Wisdom of Crowds: Cross-sectional Variation in the Informativeness of Third-Party-Generated Nonfinancial Information on Twitter

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Abstract

This paper examines whether third-party-generated nonfinancial information on Twitter, once aggregated at the firm level, is predictive of upcoming firm-level fundamentals, and if so, what factors determine the cross-sectional variation in the predictive power. First, this study finds that the predictive power of nonfinancial information on Twitter is greater for firms whose major customers are consumers than for firms whose major customers are businesses. Second, the predictive power of the volume and valence of Twitter comments about products and brands with respect to firm-level fundamentals varies with the level of advertising. However, professionals in the capital markets, such as analysts, do not fully incorporate the implications for upcoming sales of the collective wisdom on Twitter. Analysts do not revise their forecasts of sales in response to the change in Twitter information, and thus, the consensus forecast error is systematically biased conditional on nonfinancial information disseminated on Twitter.

I. Introduction

One major shortcoming of the current corporate financial reporting regulatory regime is that it does not require adequate disclosure by listed firms of nonfinancial information that would help investors and creditors to make informed decisions (Amir and Lev [1996]). This paper examines whether third-party-generated comments about products and brands on Twitter, once aggregated at the firm level, provide informative nonfinancial information that is useful in forecasting firm-level fundamentals. If so, this study further explores what factors determine the cross-sectional variation in the predictive power of nonfinancial information on Twitter. Accordingly, this study provides incremental knowledge over existing "nowcasting" studies by extending the scope of the investigation from the *average* predictive power in prior studies to the *cross-sectional variation* in the predictive power of online information.

This study chooses Twitter as the setting in examining the cross-sectional variation in the information content primarily because of the level of aggregation of nonfinancial information. Though nonfinancial information is available at the *product* level from alternative sources,[1] the assignment of various products and brands to the businesses that own them imposes a significant empirical challenge. The data provider uses its proprietary information to achieve a reliable mapping between products and brands and the entities that own them, and therefore, is able to aggregate Twitter comments about products and brands at the firm level. The aggregation of nonfinancial information at the firm level provides a significant empirical edge over other settings because the natural unit for fundamental analysis is the firm. Twitter is also one of the

[1] Examples of alternative online sources include Google, Amazon, and Yelp.

two social media platforms the Securities and Exchange Commission allows companies to use to communicate with investors. Accordingly, using Twitter as the setting has the additional benefit of juxtaposing third-party-generated nonfinancial information with firm-initiated disclosure on the same platform.

This study examines the cross-sectional variation in the informativeness of nonfinancial information on Twitter with respect to upcoming accounting fundamentals. Accordingly, the target of Twitter comments is limited to products and brands, and the holder of Twitter comments is limited to third parties rather than the company itself. The selected Twitter comments are then aggregated at the firm level using the data provider's proprietary knowledge in mapping from products and brands to the entities that own them. Two statistics are used to summarize the volume and valence of Twitter comments about products and brands. The first statistic (PURCHASE) is defined as the total number of tweets that mention an actual purchase of a product or brand in the past or a forward-looking intent to purchase. PURCHASE maps Twitter comments directly into a recent past sale or a potential sale in the future. The valence of each tweet is classified as positive, negative, or neutral. The second statistic (POSITIVE) is defined as the ratio of the number of tweets that convey a positive assessment of products and brands over the total number of tweets that convey a nonneutral (either positive or negative) assessment of products and brands. POSITIVE summarizes the collective assessment of customers with respect to their satisfaction or dissatisfaction with a company's products and brands.

The two summary statistics are likely to reflect firm-level sales through a combination of two effects. First, the two statistics summarize Twitter users' responses to products or brands, and therefore, provide easily accessible signals of the broad consumer response. This is labeled as the pure *signal* effect of Twitter comments. Second, Twitter comments could spur purchases through a *word-of-mouth* effect.

From a pure signal perspective, the ability of Twitter comments to reflect firm-level sales depends on whether those tweets are representative of the broad customer response to the company's products and brands. As Twitter is largely a social platform for leisure rather than business activities, individual consumers are more likely to share their product experiences on Twitter than are business entities. Accordingly, Twitter comments are more representative of the broad consumer response for a company whose major customers are individual consumers. Therefore, the predictive power of nonfinancial information on Twitter with respect to upcoming sales is expected to be more pronounced for firms whose major customers are individual consumers than otherwise. The empirical evidence is consistent with this cross-sectional prediction.

From the word-of-mouth perspective, the ability of Twitter comments to spur sales varies with advertising. Advertising targets a wide audience and seeks to increase sales by increasing brand awareness. The ability of the volume of Twitter comments to spur more sales works through a mechanism similar to that of advertising: A high volume of tweets increases brand awareness through the connected network on Twitter. To the extent that consumer-generated brand awareness on Twitter *substitutes* for the producer-generated brand awareness of advertising, the ability of PURCHASE to spur sales is more pronounced when advertising is limited. The empirical evidence confirms that the marginal predictive power of PURCHASE with respect to upcoming sales decreases with the level of advertising.

In contrast, the ability of the valence of Twitter comments to spur sales works through a mechanism complementary to that of advertising: A more positive customer assessment is likely to sway consumers in favor of the known product or brand, and thus, increases the likelihood of purchase. To the extent that the positivity of Twitter comments validates and reinforces what people already know from advertising, the ability of POSITIVE to spur sales is more pronounced when advertising is extensive. The empirical findings suggest that the marginal predictive power of POSITIVE with respect to upcoming sales increases with the level of advertising.

Finally, this study examines whether analysts incorporate nonfinancial information disseminated on Twitter in their forecasts. I find that, despite the wisdom of crowds, professionals in the capital markets, such as analysts, do not fully incorporate the implications for upcoming sales of the collective wisdom on Twitter. Specifically, analysts do not revise their forecasts of sales in response to the change in Twitter information, and thus, consistently underreact to nonfinancial information disseminated on Twitter.

This study contributes to both academic literature and the needs of practitioners. First, to my knowledge, this is the first study to examine the information content of third-party-generated voluntary disclosure on Twitter with respect to firm fundamentals and the determinants of the cross-sectional variation in its predictive power. Social media enables its users, including consumers, to disseminate their opinions and recommendations in a manner that is not possible through traditional information outlets (Miller and Skinner [2015]). In contrast to Sunstein [2008], who argues that the blogosphere cannot serve as a marketplace for information, this study finds that nonfinancial information on Twitter, once summarized at the firm level, is incrementally informative about fundamentals, especially for firms whose major customers are individual consumers. The findings provide empirical support for the notion of the wisdom of crowds.

Second, the finding that nonfinancial information disseminated on Twitter is informative is economically important because it works to the advantage of individual investors. An alleged market friction is that some informative signals are inaccessible to individual investors because of their high cost. Anecdotal evidence suggests that hedge funds spend huge amounts of money on satellite photos of parking lots of retailers to get an early indicator of upcoming sales. If an equally effective leading indicator is obtainable by individual investors from Twitter at virtually no cost, social media levels the playing field between institutional and individual investors. Furthermore, third-party-generated disclosure on social media improves a firm's overall information environment by providing incrementally informative nonfinancial information over and above that provided by the company itself.

Third, this paper contributes to the nowcasting literature both conceptually and empirically. On the conceptual level, it extends the scope of the investigation from the average predictive power to the cross-sectional variation in the predictive power of online information with respect to upcoming fundamentals. On the empirical level, it uses social media comments rather than web searches to determine the information content of online information. The volume of web searches largely captures information demand, but social media comments largely capture information *supply*. As information supply is defined jointly by volume and valence, this study examines the predictive power of both volume and valence of online information.

Finally, the study sheds some light on the question of whether and how collective wisdom in the product market is used by professionals in the capital markets. In particular, this study explores whether the collective wisdom of users of Twitter affects the decision making of professionals in the capital markets. Even though Twitter provides nonfinancial information that is informative about upcoming sales and such information is easily accessible, the analyst forecast error is systematically correlated with the valence and volume of tweets. The evidence suggests that analysts do not fully incorporate in their forecasts the implications for upcoming sales of the collective wisdom of the product market.

Section II discusses the institutional background and develops hypotheses. Section III presents the data and discusses the research design. Section IV presents the empirical results. Section V presents the results on sensitivity checks. Section VI concludes the study.

II. Related literature, background, and hypothesis development

2.1 Related literature

First, this study is closely related to prior studies that examine the dissemination of financial information through social media or web searches. For example, Blankespoor et al. [2014] and Jung et al. [2015] examine how companies use social media to disseminate firm-initiated disclosure and communicate with investors and the economic consequences of that use. Da et al. [2011] and Drake et al. [2012] use the volume of Google queries on ticker symbols as a proxy for investors' demand for financial information and find evidence consistent with the interpretation that Google searches facilitate the dissemination of financial information in a more timely and accessible manner. Although those studies emphasize the dissemination of financial information through social media or web searches, this study is, to the best of my knowledge, the first that examines the information content of third-party-generated information about products and brands of a given firm on Twitter and the cross-sectional variation in its predictive power. The research question is especially important to both fundamental analysis and the disclosure literature because the existing corporate financial reporting regulatory regime does not require listed companies to disclose adequate nonfinancial information that would help investors and creditors make informed decisions (Amir and Lev [1996]; Miller and Skinner [2015]).

Second, this study broadly falls into the newly emerging nowcasting literature. Nowcasting has recently become popular in economics because standard measures used to assess the state of an economy, such as gross domestic product, are determined only after a long delay. Existing nowcasting studies generally use information from web searches to predict contemporaneous information. Goel et al. [2010] provide a detailed review of work that uses web search data to predict contemporaneous information at the economy level. Ettredge et al. [2005] is the first study that suggests the usefulness of web search data in forecasting the U.S. unemployment rate. Huang and Penna [2009] examine the use of search data for measuring economy-wide consumer sentiment. Many institutions, especially central banks, use nowcasting models routinely to monitor the state of the economy in real time. McLaren and Shanbhoge [2011] summarize how web search data are used for macrolevel or regional level economic forecasting by central banks. A few other studies have examined how the volume of web searches predicts contemporaneous demand at the *industry* level. For instance, Choi and Varian [2012] find that the volume of Google queries is helpful in forecasting contemporaneous sales in automobiles and tourism. Vosen and Schmidt [2011] and Wu and Brynjolfsson [2013] examine the use of search data to forecast contemporaneous sales in the retail and housing sectors, respectively.

However, there is virtually no study that examines the predictive power of online information with respect to firm-level accounting fundamentals. The notable exception is Da et al. [2012], which examines whether an increase in the search volume of a firm's most popular product predicts positive revenue or earnings surprises at the firm level. For some firms, the revenue source could come from hundreds of products and brands. For others, the revenue source is limited to only a few products and brands. Given that the dependent variable is at the firm level and the explanatory variable is at the product level, it is no surprise that Da et al. [2012] find rather limited predictive power of the volume of Google searches for a firm's most popular product with respect to the firm-level fundamentals. Similarly, though nonfinancial information at the *product* level can be obtained from other online sources, such as Amazon or Yelp, the assignment of various products and brands to the businesses that own them imposes a significant empirical challenge. This study uses a unique data provider of Twitter comments. The data provider tracks all products and brands for a given company—new products, discontinuations, name changes, and rebrands —and uses its proprietary information to reliably map products and brands and their owners. Therefore, the use of Twitter as the setting enables the aggregation of nonfinancial information at the firm level.

Compared with existing nowcasting studies, this study differs both conceptually and empirically. Conceptually, it extends the scope of the investigation from the average predictive power to the cross-sectional variation in the predictive power of online information with respect to upcoming fundamentals. Empirically, this study chooses social media comments rather than web searches to determine the information content of online information. The launch of websites such as Facebook (February 2004), YouTube (February 2005), Reddit (June 2005), and Twitter (March 2006), enabled people to share and view user-created content on a level previously unseen. These websites all fall under the blanket term "social media." The volume of web searches largely captures information demand, but social media comments largely capture information supply, which is defined jointly by volume and valence.

2.2. Background and hypothesis development

Twitter has an influential presence in social media with currently over 304 million active users. Twitter is also one of the two social media platforms the Securities and Exchange Commission allows companies to use to communicate with investors. By 2013, about 47% of Standard & Poor's 1500 companies had used Twitter to communicate with investors (Jung et al. [2015]). The unit of information on Twitter is a tweet, which is a small blurb of up to 140 characters. Anyone that signs up on Twitter can write a tweet and view tweets written by other users. As the stream on Twitter is unfiltered, what a user signs up for is what he or she sees.

In particular, this study examines whether the volume and valence of Twitter comments, as measured by the two summary statistics, are informative about firm-level *sales* incremental to existing financial information, and what factors determine the cross-sectional variation in the predictive power. The predictive power of third-party-generated nonfinancial information on Twitter with respect to firm-level sales originates from two related sources. First, the two statistics summarize Twitter users' *responses* to products or brands, and therefore provide easily accessible signals of broad consumers' responses to products and brands. I refer to this as the pure *signal* effect of Twitter comments. All else equal, the more self-reported past purchase actions or indications of intent to purchase in the future on Twitter, the higher the contemporaneous sales or sales in the near future. The more satisfied existing customers are, the more likely they are to continue to purchase the product or brand (Ittner et al. [2003]).

Second, Twitter comments could spur or discourage more sales through a word-of-mouth effect. Word-of-mouth refers to the dissemination of information, such as opinions and recommendations, through individual-to-individual communications. Twitter provides a friendly platform for users to communicate with their connected audience. The two most important attributes of word-of-mouth communication are valence and volume. Prior studies find that, when the unit of analysis is at the product level, a high volume of tweets is more likely to increase the degree of consumer awareness and the number of informed consumers for the particular product. For instance, Liu [2006] and Asur and Huberman [2010] find that the rate at which tweets were created on Twitter was a strong indicator of a movie's box office success. When the unit of analysis is at the product level, more positive tweets are likely to sway consumers' assessments in favor of the company's products or brands. For instance, Chevalier and Mayzlin [2006] find that the valence of online book reviews influences book sales. The word-of-mouth effect of Twitter comments at the product level can easily be extrapolated to the firm level because the firm's total sales is the sum of the sales of all of its products and brands.

