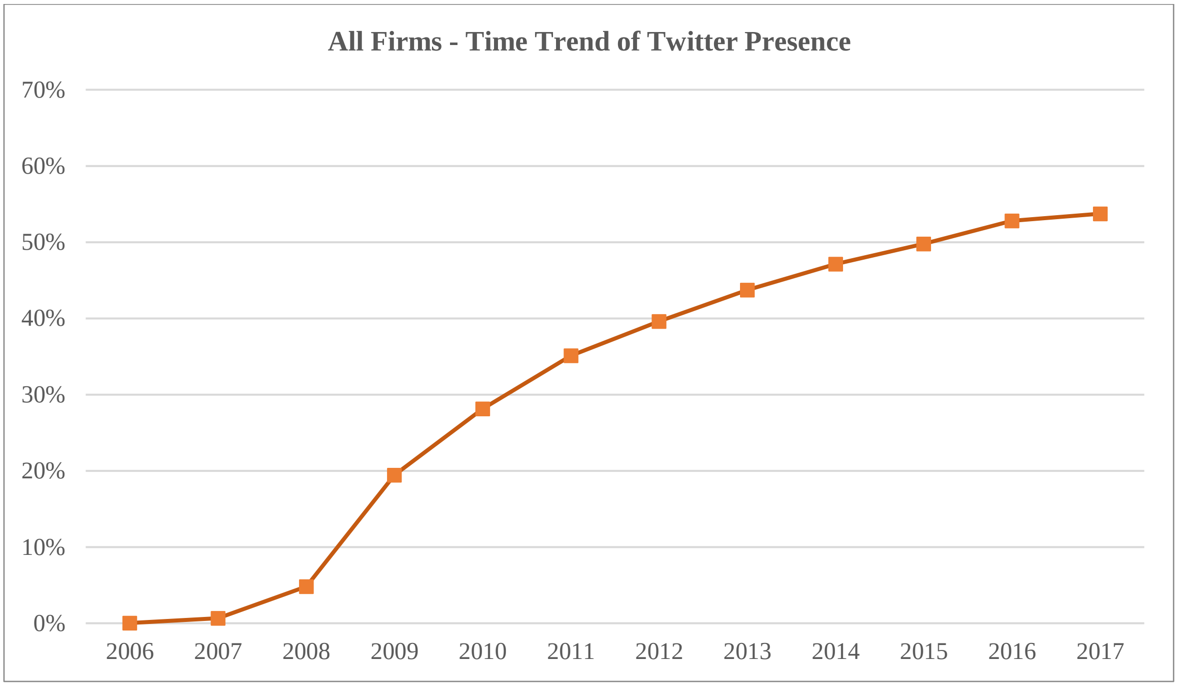

Figure 1B: Trend in Twitter Presence over Time –Firms that Initiated Official Twitter Accounts Anytime during the Sample Period

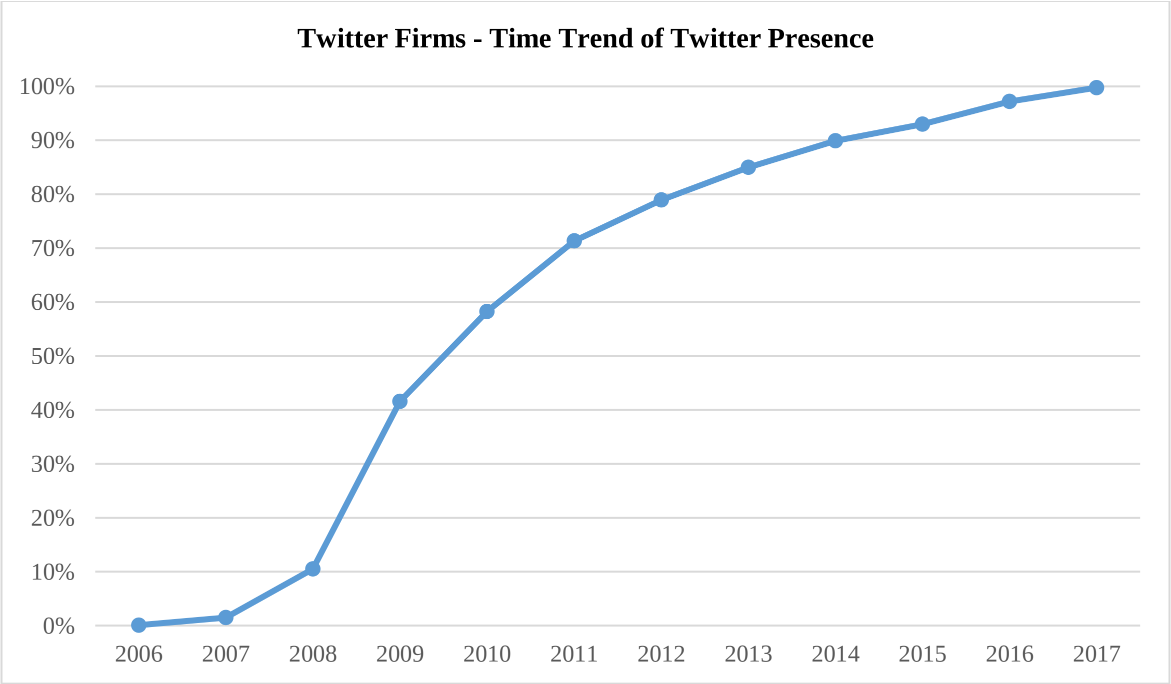

Figure 2: Distribution of Follower Responses