Customer Reactions and Analyst Stock Recommendations: Evidence from S&P 500 Electric Power Companies' Twitter Accounts

Eun-Hee Kim
(George Washington University)

Yoona Youm
(George Washington University)

ABSTRACT

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, non-governmental organizations and activists and does not incorporate the emerging possibility that individual voices such as customer voices may matter. By exploring corporate Twitter accounts, where customers can provide feedback on an ongoing basis, we show the importance of customer voices. Specifically, we demonstrate how customers' reactions to firm-initiated messages and their own messages influence 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 in cases of high volume, due to their unsubstantiated nature.

Keywords: Social media, firm-stakeholder relationship, stakeholder reactions, customers, analyst recommendations

INTRODUCTION

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 (Clarkson, 1995; Eesley and Lenox, 2006; Freeman, 1984; Mitchell, Agle, and Wood, 1997), how firms address stakeholder demands (David, Bloom, and Hillman, 2007; King, 2008; Murillo-Luna, Garcés-Ayerbe, and Rivera-Torres, 2008; Reid and Toffel, 2009), and whether firm-stakeholder relationships matter for financial performance (Margolis and Walsh, 2003). We seek to shed new light on these questions by exploring the ramifications of increased salience of individual customers in the social media space. A growing number of firms have begun using social media such as Twitter and Facebook. Notably, social media has brought about significant changes in how firms communicate with their stakeholders. 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 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, etc.

Together, these idiosyncrasies present an excellent opportunity to study the link between firm-stakeholder relationships and financial 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 Kinder, Lydenberg, Domini (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 and 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 and Nartey, 2013). The interactive nature of social media allows us to explore how stakeholders' reactions to firms' actions, i.e., 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 in examining their implications for firm performance. 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 *et al.*, 1997). Firms' use of social media enables individual customers to increase power, and possibly urgency, vis-a-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 and 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 paper, 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, Kim, Krische, and Lee, 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.*, 2013), by lowering transaction costs and easing capital constraints (Cheng, Ioannou, and Serafeim, 2014; Sharfman and Fernando, 2008), or by facilitating efficient use of resources to create greater value for customers (Harrison, Bosse, and Phillips, 2010). Based on prior work on social media, we argue that popularity in the social media space can point to good firm-stakeholder relationships. In particular, we propose that 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 (see for example, Verrecchia, 1983). 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, and other contextual factors (Anderson, Fornell, and Lehmann, 1994; Anderson and 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 and O'Sullivan, 2014). Thus, we propose 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, and we find support for this argument. This finding suggests 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 implies 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 towards 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,

[1] We list several reasons why this is the case in our empirical context in the next paragraph and describe them in more detail on pages 11-12 and in Table 1.

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 on pages 11-12 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. In doing so, we differentiate between messages that are directly and those that are indirectly related to growth. Next, we consider how customer-initiated messages may influence analyst recommendations, as customers may also initiate a conversation. We proxy customers' favorable reactions using retweets of firm-initiated messages (Kwak *et al.*, 2010; Starbird *et al.*, 2010) and examine how changes in retweets relate to changes in analyst stock recommendations.

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, it has been demonstrated that earnings surprises and earnings forecasts are important factors in gauging the value of firms (Berhardt and Campello, 2007; Francis and

Soffer, 1997; Gleason and Lee, 2003; Jegadeesh and 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 and Lee, 2003). Earnings forecasts indicate growth prospects as well as underlying firm values, and thus play an important role in making stock recommendation decisions (Bandyopadhyay, Brown and Richardson, 1995; Berhardt and Campello, 2007; Block, 1999; Bradshaw, 2004; Chatfield, Moyer and Sisneros, 1989; Francis and Soffer, 1997; La Porta, R, 1996; Sharpe, 2005).