From a pure signal perspective, the ability of Twitter comments to reflect firm-level sales depends on whether the tweets are representative of the broad customer response to the company's products and brands. When a firm's customer base consists predominantly of individual consumers (B-to-C firms), its representative customer is an individual consumer. When a firm's major customers are business clients (B-to-B firms), its representative customer is another business entity. As Twitter is largely a social platform for leisure rather than business activity, individual consumers are more likely to share their product experiences on Twitter than are business entities. Statistics confirm the intuition: When the target of Twitter comments is limited to products and brands, 99 percent of the holders of those tweets are individual consumers and 1 percent are business entities. Accordingly, when a company's major customers are individual consumers, Twitter comments are more representative of the broad consumer response to the company's products and brands. Thus, ceteris paribus, the predictive power of Twitter comments about products and brands is expected to be greater for firms whose major customers are consumers than for those whose major customers are other business entities. This leads to the first hypothesis:

H1: The predictive power of Twitter comments with respect to firm-level sales is more pronounced for firms whose major customers are consumers.

From the perspective of the word-of-mouth effect, the ability of Twitter comments to spur more sales varies with the promotional activities initiated by the company itself. A notable example is advertising, which seeks to increase sales by increasing brand awareness among potential consumers who are largely unconnected. I refer to this mechanism as producer-generated brand awareness. The word-of-mouth effect of Twitter comments, on the other hand, works through the individual-to-individual connections established on social media. The ability of the volume of Twitter comments to spur more sales works through a mechanism similar to that of advertising: A consumer's announcement of a past or potential purchase of a particular product or brand increases the product or brand awareness among her or his connected parties on Twitter. I refer to this mechanism as consumer-generated brand awareness. Once a potential customer is aware of a particular product or brand through the company's advertising campaigns, additional announcements of purchase action or intent from her or his connected parties on Twitter are unlikely to increase brand awareness, and thus, increase the likelihood of purchase. To the extent that consumer-generated brand awareness on Twitter *substitutes* for the producer-generated brand awareness of advertising, the ability of the volume of Twitter comments to spur sales is more pronounced when advertising is limited. In summary, the substitution between the two effects implies that the marginal predictive power of PURCHASE with respect to future sales decreases with the level of advertising.

In contrast, the ability of the valence of Twitter comments to spur sales works through a mechanism different from that of advertising: A more positive customer assessment is likely to sway consumers in favor of the known product or brand, and thus, increases the likelihood of purchase. The valence mechanism *complements* advertising's role in soliciting purchases in two ways. First, the positivity of Twitter comments validates and reinforces what people already know from advertising. Second, a positive assessment on Twitter is more likely to attract the attention of, and thus, trigger a sale to, consumers who are already aware of the particular product or brand. Accordingly, the ability of POSITIVE to spur sales is more pronounced when advertising is extensive. In summary, the complementarity between the two effects suggests that the marginal predictive power of POSITIVE with respect to upcoming sales increases with the level of advertising. This leads to the second hypothesis:

H2: Ceteris paribus, the predictive power of PURCHASE (POSITIVE) with respect to upcoming sales decreases (increases) with the level of advertising.

Twitter comments are easily accessible and can be acquired at a relatively low cost. A recent survey in the United Kingdom by Finextra Research reports that 62% of brokers and heads of trading desks believe investor sentiment, as revealed on social media, influences share prices. Sentiment is defined as the subjective assessment, not justified by fundamentals, of a firm's future cash flows (Baker and Wurgler [2006]). Despite the survey evidence suggesting that institutional investors appreciate the usefulness of Twitter comments in determining investor sentiment about a company or stock, it is uncertain whether capital market participants appreciate the predictive power of Twitter comments about products and brands with respect to future fundamentals. In this context, a natural question is whether analysts, as capital market participants who specialize in forecasting upcoming sales and earnings, incorporate the wisdom of crowds on Twitter in their forecasts, and, if not, whether the analyst forecast error is systematically related to nonfinancial information as disseminated on Twitter.

Analysts possess a great deal of industry knowledge and may be privy to information about a company and its products and brands. For instance, they could acquire product information that is not accessible to individual investors from site visits and direct communication with management teams in person or at industry conferences. Product information from site visits and direct communication might be equally or more informative than the collective wisdom about a company's products and brands disseminated on Twitter. Therefore, whether analyst forecast revision responds to the change in the wisdom of crowds on Twitter and whether analyst forecast error is systematically related to the volume and valence of Twitter comments remain open questions. Interestingly, even when the analyst forecast revision underreacts or overreacts to the change in Twitter comments about products and brands, analyst forecast error is not necessarily correlated with the volume and valence of Twitter comments. For instance, if nonfinancial information on Twitter is subsumed by other information that analysts have incorporated into the forecasts, the analyst forecast error is not systematically biased conditional on Twitter comments. Analyst forecast error is systematically biased conditional on the valence and volume of Twitter comments only when analysts underreact or overreact to nonfinancial information on Twitter and when Twitter provides additional nonfinancial information that is not subsumed by other sources. This leads to the third hypothesis stated in the null form:

H3a: Ceteris paribus, analyst forecast revision does not fully incorporate the change in the valence and volume of tweets about products and brands.
H3b: Ceteris paribus, analyst forecast error is not systematically biased conditional on the valence and volume of tweets about products and brands.

III. Data, validity test, and research design

3.1. Summary statistics on nonfinancial information on Twitter

I use an independent company, Likefolio, to provide the data on Twitter comments because it has proprietary information on the mapping between products and their business owners. Likefolio identifies the holder of a given tweet (that is, the person or company who initiates it) and the target of a given tweet (that is, the entity the tweet is discussing). Because the study is interested in the incremental information content of third-party generated comments about a company's products and brands, the target of the selected tweets is limited to products and brands and the holder of the selected tweets is limited to third parties, not the company itself. Next, Likefolio uses a combination of knowledge-based techniques and statistical methods to classify the content of each selected tweet.[2] Content analysis refers to the use of natural language processing, text analysis, and computational linguistics to identify and extract subjective information in source material. The first task of content analysis is classifying whether a tweet mentions a recent past purchase of a given product or brand or an intention to do so in the future. The content of each tweet is classified as either "with mentioning of purchase" or "without mentioning of purchase" (see exhibit 1 for examples). The second task is classifying the *valence* of a given tweet—whether the opinion expressed is positive, negative, or neutral (see exhibit 2 for examples under each category).

Then, Likefolio uses its proprietary information to map various products and brands to the businesses that own them and summarizes selected tweets at the *company* level. The first statistic (PURCHASE) is measured as the total number of tweets that

[2] An alternative method would be to use open source software tools that deploy machine learning, statistics, and natural language processing techniques to automate content analysis on those selected tweets myself. Because the volume of selected tweets in the sample periods is in the millions daily, the computing power required is beyond my capacity.

explicitly indicate a recent past purchase of a company's products and brands or an intention to do so in the future. To control for the growth of Twitter over time, PURCHASE is normalized on a per million basis. The second statistic (POSITIVE) is measured as the ratio of the total number of tweets that convey a positive assessment of a company's products and brands over the total number of tweets that convey a nonneutral (positive or negative) assessment of a company's products and brands. The two statistics on Twitter, PURCHASE and POSITIVE, are summarized for each company on a daily basis from January 1, 2012, to December 31, 2015.

3.2. Sample formation and validity check on the two summary measures

The dependent variable is sales growth ($SALES\_GROWTH_{i,y+1}$), which is calculated as the percentage change in the annual sales that are disclosed a couple of months after the fiscal year end ($SALES_{i,y+1}$) relative to that for the prior fiscal year ($SALES_{i,y}$). Although the dependent variable is measured at the firm-year level, PURCHASE and POSITIVE are measured on a daily basis. To ensure that explanatory variables are measured using the firm-year level as the dependent variable, I average daily values of PURCHASE and POSITVE over the last quarter of the fiscal year.[3] In particular, $AVG\_Q\_PURCHASE_{i,y+1}$ averages daily PURCHASE over the last quarter of the fiscal year. If PURCHASE is missing for any given day during the specified time period, $AVG\_Q\_PURCHASE_{i,y+1}$ is missing. $AVG\_Q\_POSITIVE_{i,y+1}$ averages daily POSITIVE over the last quarter of the fiscal year. Similarly, if POSITIVE is missing for any given day during the specified time period, $AVG\_Q\_POSITIVE_{i,y+1}$ is missing. I

[3] In the robustness check, the results are similar if the two summary statistics are averaged over the entire fiscal year.

choose Twitter comments during the last quarter of the fiscal year to ensure that Twitter comments are not stale relative to the fiscal year end.

The sample with Twitter comments consists of 7,494 firm-year observations that cover 1,936 unique companies. However, financial information for 873 firm-year observations is not available from Compustat. The final sample consists of 6,621 firm-year observations for 1,810 unique firms. The classification of a firm's major customer base follows a two-step approach. First, Likefolio identifies B-to-C firms based on their understanding of the firm's business model. Second, I use various sources to cross-examine the validity of its classification, including the business description section and the detailed disclosure of major customers in annual reports. If the information from the annual report indicates otherwise, I remove the specific firm from the B-to-C subsample. The two-step approach yields 165 unique B-to-C firms and 599 firm-year observations. B-to-C firms, as a group, have an economically significant presence on Twitter: The volume of Twitter comments discussing the products and brands from the group of B-to-C firms combined accounts for 90% of the total volume of Twitter comments about products and brands from all sample firms. The sample formation process is presented in table 1.

Next, I perform a series of validity tests on the data. First, I examine whether Likefolio has tracked all products and brands for a given company. Because the mapping of products or brands to their business owners is proprietary, it is impossible to obtain the list of products and brands for each of the sample firms. However, Likefolio shares the list of products and brands for 25 randomly selected firms whose major customers are individual consumers. (See the list of products and brands for the selected companies in exhibit 3.) For example, Lulu owns two brands, whereas Volkswagon owns more than eighty products or brands. I find no omission from the list of products and brands for each of the selected companies by cross-examination with information provided by Nielsen and other online sources.

Second, I explore the cross-sectional determinants of the volume and valence of Twitter comments to examine whether the two summary statistics are correlated with firm characteristics as predicted. The first statistic (PURCHASE) summarizes the incidences of past and potential purchases of a company's products and brands as reported on Twitter. Accordingly, this statistic is expected to be larger when the level of recent past sales is higher. The second statistic (POSITIVE) summarizes the collective assessment of customers with respect to their satisfaction or dissatisfaction with the quality of a company's products and brands. Accordingly, this statistic measures customer feedback after his or her experience with the product and brand. For customer feedback on products and services, the relevant information is not product information provided by the firm through advertising activities, but rather consumers' satisfaction with the product itself. As a result, the valence of Twitter comments is expected to be unrelated to advertising. Consistent with the intuition, as reported in table 4, AVG_Q_PURCHASE increases with the volume of past sales, whereas the partial correlation between AVG_Q_POSITIVE and the level of advertising is statistically insignificant.

3.3. Research design on the cross-sectional variation in the predictive power of Twitter

I use the following specification to examine whether the predictive power of Twitter comments about products and brands with respect to upcoming sales is more pronounced for firms whose major customers are consumers:

$$SALES\_GROWTH_{i,y+1} = \alpha + \beta_1 B2B_i + \beta_2 AVG\_Q\_PURCHASE(POSITIVE)_{i,y+1} + \boldsymbol{\beta_3 B2B_i * AVG\_Q\_PURCHASE(POSITIVE)_{i,y+1}} + \beta_4 Ln(YTD3Q\_SALES_{i,y+1}) + \beta_5 YTD3Q\_SALESGROWTH_{i,y+1} + \beta_6 SIZE_{i,y} + \beta_7 CHG\_BACKLOG_{i,y} + \beta_8 ADVERTISE_{i,y} + \boldsymbol{\varepsilon}_{it} \quad \text{Model (1)}$$

The dependent variable is $SALES\_GROWTH_{i,y+1}$, which is measured as the percentage change in upcoming sales relative to sales in the prior year. The variable of interest is the interaction term between B2B and AVG_Q_PURCHASE (AVG_Q_POSITIVE). The indicator variable B2B is defined as 1 if a firm's major customers are businesses, and 0 if a firm's major customers are consumers. As the predictive power of Twitter comments with respect to the upcoming sales is more pronounced for the subsample of firms whose major customers are consumers, I expect the slope coefficient on the interaction term to be negative and statistically significant. Given that the distributions of the two summary statistics follow the power law distribution, I use the maximum likelihood estimation to estimate models throughout the study. Furthermore, the industry fixed effect is added in the models throughout the study when estimating the slope coefficients to mitigate the omitted-correlated-variable problem.

The first control variable is the sum of sales for the first three quarters ($YTD3Q\_SALES_{i,y+1}$) because sales from the first three quarters of the year are largely available and are highly relevant for forecasting sales growth over the entire year. The second control variable is the year-to-date sales growth rate for the first three quarters relative to that for the first three quarters in the previous fiscal year

($YTD3Q\_SALESGROWTH_{i,y+1}$). The third control variable captures the size of the firm because larger firms have a larger customer base, and therefore, a greater following on Twitter. $SIZE_{i,y}$ is measured as the natural log of assets at the beginning of the fiscal year. The last two control variables are financial variables: advertising expense and the change in deferred revenue (backlog). Lev and Thiagarajan [1993] find that both variables are predictive of upcoming sales. Advertising expense ($ADVERTISE_{i,y}$) is measured as the ratio of advertising expense over sales during the previous fiscal year. The change in deferred revenue ($CHG\_BACKLOG_{i,y}$) is measured as the ratio of the change in deferred revenue over sales during the previous year.

