Can Social Media Mitigate Hurdles for Capitalizing Expenditures Related to Internally Developed Intangibles?

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Abstract

This study examines whether social media narrows the time and correlation gaps between historical costs incurred for internally generated intangibles and economic benefits. Managers leverage social media to gain previously undiscovered insights into market demand, leading to enhanced accuracy in sales forecasts and sales forecast revisions aligned with changes in customer sentiment after launching the primary corporate Twitter account. With a Twitter presence, the investment portion of SG&A expenditures becomes more sensitive to the positivity of customer comments, a "wisdom-of-crowds" measure of the value of customer-related and brand-related intangibles. Notably, investments in intangibles are associated with higher future sales growth after establishing a social media presence, but not so before. In the cross-section, investments in intangible assets are more sensitive to customer sentiment when social media's "wisdom of crowds" is more informative and when stock prices are less informative. Surprisingly, consumer-facing companies invest more in customer-related and brand-related intangibles when faced with highly *negative* customer sentiment.

Keywords: expensing versus capitalizing; disaggregation; feedback effect; social media; managerial learning

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I. INTRODUCTION

Social media platforms provide a centralized venue for a broad set of followers, including customers, investors, and other interested parties, to comment and express their opinions and for direct interactions between managers and followers. Accordingly, comments on social media are likely to provide a *real-time* “wisdom-of-crowds” measure of the *value* of customer-related and brand-related intangibles. Prior studies have primarily emphasized the *dissemination* effect of social media (e.g., Blankespoor et al. 2014; Jung et al. 2018). In contrast, this study takes a different approach by examining *whether* and *how* social media feedback influences managerial learning and shapes expenditures related to internally developed intangibles.

This study focuses on expenditures related to internally developed intangibles in investigating the *real* effect of social media for two reasons. As the economy has transitioned toward service and technology-based businesses, intangible assets like customer relationships, customer lists, distribution networks, and brands have become increasingly important. Intangible capital accounts for 34% of a company's total capital in recent years, and more than $1 trillion is invested in intangibles in the U.S. (e.g., Corrado et al. 2005; Corrado and Hulten 2010). More importantly, despite the economic significance of investments in intangible assets, the U.S. Generally Accepted Accounting Principle (GAAP) largely mandates immediate expensing expenditures related to internally developed intangibles. Two critical hurdles for capitalizing costs associated with internally developed intangibles are the time gap and the correlation gap. The time gap, which refers to the time lag between when historical costs are being incurred and when those expenditures and efforts can be demonstrated to have future economic benefits, poses a recognition hurdle. The correlation gap, which emphasizes that the historical cost is not a reliable measure of future economic benefits that those expenditures may create, poses a hurdle for measuring internally developed intangibles. As social media provides a real-time "wisdom-of-crowds" measure of the value of customer-related and brand-related intangibles, the answer to the research question sheds light on whether and how social media *narrows* the time and correlation gaps between historical costs incurred for customer-related and brand-related intangibles and economic benefits generated. Anecdotal evidence suggests that managers gain insights from social media and adjust expenditures incurred for internally developed intangibles. One noteworthy example is after a customer posted a picture of a messy Domino's pizza on social media, the company's CEO starred in a national TV commercial apologizing and the company launched social media campaigns that allowed customers to order pizza through various platforms like Twitter. The CEO says, "We've spent tens of millions of dollars to tell customers we are listening, reacting to customers, and doing something about it." [1] Despite such anecdotes, there remains a lack of systematic evidence establishing the effect of social media feedback on corporate expenditures related to internally generated intangibles.

Companies employ advanced techniques to track and analyze consumer opinions about their brands and products on social media (e.g., Dhaoui et al. 2017; Humphreys and Wang 2018). Previous studies in marketing have found that social media significantly enhances consumer awareness, and positive social media comments are associated with consumer brand choices and box office performance (e.g., Chintagunta et al. 2010; Liu and Lopez 2016). However, a study conducted by Cui et al. (2018), using data from an online apparel retailer, casts doubt on the *long-term* impact of social media information. Their findings indicate that while social media information enhances daily sales forecast accuracy within short time horizons (a few days), its

[1] Source: How Social Media Can Influence High-Stakes Business Decisions | CIO

benefit diminishes as the forecasting horizon extends. This raises a critical question: Can the observed "wisdom of crowds" from social media, evident in short-term forecasting and operational decisions such as inventory staging, also provide valuable insights for corporate decisions on expenditures related to intangible assets that tend to be more oriented towards long-term strategies?

We hypothesize that managerial learning is one channel underlying the possible feedback effect of social media on expenditures related to internally developed intangibles. Conceptually, the feedback effect of social media has distinct characteristics compared to that of stock prices (e.g., Bond et al. 2012; Chen et al. 2007; Zuo 2016). While stock prices capture investors' *composite* information about a given company, it is challenging to pinpoint precisely what *specific* information a stock price movement conveys. In contrast, managers directly engage with followers on social media and thus quickly identify *who* has communicated and what *specific* information a follower's comment conveys. For instance, customers' comments on social media capture upcoming demand for a firm's products and services and are a leading indicator of the upcoming quarter's revenue and unexpected revenue growth (Tang, 2018). Thus, stock price is not a perfect substitute for follower engagement on social media: managers gain *more granula*r insights from a *broader* set of followers on social media, especially from customers. Furthermore, serious concerns about the reliability and credibility of follower comments on social media present additional challenges.[2] It is essential to acknowledge that follower comments are voluntary and lack any financial stake, raising doubts about the incentive to provide truthful information or possessing the expertise to evaluate products (e.g., Huang 2018).

A related challenge is that investment expenditures are not separated from operating expenditures, especially for spending related to internally generated intangibles. Despite being the

[2] The dark sides (costs) of adopting social media include potential damages caused by disseminating misinformation and disinformation.

most significant expense item for many services- and knowledge-intensive businesses, companies provide little information on the breakdown of selling, general, and administrative (SG&A) costs except for research and development (R&D) and advertising costs. Expenditures on customer-related and brand-related intangibles are typically combined with operating expenditures in SG&A costs (Lev and Radhakrishnan 2005; Banker et al. 2011). We adopt the methodology proposed by Enache and Srivastava (2018) to estimate the portion of SG&A spending dedicated to investment in intangible assets other than R&D and advertising expenditures. This methodology builds on the intuition that one portion of SG&A costs comprises maintenance expenditures that support current operations, and the remaining portion is strongly linked to future economic benefits and considered investments in customer-related and brand-related intangibles. Examples of the investment portion of SG&A costs include expenditures on strategy, market research, brand awareness, customer contracts, noncontractual customer relations, and human capital.

In the empirical analysis, as Twitter is the most commonly used social media platform for businesses (Jung et al. 2018), we identify the launch of a company's primary corporate Twitter account as the starting point of its social media presence. We use two datasets to examine whether and how social media influences expenditures related to internally developed intangibles. The first dataset consists of 23.2 million follower responses from 776 companies' primary corporate Twitter accounts from 2006 to 2017. The second dataset includes customer sentiment for 1,391 companies from 2012 to 2015, where customer sentiment is the ratio of the number of customer tweets that convey a positive assessment of products and brands over the number of tweets that express a non-neutral (either positive or negative) evaluation of products and brands.

First, we identify the *specific* content of managerial learning from social media: managers learn previously undiscovered insights into the *market demand* for the company’s products and services from customer comments on social media. Utilizing the exact timing of launching a firm's primary corporate Twitter account, we find that managers forecast revenue more accurately and revise forecasts up (down) in response to improving (deteriorating) customer sentiment after launching the primary corporate Twitter account. Next, we find that, after establishing a Twitter presence, the investment portion of SG&A costs becomes more sensitive to the positivity of customer comments, a "wisdom-of-crowds" measure of the value of customer-related and brand-related intangibles. The greater investment sensitivity to customer sentiment suggests that direct interactions with customers on Twitter reduce managers' information uncertainty about market demand, and consequently, the real option value of delaying investment projects decreases (e.g., McDonald and Siegel 1986; Pindyck 1993). Notably, we find that expenditures related to customer-related and brand-related intangibles are associated with higher future sales growth after establishing a social media presence but *not before* the presence. This heightened positive association with future sales growth highlights that social media presence reduces the *time* and *correlation* gaps between historical costs incurred for customer-related and brand-related intangibles and future economic benefits associated with those expenditures. In contrast, we have not observed an increased sensitivity of R&D expenditures to the positivity of customer comments after establishing a Twitter presence. This is probably because customer sentiment is a substantially noisier real-time indicator of the value of *knowledge*-related intangible assets.

Next, we perform several cross-sectional analyses to substantiate social media as the source of the above-documented effects. As Twitter adoption at the corporate level is not exogenous, it likely correlates with corporate technology investment that affects internal information quality. If social media is the information source for the above-documented effects, we hypothesize that the baseline effects are more pronounced when social media information is more informative. First, social media provides a more informative "wisdom-of-crowds" leading signal of market demand for consumer-facing companies than non-consumer-facing companies (e.g., Tang 2018). Consistent with this cross-sectional prediction, we find that managers in consumer-facing companies revise sales forecasts up (down) in response to improving (deteriorating) customer sentiment. However, this is not the case for non-consumer-facing companies. Furthermore, the investment sensitivity to market demand increases after establishing a Twitter presence for consumer-facing companies, but not for non-consumer-facing companies. Interestingly, consumer-facing versus non-consumer-facing companies adjust investment in intangibles in the *opposite* direction in response to the positivity of customer sentiment. In particular, while non-consumer-facing companies invest more in intangibles when faced with highly *positive* customer sentiment, consumer-facing companies invest *more* in customer-related and brand-related intangibles when faced with *highly negative* customer sentiment on Twitter. This *counterintuitive* response indicates that managers in consumer-facing companies perceive the need to spend more to bolster their brand reputation and improve customer relationships to address serious consumer concerns in the face of highly negative feedback. In the cross-section, we find that expenditures related to customer-related and brand-related intangibles are more sensitive to customer sentiment when the "wisdom of crowds" from social media is more informative, as in the case of more engaged Twitter followers, and when alternative information sources, such as stock prices, are less informative. The cross-sectional variation indicates that the informativeness of social media signals (relative to other information sources) influences the strength and direction of the baseline effects.[3]

[3] If internal data quality is the sole factor underlying the documented baseline effects, the strength and direction of the baseline effects are not likely to vary with the informativeness of social media signals in the cross-section. For instance, internal data quality cannot explain the opposite direction in which consumer-facing versus non-consumer-facing companies adjust investment in intangibles in response to the positivity of customer sentiment.

The contribution of this study is multi-faceted. First, this study presents the first systematic evidence of the feedback effect of social media on investment in intangible assets that are long-term oriented. This differs from previous studies that have primarily focused on the value of comments on social media and the Internet for financial investment decisions (e.g., Huang 2018; Bartov et al. 2018) as well as internal forecasting and short-term operational decisions (e.g., Cui et al. 2018; Boone et al. 2019). It is important to note that the underlying frictions for the managerial learning channel identified by this study and the disciplining channel explored by Ang et al. (2021) differ significantly. The managerial learning channel reduces information uncertainty about market demand. In contrast, the disciplining channel addresses agency conflicts between managers and investors, with social media comments helping to prevent value-destructive mergers in Ang et al. (2021). Accordingly, this study adds to the literature on how uncertainty affects business investments by identifying information uncertainty regarding market demand as a specific category of uncertainty (e.g., Bloom et al. 2007; Goodman et al. 2014; David et al. 2016; Ferracuti and Stubben 2019).

Second, social media's feedback effect on expenditures related to internally developed intangibles has timely implications for the Financial Accounting Standards Board's agenda on intangibles. Social media platforms provide real-time measurements of the value of customer-related and brand-related intangibles, which narrow the time and correlation gaps between historical costs incurred and expected economic benefits associated with those expenditures. Consequently, with social media presence, the distinct accounting treatment of *capitalizing externally* acquired intangibles versus *expensing* expenditures related to *internally* developed intangibles is *less* justified, especially for customer-related and brand-related intangibles. Moreover, this study finds that customer sentiment on social media influences spending on *customer*-related and *brand*-related intangibles *but not R&D* expenditures related to knowledge-related intangibles. This difference highlights the benefits of disaggregating expenditures related to different types of intangible assets.

Third, this study uncovers an intriguing contrast between the use of social media and other data for investment decisions among consumer-facing companies. Ittner and Larcker (1998) find that customer satisfaction survey, as an example of classical customer feedback channels, provides a leading indicator for financial performance. Companies also rely on various alternative data sources, such as traffic and path data, to inform their short-term operational decisions (e.g., Boone et al. 2019). However, compared with those information sources that are *exclusive* to managers, social media information is publicly available to other followers and thus could generate a "word-of-mouth" effect and influence brand reputation. While other alternative data often guides managerial decision-making in line with the positivity of the feedback, this study reveals that expenditures related to customer-related and brand-related intangibles do not increase *monotonically* with the positivity of social media comments. Surprisingly, managers of consumer-facing companies invest more in intangibles by allocating more resources to building brand awareness and customer relationships when confronted with highly negative customer sentiment on social media.

