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How Do Social Media Affect Analyst Stock Recommendations? Evidence from S&P 500 Electric Power Companies' Twitter Accounts

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Research summary: *The importance of firm-stakeholder relationships is gaining increasing attention. Although a theory of the drivers and consequences of stakeholder pressure has been developing, it focuses on pressures from organized stakeholders such as shareholders, NGOs, and activists, and does not incorporate the emerging possibility that individual voices may matter. By exploring corporate Twitter, which facilitates movement of individual stakeholders such as customers to a higher stakeholder class by providing them with a greater sense of power and urgency, we study the circumstances under which customer voices significantly affect analyst stock recommendations. We find that favorable reactions to firm-initiated messages matter, directly or indirectly, depending on the messages' growth implications. Customer-initiated negative messages have a significant impact only with high volume and formal institutions that support customer opinions.*

Managerial summary: *Social media is increasingly used by firms for disclosing information and engaging stakeholders. Yet, we know little about whether and how social media usage matters. We show how corporate Twitter usage may influence analyst stock recommendations. Our interviews of securities analysts suggest that social media is not institutionalized yet, but increasingly used as a source of channel checks, especially for vibes, validations,* and so on. *Our analyses of corporate Twitter accounts show that both firm-initiated and customer-initiated tweets can have significant impact on analyst recommendations under certain conditions. For firm-initiated tweets, the extent of retweets is an important factor, along with the content of tweets, in particular, growth implications. For customer-initiated tweets, negative tweets matter, but only with high volume and regulatory structure that supports customer protection.*

The importance of firm-stakeholder relationships has gained growing interest as stakeholders become increasingly relevant to firm operations. Questions examined in the literature include which stakeholders are important and whether firm-stakeholder relationships matter for firm performance. We seek to shed new light on this stream of research by exploring the ramifications of increased salience of individual stakeholders in the social media space. A growing number of firms began using social media such as Twitter and Facebook, which has brought about significant changes in how firms communicate with their stakeholders. Notably, it allows firms not only to engage in more frequent and informal exchanges with their stakeholders as compared to more traditional means such as annual reports or shareholder meetings, but

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also to receive feedback on an ongoing basis. In addition, individual voices have begun to matter more as a result of social media, a development quite different from that of commonly studied cases of more organized stakeholders applying pressure, such as shareholder resolutions, NGO attacks, media pressure, and so on.

Together, these idiosyncrasies present an excellent opportunity to study the link between firm-stakeholder relationships and firm performance from different angles than those used by most previous studies. Prior work has largely focused on how *firms' actions* to address stakeholder interests relate to firm performance. For example, an often-used proxy for firm-stakeholder relationships is the KLD score. This provides ratings on attributes of corporate social performance such as community relations, environmental sustainability, and customer and employee protection based on how firms perform on these dimensions (see Graves & Waddock [1994] for details). However, this popular measure does not capture how firms' actions to address stakeholder concerns are, in turn, received by stakeholders and how this two-sided relationship affects firm performance. This is a critical issue that has received little attention. Stakeholder engagement efforts, if not well received, will not bring about enhanced support from external stakeholders (Henisz, Dorobantu, & Nartey, 2014). The interactive nature of social media allows us to explore how stakeholders' reactions to firms' actions, that is, firm-initiated messages, relate to firm performance. It also allows us to examine whether and how stakeholder-initiated postings matter for firm performance. Thus, we are able to extend the prior literature in ways that take into account additional aspects of firm-stakeholder relationships. This is especially important in rethinking firm-stakeholder relationships in the digital age.

Among various stakeholders, perhaps individual stakeholders such as customers stand to gain the most from firms' use of social media. Individual customers are legitimate stakeholders in a firm (Freeman, 1984), but do not necessarily have power or urgency (Mitchell, Agle, & Wood, 1997). Firms' use of social media enables individual customers to increase power, and possibly, urgency, vis-à-vis the firm for the following reasons. The voice of the individual customers itself is magnified because of the public nature of the social media space (Treem & Leonardi, 2012). Also, individual customers are able to give rave reviews or exert greater pressure on firms by amplifying their voices and those of others by actively promoting and propagating messages and raising awareness, and by connecting with other stakeholders and garnering support (Coombs, 1998; Rowley, 1997). This means that individual customers can become definite stakeholders (Mitchell et al., 1997) in the social media space.

In this article, we suggest specific mechanisms by which customer feedback on firms' social media accounts may significantly affect firm performance. A recent study shows that social performance measures such as firm-stakeholder relationships are often uncertain and ambiguous to general investors, and security analysts serve as the informational pathway connecting corporate social performance to firm stock returns (Luo et al., 2015). Accordingly, we examine how customer feedback may affect analyst stock recommendations by looking into the mechanisms of decision making. In making recommendation decisions, security analysts give significant consideration to growth potential (Bradshaw, 2004; Jegadeesh et al., 2004). Good firm-stakeholder relationships can hint at future growth prospects in various ways, such as by signaling general support for smooth operations and functioning of firms without interruptions (Henisz et al., 2014), by lowering transaction costs and easing capital constraints (Cheng, Ioannou, & Serafeim, 2014; Sharfman & Fernando, 2008), or by facilitating efficient use of resources to create greater value for customers (Harrison, Bosse, & Phillips, 2010). We argue that popularity in the social media space can point to good firm-stakeholder relationships. In particular, favorable response to firm-initiated messages indicates well-receivedness of firms' efforts to engage stakeholders and give a good impression. Positive stakeholder response is especially meaningful because social media offers a low-cost platform for firms to voluntarily disclose information, where firm-initiated messages are subject to selective disclosure bias and tend to include favorable information about the firm (Kim & Lyon, 2015). Thus, stakeholder response plays a role as a screening device to differentiate levels of receptivity.

Unless firm-initiated messages provide a direct gauge of growth, however, the implications of favorable stakeholder response for future firm growth and performance may differ across firms. Even for firms in the same industry, differences may exist due to differences in the extent of competition, market share, economic and demographic factors,

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and other contextual factors (Anderson, Fornell, & Lehmann, 1994; Anderson & Mansi, 2009; Banker et al., 1996).[1] Notably, a recent paper illustrates this by quantifying the extent to which customer satisfaction determines firm performance for each firm (O'Connell & O'Sullivan, 2014). Thus, we argue that unless firm-initiated messages are directly related to growth prospects, the extent to which customers' favorable response affects analyst recommendations depends on firm-specific links between customer satisfaction and firm performance. This means that it is important for firms to understand their own customer satisfaction sensitivity in formulating stakeholder engagement strategies. On a broader level, this, in turn, suggests that firms may have greater control over interactions with their stakeholders than previously recognized.

Our empirical context is Twitter usage in the U.S. electric power industry. Twitter is an online platform for social networking and micro-blogging. Tweets are limited to 140 characters, and users can post messages ("tweets") and repost messages ("retweet"), among other functions. Perhaps surprisingly, the electric power industry provides a good setting to test our proposition for three reasons. First, because electric power companies produce a commodity, electricity, their use of Twitter is largely targeted toward managing stakeholders, not marketing their products. Second, there is a great sense of urgency in using social media in this industry because its stakeholders, especially customers, are often faced with time-pressing issues such as blackouts after severe storms. With its unique feature allowing users to quickly send out short messages, Twitter is the most widely adopted form of social media among firms in this industry. Third, contrary to popular belief, customer satisfaction can be a very important driver of firm performance in the U.S. electric power industry for various reasons, including ratemaking, customer switching, penalties and rewards, revenue decoupling, and credit ratings, which we discuss in more detail in our discussion leading to hypothesis 2 and in Table 1.

Below, we start by examining why securities analysts might look into social media when making recommendation decisions. We then discuss how, specifically, they might consider information in the social media space, and develop hypotheses regarding how customers' favorable reactions to firm-initiated messages may relate to analyst recommendations. Next, we consider how customer-initiated messages may influence analyst recommendations, as customers may also initiate a conversation.

Analyst Recommendations and Social Media

Analysts gather and process a variety of information about different stocks, form their beliefs about the stocks' intrinsic value relative to their current market prices, and finally, rate the investment potential of each stock (Jegadeesh, et al., 2004). There are obvious proprietary costs to divulging particular methods of identifying any single security for recommended investment (Bradshaw, 2004). Accordingly, the exact process by which analysts come to make stock recommendations is a black box. However, many academics have provided insights into this process. For example, earnings surprises and earnings forecasts are important factors in gauging the value of firms (Bernhardt & Campello, 2007; Francis & Soffer, 1997; Gleason & Lee, 2003; Jegadeesh & Kim, 2010; Schipper, 1991). An earnings surprise arises when a firm's actual earnings deviate from analysts' expectations. As actual numbers are made available, analysts typically revise their projections (Gleason & Lee, 2003). Earnings forecasts indicate growth prospects as well as underlying firm values, and thus, play an important role in making stock recommendation decisions (Bernhardt & Campello, 2007; Block, 1999; Bradshaw, 2004; Chatfield, Moyer, & Sisneros, 1989; Francis & Soffer, 1997; La Porta, 1996; Sharpe, 2005).

In addition, Jegadeesh et al. (2004) showed that, on average, analysts are influenced by incentives faced by their brokerage firms, whose primary businesses are investment banking and sales and trading, and thus, existing and potential investment banking relationships can affect analyst judgment. Growth firms and firms with higher trading activity make for more attractive investment banking clients, and thus, brokerage firms have significant economic incentives to publicly endorse high-growth stocks with glamorous characteristics. These incentives may cause analysts to, knowingly or otherwise, tilt their attention and recommendations in favor of growth stocks (Jegadeesh et al., 2004). Bradshaw (2004) also found that analysts favor growth as a primary determinant of favorable

[1] We discuss this in more detail in our discussion leading to hypothesis 2 and in Table 1.

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Table 1
Sample Responses of Our Interviews with State Public Utility Commissions (PUCs)[a, b]

Regulated states

Standardized metrics:

- **Alabama**

If a utility ranks in the top third of the most recent customer value benchmark survey, it is eligible for a performance-based adder of seven basis points to its return.

- **California**

When there is a significant amount of customers' negative perception regarding a utility, the Commission can redirect the utility's revenue to enhance their services. The Commission regards reliability to be important and uses metrics, such as SAIDI (System Average Interruption Duration Index), in assessing a utility's reliability.