I then use the following specification to examine how the predictive power of the volume and valence of Twitter comments with respect to upcoming sales varies with advertising:

$$\begin{aligned} SALES\_GROWTH_{i,y+1} = {} & \alpha + \beta_1 AVG\_Q\_PURCHASE_{i,y+1} + \boldsymbol{\beta_2 ADVERTISE_{i,y} * AVG\_Q\_PURCHASE_{i,y+1}} \\ & + \beta_3 AVG\_Q\_POSITIVE_{i,y+1} + \boldsymbol{\beta_4 ADVERTISE_{i,y} * AVG\_Q\_POSITIVE_{i,y+1}} + \beta_5 Ln(YTD3Q\_SALES_{i,y+1}) \\ & + \beta_6 YTD3Q\_SALESGROWTH_{i,y} + \beta_7 SIZE_{i,y} + \beta_8 CHG\_BACKLOG_{i,y} + \beta_9 ADVERTISE_{i,y} + \boldsymbol{\varepsilon}_{it} \qquad \text{Model (2)} \end{aligned}$$

The variables of interest from model (2) are the slope coefficients on the interactions between advertising and the volume and valence of Twitter comments. The slope coefficient on the interaction between advertising and AVG_Q_PURCHASE (β_2) is expected to be negative and statistically significant, while the slope coefficient on the interaction between advertising and AVG_Q_POSITIVE (β_4) is expected to be positive and statistically significant.

3.4. Analysts' use of Twitter comments about products and brands

Consensus analyst forecasts rather than individual analyst forecasts are used to examine whether analysts on average incorporate nonfinancial information disseminated on Twitter. Consensus analyst forecasts of upcoming sales and realized sales are collected from the summary tape of the Institutional Brokers Estimate System (I/B/E/S). I use the mean forecast from the summary tape as a proxy for the consensus analyst forecast. The consensus analyst forecast is revised once a month in I/B/E/S. In calculating the analyst forecast error, I use the consensus analyst forecast during the last month of the fiscal year end as a proxy for analyst expectation. This choice ensures that the year-to-date sales for the first three quarters were available when the consensus forecast was updated during the last month. In particular, I use the following specification to examine whether the revision in the consensus forecast responds to the change in Twitter comments:

$$\text{FORECAST\_REV}_{i,y+1} = \propto + \boldsymbol{\beta_1}\textbf{CHG\_PURCHASE(POSITIVE)}_{\mathbf{i,y+1}} + \beta_2\text{Ln}(\text{NUM\_FORECAST}_{i,y+1}) + \beta_3\text{SIZE}_{i,y} + \beta_4\text{Ln}(\text{PRIOR\_FORECAST}_{i,y+1}) + \beta_5\text{GUIDE}_{i,y+1} + \boldsymbol{\varepsilon}_{it} \qquad \text{Model (3)}$$

In model (3), the dependent variable is the revision in the consensus forecast (FORECAST_REV), and the variable of interest is the change in the valence and volume of tweets about products and brands. The revision in the consensus forecast is measured as the percentage change from the mean forecast during the second-to-last month (PRIOR_FORECAST) to the mean forecast during the last month of the fiscal year (FORECAST). Correspondingly, the change in the volume (valence) of Twitter comments, CHG_PURCHASE (POSITIVE), is measured as the percentage change from PRIOR_AVG_PURCHASE (POSITIVE) to AVG_PURCHASE (POSITIVE). AVG_PURCHASE (POSITIVE) averages daily PURCHASE (POSITIVE) over the window that starts from the day after the reported date of the consensus forecast during the second-to-last month and ends three days prior to the reported date of the consensus forecast during the last month. The window ends three days prior to the consensus forecast during the last month to avoid a look-ahead bias for analysts and to allow analysts some time to process preceding Twitter comments. The average length of the time window is 28 days. Accordingly, PRIOR_AVG_PURCHASE (POSITIVE) averages daily PURCHASE (POSITIVE) over the window that starts from the day after the reported date of the consensus forecast during the 10th month and ends three days prior to the reported date of the consensus forecast during the second-to-last month.

Four control variables are included in model (3). First, I include the natural log of the number of forecasts included in the consensus forecast (Ln (NUM_FORECAST$_{i,y+1}$)). Second, I include the natural log of total assets at the beginning of the fiscal year (SIZE$_{i,y}$) to control for the possible size effect. Third, I include the consensus forecast in the second-to-last month (Ln (PRIOR_FORECAST$_{i,y+1}$)) to account for the possibility that the higher the previous consensus forecast, the lower the percentage change. The last control variable is the magnitude of the consensus forecast revision that management guidance could have triggered (GUIDE$_{i,y+1}$). This variable is measured as the percentage change from PRIOR_FORECAST to management guidance on upcoming annual sales during the window for measuring the analyst forecast revision, and is valued at zero if there is no management guidance during the specified window.

I then use the following specification to examine whether the analyst forecast error is systematically related to the volume and valence of Twitter comments:

$$\text{FORECAST\_ERROR}_{i,y+1} = \propto + \boldsymbol{\beta_1}\,\textbf{AVG\_PURCHASE (AVG\_POSITIVE)}_{\boldsymbol{i,y+1}} + \beta_2\text{SIZE}_{i,y} + \beta_3\text{Ln (NUM\_FORECAST}_{i,y+1}) + \beta_4\text{Ln(PRIOR\_FORECAST}_{i,y+1}) + \beta_5\text{ACTUAL\_FORECAST\_DAYS}_{i,y+1} + \beta_6\text{LAST\_GUIDE}_{i,\,y+1} + \beta_7\text{Ln (YTD3Q\_SALES}_{i,y+1}) + \beta_8\text{YTD3Q\_SALESGROWTH}_{i,y+1} + \beta_9\text{CHG\_BACKLOG}_{i,y} + \beta_{10}\text{ADVERTISE}_{i,y} + \boldsymbol{\varepsilon_{i\text{t}}} \qquad \text{Model (4)}$$

The consensus forecast error (FORECAST_ERROR) is measured as $FORECAST_{i,y+1}$ minus realized upcoming sales divided by realized sales ($SALES_{i,y+1}$). The variables of interest are the slope coefficients on AVG_PURCHASE and AVG_POSITIVE. I include three sets of control variables in model (4). The first set of control variables captures the characteristics of the consensus forecast. First, I include the natural log of the number of individual forecasts (Ln ($NUM\_FORECAST_{i,y+1}$)). Second, I include the natural log of the consensus forecast during the second-to-last month (Ln($PRIOR\_FORECAST_{i,y+1}$)) because it is the most recent consensus forecast prior to the consensus forecast reported during the last month. Third, I include the number of calendar days between the reported date of realized sales and the reported date of the consensus forecast ($ACTUAL\_FORECAST\_DAYS_{i,y+1}$) because prior studies suggest that the time interval between the forecast date and the announcement date influences the analyst forecast accuracy (Barron et al. [1998]).

The second control consists of a set of five financial variables to ensure that the relation between forecast error and Twitter comments is not subsumed by other available information. The five variables are the natural log of the year-to-date sales during the previous three quarters of the same fiscal year ($Ln\_YTD3Q\_SALES_{i,y}$), the year-to-date sales growth rate for the first three quarters relative to that for the first three quarters in the previous fiscal year ($YTD3Q\_SALESGROWTH_{i,y+1}$), the natural log of total assets at the beginning of the fiscal year ($SIZE_{i,y}$), advertising expense as a percentage of sales during the prior year ($ADVERTISE_{i,y}$) and the percentage change in backlog during the prior year ($CHG\_BACKLOG_{i,y}$).

The last control variable captures the expected sales growth according to management. If managers provide multiple instances of guidance on upcoming sales, I choose the last management guidance prior to the consensus analyst forecast during the last month of the fiscal year ($LAST\_GUIDE_{i,y+1}$). $LAST\_GUIDE_{i,y+1}$ is measured as the selected management guidance minus prior year's sales divided by prior year's sales. If management provides no guidance, the value of this variable is zero.

In order to test whether analysts incorporate the wisdom of crowds on Twitter, the sample used to examine analyst revision and analyst forecast error is limited to the subsample of firms whose major customers are consumers. Because a large proportion of firm-year observations are not covered by I/B/E/S, the final sample used to test model (3) and model (4) includes 330 firm-year observations that cover 141 unique firms. Figure 2 graphs the timeline for measuring nonfinancial information on Twitter and analyst forecasts of upcoming sales.

IV. Empirical Results

4.1. Descriptive statistics and correlations

Table 2 provides the descriptive statistics. The average number of tweets mentioning purchase actions or intent on a daily basis (AVG_Q_PURCHASE) is 101.63 and the median is 0.44. The average ratio of the number of positive tweets over the number of nonneutral (positive and negative) tweets on a daily basis is 88% and the median ratio is 92%. For the majority of observations, the number of nonneutral (positive and negative) tweets on a given day is zero, and therefore, daily POSITIVE is missing. When POSITIVE is missing for any given day during the specified time period, AVG_Q_POSITIVE is missing. Accordingly, the number of observations for

AVG_Q_POSITIVE is only 2,571, which is significantly lower than that for AVG_Q_PURCHASE. The standard deviation of AVG_Q_PURCHASE is 1437.2. The maximum AVG_Q_PURCHASE is 49,459 and the minimum number is 0. The comparison of the two subsamples suggests that the volume of tweets mentioning purchase is higher, but customer feedback on Twitter is less positive for firms whose major customers are consumers (B-to-C firms). Furthermore, B-to-C firms advertise more aggressively than B-to-B firms. As reported in panel B of table 2, the average (median) percentage change in AVG_PURCHASE is only 4.9% (–5.3%), and the average (median) change in AVG_POSITIVE is only 1.3% (0.3%).

Panel A of table 3 provides the correlations between the two summary statistics on Twitter and upcoming sales growth. The Spearman correlation between AVG_Q_PURCHASE and SALES_GROWTH is 0.036 and statistically significant (*p*-value = 0.003). Similarly, the Spearman correlation between AVG_Q_POSITIVE and SALES_GROWTH is 0.045 and statistically significant (*p*-value = 0.023). However, their Pearson correlations are statistically insignificant. Panel B and panel C of table 3 provides the correlations between Twitter comments and the analyst forecast revision and the analyst forecast error, respectively. Neither CHG_PURCHASE nor CHG_POSITIVE is correlated with forecast revision. Furthermore, neither AVG_PURCHASE nor AVG_POSITIVE is correlated with analyst forecast error.

Table 4 presents the empirical results on the cross-sectional variation on the volume and valence of Twitter comments on products and brands. Consistent with the underlying constructs, AVG_Q_PURCHASE is higher when the sum of the sales of the first three quarters is higher, whereas AVG_Q_POSITIVE does not vary with the level of advertising. The correlation structure validates the empirical measures for the volume and valence of Twitter comments.

4.2. Cross-sectional variation in the predictive power of Twitter comments

Table 5 presents the empirical results on whether nonfinancial information on Twitter is informative about upcoming sales and the cross-sectional variation in its predictive power. The first column is the benchmark specification in which only available financial information is included to predict upcoming sales. As shown in the second column of table 5, when AVG_Q_PURCHASE is used as the explanatory variable, the slope coefficient is 0.016 and statistically significant (p-value = 0.001). As shown in the third column of table 5, the slope coefficient on the interaction between AVG_Q_PURCHASE and B2B is –0.075 and statistically significant (p-value = 0.001). To summarize, the number of tweets with purchase action or intent is informative about upcoming sales incremental to financial information, and the predictive power is more pronounced for firms whose major customers are individual consumers. In contrast, as shown in columns 5 and 6 of table 5, neither the main effect of AVG_Q_POSITIVE nor the interaction effect between AVG_Q_POSITIVE and B2B is statistically significant.

Given that the predictive power of Twitter comments is more pronounced for the subsample of firms whose major customers are consumers, table 6 presents the results on how the predictive power of Twitter comments about products and brands varies with advertising for this particular subsample. As shown in the second column of table 6, the slope coefficient on the interaction between AVG_Q_PURCHASE and ADVERTISE is –0.368 and statistically significant, suggesting that the marginal predictive power of the volume of tweets containing purchase intent or action decreases with the level of advertising. As shown in the fourth column of table 6, the slope coefficient on the interaction between AVG_Q_POSITIVE and ADVERTISE is 5.456 and statistically significant, suggesting that the marginal predictive power of the positivity of Twitter comments increases with the level of advertising. As shown in the last column of table 6, when both summary statistics are included jointly in the model, the slope coefficient on the interaction between AVG_Q_PURCHASE and ADVERTISE is –0.325 and statistically significant, and the slope coefficient on the interaction between AVG_Q_POSITIVE and ADVERTISE is 5.079 and statistically significant. The results from table 6 are consistent with the interpretation that consumer-generated brand awareness substitutes for producer-generated brand awareness and that the word-of-mouth effect of positive customer assessment is complementary to that of advertising.

4.3. Analyst forecasts and nonfinancial information on Twitter

Table 7 presents the results on whether analysts revise their forecasts in response to the changes in nonfinancial information disseminated on Twitter. None of the sample firms issued management guidance in the specified time window, and therefore, there is no variation in GUIDE. The results from table 7 suggest that the revision in the consensus forecast is not responsive to changes in the volume and valence of Twitter comments.

Table 8 presents the results on whether analyst forecast error is systematically related to the volume and valence of Twitter comments. As shown in the first half of table 8, when financial variables are excluded from the regression, the slope coefficient on AVG_PURCHASE is –0.002 and statistically significant (p-value = 0.001). In contrast, the slope coefficient on AVG_POSITIVE is negative but statistically insignificant. Similarly, as shown in the second half of table 8, when financial variables are included as control variables, the pattern is the same: The slope coefficient on AVG_PURCHASE is negative and statistically significant, whereas the slope coefficient on AVG_POSITIVE is negative but statistically insignificant. The insignificant slope coefficient on AV_POSITIVE from model (4) is not surprising because, for the subsample of B-to-C firms, AVG_POSITIVE is not informative about upcoming sales, as shown in the 3rd column of table 6. To summarize, the results from table 8 suggest that analysts do not fully incorporate nonfinancial information contained in Twitter comments, despite its usefulness in predicting upcoming sales. In particular, the larger the number of tweets with purchase intent or action, the lower the consensus forecast relative to actual sales. Interestingly, the negative slope coefficient on AVG_PURCHASE coupled with the positive slope coefficient on ADVERTISE suggests that analysts consistently overweight advertising but underweight nonfinancial information disseminated on Twitter in forming their forecasts.