II. HYPOTHESIS DEVELOPMENT AND RELATED LITERATURE

We hypothesize that social media feedback could have a real effect on corporate investment decisions through the channel of *managerial learning*. While managers know many aspects of their firms better, 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 an interactive platform for followers to comment and express their opinions and for managers to interact directly with followers. More than 4.2 billion users are active on social media (Pew Research Center 2021). Many companies carry thousands and even millions of followers. On Twitter, Google has over 19 million followers, and Starbucks has over 11 million. Therefore, social media presence and follower engagement could potentially provide *additional "wisdom of crowds"* of outsiders about market trends, the product market demand, and the competitive landscape.

Prior literature suggests that managers learn *private* information from stock prices and incorporate such information in management forecasts and investment decisions (e.g., Bond et al. 2012; Chen et al. 2007; Zuo 2016). We highlight two features of social media that differ from stock prices. The first feature is that social media presence and follower engagement could provide more *granular* information for investment decisions. Stock prices communicate private information through the trading process and capture investors' *composite* information about all aspects of a given firm. It is challenging to pinpoint precisely 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. Because the stock price is a single aggregate number, it does not speak to specific products or types of investments (e.g., tangibles versus intangibles). Social media, on the other hand, provides a centralized platform for followers to communicate *directly* with the company. Thus, managers can quickly identify *who* has expressed and *what* specific information a follower's comment conveys. Follower comments help identify over-performing versus underperforming product lines, which provides more granular insights into which product line the firm should expand or contract investment. Thus, social media provides another source for managers to learn more *granular* signals from a *broader* set of followers on social media. The second feature is that follower comments are voluntary and lack any financial stake, raising doubts about the incentive to provide truthful information or possessing the expertise to evaluate products (e.g., Huang 2018). Thus, serious concerns about the reliability and credibility of follower comments on social media present additional challenges.[4]

We develop three hypotheses via the channel of managerial learning. First, the managerial learning channel predicts that followers on social media possess some information that managers do not have. To substantiate the condition for managerial learning and identify the specific type of uncertainty managers face, we hypothesize that managers could learn *new* insights about the demand for the firm's products and services from social media. Customers, as one essential constituent of followers on social media, could provide a wealth of real-time insights beyond those of managers—including key market trends and demand for products and brands. Managers could learn more about market demand from customer comments on Twitter on a product-by-product basis. Companies employ advanced techniques, such as Hootsuite Geo-Search on Twitter, to track consumer opinions about their brands and products and analyze customer comments on a product-by-product basis (e.g., Dhaoui et al. 2017; Humphreys and Wang 2018). Accordingly, after establishing a Twitter presence, the availability of new insights on market demand on a product-by-product basis improves the accuracy of management sales forecasts, which reflect the forecasted aggregate market demand for all products and services offered by the company.

The learning channel also implies that managers will update their beliefs about the demand for the company's products and services in the *direction* that the change in the positivity of follower engagement indicates. Tang (2018) finds that customer comments, one subset of follower comments on social media, capture upcoming demand for a firm's products and services, and are

[4] The credibility issue is exacerbated by fabricated follower identities and manipulated tweets (Luca and Zervas 2016). Twitter suspended over 70 million accounts flagged as trolls and bots (*Washington Post*, July 6, 2018).

a leading indicator of the upcoming quarter's revenue and unexpected revenue growth. The predictive power of customer comments concerning upcoming revenue comes from two sources: first, the positivity of customer comments is a broad indicator of customer satisfaction, and a more positive customer sentiment implies higher 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, the positivity of customer comments directly influences consumers' demand for a company's products and services. More positive customer comments could generate additional demand for its products and services due to the "word-of-mouth" effect. Similarly, previous studies in marketing find that social media enhances consumer awareness, and positive comments are associated with more consumer brand choices and better box office performance (e.g., Chintagunta et al. 2010; Liu and Lopez 2016; Liu 2006). Accordingly, more positive (negative) customer comments indicate improving (deteriorating) demand for the company's products and services. We make the directional prediction that managers revise sales forecasts up (down) in response to improving (deteriorating) customer sentiment.

H1a: Management sales forecasts are more accurate after establishing a Twitter presence.
H1b: Managers revise sales forecasts up (down) in response to improving (deteriorating) customer sentiment.

Second, theories suggest an option value associated with delaying investment decisions in the face of uncertainty regarding the level and variability of the future cash flows of an irreversible investment (or an investment that can only be reversed with some costs). Delaying investment allows managers to assess the investment opportunities in subsequent periods (e.g., Bernanke 1983). The real option value of delaying investment increases in the extent of fundamental and information uncertainty (McDonald and Siegel 1986; Pindyck 1993). Corporate investment decisions require managers to forecast future cash inflows and outflows from potential investment opportunities (e.g., Goodman et al. 2014). Because both managers and investors have access to comments on social media, its impact on investment is primarily driven by information uncertainty rather than information asymmetry. After establishing the company's primary corporate Twitter account, managers directly communicate with followers and learn more granular insights from customer comments. This mitigates managers' information uncertainty about market demand and reduces the real option value of delaying investment. Thus, investment in intangibles is more sensitive to market demand after establishing a social media presence (e.g., Bloom et al. 2007).

H2: The investment sensitivity to market demand increases after establishing a Twitter presence.

Despite the insights gained from customer comments on social media, the direction in which managers adjust investment in intangibles in response to the positivity of customer comments remains uncertain. On the one hand, a more positive customer sentiment on social media indicates increased consumer purchases and a potentially higher future demand for a company's products and services (Tang 2018). Consequently, the conventional wisdom suggests that managers invest more in intangibles to meet the anticipated surge in market demand. However, the anecdote concerning Domino's Pizza suggests a counterintuitive feedback effect: managers invest more to improve customer relationships and brand reputation to address serious consumer concerns when social media comments are highly negative. Accordingly, when customer comments are highly negative, investments in intangibles could increase with the *negativity* of customer comments. We hypothesize that the relation between investment in customer-related and brand-related intangibles and the positivity of customer comments is *not* monotonic.

H3: Investments in intangibles do not increase monotonically with the positivity of customer comments.

III. SAMPLE, DATA, AND BASELINE RESULTS

Sample Formation, Data, and Social Media Measures

Firms use social media platforms like Twitter, Facebook, Instagram, and YouTube. 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 is the most preferred social media platform for companies. Therefore, we use Twitter's presence as a proxy for the overall social media presence. Our dataset has the *primary* corporate Twitter accounts of all U.S. firms listed on the New York Stock Exchange, the American Stock Exchange, and NASDAQ. *PRESENCE*, the first variable of interest, is defined as one if the firm-quarter observation is *after* the firm establishes its *primary* corporate Twitter account and 0 otherwise. We hand-collected the year and quarter in which a firm initiates its primary corporate account on Twitter.[5] For instance, the quarter and the year P&G initiated its *primary corporate* Twitter account was the first quarter in 2009.

The second variable of interest, *CUSTOMERSENTIMENT*, captures the positivity of customer comments about a company's products and brands on Twitter. First, as firms use social media to introduce and advertise their products and services, customers are an integral part of followers on social media. Second, customers are the origin and source of demand for a firm's products and services (e.g., Tang 2018). Following Tang (2018), the positivity of customer comments, *CUSTOMERSENTIMENT*, is measured as the ratio of the number of customer tweets that convey a positive assessment of products and brands over the number of tweets that express a non-neutral (either positive or negative) evaluation of products and brands. The unit of analysis is at the firm-quarter level. Accordingly, product- or brand-level comments should be aggregated at the firm

[5]We define the *primary corporate* Twitter account as the account with the hashtag of the name of the corporation (e.g., @ProcterGamble, @CocaColaCo, @generalelectric), not the various accounts established separately for several brands of the corporation (e.g., @Gillette, @tide, and @Pampers for Proctor & Gamble) or regions (e.g., @CocaCola_GB, @CocaCola_Br for Coca Cola) or functions (e.g., @GECareers, @GEpublicaffairs for General Electric). The home webpage of the company, generally, has a link to its *primary corporate* Twitter account.

level, as individual firms will likely have multiple products or brands. The positivity of customer comments on Twitter is provided by LikeFolio.com, a professional data analytics outfit that sells data and insights to institutional investors and corporate research teams. Using Likefolio data enables us to achieve a significant level of product information aggregation via the data provider's proprietary information to map products and brands to companies that offer them—a challenging process if applied to alternative social media platforms (e.g., Facebook, Yelp, and Youtube). Furthermore, 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 customer sentiment more credible.

We collect financial data from Compustat and stock returns data from CRSP. We remove financial services firms from the sample because their investment decisions differ from those of non-financial firms. As shown in Table 1A, the final sample comprises 14,123 firm-quarters for 776 unique publicly traded firms that initiated *primary* corporate Twitter accounts from 2006 to 2017 (classified as *Twitter firms*). The *post-initiation* subsample includes firm-quarter observations for *Twitter firms* after establishing the *primary* corporate Twitter accounts and covers 23.2 million follower responses to 2.3 million firm-generated tweets. Data on customer sentiment covers the period from 2012 to 2015 and 1,391 firms with 10,668 firm-quarter observations. Out of 1,391 firms with available data on *CUSTOMERSENTIMENT*, only 796 have established *primary* corporate Twitter accounts. Thus, the subsample of *Twitter firms* with available data on customer sentiment includes 4,974 firm-quarters for 534 unique firms from 2012 to 2015.

Panel A of Table 1 provides the descriptive statistics. Conditional on initiating the *primary* corporate Twitter accounts, panel B of Table 1 provides descriptive statistics on follower engagement for the *post-initiation* subsample. On average, a firm tweets 253 times, and followers engage 2,514 times with firm-generated tweets each quarter.[6] The mean (median) follower response rate (*ENGAGEMENT*) is 8.06 (4), with a standard deviation of 26.75. Panel C of Table 1 provides descriptive statistics on the positivity of customer comments. The mean (median) positivity is 0.87 (0.89), and the 25th percentile is as high as 0.81. The descriptive statistic suggests that, for most firms, the number of customer tweets that convey a positive assessment of products and services dramatically exceeds the number of customer tweets that convey a negative assessment– a ratio of 0.5 means that the number of positive and negative tweets is equal.

Estimating Investment in Intangibles from SG&A

Corrado et al. (2005) suggest that many intangible investments are made in avenues other than R&D and advertising. A few studies use SG&A expenses as a proxy for investments in intangible assets. One portion of SG&A outlays, such as head office rents, customer delivery costs, and sales commissions, support current operations and, therefore, do not have an investment nature (Donelson et al. 2011; Matějka 2011). The other portion of SG&A costs includes outlays on strategy, market research, brand reputation, customer contracts, noncontractual customers, computerized data and software, and human capital that are likely to produce future benefits. Companies provide little details on SG&A's constituent items except for R&D and advertising. Adopting the method proposed by Enache and Srivastava (2018), we use the following model to estimate the investment portion of SG&A costs other than R&D and advertising expenditures by Fama-French 48 industry and time:

$$MAINSGA_{i,t} = \alpha_0 + \alpha_1 REV_{i,t} + \alpha_2 DUMMYREVDECREASE_{i,t} + \alpha_3 DUMMYLOSS_{i,t} + \varepsilon_{i,t} \qquad \textit{Equation (1A)}$$

[6] In aggregate, we find an increasing trend for the number of firm-generated tweets and the number of follower responses —from 378 (1,117) firm-generated tweets (follower responses) in 2007 to 0.56 million (5.86 million) firm-generated tweets (follower responses) in 2017.

where *MAINSGA* is defined as SG&A – R&D – Advertising expenses. *MAINSGA* and *REV* are scaled by the ending market value of equity as of the prior quarter. *DUMMYREVDECREASE* is a dummy variable that takes the value of 1 if revenue declines during the quarter and 0 otherwise, which controls for the stickiness of $MAINSGA_{i,t}$. *DUMMYLOSS*, a dummy variable that takes the value of 1 if net income is negative and 0 otherwise, is also included. Equation (1A) identifies the portion of *MAINSGA* that varies with current revenues (e.g., Dichev and Tang 2008).

Next, we calculate the maintenance component of SG&A:

$$MAINTENANCEMAINSGA_{i,t} = \tilde{\alpha}_1 \, REV_{i,t} \qquad \text{Equation (1B)}$$

Where $\tilde{\alpha}_1$ is the estimated slope coefficient from equation (1A). *MAINTENANCEMAINSGA* includes outlays, such as head office rents, customer delivery costs, and sales commissions, that support current operations and are not an investment nature.

Last, we use equation (1C) to estimate the investment portion of *MAINSGA*:

$$INVESTMENTMAINSGA_{i,t} = MAINSGA_{i,t} - MAINTENANCEMAINSGA_{i,t} \qquad \text{Equation (1C)}$$

Where *INVESTMENTMAINSGA* is the estimated investment in customer-related and brand-related intangibles and captures outlays on intangibles such as strategy, market research, customer and social relationships, computerized data and software, and human capital (e.g., Enache and Srivastava 2018).[7] These outlays improve brand awareness and customer relationships, likely producing future benefits (e.g., Eisfeldt and Papanikolaou 2013).