In addition, Jegadeesh *et al.* (2004) show 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 finds that analysts favor growth as a primary determinant of favorable recommendations. He specifically shows 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 out this possibility, we held informal conversations with several people in the financial industry. The quote below sums up 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 popularity in the social media space 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 (Al-Tuwaijri, Christensen, and Hughes, 2004; Patten, 1991, 1992; Verrecchia, 1983). 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] The propensity to selectively disclose favorable information can foster a positive image for external stakeholders (Cohen, Holder-Webb, Nath, and Wood, 2011; Dhaliwal, Li, Tsang, and Yang, 2011) and help improve stakeholder engagement and strengthen firm-stakeholder relationships (Lee and Sweeney, 2015; Neu, Warsame, and 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.*, 2013). Thus, enhanced support from external stakeholders increases investors' valuation of the firm (Henisz *et al.*, 2013). 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 and 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

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

valuable assets which can be sources of competitive advantage (Hillman and Keim, 2001). Thus, from an analyst's perspective, 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, give a good impression to securities analysts, which in turn may lead them to develop favorable evaluations of a firm. In taking into account stakeholders' propagation of firm-initiated messages, we further postulate that securities analysts differentiate those that are directly related to growth and those that are more indirectly related to growth via valuable firm-stakeholder relationships. Whereas those that are directly related to growth and well received may be viewed positively straightaway, a recent study by O'Connell and O'Sullivan (2014) suggests that those that are well received but more indirectly related to growth may be considered more conditionally.

Their findings suggest that the extent to which firm-stakeholder relationships relate to firm performance differs across firms. Specifically, O'Connell and O'Sullivan (2014) show that customer satisfaction has varying implications for firm performance even within the same industry. 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 thirty-two state PUCs that responded to

[Insert Table 1 about here]

our request have revealed that how customer satisfaction may relate 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 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 and under this mechanism, 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 a revenue decoupling mechanism. In addition, 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 the ratings into account in rewarding or penalizing utility companies.

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

[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 ORU power co.) (New York State Department of Public Service). In Maine, the average switching rate 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).

mentioned earlier, customers can be definite stakeholders in the social media space and are primary participants in firms' social media accounts (McKinsey Quarterly, 2012). They tend to publicly express their opinions in the social media space (Hennig-Thurau *et al.*, 2010; Jansen *et al.*, 2009).

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. We thus hypothesize that firm-initiated messages viewed favorably and propagated in the social media space have positive effects on analyst recommendations in alternative ways, depending on whether the messages are directly related to growth or not.

H1: Customers' favorable reactions to firm-initiated messages that are directly related to growth have a positive impact on analyst stock recommendations.

H2: Customers' favorable reactions to firm-initiated messages that are not directly related to growth have a positive impact on analyst stock recommendations, depending on the extent to which customers' opinions matter 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, and 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, thirty-three 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 relevant information to regulatory agency commissioners and staff and potentially to

[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] http://venturebeat.com/2011/03/17/study-social-media-popularity-can-predict-stock-prices/
[8] http://stocktwits.com/research/social-media-and-markets-the-coming-of-age.pdf

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, i.e., the presence of formal consumer advocates.

H3: 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 explore 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 of these observations, one of the control variables was missing,[9] so we made use of 153 firm-month observations with a total of 9,307 tweets.

To explore tweet content, content analysis was necessary. Computer-aided content analysis is often used in analyzing news articles (see, Bednar (2012) for example). We explored this option, but perhaps due to the brevity of Twitter messages 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 contained 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.

[Insert Figure 1 about here]

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.[10] More detailed descriptions of each category are shown in Figure 1. Regarding inter-coder reliability, Cohen's kappa (Cohen, 1960) was 0.75.[11] According to Banerjee, *et al.* (1999), a Cohen's kappa of 0.75 or more represents

[9] For one firm-month observation (Public Service Enterprise Group, February 2011), the residential sales/total sales variable was missing.
[10] In our empirical analysis, we make use of not only each individual category but also its combinations to account for the possibility that categories other than customers, such as CSR or rapport-building, may also be relevant to customers.
[11] The content analysis was carried out by the authors and two research assistants. The research assistants went through two training sessions; in the first session the coding scheme was explained, and the research assistants

excellent agreement, and Kvalseth (1989) notes 0.61 as representing reasonably good overall agreement.