- **Vermont**

There is a Service Quality and Reliability Plan (SQRP) for utilities in Vermont, which factors in customer satisfaction. The plans are not identical across all utilities and reflect the specifics of each company. A utility receiving a low SQRP score can be denied a rate increase or receive a conditional rate increase. For example, a company could get approval for a 5% rate increase out of the requested 10% under the condition of receiving the remaining 5% with improvements in customer service.

- **Minnesota**

The Commission has different thresholds for looking into poor customer satisfaction. For example, while a municipality or the Minnesota Department of Commerce can file a complaint with the Commission, other organizations need to file on behalf of at least 50 consumers of a utility.

Case-by-case basis:

- **Indiana**

The Commission takes a case-by-case approach in dealing with a utility's poor customer satisfaction. This involves disallowing some costs, reducing the allowed rate of return on equity, requiring the utility to report statistics on various areas of performance, and formal and informal investigations.

Credit rating:

- **Alabama**

Major credit rating agencies (e.g., Moody's, Standard and Poor's, Fitch) consider customer satisfaction when evaluating utilities' overall credit ratings. Low ratings can have a negative impact on utilities, for example, by resulting in higher interest rates in financing their projects.

Decoupling:

- **Idaho**

In the state of Idaho, only the Idaho Power Company has a decoupling mechanism (i.e., fixed cost adjustment mechanism). As the impact on rates is relatively small, decoupling is not a significant issue for customers, and does not have much impact on customer satisfaction.

Complaint resolution:

- **Kansas**

The Commission operates a division to assist in resolving issues related to service quality, such as high-bill complaints, billing errors, and outage complaints.

- **New Mexico**

The Commission has a division that deals with consumer complaints. If a complaint remains unresolved, it could become a docketed proceeding, which could result in punitive actions by the Commission.

Deregulated states

Standardized metrics:

- **New York**

The Commission monitors utilities' customer service performance using standard performance indicators (e.g., complaint rate, telephone answer response time). In addition, the Commission has approved Consumer Service Performance Incentives (CSPIs) for all major electric and/or gas utilities in New York. Since the CSPIs are typically negotiated within the context of individual utility rate cases, they differ in scope, target level, and amount at risk for nonperformance.

- **Rhode Island**

Utilities in Rhode Island must file service quality reports, and those with poor service quality can receive financial penalties.

Case-by-case basis:

- **Maine**

Poor customer satisfaction is penalized on a case-by-case basis, where the Commission can either levy fines or revoke licenses.

- **Connecticut**

The Commission takes a case-by-case approach in dealing with customer complaints either by company or by the type and severity of the complaint. Depending on the severity or the volume of complaints, the Commission convenes the utility company and other interested parties (e.g., Office of the Attorney General, the Office of Consumer Counsel) for a technical meeting session to resolve the issue. If the session is not successful or if the issue requires immediate intervention, the Commission can open a formal docketed proceeding. If a utility's violation of state statute or regulation is discovered during the investigation of the issue, the Commission will issue a fine against the utility.

- **Delaware**

Customer complaint cases that come before the Commission are evaluated case-by-case rather than by pre-determined metrics. Electric supply service to retail customers is one of the highest priorities of the Delaware Public Service Commission.

Customer switching:

- **Illinois**

In the state of Illinois, there is municipal aggregation, which allows communities to collectively select their supplier. This has resulted in significant customer switching in Illinois for smaller customers (i.e., residential and small business customers).

- **Oregon**

The state of Oregon has both regulated and deregulated utilities. Investor-owned utilities (IOUs) are regulated entities. Consumer-owned utilities (COUs), such as municipals utilities, public utility districts, and electric co-ops are not necessarily as highly regulated as IOUs. Federal law gives COUs preferential access to the output of the Federal Columbia River Power System, which provides cheap and reliable energy. As the retail rates in COU territories are generally lower than those in IOU territories, IOUs are sensitive to this rate disparity. Oregon law allows local communities to form COUs out of IOU territory resulting in efforts by local communities to create a COU. Although this is a long and expensive process, it occurs every few years, and puts pressures on the IOUs.

[a] State PUCs are governing bodies that regulate the rates and services of electric utility companies. Among the 50 states we contacted for interviews, 32 responded to our request. Interviews were conducted via phone and/or email for the following 32 states: AL, CA, CO, CT, DE, ID, IL, IN, IA, KS, LA, ME, MD, MN, MO, MT, NH, NM, NY, NC, ND, OK, OR, PA, RI, SD, TX, UT, VT, VA, WA, WV. We asked how regulation, competition, and consumer opinions may intertwine and affect firm performance. The interviews reassured us that in examining the interactions among regulation, competition, and consumer opinions, we must take into account firm heterogeneity beyond the distinction between regulation and competition.
[b] The status of regulation or deregulation was obtained from the U.S. Energy Information Administration's "Status of Electricity Restructuring by State". Some states such as New Mexico, shown in the table, have suspended deregulation and gone back to regulation.

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recommendations. He specifically showed that two popular valuation methods used by analysts are a price-earnings-to-growth model and a long-term growth projections model, in both of which growth plays an important role. Analysts favor stocks with high-growth expectations even though such expectations have already been incorporated into prices (Bradshaw, 2004).

We posit that securities analysts follow the social media messages of the firms they analyze looking for growth-related signals. To test this possibility, we held informal conversations with several people in the financial industry. The quote below summarizes well the general sentiment among them toward using social media in analyzing companies and making recommendations:

> Social media has not been institutionalized yet. But, it is increasingly used as a source of channel checks, especially for vibes, validations, etc. … (portfolio manager, phone interview, November 5, 2014).

Although the precise underlying processes are unsaid and obscured, this statement corroborates the likeliness that securities analysts follow the social media messages of the firms they analyze and take them into account when making recommendation decisions. Below, we propose three specific mechanisms by which analysts may make use of social media messages. The overarching theme is that social media popularity matters, but with some qualifications.

Firm-Initiated Messages and Analyst Recommendations

An increasing number of firms use social media and send out messages via their social media accounts. Firms send out various messages for purposes that range from informing about news and publicizing corporate social responsibility-related activities to marketing and managing customer service on a continuous basis. Firm-initiated messages are essentially voluntarily disclosed information. That is, firms choose to publicly disclose certain information when they are not required to do so. When firms opt for voluntary provision of information, the information provided tends to include favorable information about the firm (see, e.g., Kim & Lyon, 2015). For example, firms are more inclined to announce positive events such as achieving higher-than-expected quarterly earnings and taking up corporate responsibility initiatives than negatives ones, such as losing market share and sales and getting penalized for not complying with government regulations. Even with regard to managing customers, this tendency continues: When things get complicated and difficult with customers, firms often ask customers to contact them privately rather than continue the conversation publicly via their social media accounts.[2] Intriguingly, the propensity to selectively disclose favorable information can foster a positive image for external stakeholders (Cohen et al., 2011; Dhaliwal et al., 2011) and help improve stakeholder engagement and strengthen firm-stakeholder relationships (Lee & Sweeney, 2015; Neu, Warsame, & Pedwell, 1998).

Prior literature has well documented that good firm-stakeholder relationships can improve firm performance by facilitating growth opportunities. Enhanced support from external stakeholders can reduce opportunistic hold-ups by stakeholders with whom the firm has no explicit buyer or supplier contracts, but whose cooperation is nevertheless required in order for the firm to create and capture value, and to increase the probability that a business plan will proceed on schedule and on budget (Henisz et al., 2014). Thus, enhanced support from external stakeholders increases investors' valuation of the firm (Henisz et al., 2014). A good firm-stakeholder relationship can also ease capital constraints because of lower contract costs through stakeholder engagement and increased transparency through CSR reporting (Cheng et al., 2014; Sharfman & Fernando, 2008). Capital constraints play an important role in strategic decision making by directly affecting the firm's ability to undertake major investment decisions and by influencing the firm's capital structure choices, which, in turn, relate to stock market performance (Cheng et al., 2014). In addition, with good firm-stakeholder relationships, firms have a better idea of stakeholders' preferences, and thus, are able to use limited resources more wisely to take advantage of value-creation opportunities (Harrison et al., 2010) and to develop intangible yet valuable assets which can be sources of competitive advantage (Hillman & Keim, 2001). Thus, from an analyst's perspective,

[2] See, for example, "G.M. uses social media to manage customers and its reputation." *The New York Times*. March 23, 2014.

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a well-managed firm-stakeholder relationship is important because it can signal growth prospects and favorable future performance over time.

Given the biased nature of firm-initiated messages sent by corporate social media accounts, we posit that external stakeholders such as customers play a key role in validating them and providing informative signals to securities analysts about valuable firm-stakeholder relationships. In the social media space, an important type of stakeholder response is the decision to propagate messages posted by others (Van Liere, 2010). Social media users can propagate postings and messages to those in their social network with a simple click, enabling instant dissemination of information to a large audience (Lotan et al., 2011). Propagation in the social media space is generally regarded as an indication of endorsement or a vote in favor of the usefulness of a message's content, as users tend to spread information when they find the content newsworthy or important enough to share with others (Kwak et al., 2010; Starbird et al., 2010). Thus, such propagation can signal beneficial firm-stakeholder relationships to securities analysts. Also, as discussed earlier, since firm-initiated messages tend to be mostly positive due to firms' selective disclosure of favorable information, stakeholders' propagating behavior may also speed up the process by which favorable information regarding the firm is updated and disseminated.

Accordingly, we posit that widely disseminated and well-received messages as indicated by stakeholders' propagation, especially those that are directly related to growth, give a good impression to analysts, which, in turn, may lead them to develop favorable evaluations of a firm.

Hypothesis 1: Customers' favorable reactions to firm-initiated messages that are directly related to growth have a positive impact on analyst stock recommendations.