Table 2 provides descriptive statistics of key variables. The mean (median) of a firm's investment in customer-related and brand-related intangibles (*INVESTMENTMAINSGA*) is 1.4% (0.93%) of the firm's market value, which corresponds to 105.25 (69.92) million USD for the

[7] Enache and Srivastava (2018) acknowledge several limitations. For example, this measure might include wasteful expenditures, slack resources channeled into overhead and staff expenses, the fixed costs of doing business, sticky costs, and real earnings management. However, including such outlays should be biased against finding an association between investment in intangibles and the positivity of customer comments.

average (median) firm. Its standard deviation is 3.9% of the market value. The mean (median) of R&D expenditure is 1.4% (0.9%) of the market value. In un-tabulated results, the average quarterly *INVESTMENTMAINSGA* and R&D expenditure are 2.13% and 1.99% of total assets, respectively. Advertising expense (*ADVEXPENSE*) is 0.3% of the total assets, corresponding to 13.79 million USD. The descriptive statistics are similar to those in prior studies (e.g., Koh and Reeb 2015; Enache and Srivastava 2018).[8] Panels A and B of Table 3 present the correlation between the dependent and explanatory variables. *INVESTMENTMAINSGA* is positively correlated with *CUSTOMERSENTIMENT* and *PRESENCE.* To mitigate the influence of outliers, we winsorize all continuous variables at the 1 percent and 99 percent levels. We use Fama-French 48 industry and time (year-quarter) fixed-effects and cluster standard errors by firms for all the empirical analyses. All variables are defined in Appendix A.

IV. SUBSTANTIATE SPECIFIC CONTENT OF MANAGERIAL LEARNING

Social Media Presence and the Accuracy of Management Forecasts

This section examines whether social media presence is associated with the ability of managers to forecast future demand more accurately. We use the following equation to estimate whether social media presence enables more accurate forecasts of future sales:

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[8] Our empirical analysis is based on quarterly *INVESTMENTMAINSGA*, *R&D*, and *ADVEXPENSE*, whereas prior studies generally report these variables yearly. If deflated by total assets, the annualized *MAINSGA* is 26.4% of total assets in our sample, which is quantitatively similar to 27.4% of total assets as reported in Enache and Srivastava (2018). The *average* annualized *INVESTMENTMAINSGA* is 2.13%*4 = 8.52% of total assets in our sample, which is smaller than the corresponding average of 11.7% in Enache and Srivastava (2018). However, the *median* annualized *INVESTMENTMAINSGA* is 5.6% of total assets in our sample, which is greater than the corresponding median of 4.1% in Enache and Srivastava (2018). The distribution in Enache and Srivastava (2018) seems skewed more than our sample. As another validation of the estimated investment component of SG&A costs, we find that the average annualized *INVESTMENTMAINSGA* is 8.3% of total assets for the first half of the sample period from 2006 to 2012 and 8.9% for the second half from 2013 to 2017. The increase in *INVESTMENTMAINSGA* over time *within* our sample is consistent with the time trend of increased intangible capital. Annualized advertising expenses are 1.2% of total assets in our sample compared to 1.4% as reported in Enache and Srivastava (2018). Similarly, the annualized R&D in our sample is 7.9% of total assets compared to 7.3% as reported by Koh and Reeb (2015).

$$|MFESALES|_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 PRESENCE_{i,t}} + \sum \beta_n CONTROLS_{i,t} + \sum INDUSTRY_j + \sum TIME_{t+1} + \varepsilon_{i,t+1} \qquad \textit{Equation (2A)}$$

where |*MFESALES*| is the absolute difference between the most recent quarterly management forecast of sales and the realized sales scaled by the previous quarter's ending total assets. We require that the sales forecast be issued at least seven days before the earnings announcement date.[9] 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[10]. The variable of interest is the coefficient on *PRESENCE* (β_1), which is expected to be negative if management sales forecasts are more accurate after establishing a Twitter presence.

Panel A of Table 4 presents the results on social media presence and the absolute value of the sales forecast error. The first (second) column presents the results on the accuracy of sales forecasts without (with) controls. We exploit the exact timing of corporate Twitter accounts and find that the sales forecast is more accurate, as evidenced by a lower forecast error *after* the initiation of corporate Twitter accounts compared with that before initiation. As shown in columns 1 and 2, the slope coefficients on *PRESENCE* are –0.005 and –0.004 and are statistically significant at the 1 percent and 5 percent levels, respectively. Regarding economic magnitude, quarterly management sales forecast accuracy improves by 0.5% (0.4%) of lagged total assets *after* establishing a Twitter presence. This provides *direct* evidence that the Twitter presence allows managers to interact with followers directly and learn new insights about market demand for the company's products and services. It is worth noting that the improved management sales forecast is robust after controlling for stock returns and other information sources, such as analysts and press articles. To assess the

[9] 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.
[10] Missing data on control variables further reduces the number of observations in columns 2 and 3 of panel A of table 4.

timing of the managerial learning effect relative to the initiation of the Twitter presence, we include indicator variables to capture the quarter in which a firm initiates the primary corporate Twitter account and each of the subsequent three quarters — *QTR1PRESENCE*, *QTR2PRESENCE*, *QTR3PRESENCE*, and *QTR4PRESENCE*. As reported in column 3, the coefficients on *QTR1PRESENCE* and *QTR2PRESENCE* are negative and statistically significant, whereas those on *QTR3PRESENCE* and *QTR4PRESENCE* are insignificant. The results suggest that managers learn the most in the quarter during which the firm initiates its Twitter presence and the immediately following quarter.

Changes in the Positivity of Customer Comments and Forecast Revisions

If managers learn new insights about future demand for the company's products and services from follower engagement, especially customer comments, managers will update their beliefs about the market demand in the direction the change of the positivity of customer comments indicates. Thus, managers may revise sales forecasts up (down) in response to more positive (negative) customer comments, especially for managers in consumer-facing firms. This is 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 for non–consumer-facing (business-to-business) companies (e.g., Tang 2018). We use the following equation to test this prediction:

$$MFSALESREVISION_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 CHGCUSTOMERSENTIMENT_{i,t}} + \boldsymbol{\beta_2\, CHGCUSTOMERSENTIMENT_{i,t} * B2C_i} + \beta_3 B2C_i + \sum \beta_n CONTROLS_{i,t} + \sum INDUSTRY_j + \sum TIME_{t+1} + \varepsilon_{i,t+1} \qquad \text{Equation (2B)}$$

where *MFSALESREVISION* is the signed difference between the most recent sales forecast and the previous sales forecast scaled by the previous quarter's ending total assets. The change in quarterly customer sentiment is *CHGCUSTOMERSENTIMENT*. The variable of interest is the sum of the slope coefficient on *CHGCUSTOMERSENTIMENT* (β_1) and that on *CHGCUSTOMERSENTIMENT*B2C* (β_2). We predict that the sum of β_1 and β_2 is positive if managers in consumer-facing companies revise sales forecasts up (down) in response to improving (deteriorating) customer sentiment. Panel B of Table 4 presents the results when the sample is *Twitter* firms.[11] We define B2C firms as consumer-facing businesses and non-B2C firms as non-consumer-facing businesses (e.g., Hosseini et al., 2023).[12] As column 1 reports, while the coefficients on *CHGCUSTOMERSENTIMENT* and *CHGCUSTOMERSENTIMENT* B2C* are statistically insignificant, the sum of the two slope coefficients is 0.018 and statistically significant. Next, we partition the sample into B2C and non-B2C sub-samples. As shown in column 2, the coefficient on *CHGCUSTOMERSENTIMENT* is 0.019 and statistically significant for the subsample of B2C *Twitter firms*. As reported in column 3, the coefficient on *CHGCUSTOMERSENTIMENT* is not statistically significant for the subsample of non-B2C *Twitter* firms. As noted in columns 1 to 3, the results suggest that managers in B2C firms revise sales forecasts up (down) in response to improving (deteriorating) customer sentiment. Columns 4 to 6 repeat the analysis for the *post-initiation* subsample – firm-quarter observations *after* a firm establishes the Twitter presence. Column 5 has the same number of observations as column 2, suggesting that all B2C Twitter firms have a Twitter presence throughout the sample period. The

[11] In analyzing the quarterly time series of the positivity of customer comments, it becomes evident that significant amounts of data are missing. Out of the 4,974 firm-quarter observations, only 808 provide enough data to calculate the quarter-over-quarter change in customer sentiment. This begs the question of why such a substantial portion of the data is incomplete. We note that these missing observations do not stem from a lack of data collection by Likefolio or a complete absence of tweets regarding the companies and their products. Rather, the primary reason is that the data provider classifies most customer comments as neutral. Consequently, the denominator used to compute customer sentiment, namely the sum of the number of positive and negative comments, becomes zero for many observations. Missing data on control variables further reduces the number of observations. Only 734 observations have information available for sales forecast revisions, the change in customer sentiment, and control variables.

[12] Hosseini et al. (2023) use a proprietary database provided by uscompanydata.com to classify firms into B2C and non-B2C categories. We are thankful to them for sharing the data with us.

results are qualitatively similar and imply that managers in B2C firms revise sales forecasts up (down) in response to improving (deteriorating) customer sentiment *after* establishing the Twitter presence.

V. FEEDBCK EFFECT OF SOCIAL MEDIA ON INVESTMENT IN INTANGIBLES

Sensitivity of Investment in Intangibles to Market Demand

The decision to initiate a *primary* corporate Twitter account is not exogenous. It could be influenced by a firm's incentive to grow its customer base and its incentives to disseminate information promptly. Therefore, our research design is *not* to compare the *level* of investment before and after but to test the *increased responsiveness* of investment in intangibles to market demand *after* the initiation of Twitter presence. We use the investment model of Malmendier and Tate (2005) to estimate whether investments in customer-related and brand-related intangibles become more sensitive to market demand as proxied by customer sentiment after establishing a Twitter presence:

$$INVESTMENTMAINSGA_{i,t+1}=\beta_0+\boldsymbol{\beta_1 CUSTOMERSENTIMENT_{i,t}}+\boldsymbol{\beta_2 PRESENCE_{i,t} * CUSTOMERSENTIMENT_{i,t}}+\beta_3 PRESENCE_{i,t}+\sum\beta_n CONTROLS_{i,t}+\sum INDUSTRY_j+\sum TIME_{t+1}+\varepsilon_{i,t+1} \qquad \textit{Equation (3)}$$

Following Malmendier and Tate (2005), Tobin's q, cash flow, and size are included. *TOBINSQ* captures investment opportunities incorporated in stock prices, which is measured as the ratio of the market value of assets over the book value of assets, where the market value of assets is the sum of the market value of equity plus the book value of assets minus the book value of equity. We include slack, tangibility, firm age, and advertising expense as additional control variables (Chen et al. 2011; Tang 2018)[13]. The variable of interest is the slope coefficient on the interaction

[13] Compustat reports only the annual advertising expenses. We assume that firms incur advertising expenses uniformly throughout the year and, therefore, calculate the quarterly advertising expenses by dividing the annual advertising expenses by four and scaled by the ending total assets of the previous quarter.

term *CUSTOMERSENTIMENT*PRESENCE*(β_2), which is expected to be positive if investment in intangibles becomes more sensitive to market demand *after* establishing a Twitter presence.

Panel A of Table 5 shows the results for *Twitter* and *non-Twitter firms*. As reported in column 1, without the interaction term, the coefficient on *CUSTOMERSENTIMENT* is positive but statistically insignificant. As noted in column 2, while the slope coefficients on *CUSTOMERSENTIMENT* and *CUSTOMERSENTIMENT*PRESENCE* are statistically insignificant, the sum of the two coefficients is 0.028 and statistically significant. As reported in column 3, the results are similar after controlling for the interaction between *PRESENCE* and *TOBINSQ*. The coefficient on *TOBINSQ* is negative once controlling for customer sentiment. Interestingly, the sum of the coefficient on *TOBINSQ* and that on *TOBINSQ*PRESENCE* is not statistically significant, which implies no change in the investment sensitivity to stock prices after establishing a Twitter presence. As reported in Panel B of Table 5, we apply equation (3) to *Twitter firms* and find similar results. In column 4, as all B2C firms have a Twitter presence throughout the sample period, *PRESENCE* is 1 for all observations, which implies perfect collinearity between *PRESENCE* and *CUSTOMERSENTIMENT*PRESENCE*.

In summary, after controlling for advertising expenses and other information sources, such as stock prices and analyst following, investment in customer-related and brand-related intangibles becomes more responsive to market demand as proxied by the positivity of customer comments only *after* establishing a Twitter presence, particularly for B2C firms. The heightened sensitivity of investment to market demand indicates that Twitter's interactive nature reduces managers' information uncertainty about market demand and the real option value of delaying investment.