To test our hypotheses, we combined the firm-month tweet content data 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 non-varying factors, but it was not possible to use these because the data used in constructing the extent to which 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 make use of change-change specifications and use GLS estimations to address autocorrelation and heteroskedasticity concerns.[12] 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 Appendix S2 and Appendix S3, we conducted a series of extensive robustness tests.

Dependent Variable

conducted content analysis on actual tweets. In the second session, misclassifications were discussed along with clarifications of the coding scheme. The research assistants coded 9,516 tweets, and one of the authors coded 8,185 of the total of 11,278 tweets (84% and 73%, respectively).

[12] We tested for heteroskedasticity with the modified Wald statistic for groupwise heteroskedasticity, and the results were significant across all models (p-value < .000), suggesting a strong presence of heteroskedasticity. The p-values following the Wooldridge test for autocorrelation in panel data were greater than 0.05, suggesting that significant autocorrelations are not present in the models; in all models, continuous variables are mean-centered when interacted with other variables due to multicollinearity concerns (Aiken and West, 1991; Cohen et al., 2002).

Change in analyst stock recommendations. We use recommendation revisions, not levels, because previous research shows that recommendation changes are more informative than levels (Boni and Womack, 2006; Jegadeesh and 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 compute 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 proxy 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.[13] We manually checked each tweet that received retweets and confirmed that such tweets contained favorable messages regarding the firm. In line with our hypotheses H1 and H2, which differentiate customers' favorable reactions to firm-initiated tweets that are directly related to growth vs. not 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 proxy 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, firm-initiated employment tweets seem less subject to selective disclosure bias, discussed earlier, than firm-initiated investor tweets. So, we use changes in retweets of

[13] Table S1-1 (Appendix S1) 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 S1 with Table S1-1.

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 indirectly related to growth* (*Change in customer retweets* and *Change in customer/CSR/rapport-building retweets*).** For firm-initiated messages indirectly related to growth, we use alternative measures because firm-initiated tweets other than those categorized as "customers" may also affect customers' perception of a company. Thus, we use two alternative variables: 1) change in retweets of customer tweets, and 2) change in retweets of customer tweets, CSR tweets, and rapport-building tweets. The variables are expressed in firm-month units.

Unusually high volume of customer-initiated negative (positive) tweets. We measure an unusually high volume of customer-initiated negative (positive) tweets using a binary variable that indicates unusual changes in customer-initiated negative (positive) tweets. We first calculate changes in customer-initiated negative (positive) tweets compared to the prior month and then for each month identify change values that fall above a percentile threshold.[14] For example, *Change in customer-initiated negative tweets (85th percentile)* refers to a binary variable indicating 1 for changes greater than the 85^{th} percentile in customer-initiated negative tweets compared to the prior month, and 0 otherwise. We use the 85^{th} percentile threshold in Table 5 and show the results for H3 using alternative threshold values, the 70^{th}, 75^{th}, 80^{th}, 85^{th}, and 90^{th} percentiles, in Table 6. They are expressed in firm-month units.

Public consumer advocates. We operationalize the institutional structure that supports consumer protection by using data on public consumer advocates. Thirty-three states employ

[14] We did not know a priori exactly where the threshold is. Thus, we explored alternative threshold values, the 70^{th}, 75^{th}, 80^{th}, 85^{th}, and 90^{th} percentiles, and found that the 85^{th} percentile is the relevant threshold. Accordingly, in Table 6, we show regression results using the 85^{th} percentile.