Whereas those messages are directly related to growth and well received may be viewed positively straightaway, a recent study by O'Connell and O'Sullivan (2014) suggested that those that are well received but more indirectly related to growth may be considered more conditionally. Their findings suggested that the extent to which firm-stakeholder relationships relate to firm performance differs across firms. That is, customer satisfaction has varying implications for firm performance even within the same industry. For example, in our context, the most obvious reason for this is regulatory status at the state level (Kim, 2013). Traditionally, major electric utility companies were vertically integrated, owning generation, transmission, and distribution facilities, and were operated as monopolies. To keep them from taking advantage of their monopoly status and gouging customers, they were regulated under rate-of-return rules where companies were allowed to recover their costs and to earn a fair rate of return on capital invested. Cost base and capital expenditures were determined by state public utility commissions (PUCs). The U.S. electric power industry has been increasingly deregulated since then, introducing competition into the industry and giving customers a choice as to their electricity providers. Nevertheless, more than half of the U.S. states remain regulated. Customer satisfaction can be an important consideration both in regulated and deregulated states. In regulated states, state PUCs can weigh customer satisfaction in determining allowed rate of return (J.D. Power and Associates, 2012). In deregulated states, dissatisfied customers might switch to another electricity company (Joskow, 2005).

However, as shown in Table 1, our interviews of 32 state PUCs that responded to our request have revealed that how customer satisfaction relates to firm performance is far more complicated than the distinction between regulation and deregulation. First, in regulated states, the extent to which state PUCs take into account customer satisfaction differs across states, and how they do so also differs across states. Some state PUCs use a standardized metric, which is not the same across states, and other PUCs reach determinations more on a case-by-case basis. Second, in deregulated states, the extent to which customers switch to another company differs across states and across companies.[3] Moreover, competition may not be the only driver of firm performance. Rates-of-return

[3] For example, in New York, the average switching rate for residential customers in 2014 was 25% (20% for National Grid PLC, and 40% for ORUPower Co.) (New York State Department of Public Service). In Maine, it was about 19% (22% for Central Maine Power, and 9% for Emera Maine) (Maine Public Utilities Commission). In addition, some states, such as Illinois, have adopted the so-called municipal aggregation principle so communities collectively select their supplier, leading to more switching than otherwise (Illinois Commerce Division).

are sometimes determined by state PUCs, as is the case in Michigan, New Hampshire, and Oregon. Many state PUCs require companies to document customer complaints, and states such as Connecticut and Illinois have imposed fines on companies for poor customer service. Third, regardless of regulation or deregulation, some states have adopted a revenue decoupling mechanism, which decouples utility profits from sales, to encourage energy efficiency. This is a form of regulated ratemaking, under which the number of customers is an important variable in adjusting revenue. As a result, numbers of captive customers in regulated states and of customer switching in deregulated states, both of which differ across firms, can carry greater weight under this mechanism. Also, major credit rating agencies such as Moody's, Standard and Poor's, and Fitch consider customer satisfaction when evaluating utilities' overall credit ratings, and some state PUCs take this into account in rewarding or penalizing companies.

Thus, we posit that in taking into account those firm-initiated messages that are well received, but more indirectly related to growth, securities analysts consider firm-specific factors, in particular, the degree to which customer opinions and satisfaction affect firm performance.

In short, we contend that popularity in the social media space, as demonstrated by propagation of firm-initiated messages, serves as a gauge for favorable stakeholder response to firms' efforts to engage stakeholders and create a good impression. This favorable reaction thus suggests good firm-stakeholder relationships, which, in turn, can hint at future growth potential for stock analysts. Even so, the implications of good firm-stakeholder relationships for future growth and performance may differ across firms, unless firm-initiated messages provide a direct gauge of growth. Thus, we hypothesize the following.

Hypothesis 2: Customers' favorable reactions to firm-initiated messages have a positive impact on analyst stock recommendations, depending on the extent to which customer opinion matters for firm performance.

Customer-Initiated Messages and Analyst Recommendations

Firms open and maintain their social media accounts to drive stakeholders to their content. A perhaps unintended consequence is that stakeholders such as customers can also initiate their own messages and leave unfiltered messages on firms' accounts. Not surprisingly, a variety of anecdotal evidence suggests that the increased salience of customers can be challenging to firms, requiring immediate attention, or even evolving into public relations crises.[4,5,6] However, it has also been suggested that popularity demonstrated in the social media space can have a positive influence on firm performance as well, although the underlying mechanisms are unclear.[7,8]

Our interviews with securities analysts reveal that they feel customer-initiated messages are unsubstantiated and do not have much credibility. Thus, unless the circumstances are unusual, analysts do not pay much attention to customer-initiated messages. What specific circumstances are considered unusual was not conveyed to us by analysts. However, our interviews of state PUCs and the prior literature on consumer advocacy point to certain conditions under which customer-initiated messages might influence analyst recommendations.

In general, state PUCs take into account customers' opinions when there is an exceptionally high volume of activity. For example, this is the case with escalating customer complaints or extreme customer satisfaction. Formal participation of consumer advocates in the state also matters (Fremeth, Holburn, & Spiller, 2014). That is, when there is an official channel by which consumer advocates can participate in regulatory decision making, consumer opinions significantly affect firm behavior and performance. In the context of our study, 33 states employ publicly funded consumer advocates who have rights to intervene in formal rate review hearings and administrative processes conducted by state PUCs, along with the right to appeal regulatory decisions to state courts (Fremeth et al., 2014). These consumer advocates operate by providing

[4] "G.M. uses social media to manage customers and its reputation." *The New York Times*. March 23, 2014.
[5] "British Airways apologizes to man who bought promoted tweet to complain about service." September 4, 2013. FoxNews.com; "Customer buys promoted tweet to complain about British Airways." September 3, 2013. NBC News.com.
[6] "Utilities turn to Twitter to tackle complaints." *Orlando Sentinel*. March 31, 2013.
[7] "Social media popularity can predict stock prices." VentureBeat. March 17, 2011.
[8] "How to Predict Stock Market Trends through Social Media." amigobulls.com. January 24, 2015.

relevant information to regulatory agency commissioners and staff and potentially to courts and legislatures (Fremeth et al., 2014). Thus, we propose that even unsubstantiated customer-initiated postings can have a significant impact on analyst recommendations under certain exceptional circumstances—when there is an unusually high volume of activity and there is an institutional structure in place that supports consumer protection, that is, the presence of formal consumer advocates.

Hypothesis 3: An unusually high volume of customer-initiated messages has a significant impact on analyst recommendations if there is an institutional structure in place that supports consumer protection.

Data and Methods

We tested our hypotheses using the Twitter account data of U.S. electric power companies that appeared on the Standard and Poor's (S&P) 500 list in 2011. We sought to examine Twitter usage in the latest year possible, as Twitter has gained popularity over time and its usage has become more active. As we collected Twitter data in 2012, we focused on firms' Twitter usage in 2011, the closest year to 2012 for which we could collect a full year of data. There were 21 S&P 500 electric power companies with Twitter accounts in 2011, with a total of 11,278 tweets.

Testing our hypotheses required delving into firms' Twitter usage, particularly with regard to its content. Firms can post tweets on an ongoing basis, and thus, we first needed to set a time frame to measure content. We chose firm-month as the unit of analysis to capture a trend without too much random noise. Aggregating the 11,278 tweets for the 21 firms resulted in 227 firm-month observations. However, due to unavailability of the customer satisfaction data for five firms, we were only able to examine the Twitter data of 16 firms. As will be explained shortly, we explored how changes in retweets, or tweets, relate to changes in analyst stock recommendations. Thus, the first-month observation for each firm was dropped, leaving 154 firm-month observations with a total of 9,309 tweets. For one observation, one of the control variables was missing,[9] so we used 153 firm-month observations with a total of 9,307 tweets.

To explore tweet content, content analysis was necessary. Computer-aided content analysis was often used in analyzing news articles. We explored this option, but due to the brevity of tweets compared to news articles, it did not work well; using predefined or user-generated dictionaries of words often led to incorrect categorizations. It became apparent that our analysis required the comprehension of entire tweets rather than isolated keywords in the tweets. Thus, we hand-coded each tweet, which required spending significantly more time than computer-assisted content analysis would have. Our tweet coding scheme is illustrated in Figure 1.

We first made the distinction between tweets firms posted (*Firm-initiated*) and tweets other users such as customers posted (*Customer-initiated*). Most tweets in the latter category have been initiated by customers (approximately 92%). Firm-initiated tweets were then further categorized into five categories: tweets that were relevant to customers, investors, employment, corporate social responsibility (CSR), and rapport-building. More detailed descriptions of each category are shown in Figure 1. Regarding inter-coder reliability, Cohen's kappa (Cohen, 1960) was 0.75. A Cohen's kappa of 0.75 or more represents excellent agreement (Banerjee et al., 1999), and Kvalseth (1989) notes 0.61 as representing reasonably good overall agreement.

To test our hypotheses, we combined the firm-month tweet content and retweet data with analyst stock recommendation data gathered from the Institutional Brokers Estimate System (I/B/E/S) database. We also included firm-level data collected from Compustat and the U.S. Energy Information Administration, as described in more detail in the variables section.

Given that customers do not typically closely follow analyst stock recommendations, endogeneity due to reverse causality does not seem to be of serious concern. However, there could be an omitted variable issue. Fixed-effects models can control for at least time nonvarying factors, but it was not possible to use these because the customer satisfaction data used in constructing the extent to which

[9] For one firm-month observation (Public Service Enterprise Group, February 2011), the residential sales/total sales variable was missing.