Direction of Investment in Response to Customer Sentiment

As reported in Panel B of Table 4, managers revise sales forecasts gradually in response to the positivity of customer comments. We average the positivity of customer comments over the prior four quarters (*AVGCUSTOMERSENTIMENT*). *AVGCUSTOMERSENTIMENTBOTTOM* is the bottom quintile of *AVGCUSTOMERSENTIMENT*, representing the most negative customer sentiment, whereas *AVGCUSTOMERSENTIMENTTOP* is the top quintile, representing the most positive customer sentiment. We use the following model to examine the direction in which investment in intangibles responds to customer sentiment:

$$INVESTMENTMAINSGA_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 AVGCUSTOMERSENTIMENTBOTTOM_{i,t} + \beta_2 AVGCUSTOMERSENTIMENTTOP_{i,t} + \beta_3 AVGCUSTOMERSENTIMENTBOTTOM_{i,t} * PRESENCE_{i,t} + \beta_4 AVGCUSTOMERSENTIMENTTOP_{i,t} * PRESENCE_{i,t}} + \beta_5 PRESENCE_{i,t} + \sum \beta_n CONTROLS_{i,t} + \sum INDUSTRY_i + \sum TIME_{t+1} + \varepsilon_{i,t+1} \quad \textit{Equation (4)}$$

The reference group represents non-extreme customer sentiment (the middle three quintiles of *AVGCUSTOMERSENTIMENT*). As reported in column 1 of Table 6, for the subsample of *Twitter B2C firms*, the coefficient on *AVGCUSTOMERSENTIMENTBOTTOM*PRESENCE* is 0.029 and significant, but that on *AVGCUSTOMERSENTIMENTTOP*PRESENCE* is not statistically significant. The results suggest that B2C firms invest more in intangibles when the average customer sentiment is highly negative after the Twitter presence. For all *Twitter B2C* firms, *PRESENCE*, *AVGCUSTOMERSENTMENT*, and *AVGCUSTOMERSENTIMENT*PRESENCE* are perfectly collinear. As column 2 reports, for the subsample of *Twitter non-B2C* firms, the coefficient on *AVGCUSTOMERSENTIMENTBOTTOM *PRESENCE* is not statistically significant. However, the coefficient on *AVGCUSTOMERSENTIMENTOP*PRESENCE* is 0.021 and statistically significant, suggesting that non-B2C firms invest more in intangibles when the average customer sentiment is highly positive *after* establishing a Twitter presence.

The divergent responses of consumer-facing and non-consumer-facing companies to highly negative and positive customer sentiment underscore two opposing dynamics at play. Highly positive customer sentiment indicates a potential rise in future demand for a company's products (e.g., Tang 2018). Consequently, managers invest more in intangibles to meet the anticipated surge in market demand. Conversely, when confronted with highly *negative* customer comments, managers recognize the importance of investing *more* in intangibles to enhance customer relationships and brand reputation to address serious consumer concerns. This latter response is particularly significant for consumer-facing companies, as they understand the value of addressing customer concerns and leverage investments in intangibles as a strategic approach to navigate and improve their brand perception in the face of highly negative feedback. To summarize, the relation between investment in customer-related and brand-related intangibles and the positivity of customer comments is not monotonic. The specific direction depends on the business model.

Future Economic Benefits of Investment in Intangibles

This section explores whether the social-media-assisted investment in intangibles leads to better economic outcomes. Specifically, we use the following model to examine the association between investment in intangibles and future economic benefits, as measured by future sales growth:

$$AVGSALESGROWTH_{i,(t+1,\,t+2,\,t+3,\,t+4)/4} = \beta_0 + \boldsymbol{\beta_1}\ \boldsymbol{INVESTMENTMAINSGA_{i,t}} + \sum\beta_n\ CONTROLS_{i,t} + \sum INDUSTRY_i + \sum TIME_{t+1} + \varepsilon_{i,t+1} \qquad \textit{Equation (5)}$$

The dependent variable is the average sales growth over the next four quarters (*AVGSALESGROWTH*). As shown in column 1 of Table 7, the slope coefficient on *INVESTMENTMAINSGA* is 0.047 and statistically significant for the sub-sample of *post-initiation* Twitter firms. As reported in column 2, the coefficient on *INVESTMENTMAINSGA* is not statistically significant for the sub-sample of pre-initiation Twitter firms. The results suggest that expenditures related to customer-related and brand-related intangibles are associated with higher future sales growth *after* establishing a social media presence but *not before* the establishment. This heightened positive association with future sales growth underscores that social media reduces the time and correlation gaps between historical costs incurred for customer-related and brand-related intangibles and the associated future economic benefits.

Cross-sectional Variation on the Investment Sensitivity to Customer Sentiment

The managerial learning channel predicts that investment in intangibles is more sensitive to the positivity of customer comments when follower engagement on social media is more informative. Significant cross-sectional variation exists in the extent of follower engagement. For instance, on average, followers of Google react 85 times, whereas followers of Golden Enterprises respond only twice to every company-generated tweet. The more engaged the followers, the more likely managers will learn new insights from the "wisdom of crowds" of outsiders on social media. Managers could also learn from stock prices, and thus, the *incremental* learning from social media is expected to be more substantial when stock prices are less informative. Interestingly, social media comments can provide valuable novel information about a firm's fundamentals (e.g., Fornell et al. 2016; Huang 2018), which implies the potential for social media to enhance the informativeness of stock prices.

We use the following model to examine whether the investment sensitivity to customer sentiment varies with follower engagement and the informativeness of stock prices:

$$INVESTMENTMAINSGA_{i,t+1}=\beta_0+\beta_1 CUSTOMERSENTIMENT_{i,t}+\beta_2 CUSTOMERSENTIMENT_{i,t}* ENGAGEMENT(STOCKINFO)_{i,t}+\beta_3 ENGAGEMENT(STOCKINFO)_{i,t}+\beta_4 PRESENCE_{i,t} +\boldsymbol{\beta_5 CUSTOMERSENTIMENT_{i,t}*ENGAGEMENT(STOCKINFO)_{i,t}*PRESENCE_{i,t}} +\beta_6 STOCKINFO_{i,t}*PRESENCE_{i,t} +\sum\beta_n\ CONTROLS_{i,t} + \sum\ INDUSTRY_j + \sum\ TIME_t + \varepsilon_{i,t}$$

Equation (6)

ENGAGEMENT is the log transformation of the total number of followers' responses (likes, retweets, and replies) divided by the total number of firm-generated tweets.[14] We use the log

[14] We employ the same dataset of firm-generated tweets and the associated follower responses as the one used by Hosseini et al. (2023). They collect counts of firm-generated tweets and the corresponding responses using Twitter's "Historical API" and "Stream API 2.0". We are thankful to them for sharing the data with us.

transformation because it follows the power law distribution. $STOCKINFO_{it}$ is the informativeness of stock prices for firm *i* in quarter *t*. As in Chen et al. (2007), *STOCKINFO* is measured as one minus R^2, where R^2 is the adjusted R-squared from a regression of a firm's daily stock returns in quarter t on a constant, the CRSP value-weighted market return, and FF-48 industry portfolio return. *STOCKINFO* captures the variation in stock prices that the market and industry shocks cannot explain. Accordingly, a higher value of *STOCKINFO* implies that stock prices incorporate more firm-specific information, indicating more informative stock prices.

It is essential to note that follower engagement (*ENGAGEMENT*) is measurable only *after* the firm has initiated its *primary* corporate Twitter account. To put it differently, the value of *PRESENCE* is 1 for firms with data on *ENGAGEMENT*. Accordingly, the variable of interest is the sum of the coefficients on *CUSTOMERSENTIMENT* (β_1) and *CUSTOMERSENTIMENT * ENGAGEMENT* (β_2). As column 1 of Table 8 reports, while the coefficients on both *CUSTOMERSENTIMENT* and *CUSTOMERSENTIMENT*ENGAGEMENT* are positive but statistically insignificant, the sum of those two coefficients is 0.030 and statistically significant with a p-value of 0.05. The comparative statistic suggests that the more engaged the followers, the more "wisdom of crowds" of followers on social media, and the more sensitive the investment in customer-related and brand-related intangibles in response to customer sentiment.

As column 2 of Table 8 reports, the variable of interest is the coefficient on *CUSTOMERSENTIMENT*STOCKINFO*PRESENCE* (β_5). When the sample includes all firms, the coefficient on *CUSTOMERSENTIMENT*STOCKINFO*PRESENCE* is -0.444 and statistically significant at the 1% level. This negative coefficient suggests that conditional on Twitter presence, managers learn more new insights from social media when stock prices, as an alternative information source, are less informative about firm fundamentals. The comparative statistic suggests that, after establishing a Twitter presence, the *incremental* learning from customer comments about market demand becomes more pronounced when stock prices are less informative about firm fundamentals. The evidence suggests an intriguing interaction between the feedback effect of social media and the feedback effect of stock prices on investment in intangibles.

Tests for Endogeneity

We use a regression discontinuity design (RDD) to address the endogeneity concerns that some omitted correlated variables influence customer sentiment and investment in intangibles. To estimate the causal impact of customer sentiment, we exploit the feature of most consumer satisfaction ratings whereby third-party-generated ratings disclosed to the public are the result of rounding upward or downward the exact, unrounded rating scores (Hollenbeck, Moorthy and Proserpio 2019; Derrien, Garel, Petit-Romec and Weisskopf 2020). In our setting, LikeFolio rounds down or up the average customer satisfaction scores to the nearest whole number (in percentages). Only the rounded whole number is displayed on LikeFolio's website. For example, an unrounded average score of 99.49% will be rounded down and displayed as 99%, while an unrounded average score of 99.51% will be rounded up and displayed as 100%. Arguably, this assignment to groups just above or below these cutoff points is random because it is determined by an exogenous "pre-determined rule of rounding" of the data provider. Hence, we use the RDD model to estimate the causal effect of this variation on investment in intangibles:

$$INVESTMENTMAINSGA_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 CUSTOMERSENTIMENT_{i,t}} + \boldsymbol{\beta_2\, CUSTOMERSENTIMENT*ROUNDINGUP_{i,t}} + \beta_3 ROUNDINGUP_{i,t} + \sum\beta_n\, CONTROLS_{i,t} + \sum INDUSTRY + \sum TIME_{t+1} + \varepsilon_{i,t+1} \qquad \text{Equation (7)}$$

ROUNDINGUP is an indicator variable equal to one if customer sentiment is rounded up to the next integer and zero otherwise. The reference group is firm quarters where the customer sentiment has been rounded down. Table 9 reports the regression results.

As reported in column 1, the slope coefficient on *CUSTOMERSENTIMENT*ROUNDINGUP* is positive and significant at the 10% level for the subsample of *post-initiation Twitter* firms. The coefficient on *CUSTOMERSENTIMENT* is positive but not statistically significant. The sum of the coefficients on *CUSTOMERSENTIMENT* and *CUSTOMERSENTIMENT*ROUNDINGUP* is positive and statistically significant at the 1% level. As reported in columns 2 and 3, the slope coefficient on *CUSTOMERSENTIMENT*ROUNDINGUP* is insignificant for the subsamples of *pre-initiation Twitter* firms and *non-Twitter* firms. These results suggest that customer sentiment has a *causal* effect on investments in intangibles, but only *after* establishing a Twitter presence.

Reverse Causality

An alternative interpretation of the results in Table 5 could be that consumer sentiment on Twitter becomes more favorable because firms devote more resources to increasing brand awareness and building customer relationships. However, the evidence that consumer-facing companies invest more in intangibles when customer comments are highly negative (as reported in Table 6) negates this conjecture. To formally address the reverse causality concern, we reverse the lead-lag relation between customer sentiment and investment in intangibles. As reported in Table B.1, the coefficient on the variable of interest, $INVESTMENTMAINSGA_t$, is statistically insignificant, implying that customer sentiment on Twitter in the current quarter does not vary with the prior quarter's investment in intangibles, which largely rules out reverse causality.

VI. SUPPLEMENTARY ANALYSES AND ROBUSTNESS CHECKS

R&D Expenditures Related to Knowledge-based Intangibles

Prior studies have used R&D expenses to measure investment in knowledge-related intangibles (Aboody and Lev 1998; Pandit et al. 2011). We re-estimate equation (3) using R&D as another dependent variable. As reported in Table 10, we do not observe an increased sensitivity of R&D expenditures to the positivity of customer comments after establishing a Twitter presence. This is probably because customer sentiment is a substantially noisier real-time indicator of the value of *knowledge*-related intangibles. In un-tabulated results, we also find that the association between R&D expenditures and future sales growth rates does not change after establishing the company's Twitter presence.

Echo Chamber Effect and Peer Learning Effect

The echo chamber effect occurs when a harmonious group of people amalgamate and develop tunnel vision. Prior studies find evidence of an "echo chamber" effect on social media (e.g., Cinelli et al. 2021). If managers themselves fall into "echo chambers" while making investment decisions, managers only incorporate social media signals that agree with their own. We rank customer sentiment into ten deciles, with the highest (lowest) decile representing the most positive (negative) customer sentiment, and examine whether managers fall into "echo chambers." We define managers with positive (negative) management sales forecast errors in at least three out of four prior quarters as optimistic (pessimistic) managers. Column 1 (2) of Table B.2 in Appendix B presents the results for optimistic (pessimistic) managers. The reference group is the middle eight deciles of customer sentiment and represents the non-extreme customer feedback. The results imply that managers are not in "echo chambers."