V. Robustness checks

First, in the main tests, the dependent variable is the growth rate of sales in the upcoming year relative to that in the prior year, and the main variable of interest is the average of daily PURCHASE and POSITIVE over the last quarter of the fiscal year. I test two alternative specifications where the measurement window is exactly matched between the dependent variable and the two variables of interest. In the first alternative specification, both AVG_Q_PURCHASE and AVG_Q_POSITIVE remain to be averaged over the last quarter, whereas the dependent variable is the same-quarter sales growth rate for the last quarter of the fiscal year relative to that in the prior year (SALESGROWTH_Q4). The results are quantitatively similar to those reported in the main tests. For instance, in model (1), the slope coefficient on AVG_Q_PURCHASE is 0.037 and statistically significant (*p*-value = 0.001), and the slope coefficient on the interaction between AVG_Q_PURCHASE and B2B is –0.066 and statistically significant (*p*-value = 0.040). The slope coefficient on AVG_Q_POSITIVE is statistically insignificant. In model (2), the slope coefficient on the interaction between AVG_Q_PURCHASE and ADVERTISE is –0.049 and statistically significant (*p*-value = 0.001).

In the second alternative specification, the dependent variable continues to be the growth rate of sales in the upcoming year relative to that in the prior year ($SALES\_GROWTH_{i,y+1}$), and the explanatory variable is AVG_YEAR_PURCHASE (POSITIVE), which is measured as PURCHASE (POSITIVE) averaged over the entire fiscal year. The results are quantitatively similar to those reported in table 5 and table 6. For instance, in model (1), the slope coefficient on AVG_YEAR_PURCHASE is 0.025 and statistically significant (*p*-value = 0.001), and the slope coefficient on the interaction between AVG_YEAR_PURCHASE and B2B is –0.031 and statistically significant (*p*-value = 0.039). In model (2), the slope coefficient on the interaction between AVG_YEAR_PURCHASE and ADVERTISE is –0.016 and statistically significant (*p*-value = 0.01).

Second, in the main specification to test whether the consensus forecast incorporates Twitter comments, the volume and valence of Twitter comments are measured as the average of daily PURCHASE and POSITIVE during the month prior to the consensus forecast reported in the last month of the fiscal year. The underlying assumption for the timing specification is that analysts perceive the predictive power of Twitter comments for upcoming sales growth to be equal for each of the calendar date during the specified time window. In order to account for the possibility of differential salience of Twitter comments in influencing the consensus forecast, I use an alternative research design in which the variables of interest, PURCHASE and POSITIVE, are measured at the firm-day level. In order to control for the differential salience of Twitter comments for different dates, I add an additional explanatory variable ($\text{TWITTER\_FORECAST\_DAYS}_{i,t}$) in model (4), which is measured as the number of calendar days between the date when Twitter comments are generated and the reported date of the last consensus forecast in the fiscal year. I also interact this additional variable with the two summary statistics of Twitter comments. In this specification, as the dependent variable is at the firm-year level and the variables of interest are at the firm-day level, the standard errors are cluster-adjusted by both firm and fiscal year. Because the average duration of the chosen time window is close to 28 days, this alternative sample to test model (4) includes 9,074 firm-day observations. The results are quantitatively similar to those reported in table 8. For instance, when the dependent variable is analyst forecast error, the slope coefficient on daily PURCHASE is –0.002 and statistically significant (p-value = 0.001), whereas the slope coefficient on daily POSITIVE is statistically insignificant.

VI. Conclusion and Future Research

This study examines whether third-party-generated information about a company's products and brands on Twitter, once summarized, is informative about upcoming sales incremental to financial information and the cross-sectional variation in its predictive power. First, the predictive power of nonfinancial information on Twitter with respect to upcoming sales is more pronounced when a firm's major customer base consists of consumers. Second, the predictive power of the volume and valence of Twitter comments about products and brands with respect to firm-level fundamentals varies with advertising activity. However, analysts, on average, do not fully incorporate in their forecasts the implications for upcoming sales of the collective wisdom of users on Twitter. Accordingly, the analyst forecast error is systematically biased conditional on the volume of tweets mentioning purchase of a company's products and brands.

One interesting follow-up research topic is an examination of whether individual analyst forecasts of upcoming sales incorporate Twitter comments, and, if so, the potential edge that Twitter comments bring to forecast accuracy. Another follow-up research question is an examination of whether the systematic bias in analyst forecasts conditional on the volume of tweets mentioning purchase intent or actions results in a profitable trading strategy around the announcement date of sales. The scope of study can also be extended to include tweets discussing a company itself. An examination of the interplay between tweets discussing the company itself and those discussing its products and brands might clarify how information flows between product markets and capital markets.

References

AMIR, E., and B. LEV. 1996. 'Value-Relevance of Nonfinancial Information: The Wireless Communications Industry.' Journal of Accounting and Economics 22 (1996): 3–30.

ASUR, S., and B. HUBERMAN. 'Predicting the Future with Social Media.' Proceedings of the 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology 1 (2010): 492–99.

BAKER, M., and J. WURGLER. 'Investor Sentiment and the Cross-Section of Stock Returns.' Journal of Finance 61 (2006): 1645–80.

BARRON, O.E., O. KIM, S.C. LIM, and D.E. STEVENS. 'Using Analysts' Forecasts to Measure Properties of Analysts' Information Environment.' Accounting Review 73 (2003): 421–33.

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

CHEVALIER, J.A., and D. MAYZLIN. 'The Effect of Word of Mouth on Sales: Online Book Reviews.' Journal of Marketing Research 43 (2006): 345–54.

CHOI, H., and H. Varian. 'Predicting the Present with Google Trends.' Economic Record 88 (2012): 2–9.

DA, Z., J. ENGELBERG, and P. GAO. ' In Search of Attention.' Journal of Finance 5 (2011): 1461–99.

DRAKE, M.S., D. ROULSTONE, and J.R. THORNOCK. 'Investor Information Demand: Evidence from Google Searches Around Earnings Announcements.' Journal of Accounting Research 50 (2012): 1001–40.

ETTREDGE, M., J. GERDES, and G. KARUGA. 'Using Web-based Search Data to Predict Macroeconomic Statistics." Communications of the ACM 48 (2005): 87–92.

GOEL, S., J.M. HOFMAN, S. LAHAIE, D.M. PENNOCK, and D.J. WATTS. 'Predicting Consumer Behavior with Web Search.' Proceedings of the National Academy of Sciences, 107 (2010):17486–90. Available at http://www.pnas.org/content/early/2010/09/20/1005962107.

HUANG, H., and N.D. PENNA. 'Constructing Consumer Sentiment Index for U.S. Using Google Searches.' Working paper, University of Alberta, 2009. Available at https://ideas.repec.org/p/ris/albaec/2009_026.html.

ITTNER, C.D., D.F. Larcker, and M.W. Meyer. 'Subjectivity and the Weighting of Performance Measures: Evidence from a Balanced Scorecard.' Accounting Review 78 (2003): 725–58.

JUNG, M., J. NAUGHTON, A. TAHOUN, and C. WANG. 'Corporate Use of Social Media.' Unpublished paper, New York University, 2015. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2588081.

LEV, B. and S.R. THIAGARAJAN. 'Fundamental Information Analysis.' Journal of Accounting Research 31 (1993): 190–215.

LIU, Y. 'Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue.' Journal of Marketing 70 (2006): 74–89.

MCLAREN, N., and R. SHANBHOGE. 'Using Internet Data as Economic Indicators.' Bank of England Quarterly Bulletin Q2 (2011): 134–40.

MILLER, G., and D. SKINNER. 'The Evolving Disclosure Landscape: How Changes in Technology, the Media, and Capital Markets Are Affecting Disclosure.' Journal of Accounting Research 53 (2015): 221–39.

VOSEN, S., and T. SCHMIDT. 'Forecasting Private Consumption: Survey-based Indicators vs. Google Trends.' Journal of Forecasting 30 (2011): 565–78.

WU, L., and E. BRYNJOLFSSON. 'The Future of Prediction: How Google Searches Foreshadow Housing Prices and Sales.' Working paper, University of Pennsylvania, 2013. Available at http://ssrn.com/abstract=202293.

SUNSTEIN, C. Infotopia: How Many Minds Produce. New York: Oxford University Press, 2008.

Exhibit 1
Examples of Tweets Containing Purchase Intent or Action

1. I then got this iPhone 6 Plus trying to be big baller and absolutely hate it ?
2. I think I'm just going to get an iPhone 6 instead of the S7 Edege?
3. Got the iPhone 6 Plus and I feel like I'm holding a tv
4. My dad ordered me a new phone, he ordered the iPhone 6s instead of the IPhone 6. Ain't even mad?
5. My uncle just got an iPhone and i taught him how to FaceTime now he FaceTimes me all the time. At work at shoprite... Love that guy

Exhibit 2
Examples of the Valence of Tweets

A. Positive tweets

1. This technology is amazing. Talked to my mother in-law tonight on my, new to me, iPhone using Facetime. "Wind in off the water 2 weeks now."
2. Always nice to get a convert to the iPhone team. #bluebubblegoodness #welcome
3. I remember back when I was younger. All I had was an iPhone and iMovie. I remember being so excited about the footage. The thrill was great.
4. @KittyKaty_14 ? I'm glad you're jealous lol. Don't worry about it, you'll be more than fucking happy when you get new iPhone 6s Plus once.
5. @AccuWxBeck love, love, love my iPhone. I will be sad when I leave At&t and don't have it anymore

B. Neutral tweets

1. Whenever I'm around my mom act like she don't know how to work any electronic known to man , but she got that iPhone 6 tho ?
2. Anyone have an extra AT&T iPhone?
3. iPhone owners holding onto their phones longer - CNET https://t.co/kCxMZNO0KG
4. Another way to reach us... Have an iPhone and use iMessage now send us messages / photos / videos at columbuzz@icloud.com
5. Jaw-Dropping Scene Captured in Germany From The Weather Channel iPhone App. https://t.co/k0WFGnMivx https://t.co/tfO78W7nC4

C. Negative tweets

1. I then got this iPhone 6 Plus trying to be big baller and absolutely hate it ?
2. iPhone bullshit as hell for the auto correct ? I hate that shit
3. @LetsRabbit sorry to complain once again ? but whenever I use your app the wifi goes out of my iPhone or iPad (whichever I watch it on) why?
4. Dead ass, I hate this iPhone 6s battery!!!!!! I miss my iPhone 6 Plus battery!!!
5. My Iphone 6 camera sucks

Exhibit 3
List of products and brands for 25 randomly selected B-to-C firms

Company	Products and Brands			
Chipotle Mexican Grill	Chipotle Mexican Grill	Pizzeria Locale	ShopHouse Southeast Asian Kitchen	
Delta Air Lines Inc.	Delta Air Lines	Delta Sky Magazine	Delta Sky Club	SkyMiles
EBay Inc.	Close5	Decide.com	eBay	Ebay Enterprise
	GSI Commerce	Hunch	Magento	RedLaser
	Sell for Me	Start Tank	Svpply	Twice
	Half.com	Shopping.com	StubHub	
Fitbit Inc	Alta	Aria	Blaze	Charge
	Fitbit	Flex	Force	One
	Surge	Ultra	Zip	
General Motors Company	ACDelco	Buick	cascada	enclave
	Encore	Envision	lacrosse	regal
	Verano	ATS	ats-V	Cadillac
	ct6	ELR	Escalade	ESV
	SRX	XT5	XTS	camaro
	Chevrolet	Colorado	corvette	cruze
	Equinox	Impala	malibu	Silverado
	Sonic	Spark	ss sedan	Suburban
	Tahoe	Traverse	trax	Volt
	General Motors	Acadia	canyon	Denali
	GMC	Maven	savana	Sierra1500
	sierra 2500	sierra 3500	terrain	Yukon
	Holden	H2	H3	Hummer
	OnStar	Opel	G3	G5
	G6	G8	Pontiac	Solstice
	Torrent	Vibe	Sidecar	Vauxhal
GoPro, Inc.	Quik	Splice	Vemory	GoPro
	Hero	Hero Session	HeroCast	Karma
	Omni	Kolor	Stupeflix	
Groupon, Inc.	Groupon	Groupon Getaways	Groupon Pages	OrderUp
	Savored	Snap	Pretty Quick	
Hilton Worldwide	Canopy Hotel	Conrad Hotels & Resorts	Curio Hotel	DoubleTree
	Embassy Suites Hotels	Hampton	Hilton Garden Inn	Hilton Grand Vacations
	Hilton Hotels & Resorts	Hilton Hhonors	Home 2 Suites	Homewood Suites
	Parc 55	Tru Hotel	Waldorf Astoria	
L Brands, Inc.	Bath & Body Works	Henri Bendel	La Senza	Victoria's Secret
	VS Pink			
LinkedIn Corporation	Cardmunch	Compilr	Elevate	LinkedIn
	LinkedIn Job Search	LinkedIn Pulse	Rapportive	Refresh.io
	Lynda.com	Video2Brain	Newsle	LinkedIn Slideshare
Lululemon Athletica	Ivivva	Lululemon Athletica		

Exhibit 3 (continued)

Company	Products and Brands			
Hershey's	Allan Bear Bites	Allan Big Foot	Allan Sour BlueRaspberry	Allan Hot Lips
	Allan Sour Watermelon Slices	Allan Sour Wormies	Allan Wormies	BreathSavers
	Bubble Yum	Good & Plenty	Ice Breakers	Ice Breakers Duo
	Ice Breakers Ice Cubes	Jolly Rancher	Lancaster	PayDay
	Pelon Pelo Rico	Take 5	Twizzlers	ZAGNUT
	Zero	5th Avenue	Almond Joy	barkThins
	Brookside	Cadbury	Dagoba	Heath
	Hershey's	Hershey's Bliss	Hershey's Kisses	Hershey's Syrup
	Kit Kat	Krackel	Milk Duds	Mounds Bars
	Mr. Goodbar	Reese's	ROLO	Scharffen Berger
	SKOR	Symphony	Whatchamacallit	Sofit
	YORK	Krave Jerkey		
McDonald's	McDonald's			
Match Group	Match.com	OkCupid	Chemistry.com	DateHookup
	Humin	IndiaMatch	LDSPlanet	LoveAndSeek
	OurTime.com	Plenty of Fish	Singlesnet.com	Stepout
	AsianPeopleMeet	BabyBoomerPeople Meet	BBPeopleMeet.com	BlackBabyBoomerPe opleMeet
	BlackChristianPeopleMeet	BlackPeopleMeet	CatholicPeopleMeet	ChinesePeopleMeet
	DemocraticPeopleMeet	DivorcedPeopleMee t	InterracialPeopleMeet	JPeopleMeet
	LatinoPeopleMeet	LittlePeopleMeet	MarriagemindedPeopl eMeet	PetPeopleMeet
	RepublicanPeopleMeet	SeniorBlackPeople Meet	SeniorPeopleMeet	SingleParentMeet
	The Princeton Review	Tinder	Twoo	
New York Times Company	Idea Lab	International New York Times	New York Times Conferences	New York Times Cooking
	New York Times Magazine	NYTimes.com	T Brand Studio	The New York Times
	Times Digest	Times Journeys	Times Talk	
PepsiCo Inc.	AMP Energy	Cheetos	Cracker Jack	Doritos
	El Isleno	Frito-Lay	Frito's	Funyuns
	Grandma's	Lay's	Maui Style	Miss Vickie's
	Munchies	Munchos	Nut Harvest	Rold Gold
	Ruffles	Sabra	Sabritones	Santitas
	Smartfood Popcorn	Spitz	Stacy's	Sun Chips
	Tostitos	Gatorade	Mountain Dew	7UP
	Brisk	Citrus Blast	IZZE	Mug Root Beer
	Sierra Mist	1893	Pepsi	Aunt Jemima
	Cap'n Crunch	King Vitamin	Life Cereal	Quaker
	Quisp Cereal	Rice-A-Roni	Matador Beef Jerky	Aquafina
	Naked Juice	Ocean Spray	Propel Zero	Pure Leaf
	Sobe	Tropicana		