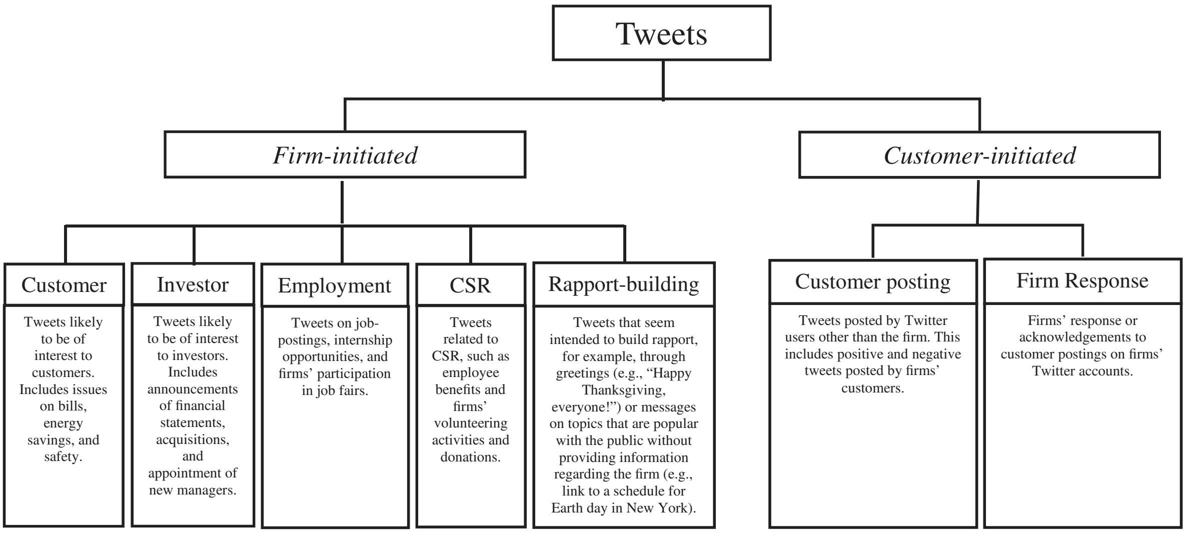

Figure 1. Tweet coding classification and description. *Firm-initiated tweets* are those posted by firms. *Customer-initiated tweets* are those posted on firms' Twitter accounts by users other than the firm, such as customers.

customers' opinions matter for firm performance (i.e., ACSI customer satisfaction data) and the data that indicate the presence of an institutional structure for promoting consumer protection are annual and do not vary across months. Thus, we instead made use of change-change specifications and used GLS estimations to address autocorrelation and heteroskedasticity concerns.[10] However, this approach does not fully address the potential omitted variables bias, and thus, as illustrated in the *Robustness Checks* section and as reported in Appendices 4 and 5, we conducted a series of extensive robustness tests.

Dependent Variable

Change in analyst stock recommendations. We used recommendation revisions, not levels, because previous research showed that recommendation changes are more informative than levels (Boni & Womack, 2006; Jegadeesh & Kim, 2010). The I/B/E/S reports the number of upgrades and the number of downgrades across five recommendation categories (strong buy, buy, hold, underperform, and sell). We computed the recommendation changes as the net number up (the number of upgrades minus the number of downgrades) at the firm-month level.

Independent Variables

Change in retweets. We proxied customers' favorable reactions to firms' postings using changes in the number of retweets that firm-initiated tweets have received in comparison to the prior month.[11] We manually checked each tweet that received retweets and confirmed that such tweets contained favorable messages regarding the firm. In line with Hypotheses 1 and 2, which differentiate customers' favorable reactions to firm-initiated tweets that are directly or more directly related to growth, we created two change-in-retweets variables as described below.

Change in retweets of firm-initiated tweets directly related to growth (change in employment retweets). We proxied firm-initiated tweets directly related to growth using firm-initiated employment tweets. Employment tweets include job posting messages and announcements about job fairs, and thus, appear to directly indicate that the firm is doing well and growing. Also,

[10] We tested for heteroskedasticity with the modified Wald statistic for groupwise heteroskedasticity, and the results were significant across all models (p-value <.000). The p-values following the Wooldridge test for autocorrelation in panel data were greater than .05.

[11] Table A1 (Appendix 1) displays the monthly mean and standard deviation of company-initiated tweets, retweets, and retweets over tweets by firm. It shows variances in the number of tweets and retweets both across and within firms. Detailed discussions on such heterogeneity along with differences between tweets and retweets are provided in Appendix 1.

firm-initiated employment tweets seem less subject to selective disclosure bias, discussed earlier, than firm-initiated investor-related tweets (Figure 1). Thus, we used changes in retweets of employment tweets as a proxy for customers' favorable reactions to firm-initiated messages directly related to growth. The variable is in firm-month units.

Change in retweets of firm-initiated tweets more indirectly related to growth (change in customer retweets and change in customer/CSR/rapport-building retweets). For firm-initiated messages more indirectly related to growth, we used alternative measures because firm-initiated tweets other than those categorized as "customers" (Figure 1) may also affect customers' perception of a company. We used two alternative variables: (a) change in retweets of customer-related tweets (Figure 1), and (b) change in retweets of customer-related, CSR-related, and rapport-building tweets (Figure 1). The variables are expressed in firm-month units.

Unusually high volume of customer-initiated negative (positive) tweets. We measured an unusually high volume of customer-initiated negative (positive) tweets using a binary variable. We first calculated changes in customer-initiated negative (positive) tweets compared to the prior month and then identified an unusually high volume based on a percentile threshold.[12] For example, *Change in customer-initiated negative tweets (85th percentile)* refers to a binary variable indicating 1 for changes greater than or equal to the 85th percentile in customer-initiated negative tweets compared to the prior month, and 0 otherwise. We show the results for Hypothesis 3 using alternative threshold values, the 70th, 75th, 80th, 85th, and 90th percentiles in Table A2 (Appendix 2). They are expressed in firm-month units.

Public consumer advocates. We operationalized the institutional structure that supports consumer protection by using data on public consumer advocates. Thirty-three states employ publicly funded consumer advocates who have rights to formally intervene in regulatory processes conducted by state PUCs, along with the right to appeal regulatory decisions to state courts (Fremeth et al., 2014). We used this data, which is state-specific and does not vary over time. We constructed a firm-level *Public consumer advocate* variable by taking into account where each subsidiary of a given firm operates. Specifically, we calculated the proportion of states with public consumer advocates among all states in which the firm's subsidiaries operate.

Customer satisfaction sensitivity. For each firm, we estimated the extent to which customer satisfaction determines firm performance (*Customer satisfaction sensitivity*) using the following regression, as described in O'Connell and Sullivan (2014). We measured customer satisfaction using the American Customer Satisfaction Index (ACSI) and firm performance using return on assets (ROA), also following O'Connell and Sullivan (2014).

$$\begin{aligned} &\mathit{One{-}period{-}ahead\ ROA} = \\ &\quad \alpha_0 + \alpha_1 \mathit{Customer\ satisfaction} + \alpha_2 \mathit{ROA} \\ &\quad + \alpha_3 \mathit{One{-}period{-}lagged\ ROA} \\ &\quad + \alpha_4 \mathit{Stock\ Returns} + \alpha_5 \mathit{One} \\ &\quad \mathit{{-}period{-}lagged\ Stock\ Returns} \end{aligned}$$

The *Customer satisfaction sensitivity* variable corresponds to the coefficient for *Customer satisfaction* (i.e., α_1) for each firm. We used annual ACSI data from 2003 to 2011, and corresponding ROA and stock returns data in estimations as they provide a sufficient number of observations given the number of parameters in the model used in O'Connell and Sullivan (2014). We estimated *Customer satisfaction sensitivity* using three models, as displayed in Table 2 (Panel A) and explained below.

We first checked for autocorrelation and heteroskedasticity for each firm. Autocorrelation was present in all 16 firms (p-value <.002 for the Wooldridge test for autocorrelation for all firms), and heteroskedasticity was absent for all but one firm (p-value >.1 for 15 firms, and p-value = .03 for one firm based on the Breusch-Pagan/Cook-Weisberg test). Thus, we used generalized linear squares (GLS) regressions with appropriate corrections for each firm in estimating *Customer satisfaction sensitivity*. We also ran ordinary least squares (OLS) regressions with the Newey-West variance estimator, which was developed to correct for autocorrelation in time series data (Newey & West, 1987). In addition, we estimated *Customer satisfaction sensitivity* using the autoregressive integrated moving average (ARIMA) dynamic regression model for time-series data as it allows for the dependent variable to be explained by lagged

[12] We empirically explored alternative threshold values (70th, 75th, 80th, 85th, and 90th percentiles), and found that the 85th percentile is the relevant threshold (See Table A2 in Appendix 2). Thus, we used the 85th percentile in Table 4.

Table 2
Estimated Coefficients for Customer Satisfaction Sensitivity using GLS, OLS with Newey-West Standard Errors and ARIMA and Comparisons of the Estimated Coefficients

Panel A: Estimated coefficients for *Customer Satisfaction Sensitivity*[a]

	GLS		OLS with Newey-West S.E.		ARIMA	
Company name	*Coefficient*	*S.E.*	*Coefficient*	*S.E.*	*Coefficient*	*S.E.*
Ameren	−0.028	(0.011)	−0.051	(0.029)	−0.051	(0.086)
American Electric Power	0.062	(0.036)	0.056	(0.094)	0.056	(0.063)
Consolidated Edison	0.013	(0.042)	0.002	(0.061)	0.002	(0.112)
DTE Energy	−0.062	(0.048)	−0.052	(0.082)	−0.052	(0.101)
Duke Energy	0.423	(0.078)	0.443	(0.226)	0.443	(0.158)
Edison International	0.255	(0.164)	0.293	(0.135)	0.293	(0.664)
Entergy	−0.272	(0.077)	−0.266	(0.165)	−0.266	(0.133)
FirstEnergy	−0.117	(0.045)	−0.105	(0.070)	−0.100	(0.334)
NextEra Energy	−0.136	(0.053)	−0.122	(0.094)	−0.122	(0.341)
Northeast Utilities	0.362	(0.244)	0.368	(0.400)	0.368	(1.055)
PPL	0.312	(0.228)	0.315	(0.266)	0.315	(1.673)
Progress Energy	0.201	(0.075)	0.184	(0.070)	0.184	(0.283)
Public Service Enterprise Group	0.141	(0.181)	−0.030	(0.208)	−0.030	(1.409)
Sempra Energy	−0.196	(0.069)	−0.178	(0.139)	−0.178	(0.341)
Southern Company	0.009	(0.046)	0.009	(0.050)	0.046	(0.461)
Xcel Energy	−0.05	(0.030)	−0.023	(0.059)	−0.023	(0.072)

Panel B: Comparisons of the estimated coefficients for *Customer Satisfaction Sensitivity*[b]

	GLS *versus* OLS		OLS *versus* ARIMA		ARIMA *versus* GLS	
Company name	*t*-Statistic	*p*-Value	*t*-Statistic	*p*-Value	*t*-Statistic	*p*-Value
Ameren	0.742	.458	0	1	−0.265	.791
American Electric Power	0.060	.952	0	1	−0.083	.934
Consolidated Edison	0.149	.882	0	1	−0.092	.927
DTE Energy	−0.105	.916	0	1	0.089	.929
Duke Energy	−0.084	.933	0	1	0.114	.909
Edison International	−0.179	.858	0	1	0.056	.955
Entergy	−0.033	.974	0	1	0.039	.969
FirstEnergy	−0.144	.886	−0.015	.988	0.050	.960
NextEra Energy	−0.130	.897	0	1	0.041	.967
Northeast Utilities	−0.013	.990	0	1	0.006	.995
PPL	−0.008	.994	0	1	0.002	.998
Progress Energy	0.166	.868	0	1	−0.058	.954
Public Service Enterprise Group	0.620	.535	0	1	−0.120	.904
Sempra Energy	−0.116	.908	0	1	0.052	.959
Southern Company	0	1	−0.080	.936	0.080	.936
Xcel Energy	−0.408	.683	0	1	0.346	.729

[a] We estimated *Customer Satisfaction Sensitivity* using generalized linear squares (GLS) regression models, correcting for the presence of autocorrelation and heteroskedasticity, and ordinary least squares (OLS) models with the Newey-West variance estimator, correcting for the presence of autocorrelation. In addition, we used autoregressive integrated moving average (ARIMA) dynamic regression models, which allow the inclusion of lagged values of the dependent variable in the models. ARIMA (p, d, q) models require the identification steps of deciding whether the model disturbance needs to be differenced (differenced d times), and whether the moving average (q lags of moving average) or autoregressive parameters (p lags of autocorrelation) for the model disturbance need to be included. Identification tests resulted in ARIMA (0, 0, 0) for the majority of firms, except two, which required the inclusion of first-order autoregressive process, hence ARIMA (1, 0, 0).
[b] See the Independent Variables section for *Customer Satisfaction Sensitivity* for more details on the *t*-test.