Managers may be able to learn by focusing on current trends and consumer preferences and "listening in" to what consumers are discussing about their competitors' products. We test this possibility, and the results are reported in columns 3 and 4 of Table B.2 in Appendix B. *PEERCUSTOMERSENTIMENT* captures the customer sentiment of the firm's peers in the same Fama-French 48 industry. The variable of interest is the sum of the slope coefficients on *PEERCUSTOMERSENTIMENT* and that on *PEERCUSTOMERSENTIMENT*PRESENCE*, which is not statistically significant. This result indicates a limited peer learning effect. After controlling for the peer-learning impact, there is still strong evidence of managerial learning from customer comments about its products and services after establishing a Twitter presence. The evidence suggests that managers emphasize customer feedback on their products and services more than relying on the sentiment expressed by their peers' customers when making investment decisions.

Robustness Checks

Social media could potentially serve as a monitoring and governance device, which disciplines managers from taking value-destructive mergers and acquisitions (e.g., Ang et al. 2021). Though not presented in the tables, we examine whether social media comments curb inefficiencies in investment in intangibles. We find that social media plays a relatively limited disciplining effect on organic growth via investment in intangibles (Wurgler 2000; Zhu 2019). This observation suggests that the visibility and scrutiny of mergers and acquisitions (M&As) on social media platforms may explain why they elicit a more significant disciplining role but exhibit a somewhat limited disciplining effect on investment in customer-related and brand-related intangibles.

VII. CONCLUSION

This study is the first to provide systematic evidence on how social media feedback shapes managerial learning and investment in customer-related and brand-related intangibles. Managers forecast revenue more accurately and revise forecasts up (down) in response to improving (deteriorating) customer sentiment after launching the primary corporate Twitter account. The evidence suggests that managers of consumer-facing companies learn previously undiscovered insights into market demand from followers on social media, especially customers, which mitigates information uncertainty about market demand. Accordingly, the investment portion of SG&A expenditures becomes more sensitive to a "wisdom-of-crowds" measure of the value of customer-related and brand-related intangibles, as indicated by the positivity of customer comments *after* establishing a social media presence. More importantly, investments in intangibles are associated with higher future sales growth after establishing a social media presence, but *not before* the presence. This heightened positive association with future sales growth underscores that social media presence reduces the *time* and *correlation* gaps between historical costs incurred for customer-related and brand-related intangibles and future economic benefits. In the cross-sectional analysis, we find that the impact of social media feedback on investment in intangibles is more pronounced when the "wisdom of crowds" on social media is more informative, as in the case of more engaged Twitter followers, and when alternative information sources, such as stock prices, are less informative. Surprisingly, when customer comments are highly negative, consumer-facing companies invest more in customer-related and brand-related intangibles, signifying an active approach to addressing severe customer concerns.

References

Aboody, D. and, B. Lev. 1998. The value relevance of intangibles: The case of software capitalization. *Journal of Accounting Research* 36: 161–191.

Ang, J.S., C. Hsu, D. Tang, and C. Wu. 2021. The role of social media in corporate governance. *The Accounting Review* 96 (2): 1-32.

Banker, R. D., R. Huang, and R. Natarajan. 2011. Equity incentives and long-term value created by SG&A expenditure. *Contemporary Accounting Research* 28 (3): 794–830.

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

Bernanke, B.S. 1983. Irreversibility, uncertainty, and cyclical investment. *Quarterly Journal of Economics* 98 (1): 85–106.

Blankespoor, E., G.S. Miller, and H.D. White. 2014. The Role of Dissemination in Market Liquidity: Evidence from Firms' Use of Twitter. *The Accounting Review* 89 (1): 79–112.

Bloom, N., S. Bond, and J. Reenen. 2007. Uncertainty and Investment Dynamics. *Review of Economic Studies* 74 (2): 391–415.

Bond, P., A. Edmans; and I. Goldstein. 2012. The Real Effects of Financial Markets. *Annual Review of Financial Economics* 4 (1): 339–360.

Boone, T., R. Ganeshan, A. Jain, and N.R. Sanders. 2019. Forecasting sales in the supply chain: Consumer analytics in the big data era. *International Journal of Forecasting* 35 (1): 170–180.

Chen, F., O. Hope, Q. Li, and X. Wang. 2011. Financial Reporting Quality and Investment Efficiency of Private Firms in Emerging Markets. *The Accounting Review* 86 (4): 1255–1288.

Chen, Q., I. Goldstein, and W. Jiang. 2007. Price Informativeness and Investment Sensitivity to Stock Price. *Review of Financial Studies* 20 (3): 619–650.

Cinelli, M., G. Morales, A. Galeazzi, W. Quattrociocchi, and M. Starnini. 2021. The echo chamber effect on social media. *Proceedings of the National Academy of Sciences* 118 (9): 1–8.

Chintagunta, P.K., S. Gopinath, and S. Venkataraman. 2010. The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets. *Marketing Science* 29 (5): 944–957.

Corrado, C., and C. Hulten. 2010. How do you Measure a "Technological Revolution"? *American Economic Review* 100 (2): 99–104.

Corrado, C., C. Hulten, and D. Sichel. 2005. Measuring Capital and Technology: An Expanded Framework. In *Measuring Capital in the New Economy*, edited by C. Corrado, J. Haltiwanger, and D. Sichel, 11–46. Chicago: University of Chicago Press.

Cui, R., S. Gallino, A. Moreno, and D.J. Zhang. 2018. The operational value of social media information. *Production and Operations Management* 27 (10): 1749 –1769.

David, J., H. Hopenhayn, and V. Venkateswaran. 2016. "Information, Misallocation, and Aggregate Productivity." *Quarterly Journal of Economics* 131 (2): 943–1005.

Derrien, F., Garel, A., A. Romec, and J. P. Weisskopf. 2020. Online reputation and debt capacity. *Journal of Financial and Quantitative Analysis*: 1–41.

Dichev, I., and V.W. Tang. 2008. Matching and the Changing Properties of Accounting Earnings over the Last 40 Years. *The Accounting Review* 83 (6): 1425–1460.

Donelson D., R. Jennings, and J. McInnis. 2011. Changes over time in the revenue-expense relation: Accounting or economics. *The Accounting Review* 86 (3): 945–974.

Dhaoui, C., C.M. Webster, and L.P. Tan. 2017. Social media sentiment analysis: lexicon versus machine learning. *Journal of Consumer Marketing* 34 (6): 480–488.

Eisfeldt A.L., and D. Papanikolaou. 2013. Organization capital and the cross section of expected returns. *Journal of Finance* 68 (4): 1365–1406.

Enache, L., and A. Srivastava. 2018. Should Intangible Investments be Reported Separately or Commingled with Operating Expenses? New Evidence. *Management Science* 64 (7): 3446–3468.

Ferracuti, E., and S. Stubben. 2019. The role of financial reporting in resolving uncertainty about corporate investment opportunities. *Journal of Accounting and Economics* 68 (2-3): 1–9.

Fornell, C., F. Morgeson, and G. Hult. 2016. Stock Returns on Customer Satisfaction Do Beat the Market: Gauging the Effect of a Marketing Intangible. *Journal of Marketing* 80 (5): 92–107.

Goodman, T., M. Neamtiu, N. Shroff, and H. D. White. 2014. Management Forecast Quality and Capital Investment Decisions. *The Accounting Review* 89 (1): 331–65.

Hollenbeck, B., S. Moorthy, and D. Proserpio. 2019. Advertising strategy in the presence of reviews: An empirical analysis. *Marketing Science* 38 (5): 793–811.

Hosseini, A., S.H. Kang, R. Savickas, and A. Singh. 2023. Who's On and Who's Not?: Technology Diffusion and Corporate Social Media Adoption Patterns. Working paper, Ball State University, and George Washington University.

Huang, J. 2018. The Customer Knows Best: The Investment Value of Consumer Opinions. *Journal of Financial Economics* 128 (1): 164–82.

Humphreys, A., and R.J.H. Wang. 2018. Automated text analysis for consumer research. *Journal of Consumer Research* 44 (6): 1274–1306.

Jung, M., J. Naughton, A. Tahoun, and C. Wang. 2018. Do Firms Strategically Disseminate? Evidence from Corporate Use of Social Media. *The Accounting Review* 93 (4): 225–252.

Koh, P., and D. Reeb. 2015. Missing R&D. *Journal of Accounting and Economics* 60 (1): 73–94.

Lev, B., and S. Radhakrishnan. 2005. The Valuation of Organization Capital. In *Measuring Capital in the New Economy*, edited by C. Corrado, J. Haltiwanger, and D. Sichel, 73–110. Chicago: University of Chicago Press.

Liu, Y. 2006. Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing* 70 (3): 74–89.

Liu, Y., and R.A. Lopez. 2016. The impact of social media conversations on consumer brand choices. *Marketing Letters* 27: 1–13.

Luca, M., and S. Zervas. 2016. Fake It Till You Make It: Reputation, Competition, and Yelp Review Fraud. *Management Science* 62 (12): 3412–3427.

Malmendier, U., and G. Tate. 2005. CEO Overconfidence and Corporate Investment. *Journal of Finance* 60 (6): 2661–2700.

Matějka, M. 2011. Discussion of "Equity incentives and long-term value created by SG&A expenditure." *Contemporary Accounting Research* 28 (3): 831–836.

McDonald, R., and D. Siegel. 1986. The Value of Waiting to Invest. *Quarterly Journal of Economics* 101 (4): 707–727.

Pandit, S., C. Wasley, and T. Zach. 2011. The Effect of Research and Development (R&D) Inputs and Outputs on the Relation between the Uncertainty of Future Operating Performance and R&D Expenditures. *Journal of Accounting, Auditing and Finance* 26 (1): 121–144.

Pindyck, R. S. 1993. A note on competitive investment under uncertainty. *The American Economic Review* 83(1): 273–277.

Tang, V.W. 2018. Wisdom of Crowds: Cross-Sectional Variation in the Informativeness of Third-Party-Generated Product Information on Twitter. *Journal of Accounting Research* 56 (3): 989–1034.

Wurgler, J. 2000. Financial markets and the allocation of capital. *Journal of Financial Economics* 58 (1-2): 187–214.

Zuo, L. 2016. The informational feedback effect of stock prices on management forecasts. *Journal of Accounting and Economics* 61(2-3): 391-413.

Zhu, C. 2019. Big Data as a Governance Mechanism. *Review of Finance Studies* 32 (5): 2021–2061.

Table 1

Descriptive Statistics of Key Social Media Variables

Panel A: All firm-quarter observations

Variables	**N**	**Mean**	**Median**	**Std. Dev.**	**Min**	**P25**	**P75**	**Max**
$PRESENCE_{i,t}$	14,123	0.65	1	0.48	0	0	1	1
$TWEETS_{i,t}$	14,123	164.37	11	1107.72	0	0	142	67256
$RESPONSE_{i,t}$	14,123	1619.64	104	8805.39	0	0	711	275379
$LIKES_{i,t}$	14,123	772.73	16	4904.09	0	0	251	173216
$RETWEETS_{i,t}$	14,123	617.88	16	3183.58	0	0	274	101914
$REPLIES_{i,t}$	14,123	229.02	12	1437.36	0	0	162	90386
$ENGAGEMENT_{i,t}$	14,123	5.20	3.16	21.82	0	0	4.62	1100.44

Panel B: Firm-quarter observations *after* the initiation of Twitter presence

Variables	**N**	**Mean**	**Median**	**P25**	**P75**	**Std. Dev.**
$TWEETS_{i,t}$	9,227	253.24	86	14	248	1366.22
$RESPONSE_{i,t}$	9,227	2514.36	419	67	1478	11014.09
$LIKES_{i,t}$	9,227	1198.31	138	20	516	6085.99
$RETWEETS_{i,t}$	9,227	960.33	151	21	584	3963.17
$REPLIES_{i,t}$	9,227	353.59	95	15	300	1771.88
$ENGAGEMENT_{i,t}$	9,227	8.06	4	3.21	5.94	26.75

Panel C: Firm-quarter observations with available data on customer sentiment from 2012 to 2015

Variables	**N**	**Mean**	**Median**	**P25**	**P75**	**Std. Dev.**
$CUSTOMERSENTIMENT_{i,t}$	4,974	0.87	0.89	0.81	0.98	0.12
$CHGCUSTOMERSENTIMENT_{i,t}$	808	-0.01	0.00	-0.03	0.02	0.09