Exhibit 3 (continued)

Company	**Products and Brands**			
Starbucks Corp.	Ethos Water	Evolution Fresh	Frappuccino	Hear Music
	La Boulange	Roy Street Coffee & Tea	Seattles Best	Starbucks
	Tazo	Teavana	Verismo	
SeaWorld Parks & Entertainment	Adventure Island	Aquatica	Busch Gardens	Discovery Cove
	SeaWorld	Sesame Place	Water Country USA	
AT&T Inc	aio Wireless	AT&T	AT&T Mobility	BellSouth
	Cricket Wireless	Audience Network	DirecTV	Southwestern Bell
	Uverse			
Target Corp.	A Bullseye View	ClearRX	Dermstore	Target
Twitter	Cover	Digits	MoPub	Periscope
	SnappyTV	Trendrr	Curator	Madbits
	Marakana	Mitro	Twitter	Vine & Zipdial
Volkswagen Group	A1, A3, A4, A5, A6, A7,A8	Allroad	Audi	Q3, Q5,Q7
	R8, RS7, XL1	S3,S4, S5,S6,S7,S8,SQ5	TT Coupe	TT Roadster
	TTS	Arnage Saloon	Azure Convertible	Azure T
	Bentayga	Brooklands	Continental	Flying Spur
	Mulsanne	State Limousine	Zagato	Bently
	Bugatti	Chiron	Veyron	748;749; 848;718
	911; 916; 996; 998; 999; 1098; 1198;	Diavel	Ducati	Hypermotard
	Monster	Multistrada	PaulSmart 1000	Scrambler
	ST	Superbike	SuperSport	Aventador
	Centenario	Diablo	Egoista	Gallardo
	Huracan	Lamborghini	Murcielago	Reventon
	Sesto Elemento	Veneno Roadster	Cayenne	Cayman
	Macan	Panamera	Porsche	Beetle
	CC	EOS	Golf	Jetta
	Passat	Tiguan	Touareg	Volkswagen
Wal-Mart Stores	Sam's Club	Vudu	Wal-Mart	Luvocracy
	Spark Studio	Walmart Labs	Yumprint	
Yahoo Inc.	Aviate	Beam It	Blink	Cooliris
	Docspad	Luminate	PlayerScale	Polyvore
	Qwiki	RayV	Summly	Vizify
	Yahoo Radar	Yahoo Screen	Zofari	MessageMe
	Yahoo Livetext	Yahoo! Mail	Yahoo! Messenger	Tumblr
	BrightRoll	Yahoo! Advertising	Yahoo! Search Marketing	Yahoo! Web Analytics
	Xobni	Yahoo	Yahoo! Buzz	Yahoo! Answers
	Yahoo! Axis	Yahoo! Developer Network	Yahoo! Directory	Yahoo! Esports
	Yahoo! Finance	Yahoo! Games	Yahoo! Green	Yahoo! Groups
	Yahoo! Kids	Yahoo! Local	Yahoo! Maps	Yahoo! Meme
	Yahoo! Mobile	Yahoo! Movies	Yahoo! Music	Yahoo! News
	Yahoo! Personals	Yahoo! Pipes	Yahoo! Publisher Network	Yahoo! Real Estate
	Yahoo! Screen	Yahoo! Search	Yahoo! Shopping	Yahoo! Sports
	Yahoo! Travel	Yahoo! TV	Yahoo! Voice	
Yum! Brands Inc	KFC	Pizza Hut	Taco Bell & Winestreet	U.S. Taco Co and Urban Taproom

Figure 1
Interplay between the Word-of-Mouth Effect of Twitter Comments and Advertising

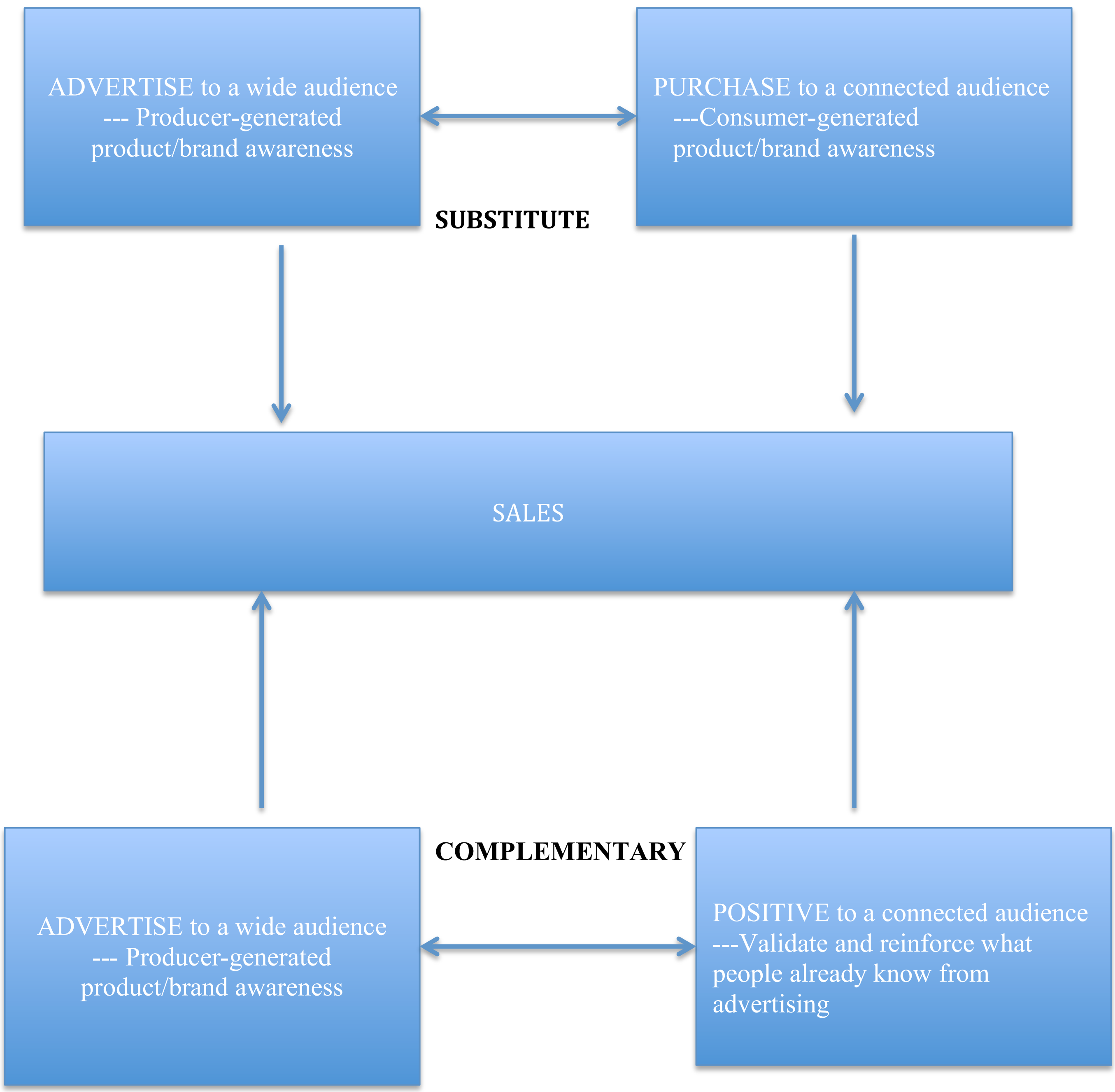

Figure 2
Timeline for Measuring Analyst Forecasts and Corresponding Twitter Comments

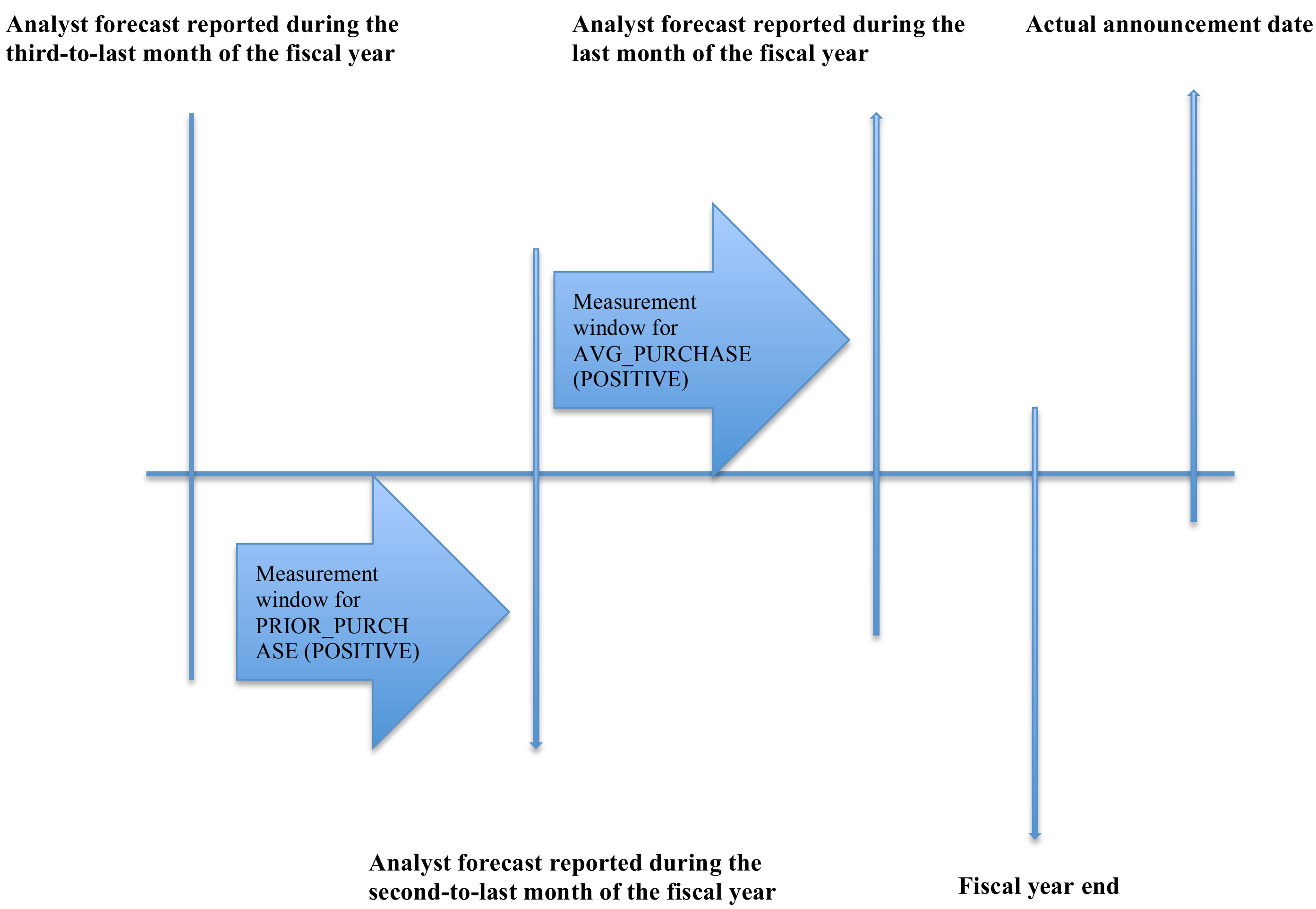

Table 1
Sample Formation

	Number of firms	**Number of firm-year observations**
Twitter	1,936	7,494
Missing information from Compustat	(126)	(873)
Available information from both Twitter & Compustat	1,810	6,621
Final sample to test whether the predictive power of Twitter comments varies with a firm's major customer base for model (1)	1,810	6,621
B-to-B subsample of firms whose major customer base is consumers	1,645	6,022
B-to-C subsample of firms whose major customer base is business entities	165	599
Final sample to test whether the predictive power of Twitter comments varies with advertising activities for B-to-C subsample for model (2)	165	599
Missing information on I/B/E/S	(24)	269
Final sample to test whether analyst forecasts incorporate Twitter comments for model (3) and model (4)	141	330

Table 2
Descriptive Statistics

Panel A: Descriptive statistics of the sample used to test the cross-sectional variation in the predictive power of Twitter