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values of the dependent variable (Greene, 2003).[13] We examined potential differences between the alternative coefficient estimates of *Customer satisfaction sensitivity* using the *t*-test, assuming the covariances between the estimates are zero, and all *p*-values are greater than .1 as shown in Table 2 (Panel B).[14] This suggests that the three alternative coefficient estimates are not significantly different from each other.

As shown in Table 2, although one might expect *Customer satisfaction sensitivity* to take positive values, this is not necessarily the case for all firms. *Customer satisfaction sensitivity* can take negative values, which means that customer satisfaction can have a negative impact on financial performance. The basic rationale for the negative relationship identified in the prior literature is that investing in customer satisfaction can be a waste of limited resources (Ittner & Larcker, 1998; Fornell et al., 2006).

Control Variables

The control variables are displayed in Table 3 along with our variables of interest.

Following prior literature, we controlled for factors that are likely to cause changes in analyst recommendations. Analysts' recommendations basically reflect price-to-value comparisons (Conrad et al., 2006; Francis & Soffer, 1997; Stickel 1985; Womack 1996), and by evaluating a company's value in conjunction with its stock's price, analysts identify stocks that are overvalued or undervalued. Accordingly, changes in either the price or the value of a company can trigger changes in analysts' recommendations. Changes in price can be directly measured with stock price data, which we include as a control.

However, measuring changes in value is not as straightforward. How exactly changes in value are modeled depends on analysts and is proprietary information. Factors that are commonly considered in modeling values are changes in consensus earnings forecasts. Following the prior literature, we controlled for three measures (Francis & Soffer, 1997; Jegadeesh & Kim, 2010; Schipper, 1991); earnings surprise, change in consensus earnings estimates for the near future (current year), and change in long-term earnings forecasts (3–5 years). We construct earnings surprise in two steps. First, we calculated the actual quarterly earnings minus the analyst forecast that is closest to and prior to the quarterly earnings announcement (Brown, 2001). Next, we adjusted this value by stock price, which is the stock price of the final month of the forecasted quarter (Skinner & Sloan, 2002).

In addition, we controlled for firm size as measured by firm assets because analysts are likely to consider firms' financial resources in making evaluations of the firm (Benner & Ranganathan, 2013). We also included growth and momentum factors as they are related to stock returns (Carhart, 1997; Fama & French, 1993). Moreover, we included the number of competitors, market share, and residential sales over total sales because these variables may affect the extent to which securities analysts value consumer opinions. Deregulation is included due to its potential impact on analysts' evaluations of firms. We constructed the *Deregulation* variable based on prior studies (Kim, 2013; Delmas, Russo, & Montes-Sancho, 2007). Each subsidiary of a given firm takes a value of 1 if it operates in a deregulated state in a given year, and 0 if it operates in a regulated state. This dummy variable is then weighted by the subsidiary's sales over the firm's total sales, and aggregated by firms. Hence, it ranges from 0 to 1, and a greater number indicates a greater degree of deregulation. We also include seasonal dummy variables. Given our context, we sought to control for weather-related factors using these variables. They also lessen the extent to which our empirical results are subject to industry specificity.

Finally, we controlled for changes in retweets of other types of firm-initiated tweets. Specifically, for models using *Changes in customer retweets* in testing Hypothesis 2, we controlled for changes

[13] ARIMA (p, d, q) models require the identification steps of deciding whether the model disturbance needs to be differenced (differenced d times), and whether the moving average (q lags of moving average) or autoregressive parameters (p lags of autocorrelation) for the model disturbance need to be included. The results of the Dickey-Fuller unit-root test for the residuals were statistically significant at the 0.1 level for all firms, rejecting the null hypothesis of the existence of unit root. The results exhibited stationary processes for the residuals and so did not warrant differencing of the data (i.e., $d = 0$). Examination of autocorrelations, partial correlations using a correlogram and Portmanteau tests for white noise did not show any significant moving average component (i.e., $q = 0$) or autocorrelation except for two firms (FirstEnergy and Southern Company) with a first-order autoregressive process (i.e., $p = 1$ for FirstEnergy and Southern Company and $p = 0$ for the remaining firms). Given the identification steps, we identified an ARIMA (1, 0, 0) model for FirstEnergy and Southern Company, and ARIMA (0, 0, 0) for the remaining firms.

[14] Specifically, we used $t = \left(\bar{x}_1 - \bar{x}_2\right) / \sqrt{s_1^2 + s_2^2}$, where $\bar{x}_1$ and $\bar{x}_2$ are means, and s_1^2 and s_2^2 are standard deviations.

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Table 3
Summary of Variables

Variable	Description
Dependent variable	
Change in analyst stock recommendations[a]	The net number of upgrades of analyst recommendations, which is computed as the number of upgrades minus the number of downgrades by firm-month.
Independent variables	
Change in retweets of firm-initiated tweets directly related to growth (*Change in employment retweets*)	Changes in the number of retweets that firm-initiated tweets directly related to growth have received in comparison to the prior month. We proxy this variable by using the changes in retweets of firm-initiated employment tweets. In firm-month.
Change in retweets of firm-initiated tweets indirectly related to growth (*Change in customer retweets* and *Change in customer/CSR/rapport-building retweets*)	Changes in the number of retweets that firm-initiated tweets indirectly related to growth have received in comparison to the prior month. We use two alternative measures: 1) the changes in retweets of firm-initiated customer tweets, and 2) the changes in retweets of firm-initiated customer, CSR, and rapport-building tweets. In firm-month.
Customer satisfaction sensitivity	The extent to which customer satisfaction affects firm financial performance. Refer to the Independent Variables Section for more details. In firm-year.
Public consumer advocates[b]	The presence of an institutional structure that supports consumer protection. It is calculated as the proportion of states with public consumer advocates among all states in which a firm's subsidiaries operate. Refer to the Independent Variables Section for more details.
Unusually high volume of customer-initiated negative (positive) tweets	Binary variable indicating 1 for unusually high volume of customer-initiated negative (positive) tweets compared to the prior month, and 0 otherwise. We examine alternative percentile thresholds for high volumes of customer-initiated tweets (70th, 75th, 80th, 85th, 90th percentiles). In firm-month.
Control variables	
Change in retweets of other firm-initiated tweets (*Change in investor retweets*, *Change in CSR retweets*, *Change in rapport-building retweets*)	Changes in the number of retweets that other types of firm-initiated tweets have received in comparison to its prior month. In firm-month.
Deregulation	A greater number reflects a greater degree of deregulation. Refer to the Control Variables Section for more details. In firm-year.
Growth in total revenue[c]	Growth in terms of total revenue. In firm-quarter.
Momentum factor[d]	Monthly momentum factor obtained from the Kenneth French Data Library. In firm-month.
Firm size: assets[c]	Quarterly firm assets (in thousands). In firm-quarter.
Market share[e]	Weighted market share based on a firm's monthly net generation. Calculated as the sum of a firm's market share in each state in which its subsidiaries operate weighted by the firm's generation in each state over its total generation. In firm-month.
Residential sales/total sales[f]	The ratio of residential sales over total sales (MWh). In firm-month.
Number of competitors[g]	Weighted number of competitors by firm. This is the number of competitors (investor-owned utilities) in all states in which a firm's subsidiaries operate weighted by the firm's sales in each state. In firm-year.
Seasonal dummy variables	Dummy variables for summer (months 6, 7, and 8), fall (9, 10 and 11) and winter (12, 1, and 2) (baseline is spring for months 3, 4, and 5).
Change in stock price[c]	Change in stock price. In firm-month.
Earnings surprise[a]	Actual quarterly earnings minus the analyst forecast adjusted by stock price. In firm-quarter.
Change in current year earnings forecast[a]	Change in current year earnings forecast. In firm-month.
Change in long-term earnings forecast[a]	Change in long-term earnings forecast. In firm-month.

[a] I/B/E/S.
[b] Fremeth, Holburn, and Spiller (2014), Table 1.
[c] Compustat.
[d] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research.
[e] Form EIA−923 "Power plant operating data".
[f] Form EIA−826 "Electric power sales and revenue data−monthly".
[g] Form EIA−861 "Electric power sales, revenue and energy efficient data−annual".

in retweets of investor-related, CSR-related, and rapport-building tweets. For models using the alternative measure, *Changes in customer/CSR/rapport-building retweets* in testing Hypothesis 2, we controlled for changes in retweets of investor-related tweets.

Results

Descriptive statistics and correlations are shown in Table A3 in Appendix 3. The correlations among variables are generally low. A notable exception is the high correlation between *Change in customer retweets* and *Change in customer/CSR/rapport-building retweets* because *Change in customer/CSR/rapport-building retweets* is partly composed of customer retweets. However, this is not of concern as they are alternatively included in the models. The correlations between *Deregulation* and *Firm size* and *Residential sales/total sales* and *Number of competitors* are somewhat high at −0.66 and 0.51, respectively. In order to make sure that multicollinearity is not a potential problem, we computed the variance inflation factors (VIF) for each model we used (Cohen et al., 2002; Greene, 2003). The VIFs were less than 5 in all models, which is considerably lower than the generally accepted threshold of 10 (Cohen et al., 2002).[15]

Table 4 shows GLS regressions results predicting changes in analyst recommendations.