All variables are as defined in Appendix A

Table 2

Descriptive Statistics of Key Variables

Variables	Observations	Mean	Median	P25	P75	Std. Dev.
$\lvert MFESALES_{i,t+1}\rvert$	14,213	0.012	0.00	0.00	0.012	0.022
$MFSALESREVISION_{i,t+1}$	14,213	-0.0004	0.00	0.00	0.000	0.010
$INVESTMENTMAINSGA_{i,t+1}$	14,213	0.014	0.009	0.000	0.024	0.039
$MAINSGA_{i,t+1}$	14,213	0.051	0.033	0.019	0.062	0.060
$R\&D_{i,t+1}$	14,213	0.014	0.009	0.000	0.019	0.018
$MARKETVALUEEQUITY_{i,t}$	14,213	7517.845	1156.413	378.431	3824.789	33818.720
$TOBINSQ_{i,t}$	14,213	2.346	1.874	1.366	2.789	1.560
$TANGIBILITY_{i,t}$	14,213	0.131	0.095	0.052	0.171	0.121
$FIRMAGE_{i,t}$	14,213	227.823	198.000	123.000	288.000	145.392
B2C	14,213	0.045	0	0	0	0.207
$LEVERAGE_{i,t}$	14,213	0.123	0.049	0	0.207	0.158
$CASHFLOW_{i,t}$	14,213	0.016	0.021	0.008	0.034	0.045
$ADVEXPENSE_{i,t}$	14,213	0.003	0.000	0	0.002	0.007
$LOG(MEDIACOVERAGE)_{i,t}$	14,213	1.545	1.386	0	2.398	1.503
$LOG(PRESSRELEASES)_{i,t}$	14,213	0.964	0	0	1.946	1.315
$LOG(ANALYST)_{i,t}$	14,213	2.137	2.303	1.792	2.773	0.862
$SALESFORECASTPRECISION_{i,t}$	14,213	0.010	0.01	0.00	0.013	0.010
$\sigma(CFO)_{i,\mathbf{t}}$	14,213	0.061	0.046	0.031	0.067	0.090
$SALESGROWTH_{i,t}$	14,213	0.037	0.027	-0.034	0.085	0.196
$ROA_{i,t}$	14,213	0.006	0.012	-0.002	0.024	0.044
$SLACK_{i,t}$	14,213	5.055	2.224	0.761	5.295	10.444
$ENGAGEMENT_{i,t}$	14,213	5.20	3.16	21.82	0	1100.44
$STOCKRETURN_{i,t}$	13,918	0.036	0.028	-0.096	0.149	0.221
$AVGSALESGROWTH_{i,(t+1,t+2,t+3,t+4)/4}$	13,865	0.035	0.025	0.001	0.055	0.076
$\sigma(STOCKRETURN)_{i,\mathbf{t}}$	11,848	0.027	0.024	0.018	0.032	0.014
$STOCKINFO_{i,t}$	10,855	0.727	0.753	0.603	0.878	0.186

All variables are as defined in Appendix A.

Table 3

Correlation Tables

Panel A: Correlations between Investment in Intangibles and Explanatory Variables

Pearson/Spearman	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)INVESTMENTMAINSGA$_{i,t+1}$	1	0.20***	-0.07*	0.11***	0.15***	0.05*	-0.12***	0.08**	-0.40***	-0.11***	-0.19***	0.10**
(2)R&D$_{i,t+1}$	0.21***	1	0.05**	-0.01	-0.05	0.06*	-0.20***	-0.23***	-0.02	-0.11***	0.03	0.15***
(3)AVGSALESGROWTH$_{i,(t+1,t+2,t+3,t+4)/4}$	-0.03***	-0.04***	1	-0.06	-0.12***	-0.019	-0.04	0.20***	-0.015	-0.23***	0.025***	0.03
(4)PRESENCE$_{i,t}$	0.04***	0.06***	0.01	1	0.05	0.46***	-0.01	0.19***	-0.16	-0.03	-0.12***	0.03
(5)CUSTOMERSENTIMENT$_{i,t}$	0.11***	-0.03	0.04	0.02	1	-0.02	0.02	-0.02	-0.18***	0.07**	-0.16	-0.02
(6)LOG(ENGAGEMENT)$_{i,t}$	0.04***	0.01	0.01	0.71***	-0.03	1	0.05	0.27***	0.10***	-0.10***	0.13***	0.04
(7)CASHFLOW$_{i,t}$	-0.20***	-0.31***	-0.05***	-0.01***	0.04	0.01	1	0.31***	0.20***	0.27***	0.18***	-0.12***
(8)TOBINSQ$_{i,t}$	-0.04***	-0.24***	0.17***	0.07***	0.02	0.16***	0.15***	1	-0.02	-0.16***	0.05	-0.11***
(9)LOG(ASSET)$_{i,t}$	-0.30***	-0.23***	-0.10***	0.07***	-0.11***	0.20***	0.24***	-0.10***	1	0.48***	0.31***	-0.38***
(10)FIRMAGE$_{i,t}$	-0.13***	-0.09***	-0.16***	0.08***	0.09**	0.08***	0.14***	-0.18***	0.49***	1	0.00	-0.30***
(11)ADVEXPENSE$_{i,t}$	-0.02*	-0.10***	-0.04***	-0.00	-0.18***	0.16***	0.10***	0.07***	0.41***	0.15***	1	0.015
(12)STOCKINFO$_{i,t}$	0.15***	0.12***	0.05***	-0.04***	-0.02	0.00	-0.13***	0.05***	-0.38***	-0.26***	-0.04***	1

Table 3

(continued)

Panel B: Correlations between Management Forecasts and Explanatory Variables

Pearson/Spearman	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)$\|MFESALES\|_{i,t+1}$	1	0.10***	-0.13***	0.11***	0.28***	-0.09**	-0.06*	0.01	-0.06	0.12***	0.12***	0.05
(2)$MFSALESREVISION_{i,t+1}$	-0.006	1	-0.00	-0.02	0.01	0.02	0.06	0.04	-0.01	0.01	-0.00	0.06*
(3)$PRESENCE_{i,t}$	-0.06***	0.02**	1	-0.00	0.09**	-0.18***	0.16***	-0.02	-0.14***	-0.08**	0.11***	0.10***
(4)$CHGCUSTOMERSENTIMENT_{i,t}$	-0.0193	0.07*	-0.02	1	0.04	0.01	0.04	0.03	-0.07*	0.07*	0.05	0.07*
(5)$SALESFORECASTPRECISION_{i,t}$	0.20***	-0.00	-0.01	0.04	1	-0.17***	-0.01	0.04	-0.09*	0.04	0.14***	0.02
(6)$LOG(ASSET)_{i,t}$	-0.05***	0.01	0.07***	-0.02	-0.18***	1	0.03	0.23***	0.34***	0.09**	-0.06*	-0.05
(7)$TOBINSQ_{i,t}$	-0.0094	0.01	0.07***	0.06	-0.07***	-0.10***	1	0.28***	-0.08*	0.20***	0.44***	0.12***
(8)$ROA_{i,t}$	-0.05***	0.02*	-0.02***	-0.02	-0.03***	0.25***	0.145***	1	0.06*	0.10***	0.30***	0.11***
(9)$LEVERAGE_{i,t}$	-0.03***	0.01*	0.07***	-0.05	-0.10***	0.34***	-0.12***	-0.03***	1	0.06*	-0.03	-0.02
(10)$STOCKRETURN_{i,t}$	0.02*	0.06***	0.06***	-0.07***	0.02**	-0.01	0.18***	0.14***	-0.01	1	0.11***	0.05
(11)$\sigma(CFO)_{i,t}$	0.05***	0.01	-0.03***	0.15***	0.07***	-0.12***	0.32***	0.00	-0.09***	0.00	1	0.06*
(12)$SALESGROWTH_{i,t}$	0.00	0.02**	-0.02*	0.06	0.07***	-0.02**	0.09***	0.13***	-0.032**	0.10***	0.11***	1

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

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

Table 4

Management Sales Forecasts and Social Media Presence

Panel A: The Accuracy of Management Sales Forecasts and Twitter Presence

		Dependent Variable = |MFESALES$_{i,t+1}$|		
VARIABLES	***Predicted Sign***	(1)	(2)	(3)
PRESENCE$_{i,t}$	***(-)***	**-0.005***** **(-3.082)**	**-0.004***** **(-2.723)**	**-0.004**** **(-2.573)**
QTR1PRESENCE$_{i,t}$	***(-)***			**-0.002*** **(-1.713)**
QTR2PRESENCE$_{i,t}$	***(-)***			**-0.003**** **(-2.346)**
QTR3PRESENCE$_{i,t}$	***(-)***			0.000 (0.317)
QTR4PRESENCE$_{i,t}$	***(-)***			-0.001 (-1.405)
SALESFORECASTPRECISION$_{i,t}$			0.388*** (4.540)	0.400*** (4.615)
LOG(ASSET)$_{i,t}$			0.000 (0.838)	0.000 (0.813)
TOBINSQ$_{i,t}$			-0.000 (-0.760)	-0.000 (-0.828)
ROA$_{i,t}$			-0.023** (-2.442)	-0.023** (-2.462)
LEVERAGE$_{i,t}$			-0.004 (-1.630)	-0.004 (-1.566)
STOCKRETURN$_{i,t}$			0.004*** (3.644)	0.004*** (3.601)
σ(STOCKRETURN)$_{i,t}$			0.080* (1.702)	0.079* (1.664)
σ(CFO)$_{i,t}$			0.012* (1.948)	0.012* (1.892)
SALESGROWTH$_{i,t}$			-0.003* (-1.780)	-0.003* (-1.730)
INTERCEPT		0.013*** (9.155)	0.005 (1.341)	0.400*** (4.615)
Observations		14,213	11,848	11,848
R-squared		0.035	0.082	0.079
Fixed Effects		Time, Industry	Time, Industry	Time, Industry
Clustering of Errors		Firm	Firm	Firm

Table 4 (continued)

Panel B: Management Sales Forecast Revision and the Change in Customer Sentiment – Twitter Firms

		Dependent Variable = $MFSALESREVISION_{i,t+1}$					
	Predicted Sign	***Twitter Firms***	***Twitter B2C Firms***	***Twitter Non-B2C Firms***	***Post-Initiation Subsample***	***Post-Initiation B2C Subsample***	***Post-Initiation Non- B2C Subsample***
VARIABLES		(1)	(2)	(3)	(4)	(5)	(6)
$CHGCUSTOMERSENTIMENT_{i,t}$		**0.003**	**0.019***	0.003	0.004	**0.019***	0.003
		(0.756)	**(2.073)**	(0.746)	(1.195)	**(2.073)**	(1.224)
$CHGCUSTOMERSENTIMENT_{i,t}$*$B2C_i$		**0.015**			0.018		
		(1.487)			(1.495)		
$\beta_1 + \beta_2$	*(+)*	***0.018****			***0.021*****		
Joint Significance ($\beta_1 + \beta_2$ =0) p-value		***0.059***			***0.015***		
$B2C_i$		-0.012			0.001		
		(-1.285)			(0.579)		
$SALESFORECASTPRECISION_{i,t}$		-0.023	0.059	-0.019	0.009	0.059	0.002
		(-0.751)	(0.422)	(-0.528)	(0.201)	(0.422)	(0.037)
Controls		Yes	Yes	Yes	Yes	Yes	Yes
Intercept		Yes	Yes	Yes	Yes	Yes	Yes
Observations		734	57	677	606	57	549
R-squared		0.084	0.658	0.068	0.06	0.658	0.065
Fixed Effects		Time, Industry	Time, Industry	Time, Industry	Time, Industry	Time, Industry	Time, Industry
Clustering of Errors		Firm	Firm	Firm	Firm	Firm	Firm

Panel A shows the results of OLS regression using equation 2A: $|MFESALES|_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 PRESENCE_{i,t}} + \sum \beta_n CONTROLS_{i,t} + \sum INDUSTRY_j + \sum TIME_{t+1} + \varepsilon_{i,t+1}$

Panel B shows the results of OLS regression using equation 2B: $MFSALESREVISION_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 CHGCUSTOMERSENTIMENT_{i,t}} + \boldsymbol{\beta_2 CHGCUSTOMERSENTIMENT_{i,t} * B2C} + \beta_3 B2C + \sum \beta_n CONTROLS_{i,t} + \sum INDUSTRY_j + \sum TIME_{t+1} + \varepsilon_{i,t+1}$

The sample is *Twitter firms* (firms that initiated the primary corporate Twitter account during the sample period 2006-2017) for panel A and columns 1 to 3 of panel B and the *Post-initiation subsample* for columns 4 to 6 of panel B (firm-quarter observations after the initiation of primary corporate 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