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 use this data, which is state-specific and does not vary over time. We construct a firm-level *Public consumer advocate* variable by taking into account where each subsidiary of a given firm operates. Specifically, we calculate 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 estimate 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 measure customer satisfaction using the American Customer Satisfaction Index (ACSI) and firm performance using return on assets (ROA), also following O'Connell and Sullivan (2014).

$$One-period-ahead\ ROA = \alpha_0 + \alpha_1 Customer\ satisfaction + \alpha_2 ROA + \alpha_3 One-period-lagged\ ROA + \alpha_4 Stock\ Returns + \alpha_5 One-period-lagged\ Stock\ Returns$$

The *Customer satisfaction sensitivity* variable corresponds to the coefficient for *Customer satisfaction* (i.e., α_1) for each firm. We use 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 estimate *Customer satisfaction sensitivity* using three models, as displayed in Table 2 (Panel A) and explained below.

[Insert Table 2 about here]

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 and 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 values of the dependent variable (Greene, 2003).[15] 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 0.1 as shown in Table 2 (Panel B).[16] 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 and Larcker, 1998; Fornell *et al.*, 2006).

---

[15] 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.

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

Control Variables

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

[Insert Table 3 about here]

Following prior literature, we control for factors that are likely to cause changes in analyst recommendations. Analysts' recommendations basically reflect price-to-value comparisons (Conrad, et al, 2006; Francis and 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 control for three measures (Francis and Soffer, 1997; Jegadeesh and 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 calculate the actual quarterly earnings minus the analyst forecast that is closest to and prior to the quarterly earnings announcement (Brown, 2001). Next, we adjust this value by stock price, which is the stock price of the final month of the forecasted quarter (Skinner and Sloan, 2002).

In addition, we control for firm size as measured by firm assets because analysts are likely to consider firms' financial resources in making evaluations of the firm (Benner and Ranganathan, 2013). We also include growth and momentum factors as they are related to stock returns (Cahart, 1997; Fama and French, 1993). Moreover, we include 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 construct the *Deregulation* variable based on prior studies (Delmas, Russo, and Montes-Sancho, 2007; Kim, 2013). 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 seek 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 control for changes in retweets of other types of firm-initiated tweets. Specifically, for models using *Changes in customer retweets* in testing H2, we control for changes in retweets of investor tweets, CSR tweets, and rapport-building tweets. For models using the alternative measure, *Changes in customer/CSR/rapport-building retweets* in testing H2, we control for changes in retweets of investor tweets.

RESULTS

Descriptive statistics and correlations are shown in Table 4.

[Insert Table 4 about here]

The correlations among variables are generally low. A notable exception is the correlation between *Change in customer retweets* and *Change in customer/CSR/rapport-building retweets* (correlation 0.97) 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 individual 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 use (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).

Table 5 shows GLS regressions results predicting changes in analyst recommendations.

[Insert Table 5 about here]

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 5 provide strong support for H1, 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 $p < 0.01$, 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 $\beta = 0.065$, $p < 0.05$. However, the interaction term, *Change in employment retweets* × *Customer satisfaction sensitivity*, is generally not significant (it is weakly significant in model 4 with $\beta = 0.313$, $p < 0.1$ and insignificant in model 8 with $\beta = 0.241$, $p = 0.190$). 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, i.e., 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* ($\beta = 0.040$, $p < 0.01$), the results show that when employment retweets increase by 10 retweets, analyst stock recommendations increase by 0.4.

H2 tests the conditional impact of firm-initiated messages that are indirectly related to growth depending on the extent to which customers' opinions matters for firm performance. We find support for H2 as the interaction term *Change in customer retweets* × *Customer satisfaction sensitivity* is positive and significant (model 4: $\beta = 0.008$, $p < 0.01$), which is also true for the interaction term *Change in customer/CSR/rapport-building retweets* × *Customer satisfaction sensitivity* (model 8: $\beta = 0.004$, $p < 0.01$). 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 = 0.2084).

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,[17] when customer retweets (retweets of firm-initiated tweets relevant to customers) increase by 10 retweets, analyst stock recommendations increase by 0.011.[18] 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.[19] 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 H3, 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 < 0.01). 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 = 0.302). Thus, for customer-initiated positive tweets, empirical evidence is weak.