Overall, Models 1 through 4 present results using *Change in customer retweets*; and Models 5 through 8, using the alternative measure, *Change in customer/CSR/rapport-building retweets*. Specifically, Models 1 and 5 include the main variables—*Change in customer retweets* (*Change in customer/CSR/rapport-building retweets*) and *Customer satisfaction sensitivity*—without their interaction terms in order to examine the first-order effects. Building on Models 1 and 5, Models 2 and 6 further control for other types of changes in retweets. Models 3 and 7 include the interaction terms between changes in retweets and *Customer satisfaction sensitivity*. Building on Models 3 and 7, Models 4 and 8 further control for other types of changes in retweets and their interaction terms with *Customer satisfaction sensitivity*. In all models, we include *Unusually high volume of customer-initiated negative (positive) tweets (85th percentile)* and their interactions with *Public consumer advocates*. Also, the following control variables discussed earlier are included: change in stock price, earnings surprise, change in current year earnings forecast, change in long-term earnings forecast, firm size, growth in total revenue, momentum factor, number of competitors, market share, residential sales ratio, deregulation, and seasonal dummies.

The regression results in Table 4 provide strong support for Hypothesis 1, that customers' favorable reactions to firm-initiated messages directly related to growth have a positive impact on analyst stock recommendations. The coefficients for *Change in employment retweets* are positive and significant across all models; for example, in Model 4, which is the full model using the change in customer retweets to gauge favorable stakeholder response, the coefficient for *Change in employment retweets* is positive and significant with $\beta = 0.072$ and $p < .01$, and in Model 8, which is the full model using the alternative measure of change in customer/CSR/rapport-building retweets, the coefficient for *Change in employment retweets* is positive and significant with $\beta = 0.065$, $p < .05$. However, the interaction term, *Change in employment retweets × Customer satisfaction sensitivity*, is generally not significant (it is weakly significant in Model 4 with $\beta = 0.313$, $p < .1$ and insignificant in Model 8 with $\beta = 0.241$, $p = .190$). That is, well-received firm-initiated messages that indicate that the firm is doing well and is growing tend to have a positive impact on analyst recommendations straightaway, *that is*, without the moderator variable, *Customer satisfaction sensitivity*. Specifically, based on the results of Model 2, which only includes the main effect for *Change in employment retweets* ($\beta = 0.040$, $p < .01$), the results show that when employment retweets increase by 10 retweets, analyst stock recommendations increase by 0.4.

Hypothesis 2 tests the conditional impact of firm-initiated messages that are more indirectly related to growth depending on the extent to which customers' opinions matters for firm performance. We find support for Hypothesis 2 as the interaction term *Change in customer retweets × Customer satisfaction sensitivity* is positive and significant (Model 4: $\beta = 0.008$, $p < .01$), which

[15] In all models, continuous variables are mean-centered when interacted with other variables due to multicollinearity concerns (Aiken & West, 1991; Cohen et al., 2002).

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Table 4
GLS Regression Results for Change in Analyst Recommendations[a]

DV: Change in analyst stock recommendations	Change in Customer Retweets				Change in Customer/CSR/Rapport-building Retweets			
Variable	Only customer retweets (1)	Including other retweets (2)	Including interaction (3)	Including other retweets and interactions (4)	Only Customer/CSR/Rapport retweets (5)	Including other retweets (6)	Including interaction (7)	Including other retweets and interactions (8)
Customer satisfaction sensitivity	0.319 (0.254)	0.292 (0.246)	0.452 (0.248)	0.472 (0.237)	0.331 (0.253)	0.298 (0.247)	0.401 (0.245)	0.418 (0.239)
Public consumer advocates	0.061 (0.288)	0.173 (0.282)	0.214 (0.288)	0.338 (0.284)	0.063 (0.286)	0.174 (0.277)	0.149 (0.284)	0.230 (0.272)
Change in customer retweets	0.0001 (0.0004)	0.0005 (0.0004)	−0.0009 (0.0004)	−0.0005 (0.0005)				
Change in customer retweets × Customer satisfaction sensitivity			0.010 (0.003)	0.008 (0.003)				
Change in customer/CSR/rapport-building retweets					−0.0001 (0.0003)	0.0004 (0.0003)	−0.0004 (0.0003)	0.0001 (0.0003)
Change in customer/CSR/rapport retweets × Customer satisfaction sensitivity							0.006 (0.002)	0.004 (0.002)
Change in employment retweets		0.040 (0.014)		0.072 (0.027)		0.041 (0.013)		0.065 (0.026)
Change in employment retweets × Customer satisfaction sensitivity				0.313 (0.185)				0.241 (0.179)
Change in investor retweets		−0.006 (0.006)		−0.003 (0.006)		−0.006 (0.006)		−0.002 (0.006)
Change in investor retweets × Customer satisfaction sensitivity				−0.017 (0.026)				−0.024 (0.026)
Change in CSR retweets		−0.001 (0.001)		0.004 (0.004)				
Change in CSR retweets × Customer satisfaction sensitivity				0.031 (0.020)				
Change in rapport-building retweets		0.0008 (0.0025)		0.0003 (0.0025)				
Change in rapport-building retweets × Customer satisfaction sensitivity				−0.008 (0.014)				
Unusually high volume of customer-initiated negative tweets (85th percentile)	−0.216 (0.141)	−0.243 (0.140)	−0.255 (0.142)	−0.284 (0.145)	−0.221 (0.140)	−0.251 (0.138)	−0.251 (0.141)	−0.267 (0.143)
Unusually high volume of customer-initiated negative tweets × Public consumer advocates	−1.486 (0.334)	−1.416 (0.345)	−1.545 (0.320)	−1.567 (0.341)	−1.503 (0.325)	−1.423 (0.336)	−1.520 (0.311)	−1.419 (0.300)
Unusually high volume of customer-initiated positive tweets (85th percentile)	0.098 (0.140)	0.080 (0.138)	0.042 (0.141)	−0.011 (0.146)	0.118 (0.139)	0.093 (0.135)	0.055 (0.140)	0.042 (0.144)

Table 4
(Continued)

DV: Change in analyst stock recommendations	Change in Customer Retweets				Change in Customer/CSR/Rapport-building Retweets			
Variable	Only customer retweets (1)	Including other retweets (2)	Including interaction (3)	Including other retweets and interactions (4)	Only Customer/ CSR/Rapport retweets (5)	Including other retweets (6)	Including interaction (7)	Including other retweets and interactions (8)
Unusually high volume of customer-initiated positive tweets × Public consumer advocates	0.986	0.588	0.677	0.367	0.993	0.569	0.802	0.489
	(0.340)	(0.372)	(0.337)	(0.349)	(0.330)	(0.361)	(0.320)	(0.301)
Change in stock price	−0.079	−0.038	−0.076	−0.042	−0.086	−0.037	−0.079	−0.050
	(0.036)	(0.033)	(0.035)	(0.033)	(0.036)	(0.034)	(0.034)	(0.032)
Earnings surprise	0.258	0.235	0.283	0.275	0.263	0.235	0.280	0.230
	(0.140)	(0.134)	(0.139)	(0.137)	(0.140)	(0.134)	(0.139)	(0.136)
Change in current year earnings forecast	0.834	0.731	0.819	0.797	0.833	0.702	0.850	0.812
	(0.455)	(0.426)	(0.453)	(0.423)	(0.454)	(0.427)	(0.449)	(0.437)
Change in long-term earnings forecast	0.029	0.038	0.038	0.041	0.027	0.039	0.029	0.031
	(0.030)	(0.029)	(0.030)	(0.029)	(0.030)	(0.029)	(0.029)	(0.029)
Deregulation	−0.158	−0.133	−0.171	−0.193	−0.174	−0.150	−0.177	−0.191
	(0.216)	(0.212)	(0.219)	(0.216)	(0.216)	(0.206)	(0.215)	(0.214)
Growth in total revenue	0.178	0.155	0.306	0.271	0.161	0.140	0.218	0.181
	(0.311)	(0.304)	(0.305)	(0.295)	(0.311)	(0.303)	(0.302)	(0.298)
Market share	−0.006	−0.005	−0.005	−0.004	−0.006	−0.005	−0.005	−0.005
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
Residential sales/total sales	0.163	0.064	−0.018	−0.050	0.166	0.076	0.043	0.014
	(0.474)	(0.453)	(0.461)	(0.440)	(0.470)	(0.454)	(0.456)	(0.435)
Number of competitors	−0.120	−0.112	−0.123	−0.121	−0.118	−0.114	−0.112	−0.119
	(0.081)	(0.077)	(0.079)	(0.077)	(0.080)	(0.076)	(0.078)	(0.072)
Momentum factor	−0.048	−0.042	−0.037	−0.047	−0.051	−0.039	−0.054	−0.051
	(0.032)	(0.031)	(0.032)	(0.031)	(0.032)	(0.031)	(0.031)	(0.030)
Firm size	−0.003	−0.003	−0.006	−0.006	−0.003	−0.003	−0.005	−0.005
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Seasonal dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.670	0.634	0.857	0.888	0.693	0.632	0.824	0.849
	(0.336)	(0.333)	(0.332)	(0.320)	(0.334)	(0.333)	(0.329)	(0.320)
Observations	153	153	153	153	153	153	153	153
Wald χ^2	59.15	66.46	83.18	110.7	65.13	69.11	89.37	154.0
df	21	25	22	30	21	23	22	26

[a] Aggregating the 11,278 tweets for the 21 firms in 2011 by firm-month resulted in 227 observations. Among the 21 firms, five firms were dropped due to unavailability of the customer satisfaction data. In addition, the first-month observation for each firm was dropped (i.e., 16 observations) due to the construction of change in retweet variables, and one observation was dropped due to the unavailability of the *Residential sales/total sales* variable, resulting in 153 observations (9,307 tweets). GLS is generalized least squares. Continuous variables are mean-centered when interacted with other variables due to multicollinearity concerns. Standard errors are in parentheses.

is also true for the interaction term *Change in customer/CSR/rapport-building retweets* × *Customer satisfaction sensitivity* (Model 8: $\beta = 0.004$, $p < .05$). Also, from Models 1, 2, 5, and 6, we can see that the significance of the interaction terms is not due to first-order effects (for example, *Change in customer retweets* in Model 2 is insignificant with $\beta = 0.0005$, $p = .2084$).