Sensitivity of Investment in Intangibles to the Positivity of Customer Comments

Panel A: All Firms with or without Twitter Presence

	Dependent Variable = INVESTMENTMAINSGA$_{i,t+1}$			
VARIABLES	***Predicted Sign***	(1)	(2)	(3)
CUSTOMERSENTIMENT$_{i,t}$	***(?)***	0.022	0.013	0.015
		(1.535)	(0.422)	(0.494)
PRESENCE$_{it}$*CUSTOMERSENTIMENT$_{i,t}$	***(+)***		0.015	0.011
			(0.517)	(0.327)
$\boldsymbol{\beta_1 + \beta_2}$	***(+)***		***0.028****	***0.026****
Joint Significance ($\beta_1 + \beta_2$ =0) p-value			***0.015***	***0.027***
TOBINSQ$_{i,t}$		-0.003**	-0.003***	-0.003*
		(-2.501)	(-2.895)	(-1.779)
PRESENCE$_{i,t}$*TOBINSQ$_{i,t}$				0.001
				(0.372)
PRESENCE$_{i,t}$			-0.004	-0.006
			(-0.140)	(-0.240)
LOG(ASSET)$_{i,t}$		-0.009***	-0.008***	-0.008***
		(-3.279)	(-2.932)	(-2.942)
CASHFLOW$_{i,t}$		-0.093*	-0.095**	-0.097**
		(-1.944)	(-2.072)	(-2.107)
TANGIBILITY$_{i,t}$		0.014	0.013	0.013
		(0.95)	(0.907)	(0.944)
SLACK$_{i,t}$		-0.000	-0.000	-0.000
		(-0.859)	(-0.339)	(-0.300)
FIRMAGE$_{i,t}$		0.000	-0.000	-0.000
		(0.087)	(-0.057)	(-0.013)
ADVEXPENSE$_{i,t}$		-0.369	-0.37	-0.365
		(-1.064)	(-1.033)	(-1.039)
LOG(PRESSRELEASES)$_{i,t}$		-0.003**	-0.003*	-0.003*
		(-2.076)	(-1.870)	(-1.862)
LOG(MEDIACOVERAGE)$_{i,t}$		0.001	0.001	0.001
		(0.949)	(0.607)	(0.607)
LOG(ANALYST)$_{i,t}$		-0.002	-0.002	-0.002
		(-0.848)	(-0.981)	(-0.983)
INTERCEPT		0.080***	0.084***	0.084***
		(3.804)	(3.467)	(3.496)
Observations		1,335	1,335	1,335
R-squared		0.31	0.313	0.314
Fixed Effects		Time, Industry	Time, Industry	Time, Industry
Clustering of Errors		Firm	Firm	Firm

Table 5 (Continued)

Panel B: Firms with Twitter Presence

		Dependent Variable = INVESTMENTMAINSGA$_{i,t+1}$				
		Twitter Firms			***Twitter B2C Firms***	***Twitter Non-B2C Firms***
VARIABLES	***Predicted Sign***	(1)	(2)	(3)	(4)	(5)
CUSTOMERSENTIMENT$_{i,t}$	***(?)***	**0.028****	0.017	0.017	-	0.043
		(2.425)	(0.816)	(0.615)		(0.749)
CUSTOMERSENTIMENT$_{i,t}$* PRESENCE$_{i,t}$	***(+)***		0.014	0.013	**0.068***	-0.008
			(0.261)	(0.173)	**(2.041)**	(-0.149)
$\beta_1 + \beta_2$	***(+)***		***0.031******	***0.030*****		
Joint Significance ($\beta_1 + \beta_2$ =0) p-value			***0.003***	***0.0132***		
TOBINSQ$_{i,t}$		-0.002	-0.002**	-0.002	-	-0.002
		(-1.618)	(-2.006)	(-0.375)		(-0.229)
PRESENCE$_{i,t}$*TOBINSQ$_{i,t}$				0.001	0.005	-0.001
				(0.058)	(1.312)	(-0.087)
PRESENCE$_{i,t}$			0.019	0.018	-	0.024
			(0.449)	(0.389)		(0.516)
Controls		Yes	Yes	Yes	Yes	Yes
Intercept		Yes	Yes	Yes	Yes	Yes
Observations		903	903	903	83	820
R-squared		0.369	0.382	0.382	0.617	0.391
Fixed Effects		Time, Industry	Time, Industry	Time, Industry	Time, Industry	Time, Industry
Clustering of Errors		Firm	Firm	Firm	Firm	Firm

The table shows the results of OLS regression using equation 3: *INVESTMENTMAINSGA$_{i,t+1}$* = β_0+ ***β_1CUSTOMERSENTIMENT$_{i,t}$*** + ***β_2CUSTOMERSENTIMENT$_{i,t}$*** * ***PRESENCE$_{i,t}$*** + ***β_3PRESENCE$_{i,t}$*** + $\sum\beta_n$ *CONTROLS$_{i,t}$* + $\sum$ *INDUSTRY$_j$* + $\sum$ *TIME$_{t+1}$* + $\varepsilon_{i,t+1}$. The sample is all firms (all firms with or without a primary corporate Twitter account) in Panel A and *Twitter firms* (firms that initiated the primary corporate Twitter account) in Panel B. Investment in intangibles is measured as the investment portion of SG&A (*INVESTMENTMAINSGA$_{i,t+1}$*). We define *MAINSGA$_{i,t+1}$* = SG&A$_{i,t+1}$ – R&D$_{i,t+1}$ – Advertising$_{i,t+1}$ and then estimate the following regression by industry (FF-48) and year-quarter using equation 1A: *MAINSGA$_{i,t+1}$* = $\alpha_0 + \alpha_1$REV$_{i,t+1}$+ α_2DUMMYREVDECREASE$_{i,t+1}$ + α_3DUMMYLOSS$_{i,t+1}$ + $\varepsilon_{i,t+1}$ where *i* indexes firm, and *t* indexes year-quarter. We then calculate *MAINTENANCEMAINSGA* for each firm as *MAINTENANCEMAINSGA$_{i,t+1}$* = $\tilde{\alpha}_1$ Rev$_{i,t+1}$ where $\tilde{\alpha}_1$ is the estimated slope coefficient from equation 1A. Finally, we calculate *INVESTMENTMAINSGA$_{i,t+1}$* = *MAINSGA$_{i,t+1}$* – *MAINTENANCEMAINSGA$_{i,t+1}$*

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

Table 6

Direction of Investment in Intangibles in Response to the Positivity of Customer Comments

		Dependent Variable = $INVESTMENTMAINSGA_{i,t+1}$	
	Predicted Sign	***Twitter B2C Firms***	***Twitter Non-B2C Firms***
VARIABLES		(1)	(2)
$AVGCUSTOMERSENTIMENTBOTTOM_{i,t}$	***(?)***	**-**	-0.017
			(-1.173)
$AVGCUSTOMERSENTIMENTTOP_{i,t}$	***(?)***	**-**	-0.019
			(-1.651)
$AVGCUSTOMERSENTIMENTBOTTOM_{i,t}*PRESENCE_{i,t}$	*(?)*	***0.029****	*0.004*
		(2.058)	*(0.270)*
$AVGCUSTOMERSENTIMENTTOP_{i,t}*PRESENCE_{i,t}$	*(?)*	*0.001*	***0.021*****
		(0.076)	***(2.007)***
$PRESENCE_{i,t}$		**-**	0.014
			(1.439)
Controls		Yes	Yes
Intercept		Yes	Yes
Observations		68	554
R-squared		0.717	0.404
Fixed Effects		Time, Industry	Time, Industry
Clustering of Errors		Firm	Firm

Investment in intangibles is measured as the investment portion of SG&A ($INVESTMENTMAINSGA_{i,t+1}$).

We define $MAINSGA_{i,t+1}$ = $SG\&A_{i,t+1} - R\&D_{i,t+1} - Advertising_{i,t+1}$ and then estimate the following regression by industry (FF-48) and year-quarter using equation 1A: $MAINSGA_{i,t+1} = \alpha_0 + \alpha_1 REV_{i,t+1} + \alpha_2 DUMMYREVDECREASE_{i,t+1} + \alpha_3 DUMMYLOSS_{i,t+1} + \varepsilon_{i,t+1}$ where *i* indexes firm, and *t* indexes year-quarter. We then calculate *MAINTENANCEMAINSGA* for each firm as $MAINTENANCEMAINSGA_{i,t+1} = \tilde{\tilde{\alpha}}_1 Rev_{i,t+1}$ where $\tilde{\tilde{\alpha}}_1$ is the estimated slope coefficient from equation 1A. Finally, we calculate $INVESTMENTMAINSGA_{i,t+1} = MAINSGA_{i,t+1} - MAINTENANCEMAINSGA_{i,t+1}$

The positivity of customer sentiment averaged over the prior four quarters is ranked into quintiles, and the middle three quintiles are the reference group. The table shows the results of OLS regression using equation 4: $INVESTMENTMAINSGA_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 AVGCUSTOMERSENTIMENTBOTTOM_{i,t} + \beta_2 AVGCUSTOMERSENTIMENTTOP_{i,t} + \beta_3 AVGCUSTOMERSENTIMENTBOTTOM_{i,t} * PRESENCE_{i,t} + \beta_4 AVGCUSTOMERSENTIMENTTOP_{i,t} * PRESENCE_{i,t}} + \beta_5 PRESENCE_{i,t} + \sum \beta_n CONTROLS_{i,t} + \sum INDUSTRY_i + \sum TIME_{t+1} + \varepsilon_{i,t+1}$

The sample includes *Twitter firms* (firms that initiated the primary corporate Twitter account during the sample period 2006-2017). Column(1) shows the results for B2C firms and column (2) for non-B2C firms.

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

Table 7

Investment in Intangibles and Future Sales Growth

		Dependent Variable = $AVGSALESGROWTH_{i,(t+1,t+2,t+3,t+4)/4}$	
	Predicted Sign	***Post-Initiation Subsample***	***Pre-Initiation Subsample***
VARIABLES		(1)	(2)
$INVESTMENTMAINSGA_{i,t}$	***(+)***	**0.047***	0.037
		(1.824)	(1.088)
$LOG(ASSET)_{i,t}$		-0.005***	-0.006***
		(-4.430)	(-5.659)
$TOBINSQ_{i,t}$		0.009***	0.010***
		(8.573)	(4.284)
$LOG(PRESSRELEASES)_{i,t}$		-0.003***	-0.006*
		(-3.218)	(-1.825)
$LOG(MEDIACOVERAGE)_{i,t}$		-0.000	0.002**
		(-0.062)	(2.030)
$LOG(ANALYST)_{i,t}$		0.001	-0.001
		(0.780)	(-0.763)
$ADVEXPENSE_{i,t}$		0.304	0.601*
		(1.242)	(1.947)
$SALESGROWTH_{i,t}$		0.021**	-0.001
		(2.313)	(-0.183)
$CHGBACKLOG_{i,t}$		0.092***	0.083***
		(6.701)	(4.018)
INTERCEPT		0.088***	0.065***
		(2.979)	(5.659)
Observations		34,155	20,026
R-squared		0.108	0.147
Fixed Effects		Time, Industry	Time, Industry
Clustering of Errors		Firm	Firm

The table shows the results of OLS regression using equation 5: $AVGSALESGROWTH_{i,(t+1,t+2,t+3,t+4)/4} = \beta_0 + \boldsymbol{\beta_1}$ $\boldsymbol{INVESTMENTMAINSGA_{i,t}} + \sum\beta_n CONTROLS_{i,t} + \sum INDUSTRY_i + \sum TIME_{t+1} + \varepsilon_{i,t+1}$

where $AVGSALESGROWTH_{i,(t+1,t+2,t+3,t+4)/4}$ is the average sales growth over four quarters, and sales growth is calculated as $(sales_{i,t} – sales_{i,t-1})/ sales_{i,t-1}$

The sample is *the Post-initiation subsample (firm-quarter observations after the initiation of primary corporate Twitter account during the sample period 2006-2017) in column (1) and the Pre-initiation subsample* (firm-quarter observations before the initiation of primary corporate Twitter account during the sample period 2006-2017) in column (2).