	Overall Sample						Subsample where major customer base is businesses (N = 6,022)		Subsample where major customer base is consumers (N =599)	
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Median**	**Mean**	**Median**
$AVG\_Q\_PURCHASE_{i,y+1}$	6,621	101.63	0.44	1437.18	0.00	49459.29	2.70	0.26	1094.96***	71.19***
$AVG\_Q\_POSITIVE_{i,y+1}$	2,571	0.88	0.92	0.13	0.00	1.00	0.90	0.96	0.81***	0.82***
$SALES\_GROWTH_{i,y+1}$	6,621	0.17	0.04	2.22	-1.00	156.91	0.18	0.04	0.08	0.04
$YTD3Q\_SALES_{i,y+1}$	6,621	5,197	491	18,199	0	354,086	3,201	369	25,241***	8,805***
$YTD3Q\_SALESGROWTH_{i, y+1}$	6,621	0.28	0.04	6.89	-1.00	507.40	0.30	0.04	0.10	0.04
$ASSETS_{i,y}$	6,621	25,364	1,586	153,368	1	2,807,491	16,296	1,300	116,401***	13,905***
$ADVERTISE_{i,y}$	6,621	0.02	0.00	0.05	0.00	1.21	0.02	0.00	0.03***	0.02***
$CHG\_BACKLOG_{i,y}$	6,621	0.24	0.00	13.96	-31.53	994.08	0.27	0.00	0.01	0.00

*** Differences are significant at the 0.01 level between the two subsamples.

Table 2 (continued)

Panel B: Descriptive statistics of the sample used to test whether analyst forecasts incorporate Twitter comments for the subsample of firms whose major customer base is consumers

Variable	N	Mean	Median	Std. Dev.	Minimum	Maximum
$CHG\_PURCHASE_{i,y+1}$	330	0.049	-0.053	0.474	-0.880	3.100
$CHG\_POSITIVE_{i,y+1}$	330	0.013	0.003	0.111	-1.000	0.600
$AVG\_PURCHASE_{i,y+1}$	330	1044.74	70.03	4479.36	2.20	41280.47
$AVG\_POSITIVE_{i,y+1}$	330	0.82	0.83	0.11	0.00	1.00
$FORECAST\_ERROR_{i,y+1}$	330	-0.0004	0.000	0.005	-0.030	0.050
$FORECAST\_REV_{i,y+1}$	330	-0.0004	0.000	0.017	-0.150	0.070
$ACTUAL\_FORECAST\_DAYS_{i,y+1}$	330	20.370	20.000	9.250	1.000	51.000
$PRIOR\_FORECAST_{i,y+1}$	330	35,539	12,262	64,669	133	487,118
$NUM\_FORECAST_{i,y+1}$	330	46.646	47.000	11.078	21.000	76.000
$GUIDE_{i,y+1}$	330	0.000	0.000	0.000	0.000	0.000
$LAST\_GUIDE_{i, y+1}$	330	0.025	0.000	0.116	-0.900	1.060
$ASSETS_{i,y}$	330	105,033	12,696	325,616	116	2,415,689
$YTD3Q\_SALES_{i,y+1}$	330	26,105	8,659	46,489	98	354,086
$YTD3Q\_SALESGROWTH_{i,y+1}$	330	0.116	0.043	0.694	-0.640	12.080
$CHG\_BACKLOG_{i,y}$	330	0.016	0.000	0.162	-0.060	2.850
$ADVERTISE_{i,y}$	330	0.035	0.023	0.041	0.000	0.270

Table 2
(continued)

PURCHASE is the number of tweets on Twitter that express purchase intent for a company *i*'s products and brands on a daily basis. POSITIVE is the ratio of the number of positive tweets over the number of nonneutral (positive and negative) tweets about a company *i*'s products and brands on a daily basis. AVG_Q_PURCHASE$_{i,y+1}$ averages daily PURCHASE over the last quarter of the fiscal year. AVG_Q_POSITIVE$_{i,y+1}$ averages daily POSITIVE over the last quarter of the fiscal year. I choose Twitter comments during the last quarter of the fiscal year to ensure that Twitter comments are not stale relative to the fiscal year end. SALES_GROWTH$_{i,y+1}$ is measured as the percentage change in upcoming sales relative to sales in the prior year. B2B is defined as 1 if a firm's major customers are businesses, and 0 if a firm's major customers are consumers. YTD3Q_SALES$_{i,y+1}$ is measured as sales from the year-to-date sales over the first three quarters of the fiscal year. YTD3Q_SALESGROWTH$_{i,y+1}$ is measured as the year-to-date sales growth rate for the first three quarters relative to that for the first three quarters in the previous fiscal year. ASSETS$_{i,y}$ is measured as total assets at the beginning of the fiscal year. ADVERTISE$_{i,y}$ is measured as the ratio of advertising expense over sales during the previous fiscal year. CHG_BACKLOG$_{i,y}$ is measured as the ratio of the change in deferred revenue over sales during the previous year. FORECAST_REV$_{i,y+1}$ is measured as the percentage change from the mean forecast during the second-to-last month (PRIOR_FORECAST$_{i,y+1}$) to the mean forecast during the last month of the fiscal year (FORECAST$_{i,y+1}$). CHG_PURCHASE$_{i,y+1}$ is measured as the percentage change from PRIOR_AVG_ PURCHASE$_{i,y+1}$ to AVG_PURCHASE$_{i,y+1}$. AVG_PURCHASE$_{i,y+1}$ averages daily PURCHASE over the window that starts from the day after the reported date of the consensus forecast during the second-to-last month and ends three days prior to the reported date of the consensus forecast during the last month. PRIOR_AVG_PURCHASE$_{i,y+1}$ averages daily PURCHASE over the window that starts from the day after the reported date of the consensus forecast during the 10th month and ends three days prior to the reported date of the consensus forecast during the second-to-last month. CHG_POSITIVE$_{i,y+1}$ is measured as the percentage change from PRIOR_AVG_ POSITIVE$_{i,y+1}$ to AVG_POSITIVE$_{i,y+1}$. AVG_POSITIVE$_{i,y+1}$ averages daily POSITIVE over the window that starts from the day after the reported date of the consensus forecast during the second-to-last month and ends three days prior to the reported date of the consensus forecast during the last month. PRIOR_AVG_POSITIVE$_{i,y+1}$ averages daily POSITIVE over the window that starts from the day after the reported date of the consensus forecast during the 10th month and ends three days prior to the reported date of the consensus forecast during the second-to-last month. NUM_FORECAST$_{i,y+}$1 is the number of forecasts included in the consensus forecast. PRIOR_FORECAST$_{i,y+1}$ is measured as the mean forecast during the second-to-last month of the fiscal year. FORECAST$_{i,y+1}$ is measured as the mean forecast during the last month of the fiscal year. GUIDE$_{i,y+1}$ is measured as the percentage change from PRIOR_FORECAST$_{i,y+1}$ to management guidance on upcoming annual sales during the window for measuring the analyst forecast revision and is valued at zero if there is no management guidance during the specified window. FORECAST_ERROR$_{i,y+1}$ is measured as FORECAST$_{i,y+1}$ minus realized upcoming sales divided by realized sales (SALES$_{i,y+1}$). ACTUAL_FORECAST_DAYS$_{i,y+1}$ is measured as number of calendar days between the reported date of realized sales and the reported date of the consensus forecasts. LAST_GUIDE$_{i,y+1}$ is measured as the selected management guidance minus prior year's sales divided by prior year's sales. If management provides no guidance, the value of LAST_GUIDE$_{i,y+1}$ is zero.

Table 3
Correlation Table (Pearson Correlations above Diagonal and Spearman Correlations below Diagonal)

Panel A: Correlation of the sample used to examine the cross-sectional variation in the predictive power of Twitter comments

	SALES _GROWTH	LN(AVG_Q_PURCHASE)	AVG_Q_POSITIVE	SIZE	Ln (YTD3Q_SALES)	YTD3Q_SALES GROWTH	ADVERTISE	CHG_ BACKLOG
$SALES\_GROWTH_{i,y+1}$	**1.000**	**-.019**	**.007**	**-.074****	**-.068****	**.215****	**.020**	**.010**
		.123	*.728*	*.000*	*.000*	*.000*	*.099*	*.399*
$Ln\ (AVG\_Q\_PURCHASE)_{i,y+1}$	**.036****	**1.000**	**-.249****	**.369****	**.484****	**-.013**	**.224****	**-.011**
	.003		*.000*	*.000*	*0.000*	*.281*	*.000*	*.386*
$AVG\_Q\_POSITIVE_{i,y+1}$	**.045***	**-.397****	**1.000**	**-.197****	**-.173****	**.009**	**.001**	**-.057****
	.023	*.000*		*.000*	*.000*	*.659*	*.955*	*.004*
$SIZE_{i,y+1}$	**-.095****	**.343****	**-.276****	**1.000**	**.803****	**-.043****	**-.106****	**-.021**
	.000	*.000*	*.000*		*0.000*	*.000*	*.000*	*.089*
$Ln\ (YTD3Q\_SALES)_{i,y+1}$	**.019**	**.527****	**-.304****	**.794****	**1.000**	**-.048****	**.034****	**-.024**
	.123	*0.000*	*.000*	*0.000*		*.000*	*.006*	*.055*
$YTD3Q\_SALESGROWTH_{i,y+1}$	**.945****	**.044****	**.046***	**-.087****	**.034****	**1.000**	**.010**	**.005**
	0.000	*.000*	*.019*	*.000*	*.006*		*.416*	*.675*
$ADVERTISE_{i,y+1}$	**.082****	**.454****	**-.095****	**-.080****	**.230****	**.090****	**1.000**	**-.006**
	.000	*0.000*	*.000*	*.000*	*.000*	*.000*		*.618*
$CHG\_BACKLOG_{i,y+1}$	**.150****	**.146****	**-.004**	**.013**	**.092****	**.164****	**.156****	**1.000**
	.000	*.000*	*.830*	*.307*	*.000*	*.000*	*.000*	

The correlation coefficient is in bold. *P*-value for correlation coefficients is in italic ** Correlations are significant at 0.01 level. * Correlations are significant at 0.05 level.

Table 3
(continued)

Panel B: Correlation of the sample used to test whether the analyst forecast revision incorporates Twitter comments

	FORECAST_REV	CHG_PURCHASE	CHG_POSITIVE	SIZE	Ln (NUM_FORECAST)	Ln (PRIOR_FORECAST)
$FORECAST\_REV_{i,y+1}$	**1.000**	**-.034**	**-.006**	**-.147****	**-.009**	**-.160****
		.542	*.911*	*.008*	*.871*	*.003*
$CHG\_PURCHASE_{i,y+1}$	**.045**	**1.000**	**.102**	**.089**	**.000**	**.030**
	.418		*.064*	*.105*	*.999*	*.591*
$CHG\_POSITIVE_{i,y+1}$	**.041**	**.068**	**1.000**	**.163****	**.098**	**.148****
	.462	*.218*		*.003*	*.076*	*.007*
$SIZE_{i,y+1}$	**-.119***	**.059**	**.136***	**1.000**	**.057**	**.873****
	.030	*.285*	*.013*		*.305*	*.000*
Ln $(NUM\_FORECAST)_{i,y+1}$	**.060**	**-.024**	**.037**	**.144****	**1.000**	**.063**
	.275	.670	.505	.009		.256
Ln $(PRIOR\_FORECAST)_{i,y+1}$	**-.091**	**.016**	**.128***	**.893****	**.136***	**1.000**
	.098	*.767*	*.020*	*.000*	*.013*	

The correlation coefficient is in bold. *P*-value for correlation coefficients is in italic. ** Correlations are significant at 0.01 level. * Correlations are significant at 0.05 level.

Table 3
(continued)

Panel C: Correlation of the sample used to test whether the analyst forecast error is systematically related to Twitter

	FORECAST _ERROR	Ln (AVG_PURCHASE)	AVG_POSITIVE	ACTUAL_ FORECST _DAYS	Ln (PRIOR_FORECAST)	Ln (NUM_FORECAST)	LAST GUIDE	SIZE	Ln (YTD3Q_SALES)	YTD3Q_ SALESGROWTH	CHG_ BACKLOG	ADVERTISE
FORECAST_ERROR	**1.000**	**-.087**	**-.013**	**-.151****	**.075**	**.195****	**-.112***	**.048**	**.071**	**-.235****	**.061**	**-.003**
		.114	*.811*	*.006*	*.173*	*.000*	*.042*	*.386*	*.198*	*.000*	*.271*	*.959*
Ln (AVG_PURCHASE)	**.013**	**1.000**	**-.012**	**-.132***	**.239****	**.288****	**.109***	**.193****	**.232****	**.052**	**.122***	**-.041**
	.821		*.823*	*.016*	*.000*	*.000*	*.047*	*.000*	*.000*	*.349*	*.027*	*.461*
AVG_POSITIVE	**-.023**	**-.067**	**1.000**	**.013**	**.024**	**-.015**	**.031**	**-.011**	**.022**	**-.038**	**-.015**	**.010**
	.671	*.223*		*.808*	*.661*	*.789*	*.572*	*.844*	*.691*	*.497*	*.788*	*.859*
ACTUAL_FORECAST _DAYS$_{i,y+1}$	**-.079**	**-.096**	**.080**	**1.000**	**-.426****	**-.343****	**.081**	**-.509****	**-.429****	**.138***	**.175****	**.076**
	.151	*.081*	*.145*		*.000*	*.000*	*.140*	*.000*	*.000*	*.012*	*.001*	*.166*
Ln (PRIOR_FORECAST$_{i,y+1}$)	**.207****	**.214****	**-.026**	**-.424****	**1.000**	**.063**	**-.133***	**.873****	**.998****	**-.151****	**-.193****	**-.173****
	.000	*.000*	*.643*	*.000*		*.256*	*.015*	*.000*	*0.000*	*.006*	*.000*	*.002*
Ln (NUM_FORECAST$_{i,y+1}$)	**-.002**	**.382****	**-.058**	**-.347****	**.136***	**1.000**	**.126***	**.057**	**.059**	**-.019**	**-.048**	**-.031**
	.971	*.000*	*.291*	*.000*	*.013*		*.022*	*.305*	*.281*	*.736*	*.387*	*.574*
LASTGUIDE$_{i,y+1}$	**-.087**	**.082**	**.052**	**.049**	**-.113***	**.146****	**1.000**	**-.125***	**-.130***	**.115***	**-.054**	**.019**
	.116	*.136*	*.348*	*.376*	*.041*	*.008*		*.024*	*.018*	*.037*	*.330*	*.734*
SIZE	**.152****	**.194****	**-.029**	**-.466****	**.893****	**.144****	**-.136***	**1.000**	**.879****	**-.165****	**-.204****	**-.079**
	.006	*.000*	*.596*	*.000*	*.000*	*.009*	*.013*		*.000*	*.003*	*.000*	*.152*
Ln (YTD3Q_SALES)	**.200****	**.203****	**-.028**	**-.422****	**.998****	**.131***	**-.116***	**.896****	**1.000**	**-.155****	**-.195****	**-.173****
	.000	*.000*	*.609*	*.000*	*0.000*	*.018*	*.035*	*.000*		*.005*	*.000*	*.002*
YTD3Q_SALESGROWTH	**-.342****	**.086**	**.114***	**.179****	**-.286****	**.126***	**.313****	**-.330****	**-.277****	**1.000**	**-.049**	**.051**
	.000	*.120*	*.039*	*.001*	*.000*	*.022*	*.000*	*.000*	*.000*		*.378*	*.354*
CHG_BACKLOG	**.046**	**.256****	**-.018**	**.190****	**-.202****	**-.063**	**-.028**	**-.229****	**-.209****	**-.110***	**1.000**	**-.044**
	.407	*.000*	*.745*	*.001*	*.000*	*.257*	*.610*	*.000*	*.000*	*.046*		*.422*
ADVERTISE	**-.052**	**.157****	**.040**	**-.173****	**-.054**	**.211****	**.034**	**-.063**	**-.061**	**.211****	**-.068**	**1.000**
	.346	*.004*	*.473*	*.002*	*.326*	*.000*	*.535*	*.252*	*.267*	*.000*	*.217*	

The correlation coefficient is in bold. *P*-value for correlation coefficients is in italic. ** Correlations are significant at 0.01 level. * Correlations are significant at 0.05 level.