Based on Model 4, we examine the expected impact of customers' favorable reactions to firms' postings on analyst stock recommendations depending on the values of *Customer satisfaction sensitivity*. For example, for a positive value of *Customer satisfaction sensitivity* at 0.2,[16] when customer retweets (retweets of firm-initiated tweets relevant to customers) increase by 10 retweets, analyst stock recommendations increase by 0.011.[17] Conversely, for a negative value of *Customer satisfaction sensitivity* at −0.2, when customer retweets increase by 10 retweets, analyst stock recommendations *decrease* by 0.021.[18] The direction of the impact is not surprising given that *Customer satisfaction sensitivity* can take positive or negative values. What is surprising, however, is the magnitude of the impact, especially in comparison to employment retweets. The impact of employment retweets is about one order of magnitude higher than the impact of customer retweets. In other words, changes in retweets directly related to firm growth have a larger impact on analyst recommendations than retweets indirectly related to growth.

For Hypothesis 3, the regression results provide strong support for an unusually high volume of customer-initiated negative tweets. More specifically, the coefficient for *Unusually high volume of customer-initiated negative tweets* × *Public consumer advocate* is consistently negative and significant across all models (e.g., Model 4: $\beta = -1.567$, $p < .01$). However, the coefficient for *Unusually high volume of customer-initiated positive tweets* × *Public consumer advocate* is not always significant, although consistently positive (for example, it is insignificant in Model 4 with $\beta = 0.367$, $p = .302$). Thus, for customer-initiated positive tweets, empirical evidence is weak. These results suggest that even under the same conditions of high volume of customer feedback and an institutional structure that protects customers, negative feedback has a stronger impact on analyst recommendations than positive feedback. These results are actually consistent with our interviews of the Public Utility Commissions, who tended to show greater concern about customer complaints than compliments. PUCs typically monitor customer complaints and poor customer services, and a large number of complaints often leads to punitive actions of varying degrees, ranging from levying fines to denying rate increase requests, and redirecting the utility's revenue to enhance customer services. Yet, it is rare that a large number of compliments generate rewards. As long as utilities provide reliable and good quality services, exceptional service is typically not rewarded by the PUCs with tangible benefits. Among the PUCs we interviewed, an exception is Alabama's. Alabama rewards a utility if it ranks in the top third on the most recent customer survey. Our findings seem to align well with this general trend.

Table A2 (Appendix 2) displays a summary of the results for Hypothesis 3 using the alternative threshold values, specifically the 70th, 75th, 80th, 85th, and 90th percentiles. For convenience, Table A2 (Appendix 2) displays the coefficients only for our variables of interest. The interaction terms between *Unusually high volume of customer-initiated negative (positive) tweets* and *Public consumer advocate* are not significant at the 70th and 75th percentile thresholds. At the 80th percentile threshold, *Unusually high volume of customer-initiated positive tweets* × *Public consumer advocate* remains insignificant, while *Unusually high volume of customer-initiated negative tweets* × *Public consumer advocate* starts to become significant in some models. *Unusually high volume of customer-initiated negative tweets* × *Public consumer advocate* becomes much more significant at the 85th percentile threshold and the 90th percentile threshold, with higher significance and magnitude. *Unusually high volume of customer-initiated positive tweets* × *Public consumer advocate* is consistently positive but significant only in some models. These results are consistent with those shown in Table 4.

[16] As shown in Table A3, *Customer satisfaction sensitivity* of 0.2 or −0.2 is roughly one standard deviation higher or lower than the mean.

[17] $0.011 = -0.0005 \times 10$(change in retweets) $+ 0.008 \times 10$(change in retweets) $\times 0.2$(Customer satisfaction sensitivity).

[18] $-0.021 = -0.0005 \times 10$(change in retweets) $+ 0.008 \times 10$(change in retweets) $\times -0.2$(Customer satisfaction sensitivity).

Robustness Checks

There are credible alternatives to our argument that changes in retweets of firm-initiated tweets (for Hypotheses 1 and 2) and changes in customer-initiated tweets (for Hypothesis 3) cause changes in analyst recommendations. We discuss potential identification concerns and how we address them.

Subsample Analyses

Our identification strategy for Hypotheses 1 and 2 relies on the assumption that changes in retweets of firm-initiated tweets are exogenous with respect to changes in analyst recommendations. A potential concern is that omitted variables such as the growth potential of the firm or the quality of the firm may cause a spurious relationship between changes in retweets and changes in analyst recommendations. For example, it could be that growing or higher quality firms get more retweets from customers that may positively relate to analysts recommendation. As discussed earlier, to mitigate this concern, in our regressions, we control for factors that generally cause analyst recommendations to change, such as stock prices, earnings surprises, and earnings forecasts, which indicate growth prospects as well as underlying quality. Below, we address this potential issue further with subsample analyses.

We perform a series of subsample analyses excluding high-growth/quality firms in turn. Since our sample size is relatively small, we take this approach instead of splitting our sample into high- or low-growth/quality groups. We use both financial and nonfinancial measures that indicate high growth/quality. For financial measures, we use return on assets (ROA) and price-to-earnings ratio (P/E ratio). ROA demonstrates how profitable a company is relative to its total assets and gives an idea as to how efficient the company is at using its assets to generate earnings. It is thus often used as a measure of firm quality (Chung & Luo, 2013; Stevens et al., 2015). P/E ratio measures how much investors are willing to pay per dollar of earnings and shows market expectations for a company's growth (Desarbo & Grewal, 2008; Lev & Nissim, 2004; Pandher & Currie, 2013). Since we are comparing companies in the same sector, both variables are especially useful in gauging firm quality and growth prospects. We perform our subsample analyses by excluding firms in the top 10 and 20% in terms of ROA and P/E ratio.

Nonfinancial measures are increasingly shown to have significant impacts on overall firm performance and growth (see, e.g., Henisz et al., 2014), and thus, nonfinancial variables can also provide important quality/growth considerations. We use several variables that indicate alternative dimensions of nonfinancial performance. Specifically, we use KLD scores on three dimensions: Corporate Governance, Community, and Environment scores (Chatterji & Toffel, 2010; Flammer, 2015; Perrault & Quinn, 2016). We exclude firms with the highest KLD scores in terms of their Corporate Governance, Community, and Environment performance and examine whether our main findings still hold. In addition, we make use of the Corporate Social Responsibility Index (CSRI) developed by the Reputation Index and the Boston College Center for Corporate Citizenship. The CSRI is based on the public's perception of firms along the dimensions of citizenship, governance and workplace. We exclude firms included in the list of *CSRI Top 50 Firms* and check the robustness of our results. Table 5 and Table A4 (Appendix 4) show the subsample analysis results using financial and nonfinancial measures, respectively.

Table 5 and Table A4 show that our main findings are robust across the subsample analyses. The significance and magnitude of our retweet and tweet variables of interest are similar to those in Table 4. These results corroborate that our main findings are not driven by omitted variables that indicate the growth potential of the firm or the quality of the firm.

Difference-in-Difference-in-Differences (DDD)

Our identification strategy for Hypothesis 3 rests on the assumption that changes in customer-initiated tweets are exogenous with respect to changes in analyst recommendations. This exogeneity assumption is again violated if omitted variables drive a spurious relationship between changes in customer-initiated tweets and analyst recommendations. To address this concern, we take a difference-in-differences approach, making use of a major weather event—Hurricane Irene—that prompted potential power loss for a significant number of customers and triggered a high volume of customer-initiated tweets. Since Hypothesis 3 is about the impacts of an unusually high volume of

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Table 5
Robustness checks: subsample analyses based on financial measures (ROA and PE Ratio)[a]

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Subsample analysis based on ROA – (1) Without top 2 firms (about 10%)								
Change in customer retweets × Customer			0.009	0.009				
satisfaction sensitivity			(0.003)	(0.003)				
Change in customer/CSR/rapport-building retweets							0.006	0.004
× Customer satisfaction sensitivity							(0.002)	(0.002)
Change in employment retweets		0.043		0.083		0.039		0.072
		(0.016)		(0.030)		(0.015)		(0.029)
Unusually high volume of customer-initiated	−1.100	−1.078	−1.146	−1.149	−1.093	−0.994	−1.128	−0.970
negative tweets (85th percentile)	(0.383)	(0.417)	(0.375)	(0.420)	(0.374)	(0.400)	(0.383)	(0.386)
× Public consumer advocates								
Unusually high volume of customer-initiated	1.107	0.725	0.726	0.518	1.122	0.697	0.883	0.614
positive tweets (85th percentile) × Public	(0.394)	(0.450)	(0.394)	(0.438)	(0.384)	(0.437)	(0.400)	(0.401)
consumer advocates								
Constant	0.326	0.278	0.579	0.615	0.316	0.252	0.460	0.484
	(0.384)	(0.381)	(0.377)	(0.372)	(0.382)	(0.381)	(0.379)	(0.373)
Observations	139	139	139	139	139	139	139	139
Panel B: Subsample analysis based on ROA – (2) Without top 3 firms (about 20%)								
Change in customer retweets × Customer			0.009	0.008				
satisfaction sensitivity			(0.003)	(0.003)				
Change in customer/CSR/rapport-building retweets							0.006	0.005
× Customer satisfaction sensitivity							(0.002)	(0.002)
Change in employment retweets		0.040		0.083		0.038		0.071
		(0.016)		(0.029)		(0.015)		(0.029)
Unusually high volume of customer-initiated	−1.043	−0.989	−1.107	−1.003	−1.029	−0.940	−1.068	−0.957
negative tweets (85th percentile) × Public	(0.396)	(0.419)	(0.389)	(0.417)	(0.390)	(0.411)	(0.407)	(0.409)
consumer advocates								
Unusually high volume of customer-initiated	1.189	0.822	0.847	0.564	1.204	0.792	0.962	0.722
positive tweets (85th percentile) × Public	(0.409)	(0.451)	(0.410)	(0.424)	(0.401)	(0.449)	(0.427)	(0.435)
consumer advocates								
Constant	0.270	0.200	0.522	0.573	0.267	0.196	0.418	0.463
	(0.397)	(0.396)	(0.390)	(0.379)	(0.395)	(0.397)	(0.391)	(0.386)
Observations	128	128	128	128	128	128	128	128
Panel C: Subsample analysis based on P/E ratio – (1) Without top 2 firms (about 10%)								
Change in customer retweets × Customer			0.010	0.009				
satisfaction sensitivity			(0.003)	(0.003)				
Change in customer/CSR/rapport-building retweets							0.006	0.004
× Customer satisfaction sensitivity							(0.002)	(0.002)
Change in employment retweets		0.039		0.094		0.039		0.087
		(0.014)		(0.031)		(0.013)		(0.030)
Unusually high volume of customer-initiated	−1.465	−1.301	−1.497	−1.360	−1.478	−1.329	−1.454	−1.232
negative tweets (85th percentile) × Public	(0.387)	(0.405)	(0.363)	(0.389)	(0.373)	(0.391)	(0.372)	(0.350)
consumer advocates								
Unusually high volume of customer-initiated	0.962	0.570	0.558	0.351	0.971	0.566	0.770	0.484
positive tweets (85th percentile) × Public	(0.378)	(0.410)	(0.366)	(0.377)	(0.362)	(0.397)	(0.364)	(0.334)
consumer advocates								
Constant	1.062	1.055	1.269	1.261	1.084	1.058	1.188	1.203
	(0.373)	(0.369)	(0.360)	(0.346)	(0.367)	(0.369)	(0.358)	(0.349)
Observations	140	140	140	140	140	140	140	140
Panel D: Subsample analysis based on P/E ratio – (2) Without top 3 firms (about 20%)								
Change in customer retweets × Customer			0.009	0.008				
satisfaction sensitivity			(0.003)	(0.003)				
Change in customer/CSR/rapport-building retweets							0.006	0.005
× Customer satisfaction sensitivity							(0.002)	(0.002)
Change in employment retweets		0.037		0.092		0.038		0.084
		(0.015)		(0.030)		(0.013)		(0.030)