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

Table 8
Cross-sectional Variation on the Effect of Social Media Feedback

		Dependent Variable = INVESTMENTMAINSGA$_{i,t+1}$	
	Predicted	***Post-Initiation Subsample***	***All Firms***
VARIABLES	***Sign***	(1)	(2)
CUSTOMERSENTIMENT$_{i,t}$	**(?)**	0.002	-0.301***
		(0.299)	(-2.903)
CUSTOMERSENTIMENT$_{i,t}$*LOG(ENGAGEMENT)$_{i,t}$	**(+)**	0.028	
		(1.343)	
$\beta_1 + \beta_2$	*(+)*	***0.030*****	
Joint Significance ($\beta_1 + \beta_2$ =0) p-value		***0.049***	
LOG(ENGAGEMENT)$_{i,t}$		0.001	
		(0.198)	
PRESENCE$_{i,t}$			-0.262***
			(-2.743)
CUSTOMERSENTIMENT$_{i,t}$*STOCKINFO$_{i,t}$			0.431***
			(2.828)
CUSTOMERSENTIMENT$_{i,t}$*STOCKINFO$_{i,t}$*PRESENCE$_{i,t}$	*(-)*		**-0.444*****
			(-2.827)
STOCKINFO$_{i,t}$* PRESENCE$_{i,t}$			0.358**
			(2.556)
CUSTOMERSENTIMENT$_{i,t}$* PRESENCE$_{i,t}$	*(+)*		0.340***
			(3.136)
Controls		Yes	Yes
Constant		Yes	Yes
Observations		830	885
R-squared		0.42	0.468
Fixed Effects		Time, Industry	Time, Industry
Clustering of Errors		Firm	Firm

The table shows the results of OLS regression using equation 6.
The sample is a *Post-initiation subsample* in column 1 because follower engagement is only measurable after initiating the primary corporate Twitter account and all firms (with or without a primary corporate Twitter account during the sample period 2006-2017) in column 2.
t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All variables are defined in Appendix A

Table 9

Regression Discontinuity Design (RDD) to Mitigate Endogeneity Concern

		Dependent Variable = INVESTMENTMAINSGA$_{i,t+1}$		
		Twitter Firms		***Non-Twitter Firms***
		Post-Initiation Subsample	***Pre-Initiation Subsample***	
VARIABLES	***Predicted Sign***	(1)	(2)	(3)
CUSTOMERSENTIMENT$_{i,t}$		0.022	-0.075	0.029
		(1.547)	(-1.271)	(0.563)
CUSTOMERSENTIMENT$_{i,t}$*ROUNDINGUP$_{i,t}$	*(+)*	**0.023***	0.112	0.021
		(1.749)	(0.524)	(0.639)
$\beta_1 + \beta_2$	*(+)*	***0.045******	*0.037*	*0.05*
Joint Significance ($\beta_1 + \beta_2$=0) p-value		***0.002***	*0.869*	*0.196*
ROUNDINGUP$_{i,t}$		-0.020*	-0.112	-0.023
		(-1.678)	(-0.605)	(-0.829)
Controls		Yes	Yes	Yes
Intercept		Yes	Yes	Yes
Observations		830	73	432
R-squared		0.415	0.773	0.406
Fixed Effects		Year, Industry	Year, Industry	Year, Industry
Clustering of Errors		Firm	Firm	Firm

Investment in intangibles is measured as the investment portion of SG&A (*INVESTMENTMAINSGA$_{i,t+1}$*).

Table shows the results of testing for endogeneity using equation 7: $INVESTMENTMAINSGA_{i,t+1} = \beta_0 + \beta_1 CUSTOMERSENTIMENT_{i,t} + \beta_2 CUSTOMERSENTIMENT*ROUNDINGUP_{i,t} + \beta_3 ROUNDINGUP_{i,t} + \sum\beta_n CONTROLS_{i,t} + \sum INDUSTRY + \sum TIME_{t+1} + \varepsilon_{i,t+1}$. The *Post-initiation Twitter* firms in column (1), *Pre-initiation Twitter* firms in column (2), and *non-Twitter firms* (firms that never initiated a primary corporate Twitter account during the sample period 2006-2017) in column (3).

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

Table 10

The Effect of Social Media Feedback on Investment in Knowledge-based Intangibles

		Dependent Variable = $R\&D_{i,t+1}$	
		All Firms	***Twitter Firms***
VARIABLES	***Predicted Sign***	(1)	(2)
$CUSTOMERSENTIMENT_{i,t}$	**(?)**	0.006	0.013
		(0.902)	(0.839)
$CUSTOMERSENTIMENT_{i,t}$* $PRESENCE_{i,t}$	**(+)**	-0.010	-0.018
		(-0.794)	(-1.002)
$\beta_1 + \beta_2$	***(+)***	*-0.004*	*-0.005*
Joint Significance ($\beta_1 + \beta_2$ =0) p-value		*0.789*	*0.655*
$PRESENCE_{i,t}$		0.013	0.017
		(1.176)	(1.019)
Controls		Yes	Yes
Intercept		Yes	Yes
Observations		1,335	903
R-squared		0.340	0.369
Fixed Effects		Time, Industry	Time, Industry
Clustering of Errors		Firm	Firm

Table shows the results for R&D using a model similar to equation 3: $R\&D_{i,t+1} = \beta_0 + \boldsymbol{\beta_1 CUSTOMERSENTIMENT_{i,t}} + \boldsymbol{\beta_2 CUSTOMERSENTIMENT_{i,t} * PRESENCE_{i,t}} + \sum\beta_n\ CONTROL\ VARIABLES_{i,t} + \sum INDUSTRY_j + \sum TIME_{t+1} + \varepsilon_{i,t+1}$

The sample is all firms (all firms with or without a primary corporate Twitter account during the sample period 2006-2017) for column (1) and *Twitter firms* (firms that initiated the primary corporate Twitter account during the sample period 2006-2017) for column (2).

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

Appendix A

Variables Description

Variables of Interest	
PRESENCE	Indicator variable that takes the value of one if the firm has a Twitter account and zero otherwise.
CUSTOMERSENTIMENT	The ratio of the number of customer-initiated tweets that convey a positive assessment of products and brands over the number of tweets that express a non-neutral (either positive or negative) evaluation of products and brands.
CHGCUSTOMERSENTIMENT	Change in customer sentiment from the previous quarter.
RESPONSES	The sum of total retweets, total likes, and total replies by a firm's primary corporate Twitter account followers.
LOG(ENGAGEMENT)	Log (1 plus RESPONSES/TWEETS).
STOCKINFO	Informativeness of stock prices is measured as one minus R^2, where R^2 is the adjusted R-squared from a regression of the firm's daily stock returns in quarter t-1 on a constant, the CRSP value-weighted market return, and the return of the FF-48 industry portfolio.
Dependent Variables:	
INVESTMENTMAINSGA	Investment in intangibles portion of *MAINSGA* is calculated for each firm as $INVESTMENTMAINSGA_{i,t} = MAINSGA_{i,t} - MAINTENANCE\ MAINSGA_{i,t}$ $MAINSGA_{i,t}$ is estimated at industry (FF-48) and year-quarter level using equation (1A) $MAINSGA_{i,t} = \alpha_0 + \alpha_1 REV_{i,t} + \alpha_2 DUMMYREVDECREASE_{i,t} + \alpha_3 DUMMYLOSS_{i,t} + \varepsilon_{i,t}$ where *MAINSGA* and *REV* are scaled by ending market value of equity of previous quarter. *MAINSGA* is defined as SG&A – R&D – Advertising expenses. Equation (1A) identifies the portion of *MAINSGA* that varies with current revenues (Dichev and Tang 2008). The maintenance component is then calculated for each firm using equation (1B) as $MAINTENANCEMAINSGA_{i,t} = \tilde{\alpha}_1\ REV_{i,t}$ where $\tilde{\alpha}_1$ is the estimated slope coefficient from equation (1A).
/MFESALES/	The absolute value of the difference between the quarterly management sales forecast and the actual sales scaled by the previous quarter's end's total assets.
MFSALESREVISION	The signed difference between the most recent sales forecast and the previous sales forecast scaled by the last quarter's total assets.

AVGSALESGROWTH	Average sales growth over four quarters where sales growth is calculated as $(sales_{i,t} – sales_{i,t-1})/ sales_{i,t-1}$
R&D	Research and development expenditure scaled by the previous quarter's market value of equity.
Explanatory Variables	
B2C	The indicator variable takes one if the firm belongs to a consumer-facing industry and 0 otherwise.
CASHFLOW	The sum of income before extraordinary items and depreciation divided by total assets.
FIRMAGE	The firm's age in months is measured from when it first appears in Compustat.
ADVEXPENSE	Annual advertising expenses scaled by ending total assets of previous quarter and then divided by four to calculate the quarterly advertising expenses.
LOG(ANALYST)	Log (1 plus the number of analysts following a firm)
LOG(PRESSRELEASES)	Log (1 plus the number of press releases issued by the firm and distributed via a news provider)
LOG(MEDIACOVERAGE)	Log (1 plus the number of news articles written about a firm)
LEVERAGE	The ratio of long-term debt to total assets.
LOG(ASSET)	Log of total assets.
σ (CFO)	The standard deviation of cash flows from operations deflated by average assets from t-5 to t-1.
σ (STOCKRETURN)	The standard deviation of daily stock returns of the quarter.
SALESGROWTH	Percentage change in sales during the quarter.
SALESFORECASTPRECISION	The difference between the upper and lower bounds of management sales forecast divided by the previous quarter's
MTB	The ratio of the market value of equity to the book value of
ROA	Income before extraordinary items divided by the average total assets.
STOCKRETURN	Quarterly stock returns of the firm.
SLACK	Cash divided by property, plant, and equipment
TANGIBILITY	The ratio of PPE to total assets.
TOBINSQ	(Book value of assets - book value of equity + market value of equity)/ book value of assets.

Appendix B

Table B.1

Reverse Causality –Customer Sentiment in the Current Quarter and Investment in Intangible Assets in the Previous Period

		Dependent Variable = CUSTOMERSENTIMENT$_{i,t+1}$	
VARIABLES	***Predicted Sign***	(1)	(2)
INVESTMENTMAINSGA$_{i,t}$	***(?)***	0.537	0.525
		(1.637)	(1.629)
LOG(ASSET)$_{i,t}$		-0.010*	-0.001
		(-1.946)	(-0.148)
MTB$_{i,t}$		0.003***	0.003***
		(3.327)	(3.251)
TANGIBILITY$_{i,t}$		0.062	0.070
		(0.842)	(0.939)
FIRMAGE$_{i,t}$		0.019	0.011
		(1.118)	(0.600)
ADVEXPENSE$_{i,t}$		-1.796*	-1.935*
		(-1.758)	(-1.869)
ROA$_{i,t}$		0.054	0.105
		(0.319)	(0.606)
SALESGROWTH$_{i,t}$			-0.007
			(-0.410)
LOG(MEDIACOVERAGE)$_{i,t}$			-0.011
			(-1.532)
INTERCEPT		0.855***	0.857***
		(8.254)	(8.324)
Observations		903	903
R-squared		0.223	0.233
Fixed Effects		Time, Industry	Time, Industry
Clustering of Errors		Firm	Firm

Investment in intangibles is measured as the investment portion of SG&A (*INVESTMENTMAINSGA$_{i,t+1}$*).

The table shows the results of OLS regression using the equation: $CUSTOMERSENTIMENT_{i,t+1} = \beta_0 + \beta_1 INVESTMENTMAINSGA_{i,t} + \sum\beta_n CONTROLS_{i,t} + \sum INDUSTRY + \sum TIME_{t+1} + \varepsilon_{i,t+1}$

The sample includes *Twitter firms* (firms that initiated the primary corporate 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 B.2

Echo Chamber Effect and Peer Learning Effect

		Dependent Variable = $INVESTMENTMAINSGA_{i,t+1}$			
		Echo Chamber Effect		***Peer Learning Effect***	
	Predicted Sign	***Optimistic Managers***	***Pessimistic Managers***	***Twitter Firms***	***Non-Twitter Firms***
VARIABLES		(1)	(2)	(3)	(4)
$CUSTOMERSENTIMENT_{Rank1/10\ i,t}$	***(?)***	*0.01*	*-0.004*		
		(0.407)	*(-0.818)*		
$CUSTOMERSENTIMENT_{Rank10/10\ i,t}$	***(?)***	*-0.016*	*0.009*		
		(-1.104)	*(0.775)*		
$\mathbf{CUSTOMERSENTIMENT_{i,t}}$	**(+)**			0.013	0.053
				(0.806)	(0.951)
$\mathbf{CUSTOMERSENTIMENT_{i,t}*PRESENCE_{i,t}}$	**(+)**			0.016	
				(0.387)	
$\boldsymbol{\beta_1 + \beta_2}$	**(+)**			**0.029****	
Joint Significance $\boldsymbol{(\beta_1 + \beta_2 = 0)}$ **p-value**				**0.012**	
$\mathbf{PEERCUSTOMERSENTIMENT_{i,t}}$	**(?)**			-0.090	-0.088
				(-0.816)	(-1.234)
$\mathbf{PEERCUSTOMERSENTIMENT_{i,t}*PRESENCE_{i,t}}$	**(?)**			0.071	
				(0.625)	
$\boldsymbol{\beta_3 + \beta_4}$	***(?)***			***-0.019***	
Joint Significance $\boldsymbol{(\beta_1 + \beta_2 = 0)}$ ***p-value***				***0.446***	
Controls		Yes	Yes	Yes	Yes
Intercept		Yes	Yes	Yes	Yes
Observations		94	403	903	432
R-squared		0.966	0.329	0.387	0.407
Fixed Effects		Time, Industry	Time, Industry	Time, Industry	Time, Industry
Clustering of Errors		Firm	Firm	Firm	Firm

Columns 1 and 2 show the results of the echo chamber effect. Customer sentiment is ranked into ten groups; the middle eight groups are the reference group. Column (1) shows the results for the most optimistic, and column (2) for the most pessimistic managers. Columns 3 and 4 show the results of peer learning effect using the equation: The sample is *Twitter firms* (firms that initiated the primary corporate Twitter account during the sample period 2006-2017) in columns 1,2 and 3, and *non-Twitter firms* (firms that ever initiated a primary corporate Twitter account during the sample period 2006-2017) in column 4. t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All variables are defined in Appendix A.