[17] As shown in Table 4, *Customer satisfaction sensitivity* of 0.2 or -0.2 is about one standard deviation higher or lower than the mean.

[18] 0.011 = -0.0005×10(change in retweets) + 0.008×10(change in retweets)×0.2(Customer satisfaction sensitivity)

[19] -0.021 = -0.0005×10(change in retweets) + 0.008×10(change in retweets)×-0.2(Customer satisfaction sensitivity)

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 6 displays a summary of the results for H3 using the alternative threshold values, specifically the 70th, 75th, 80th, 85th, and 90th percentiles. For convenience, Table 6 displays the coefficients and standard deviations only for our variables of interest.

[Insert Table 6 about here]

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 5.

ROBUSTNESS CHECKS

There are credible alternatives to our argument that changes in retweets of firm-initiated tweets (for H1 and H2) and changes in customer-initiated tweets (for H3) cause changes in analyst recommendations. In the following, we discuss potential identification concerns and describe how we address them.

Sub-sample analyses

Our identification strategy for H1 and H2 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 and 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 and Grewal, 2008; Lev and Nissim, 2004; Pandher and 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 for example, 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 and Toffel, 2010; Flammer, 2015; Perrault and 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. Tables 7 and 8 show the regression results of our subsample analyses using financial and nonfinancial measures, respectively.

[Insert Tables 7 about here]

[Insert Tables 8 about here]

Tables 7 and 8 show that our main findings are robust across the alternative subsample analyses. The significance and magnitude of our retweet and tweet variables of interest are similar to those in Table 5. 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 H3 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 H3 is about the impacts of an unusually high volume of 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 and Wooldridge, 2007). A detailed explanation of our approach is provided in Appendix S2.

We ran the basic DDD model, including two separate variables for negative tweets and positive tweets, and replicated our main regressions in Table 9 with additional treatment-

[Insert Table 9 about here]

related variables. 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 and Porro, 2012). Detailed explanation of the three sets of analyses and the results are provided in Appendix S3. 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, etc.

This paper focuses on the increased salience of customer voices in the social media space and its implications. By opening social media accounts, firms facilitate movement of individual customers to a higher stakeholder class by providing them with power and perhaps a greater sense of urgency. We demonstrate that customer voices have a significant influence on analyst stock recommendations through specific mechanisms. Regarding firm-initiated messages, favorable customer reactions to firms' postings on their social media accounts significantly influence analyst stock recommendations depending on whether firms' postings are directly related to growth or not. Well-received firm-initiated messages that are directly related to growth have a relatively large positive impact on analyst recommendations straightaway. Well-received firm-initiated messages that are not directly related to growth have a relatively small significant impact on analyst stock recommendations, depending on the extent to which customers' opinions matter to firm performance. Concerning customer-initiated messages, securities analysts take them seriously 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 two-sided information provides a more complete picture of the potential influence of firm-stakeholder relationships on firm performance than just examining one-sided evidence.

Second, prior literature tends to assume a uniform effect of firm-stakeholder relationships on firm performance, whether positive or negative, and pays little attention to how firm heterogeneity might play a role in the link between firm-stakeholder relationships and firm performance. Our findings suggest that firm heterogeneity is an important factor to take into account: good firm-stakeholder relationships can improve firm performance for some firms but can also lead to performance deterioration for other firms. For the latter firms, investing in improving firm-stakeholder relationships may be a waste of limited resources. Firm heterogeneity may help solve a long-standing empirical puzzle, i.e., mixed results on the link between firm-stakeholder relationships and firm performance.

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 affects their firm's performance.

The findings of this paper 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 paper 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 more deeply 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 vs. 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 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.

Firms are increasingly adopting social media, which accompanies changes in how firms communicate with their stakeholders. Our exploration of firm-stakeholder relationships on social media, in particular Twitter, enabled us to examine the increased salience of individual stakeholders, in particular, different mechanisms by which customer voices may matter for firm performance via stock analyst recommendations. Moreover, our work highlights the importance of taking into account firm heterogeneity in better understanding the link between firm-stakeholder relationship and firm performance.