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Table 5
(Continued)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unusually high volume of customer-initiated negative tweets (85th percentile) × Public consumer advocates	−1.448	−1.315	−1.484	−1.316	−1.451	−1.341	−1.425	−1.262
	(0.408)	(0.403)	(0.390)	(0.389)	(0.397)	(0.392)	(0.402)	(0.372)
Unusually high volume of customer-initiated positive tweets (85th percentile) × Public consumer advocates	0.996	0.646	0.664	0.409	1.000	0.609	0.778	0.539
	(0.401)	(0.420)	(0.393)	(0.388)	(0.388)	(0.400)	(0.395)	(0.366)
Constant	1.037	1.031	1.222	1.236	1.064	1.038	1.175	1.188
	(0.366)	(0.368)	(0.359)	(0.347)	(0.359)	(0.365)	(0.352)	(0.345)
Observations	129	129	129	129	129	129	129	129

[a] Subsample analyses of the models in Table 4. We only show relevant coefficients. Standard errors are in parentheses.

customer-initiated tweets on analyst recommendations in the presence of public consumer advocates, our variable of interest is two-way interaction, even before taking into account the weather event. Thus, in incorporating the weather event, we use a Difference-in-Difference-in-Differences (DDD) estimator instead of the usual Difference-in-Differences (Imbens & Wooldridge, 2007). A detailed explanation of our approach is provided in Appendix 5.

We ran the basic DDD model, including two separate variables for negative tweets and positive tweets, and replicated our main regressions in Table 4 with additional treatment-related variables. The results are shown Table A5-1 (Appendix 5). Consistent with our prior results, for customer-initiated negative tweets, the three-way interaction variable is highly significant and negative throughout alternative specifications, and for customer-initiated positive tweets, the coefficients are positive but not always significant. Overall, using a major weather event, Hurricane Irene, we confirm our prior findings that an unusually high volume of customer-initiated negative tweets has a significant negative impact on analyst recommendations in the presence of public consumer advocates.

We further conducted robustness checks for our DDD estimates using three sets of additional analyses: interactions between our main variables and time fixed effects, controlling for alterative stakeholder orientations, and addressing potential differences between the treatment and control group by using coarsened exact matching (Iacus, King, & Porro, 2012). Detailed explanation of the three sets of analyses and the results are provided in Appendix 5 and Table A5-2. Overall, the regression coefficients were similar to the main DDD estimates in terms of significance and magnitude.

Discussion and Conclusion

Social media has brought about significant changes in how people communicate. As an increasing number of firms adopt social media, how firms manage their stakeholders has also begun to change. Most of all, firms are under pressure to pay greater attention to individual voices, a development quite different from that of commonly studied cases of more organized stakeholders applying pressure, such as shareholder resolutions, NGOs, activists, and so on. This article focuses on this aspect and examines whether and how individual voices may influence analyst stock recommendations.

Given that social media is a low-cost form of communication, we argue that stakeholder response in the social media space plays a key role in differentiating the different levels of receptivity. Favorable stakeholder response indicates well-receivedness of firms' efforts to engage stakeholders, and thus, points to good firm-stakeholder relationships that can help improve firm performance by facilitating growth opportunities. Our results show that favorable reactions to firm-initiated messages significantly affect analyst stock recommendations depending on the messages' growth implications. Well-received messages that are directly related to growth have a relatively large positive impact on analyst recommendations straightaway. Well-received firm-initiated messages that are more indirectly related to growth have a relatively small significant impact and this impact is also moderated by the extent to which customer opinion matters for firm performance. In addition, our findings demonstrate the circumstances under which customer voices themselves matter. Securities analysts do consider customer-initiated messages when there is an unusually high volume of negative comments and there is an official channel by which consumer opinions are taken into account in regulatory and administrative decisions.

Our findings contribute to the literature on firm-stakeholder relationships in three respects. First, our findings suggest that it is important to take into account the two-sided nature of the firm-stakeholder relationship to accurately assess its impact on firm performance. We show that although firms attempt to proactively manage the changing stakeholder environment in the social media space, what matters for analyst stock recommendations is not how firms proactively manage stakeholders but how stakeholders in turn view firms' initiatives. This illustrates that incorporating stakeholders' reactions to firms' actions to address their concerns is an important step in understanding the impact of firm-stakeholder relationships on firm performance. Analyzing both sides provides a more complete picture of the potential influence of firm-stakeholder relationships on firm performance than just examining one-sided evidence.

Second, we show that there are returns to good firm-stakeholder relationships as manifested in the social media space, and demonstrate specific mechanisms by which these relationships matter through analyst stock recommendations. Furthermore, our findings show that the extent to which firms benefit from good firm-stakeholder relationships is not the same across companies, highlighting the importance of firm heterogeneity.

Third, the previous point in turn indicates that firms may have greater control over interactions with their stakeholders than previously recognized. In our context, firms are increasingly investing in managing customers in the social media space. For firms with a positive value of customer satisfaction sensitivity, this is a good thing. This investment is likely to lead to better firm performance, although whether this is the best use of limited resources has yet to be examined. However, for firms with a negative value of customer satisfaction sensitivity, our findings suggest that investing in managing customers in the social media space is likely to harm firm performance. Thus, instead of simply following the latest trend in social media, firms need to first understand their own customer satisfaction sensitivity, that is, how customers' opinions and satisfaction affect their firm's performance.

The findings of this article also suggest some future research directions. First, our findings show that stakeholders' reactions matter for analyst stock recommendations. However, we do not theoretically discuss what drives favorable stakeholders' reactions because our focus in this article is on how securities analysts make use of stakeholder feedback. Future research can enhance our understanding of the implications of firm-stakeholder relationships for firm performance by looking into the drivers of favorable stakeholders' reactions.

Second, prior studies tend to assume that relevant and important stakeholders are externally determined. Our work suggests that this may not necessarily be the case. For example, firms may inadvertently engage and empower stakeholders by opening social media accounts. A potential next step is to see whether stakeholders who have risen to higher status by their own efforts versus by firms' facilitation have any differential impact on firms in terms of firm responsiveness. It is conceivable that claims from stakeholders who have risen to higher status through firms' facilitation are more readily anticipated because firms are well aware of their increased salience, whereas claims from stakeholders who have risen to higher status through their own efforts present more of a surprise. Are firms better prepared to deal with requests from those stakeholders who have risen to higher status through firms' facilitation?

Third, we find that even unsubstantiated customer-initiated postings can have a significant impact on analyst recommendations when there is a high volume of negative feedback and an institutional structure that values consumer opinions. Further exploring what prompts external stakeholders such as customers to initiate negative postings in the social media space should deepen our understanding of the circumstances under which customer opinions affect firm value. In addition, alternative channels other than a formal institutional structure might help magnify the impact of customer feedback.

Fourth, our limitations include small sample size. Our findings are based on a sample of 16 firms. Although this does not invalidate our approach or findings, larger scale future research would help substantiate our results. Also, it would be valuable to study whether our findings are robust to other

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industry contexts, and if there is any difference, what drives the difference. We attempt to control for industry effects using seasonal dummies because operations in the electric utility industry are particularly vulnerable to weather conditions. Yet, this may not fully address potential industry effects. In particular, our setting could lead us to underestimate the significance or the size effect of individual consumers on social media usage because the extent of marketing is limited in our context as electric power companies produce a commodity, although consumers might opt for renewable electricity. Relatedly, the link between customer satisfaction and firm performance may be underestimated in the electric power industry compared to other industries such as consumer goods industries.

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Supporting Information

Additional supporting information may be found in the online version of this article:

Appendix 1. Tweets and Retweets: Variance Across and Within Firms.
Table A1. Monthly Mean and Standard Deviation of Tweets, Retweets, and Retweets/Tweets.
Appendix 2
Table A2. Summary Results for H3: Alternative Percentiles for Unusually High Volume of Customer-initiated Negative (Positive) Tweets.
Appendix 3
Table A3. Descriptive Statistics and Correlations.
Appendix 4
Table A4. Robustness Checks: Subsample Analyses based on Non-financial Measures (KLD & CSRI).
Appendix 5. Robustness Checks using Difference-in-Difference-in-Differences (DDD).
Table A5-1. Summary of Difference-in-Difference-in-Differences (DDD) Models.
Table A5-2. Summary of Robustness Checks for the Difference-in-Difference-in-Differences (DDD) Models.
Table A5-3. T-Tests on the Pre-Treatment Average Values between the Control and Treatment Group.