Table 3
(continued)

PURCHASE is the number of tweets on Twitter that express purchase intent for a company *i*'s products and brands on a daily basis. POSITIVE is the ratio of the number of positive tweets over the number of nonneutral (positive and negative) tweets about a company *i*'s products and brands on a daily basis. AVG_Q_PURCHASE$_{i,y+1}$ averages daily PURCHASE over the last quarter of the fiscal year. AVG_Q_POSITIVE$_{i,y+1}$ averages daily POSITIVE over the last quarter of the fiscal year. I choose Twitter comments during the last quarter of the fiscal year to ensure that Twitter comments are not stale relative to the fiscal year end. SALES_GROWTH$_{i,y+1}$ is measured as the percentage change in upcoming sales relative to sales in the prior year. B2B is defined as 1 if a firm's major customers are businesses, and 0 if a firm's major customers are consumers. YTD3Q_SALES$_{i,y+1}$ is measured as sales from the year-to-date sales over the first three quarters of the fiscal year. YTD3Q_SALESGROWTH$_{i,y+1}$ is measured as the year-to-date sales growth rate for the first three quarters relative to that for the first three quarters in the previous fiscal year. SIZE$_{i,y}$ is measured as the natural log of total assets at the beginning of the fiscal year. ADVERTISE$_{i,y}$ is measured as the ratio of advertising expense over sales during the previous fiscal year. CHG_BACKLOG$_{i,y}$ is measured as the ratio of the change in deferred revenue over sales during the previous year. FORECAST_REV$_{i,y+1}$ is measured as the percentage change from the mean forecast during the second-to-last month (PRIOR_FORECAST$_{i,y+1}$) to the mean forecast during the last month of the fiscal year (FORECAST$_{i,y+1}$). CHG_PURCHASE$_{i,y+1}$ is measured as the percentage change from PRIOR_AVG_ PURCHASE$_{i,y+1}$ to AVG_PURCHASE$_{i,y+1}$. AVG_PURCHASE$_{i,y+1}$ averages daily PURCHASE over the window that starts from the day after the reported date of the consensus forecast during the second-to-last month and ends three days prior to the reported date of the consensus forecast during the last month. PRIOR_AVG_PURCHASE$_{i,y+1}$ averages daily PURCHASE over the window that starts from the day after the reported date of the consensus forecast during the 10th month and ends three days prior to the reported date of the consensus forecast during the second-to-last month. CHG_POSITIVE$_{i,y+1}$ is measured as the percentage change from PRIOR_AVG_ POSITIVE$_{i,y+1}$ to AVG_POSITIVE$_{i,y+1}$. AVG_POSITIVE$_{i,y+1}$ averages daily POSITIVE over the window that starts from the day after the reported date of the consensus forecast during the second-to-last month and ends three days prior to the reported date of the consensus forecast during the last month. PRIOR_AVG_POSITIVE$_{i,y+1}$ averages daily POSITIVE over the window that starts from the day after the reported date of the consensus forecast during the 10th month and ends three days prior to the reported date of the consensus forecast during the second-to-last month. NUM_FORECAST$_{i,y+}$1 is the number of forecasts included in the consensus forecast. PRIOR_FORECAST$_{i,y+1}$ is measured as the mean forecast during the second-to-last month of the fiscal year. FORECAST$_{i,y+1}$ is measured as the mean forecast during the last month of the fiscal year. GUIDE$_{i,y+1}$ is measured as the percentage change from PRIOR_FORECAST$_{i,y+1}$ to management guidance on upcoming annual sales during the window for measuring the analyst forecast revision and is valued at zero if there is no management guidance during the specified window. FORECAST_ERROR$_{i,y+1}$ is measured as FORECAST$_{i,y+1}$ minus realized upcoming sales divided by realized sales (SALES$_{i,y+1}$). ACTUAL_FORECAST_DAYS$_{i,y+1}$ is measured as number of calendar days between the reported date of realized sales and the reported date of the consensus forecasts. LAST_GUIDE$_{i,y+1}$ is measured as the selected management guidance minus prior year's sales divided by prior year's sales. If management provides no guidance, the value of LAST_GUIDE$_{i,y+1}$ is zero.

Table 4
Validation Check: Cross-sectional Determinants of the Volume and Valence of Twitter Comments

	Dependent Variable = Ln (AVG_Q_PURCHASE)			Dependent Variable = AVG_Q_POSITIVE		
	Expected sign	Coefficient (*chi*-square)	Coefficient (*chi*-square)	Expected sign	Coefficient (*chi*-square)	Coefficient (*chi*-square)
Intercept		Included	Included		Included	Included
$B2B_i$	**(-)**		-3.503*** (282.237)	**(?)**		0.077*** (71.444)
$SIZE_{i,y}$	(?)	0.016 (0.238)	-0.031** (4.182)	**(?)**	-0.011*** (9.532)	-0.010*** (9.958)
Ln ($YTD3Q\_SALES_{i,y+1}$)	**(+)**	**0.282*** (57.435)**	**0.161*** (92.039)**	**(insignificant)**	**-0.001 (0.018)**	**0.005 (1.089)**
$YTD3Q\_SALESGROWTH_{i,y+1}$	(?)	0.002* (3.643)	0.001 (0.412)	(?)	-0.002 (1.699)	-0.001 (0.567)
$ADVERTISE_{i,y}$	**(?)**	6.800*** (22.224)	4.376*** (22.947)	**(insignificant)**	**-0.075 (1.648)**	**-0.007 (0.023)**
Industry fixed effects		Yes	Yes		Yes	Yes
Number of observations		6,621	6,621		2,571	2,571
Likelihood ratio		10866.03	5248.11		53.58	53.39

Table 4
(continued)

PURCHASE is the number of tweets on Twitter that express purchase intent for a company *i*'s products and brands on a daily basis. POSITIVE is the ratio of the number of positive tweets over the number of nonneutral (positive and negative) tweets about a company *i*'s products and brands on a daily basis. $AVG\_Q\_PURCHASE_{i,y+1}$ averages daily PURCHASE over the last quarter of the fiscal year. $AVG\_Q\_POSITIVE_{i,y+1}$ averages daily POSITIVE over the last quarter of the fiscal year. I choose Twitter comments during the last quarter of the fiscal year to ensure that Twitter comments are not stale relative to the fiscal year end. $SALES\_GROWTH_{i,y+1}$ is measured as the percentage change in upcoming sales relative to sales in the prior year. B2B is defined as 1 if a firm's major customers are businesses, and 0 if a firm's major customers are consumers. $YTD3Q\_SALES_{i,y+1}$ is measured as sales from the year-to-date sales over the first three quarters of the fiscal year. $YTD3Q\_SALESGROWTH_{i,y+1}$ is measured as the year-to-date sales growth rate for the first three quarters relative to that for the first three quarters in the previous fiscal year. $SIZE_{i,y}$ is measured as the natural log of total assets at the beginning of the fiscal year. $ADVERTISE_{i,y}$ is measured as the ratio of advertising expense over sales during the previous fiscal year. $CHG\_BACKLOG_{i,y}$ is measured as the ratio of the change in deferred revenue over sales during the previous year.

Table 5
Nonfinancial Information on Twitter and Upcoming Sales for the Entire Sample

	Dependent variable = $SALES\_GROWTH_{i,y+1}$						
	Expected sign	Coefficient (*chi*-value)	Coefficient (*chi*-value)	Coefficient (*chi*-square)	Coefficient (*chi*-square)	Coefficient (*chi*-value)	Coefficient (*chi*-value)
Intercept		Included	Included	Included	Included	Included	Included
$B2B_i$	**(?)**			**0.043 (0.879)**		**-0.133 (1.506)**	**0.085* (3.597)**
Ln ($AVG\_Q\_PURCHASE_{i,y}$)	**(+)**		**0.016** (4.314)**	**0.031*** (10.127)**			**0.020*** (5.488)**
AVG_Q_POSITIVE	**(+)**				**-0.100 (1.579)**	**-0.075 (0.765)**	**-0.074 (0.678)**
Ln ($AVG\_Q\_PURCHASE_{i,y}$)*$B2B_i$	**(+)**			**-0.075** (5.950)**			**-0.042*** (6.944)**
$AVG\_Q\_POSITIVE_{i,y}$*$B2B_i$	**(-)**					**-0.001 (0.552)**	**-0.003 (0.005)**
$SIZE_{i,y}$	(?)	-0.012 (0.911)	-0.011 (0.958)	-0.011 (0.944)	-0.012 (0.901)	-0.012 (0.977)	-0.012 (0.952)
$Ln\_YTD3Q\_SALES_{i,y+1}$	(-)	-0.021* (3.217)	-0.022* (3.418)	-0.021* (3.521)	-0.022* (3.119)	-0.021* (3.272)	-0.021* (3.346)
$YTD3Q\_SALES\_GROWTH_{i,y+1}$	(+)	0.310*** (11.201)	0.313*** (11.001)	0.311*** (12.001)	0.312*** (11.800)	0.311*** (11.563)	0.312*** (11.743)
$ADVERTISE_{i,y}$	(?)	-0.008 (0.581)	-0.007 (0.481)	-0.008 (0.810)	-0.006 (0.561)	-0.005 (0.551)	-0.005 (0.501)
$CHG\_BACKLOG_{i,y}$	(+)	0.055 (0.059)	0.052 (0.049)	0.054 (0.064)	0.055 (0.069)	0.056 (0.069)	0.055 (0.078)
Industry fixed effects		YES	YES	YES	YES	YES	YES
Number of observations		6,621	6,621	6,621	2,571	2,571	2,571
Likelihood ratio		666.8	668.4	747.3	668.4	671.7	674.1

*** Coefficients are significant at 0.01 level. ** Coefficients are significant at 0.05 level. * Coefficients are significant at 0.10 level.

Table 5
(continued)

Regression results from model (1):

$SALES\_GROWTH_{i,y+1} = \alpha + \beta_1 B2B_i + \beta_2 AVG\_Q\_PURCHASE(POSITIVE)_{i.y+1} + \boldsymbol{\beta_3 B2B_i * AVG\_Q\_PURCHASE(POSITIVE)_{i.y+1}} + \beta_4 Ln(YTD3Q\_SALES_{i,y+1})$
$+ \beta_5 YTD3Q\_SALESGROWTH_{i,y} + \beta_6 SIZE_{i,y} + \beta_7 CHG\_BACKLOG_{i,y} + \beta_8 ADVERTISE_{i,y} + \boldsymbol{\varepsilon}_{it}$

PURCHASE is the number of tweets on Twitter that express purchase intent for a company *i*'s products and brands on a daily basis. POSITIVE is the ratio of the number of positive tweets over the number of non-neutral (positive and negative) tweets about a company *i*'s products and brands on a daily basis. $AVG\_Q4\_PURCHASE_{i,y+1}$ averages daily PURCHASE over the last quarter of the fiscal year. $AVG\_Q4\_POSITIVE_{i,y+1}$ averages daily POSITIVE over the last quarter of the fiscal year. I choose Twitter comments during the last quarter of the fiscal year to ensure that Twitter comments are not stale relative to the fiscal year end. $SALES\_GROWTH_{i,y+1}$ is measured as the percentage change in upcoming sales relative to sales in the prior year. B2B is defined as 1 if a firm's major customers are businesses, and 0 if a firm's major customers are consumers. $YTD3Q\_SALES_{i,y+1}$ is measured as sales from the year-to-date sales over the first three quarters of the fiscal year. $YTD3Q\_SALESGROWTH_{i,y+1}$ is measured as the year-to-date sales growth rate for the first three quarters relative to that for the first three quarters in the previous fiscal year. $SIZE_{i,y}$ is measured as the natural log of total assets at the beginning of the fiscal year. $ADVERTISE_{i,y}$ is measured as the ratio of advertising expense over sales during the previous fiscal year. $CHG\_BACKLOG_{i,y}$ is measured as the ratio of the change in deferred revenue over sales during the previous year.

Table 6
Interplay Between the Word-of-Mouth Effect of Twitter Comments and Advertising for the B-to-C Subsample

	Dependent Variable = $SALES\_GROWTH_{i,y+1}$					
	Expected sign	Coefficient (*chi*-value)	Coefficient (*chi*-square)	Coefficient (*chi*-square)	Coefficient (*chi*-square)	Coefficient (*chi*-square)
Intercept		Included	Included	Included	Included	Included
Ln($AVG\_Q\_PURCHASE_{i,y}$)		0.021*** (6.680)	0.033*** (6.199)			0.032** (6.508)
Ln($AVG\_Q\_PURCHASE_{i,y}$)*$ADVERTISE_{i,y}$	**(-)**		**-0.368* (3.277)**			**-0.325* (3.369)**
POSITIVE				-0.023 (0.108)	-0.199** (4.224)	-0.146** (4.394)
$AVG\_Q\_POSITIVE_{i,y}$*$ADVERTISE_{i,y}$	**(+)**				**5.456** (6.527)**	**5.079*** (7.434)**
$SIZE_{i,y}$	(?)	-0.007 (0.980)	-.005 (0.468)	-0.009 (1.814)	-0.011* (2.971)	-0.006 (0.873)
$Ln\_YTD3Q\_SALES_{i,y+1}$	(-)	-0.028 (2.466)	-0.029* (3.027)	-0.019 (1.195)	-0.019 (1.440)	-0.029* (3.628)
$YTD3Q\_SALES\_GROWTH_{i,y+1}$	(+)	0.396*** (24.218)	0.393*** (25.394)	0.404*** (21.669)	0.401*** (22.317)	0.390*** (26.174)
$CHG\_BACKLOG_{i,y}$	(+)	0.128*** (10.097)	0.124*** (11.413)	0.132*** (7.094)	0.137*** (7.757)	0.129*** (13.173)
$ADVERTISE_{i,y}$	(?)	-0.434** (5.640)	1.185 (1.838)	-0.238* (2.865)	-4.777*** (6.634)	-3.236** (4.772)
Industry fixed effects		Yes	Yes	Yes	Yes	Yes
Number of observations		599	599	599	599	599
Likelihood ratio		23.4	25.1	24.2	25.9	28.9

*** Coefficients are significant at 0.01 level. ** Coefficients are significant at 0.05 level. * Coefficients are significant at 0.10 level.

Table 6
(continued)

Regression results from model (2):

$SALES\_GROWTH_{i,y+1} = \alpha + \beta_1 AVG\_Q\_PURCHASE_{i.y+1} + \boldsymbol{\beta_2 ADVERTISE_{i,y}*AVG\_Q\_PURCHASE_{i.y+1}} + \beta_3 AVG\_Q\_POSITIVE_{i.y+1}$
$+ \boldsymbol{\beta_4 ADVERTISE_{i,y}*AVG\_Q\_POSITIVE_{i.y+1}} + \beta_5 Ln(YTD3Q\_SALES_{i,y+1}) + \beta_6 YTD3Q\_SALESGROWTH_{i,y} + \beta_7 SIZE_{i,y} + \beta_8 CHG\_BACKLOG_{i,y} + \beta_9 ADVERTISE_{i,y} + \boldsymbol{\varepsilon}_{it}$

PURCHASE is the number of tweets on Twitter that express purchase intent for a company *i*'s products and brands on a daily basis. POSITIVE is the ratio of the number of positive tweets over the number of nonneutral (positive and negative) tweets about a company *i*'s products and brands on a daily basis. $AVG\_Q4\_PURCHASE_{i,y+1}$ averages daily PURCHASE over the last quarter of the fiscal year. $AVG\_Q4\_POSITIVE_{i,y+1}$ averages daily POSITIVE over the last quarter of the fiscal year. I choose Twitter comments during the last quarter of the fiscal year to ensure that Twitter comments are not stale relative to the fiscal year end. $SALES\_GROWTH_{i,y+1}$ is measured as the percentage change in upcoming sales relative to sales in the prior year. B2B is defined as 1 if a firm's major customers are businesses, and 0 if a firm's major customers are consumers. $YTD3Q\_SALES_{i,y+1}$ is measured as sales from the year-to-date sales over the first three quarters of the fiscal year. $YTD3Q\_SALESGROWTH_{i,y+1}$ is measured as the year-to-date sales growth rate for the first three quarters relative to that for the first three quarters in the previous fiscal year. $SIZE_{i,y}$ is measured as the natural log of total assets at the beginning of the fiscal year. $ADVERTISE_{i,y}$ is measured as the ratio of advertising expense over sales during the previous fiscal year. $CHG\_BACKLOG_{i,y}$ is measured as the ratio of the change in deferred revenue over sales during the previous year.

Table 7
Analyst Forecast Revision and the Change in Nonfinancial Information on Twitter

	DEPENDENT VARIABLE = FORECAST_REV$_{i,y+1}$			
	Expected sign	Coefficient (*chi*-square)	Coefficient (*chi*-square)	Coefficient (*chi*-square)
Intercept		INCLUDED	INCLUDED	INCLUDED
CHG_PURCHASE$_{i,T}$	**(?)**	**0.018 (1.224)**		**0.014 (0.853)**
CHG_POSITIVE$_{i,t}$	**(?)**		**0.021 (1.438)**	**0.016 (1.029)**
Ln (PRIOR_FORECAST$_{i,y+1}$)	(?)	-0.139 (1.591)	-0.140 (1.535)	-0.138 (1.428)
Ln (NUM_FORECAST$_{i,y+1}$)	(?)	0.037 (1.520)	0.034 (0.765)	0.001 (0.377)
SIZE$_{i,y}$	(?)	-0.033 (1.101)	-0.034 (0.002)	-0.037 (0.001)
Number of observations		330	330	330
Likelihood ratio		8.90	8.77	9.05

Table 7
(continued)

Regression results from model (3):

$$FORECAST\_REV_{i,y+1} = \propto + \boldsymbol{\beta_1}\mathbf{CHG\_PURCHASE(POSITIVE)_{i,y+1}} + \beta_2 Ln\ (NUM\_FORECAST_{i,y+1}) + \beta_3 Ln\ (PRIOR\_FORECAST_{i,y+1}) + \beta_4 SIZE_{i,y} + \beta_5 GUIDE_{i,y+1} + \boldsymbol{\varepsilon}_{it}$$

PURCHASE is the number of tweets on Twitter that express purchase intent for a company *i*'s products and brands on a daily basis. POSITIVE is the ratio of the number of positive tweets over the number of nonneutral (positive and negative) tweets about a company *i*'s products and brands on a daily basis. $SIZE_{i,y}$ is measured as the natural log of total assets at the beginning of the fiscal year. $FORECAST\_REV_{i,y+1}$ is measured as the percentage change from the mean forecast during the second-to-last month ($PRIOR\_FORECAST_{i,y+1}$) to the mean forecast during the last month of the fiscal year ($FORECAST_{i,y+1}$). $CHG\_PURCHASE_{i,y+1}$ is measured as the percentage change from $PRIOR\_AVG\_ PURCHASE_{i,y+1}$ to $AVG\_PURCHASE_{i,y+1}$. $AVG\_PURCHASE_{i,y+1}$ averages daily PURCHASE over the window that starts from the day after the reported date of the consensus forecast during the second-to-last month and ends three days prior to the reported date of the consensus forecast during the last month. $PRIOR\_AVG\_PURCHASE_{i,y+1}$ averages daily PURCHASE over the window that starts from the day after the reported date of the consensus forecast during the 10th month and ends three days prior to the reported date of the consensus forecast during the second-to-last month. $CHG\_POSITIVE_{i,y+1}$ is measured as the percentage change from $PRIOR\_AVG\_ POSITIVE_{i,y+1}$ to $AVG\_POSITIVE_{i,y+1}$. $AVG\_POSITIVE_{i,y+1}$ averages daily POSITIVE over the window that starts from the day after the reported date of the consensus forecast during the second-to-last month and ends three days prior to the reported date of the consensus forecast during the last month. $PRIOR\_AVG\_POSITIVE_{i,y+1}$ averages daily POSITIVE over the window that starts from the day after the reported date of the consensus forecast during the 10th month and ends three days prior to the reported date of the consensus forecast during the second-to-last month. $NUM\_FORECAST_{i,y+}1$ is the number of forecasts included in the consensus forecast. $PRIOR\_FORECAST_{i,y+1}$ is measured as the mean forecast during the second-to-last month of the fiscal year. $FORECAST_{i,y+1}$ is measured as the mean forecast during the last month of the fiscal year.

Table 8
Analyst Forecast Error and Nonfinancial Information on Twitter

	Dependent Variable = $FORECAST\_ERROR_{i,y+1}$					
	Without financial information as control			With financial information as control		
	Coefficient (*Chi*-square)	Coefficient (*Chi*-square)	Coefficient (*Chi*-square)	Coefficient (*Chi*-square)	Coefficient (*Chi*-square)	Coefficient (*Chi*-square)
Intercept	INCLUDED	INCLUDED	INCLUDED	INCLUDED	INCLUDED	INCLUDED
Ln($AVG\_PURCHASE_{i,y+1}$)	**-0.002*** (8.456)**		**-0.002*** (8.485)**	**-0.002*** (9.666)**		**-0.002*** (9.719)**
$AVG\_POSITIVE_{i,y+1}$		**-0.001 (0.035)**	**-0.002 (0.140)**		**-0.003 (0.120)**	**-0.003 (0.203)**
$SIZE_{i,y}$	-0.001 (1.507)	-0.001 (1.404)	-0.001 (1.540)	-0.001 (1.161)	-0.001 (1.326)	-0.001 (1.216)
Ln ($PRIOR\_FORECAST_{i,y+1}$)	0.002 (2.477)	0.001 (1.326)	0.002 (2.522)	0.015 (2.353)	0.012 (1.358)	0.015 (2.402)
Ln ($NUM\_FORECAST_{i,y+1}$)	0.006*** (14.300)	0.005*** (9.432)	0.006*** (14.274)	0.006*** (14.879)	0.005*** (9.508)	0.006*** (14.828)
$ACTUAL\_FORECAST\_DAYS_{i,t}$	0.001 (1.667)	0.001 (2.064)	0.001 (1.668)	0.001 (1.682)	0.001 (1.890)	0.001 (1.683)
$LAST\_GUIDE_{i,y+1}$	-0.016** (4.136)	-0.018** (5.413)	-0.016** (4.092)	-0.011 (2.136)	-0.014* (3.331)	-0.011 (2.078)
Ln ($YTD3Q\_SALES_{i,y+1}$)				-0.013 (1.747)	-0.010 (1.019)	-0.013 (1.779)
$YTD3Q\_SALESGROWTH_{i,y+1}$				-0.005*** (14.348)	-0.005*** (16.506)	-0.005*** (14.480)
$CHG\_BACKLOG_{i,y}$				0.004 (0.487)	0.002 (0.415)	0.004 (0.502)
$ADVERTISE_{i,y}$				0.040* (3.295)	0.026 (1.377)	0.040* (3.277)
Number of observations	330	330	330	330	330	330
Likelihood ratio	26.92	17.35	27.03	47.14	36.25	47.40

Table 8
(continued)

*** Coefficients are significant at 0.01 level. ** Coefficients are significant at 0.05 level. * Coefficients are significant at 0.10 level.

Regression results from model (4):

$\text{FORECAST\_ERROR}_{i,y+1} = \propto + \boldsymbol{\beta_1}\ \textbf{AVG\_PURCHASE (POSITIVE)}_{\boldsymbol{i,y+1}} + \beta_2\text{SIZE}_{i,y} + \beta_3\text{Ln (NUM\_FORECAST}_{i,y+1}) + \beta_4\text{Ln (PRIOR\_FORECAST}_{i,y+1})$
$+ \beta_5\text{ACTUAL\_FORECAST\_DAYS}_{i,y+1} + \beta_6\text{LAST\_GUIDE}_{i,y+1} + \beta_7\text{Ln (YTD3Q\_SALES}_{i,y+1}) + \beta_8\text{YTD3Q\_SALESGROWTH}_{i,y+1} + \beta_9\text{CHG\_BACKLOG}_{i,y}$
$+ \beta_{10}\text{ADVERTISE}_{i,y} + \boldsymbol{\varepsilon_{it}}$

PURCHASE is the number of tweets on Twitter that express purchase intent for a company *i*'s products and brands on a daily basis. POSITIVE is the ratio of the number of positive tweets over the number of nonneutral (positive and negative) tweets about a company *i*'s products and brands on a daily basis. $\text{AVG\_Q4\_PURCHASE}_{i,y+1}$ averages daily PURCHASE over the last quarter of the fiscal year. $\text{AVG\_Q4\_POSITIVE}_{i,y+1}$ averages daily POSITIVE over the last quarter of the fiscal year. I choose Twitter comments during the last quarter of the fiscal year to ensure that Twitter comments are not stale relative to the fiscal year end. $\text{SALES\_GROWTH}_{i,y+1}$ is measured as the percentage change in upcoming sales relative to sales in the prior year. B2B is defined as 1 if a firm's major customers are businesses, and 0 if a firm's major customers are consumers. $\text{YTD3Q\_SALES}_{i,y+1}$ is measured as sales from the year-to-date sales over the first three quarters of the fiscal year. $\text{YTD3Q\_SALESGROWTH}_{i,y+1}$ is measured as the year-to-date sales growth rate for the first three quarters relative to that for the first three quarters in the previous fiscal year. $\text{SIZE}_{i,y}$ is measured as the natural log of total assets at the beginning of the fiscal year. $\text{ADVERTISE}_{i,y}$ is measured as the ratio of advertising expense over sales during the previous fiscal year. $\text{AVG\_PURCHASE}_{i,y+1}$ averages daily PURCHASE over the window that starts from the day after the reported date of the consensus forecast during the second-to-last month and ends three days prior to the reported date of the consensus forecast during the last month. $\text{AVG\_POSITIVE}_{i,y+1}$ averages daily POSITIVE over the window that starts from the day after the reported date of the consensus forecast during the second-to-last month and ends three days prior to the reported date of the consensus forecast during the last month. $\text{NUM\_FORECAST}_{i,y+}1$ is the number of forecasts included in the consensus forecast. $\text{PRIOR\_FORECAST}_{i,y+1}$ is measured as the mean forecast during the second-to-last month of the fiscal year. $\text{FORECAST}_{i,y+1}$ is measured as the mean forecast during the last month of the fiscal year. $\text{FORECAST\_ERROR}_{i,y+1}$ is measured as $\text{FORECAST}_{i,y+1}$ minus realized upcoming sales divided by realized sales ($\text{SALES}_{i,y+1}$). $\text{ACTUAL\_FORECAST\_DAYS}_{i,y+1}$ is measured as number of calendar days between the reported date of realized sales and the reported date of the consensus forecasts. $\text{LAST\_GUIDE}_{i,y+1}$ is measured as the selected management guidance minus prior year's sales divided by prior year's sales. If management provides no guidance, the value of $\text{LAST\_GUIDE}_{i,y+1}$ is zero.