REFERENCES

Aiken LS, West SG. 1991. Multiple regression: testing and interpreting interactions. Sage: Thousand Oaks, CA.

Al-Tuwaijri SA, Christensen TE, Hughes KE. 2004. The relations among environmental disclosure, environmental performance, and economic performance: a simultaneous equations approach, *Organizations and Society* **29**(5-6): 447-471.

Anderson EW, Fornell C, Lehmann DR. 1994. Customer satisfaction, market share, and profitability: findings from Sweden. *The Journal of Marketing* **58**(3): 53-66.

Anderson EW, Mansi SA. 2009. Does customer satisfaction matter to investors? Findings from the bond market. *Journal of Marketing Research* **46**(5): 703-714.

Bandyopadhyay SP, Brown LD, Richardson GD. 1995. Analysts' use of earnings forecasts in predicting stock returns: Forecast horizon effects. *International Journal of Forecasting* **11**(3): 429-445.

Banerjee M, Capozzoli M, McSweeney L, Sinha D. 1999. Beyond kappa: a review of interrater agreement measures. *The Canadian Journal of Statistics* **27**(1): 3-23.

Banker RD, Lee SY, Potter G, Srinivasan D. 1996. Contextual analysis of performance impacts of outcome-based incentive compensation. *Academy of Management Journal* **39**(4):920-948.

Bednar MK. 2012. Watchdog or lapdog? A behavioral view of the media as a corporate governance mechanism. *Academy of Management Journal* **55**(1): 131-150.

Benner MJ, Ranganathan R. 2013. Divergent reactions to convergent strategies: Investor beliefs and analyst reactions during technological change. *Organization Science* **24**(2): 378-394.

Bernhardt D, Campello M. 2007. The dynamics of earnings forecast management. *Review of Finance* **11**(2): 287-324.

Block SB. 1999. A study of financial analysts: Practice and theory. *Financial Analysts Journal* **55** (4): 86-95.

Boni L, Womack KL. 2006. Analysts, Industries, and Price Momentum. *Journal of Financial & Quantitative Analysis* **41**(1):85–109.

Bradshaw MT. 2004. How Do Analysts Use Their Earnings Forecasts in Generating Stock Recommendations? *The Accounting Review* **79**(1): 25-50.

Brown LD. A 2001. A temporal analysis of earnings surprises: Profits versus losses. *Journal of Accounting Research* **39**(2): 221-241.

Carhart MM. 1997. On persistence in mutual fund performance. *Journal of Finance* **52**(1):57-82.

Chatterji AK, Toffel MW. 2010. How firms respond to being rated. *Strategic Management Journal* **31**(9):.917-945.

Chatfield RE, Moyer RC, Sisneros PM. 1989. The Accuracy of Long-Term Earnings Forecasts for Industrial Firms. *Quarterly Journal of Business and Economics* **28**(3): 91–104.

Cheng B, Ioannou I, Serafeim G. 2014. Corporate Social Responsibility and Access to Finance. *Strategic Management Journal* **35**(1): 1-23.

Chung CN, Luo XR. 2013. Leadership succession and firm performance in an emerging economy: Successor origin, relational embeddedness, and legitimacy. *Strategic Management Journal* **34**(3), 338-357.

Clarkson ME. 1995. A stakeholder framework for analyzing and evaluating corporate social performance. *Academy of Management Review* **20**(1): 92-117.

Cohen J. 1960. A coefficient of agreement for nominal scales. *Educational and Psychological Measurement* **20**(1): 37-46.

Cohen J, Cohen P, West SG, Aiken LS. 2002. *Applied multiple regression/correlation analysis for the Behavioral Sciences*. Mahwah, NJ: Erlbaum.
Cohen J, Holder-Webb L, Nath L, Wood D. 2011. Retail investors' perceptions of the decision-usefulness of economic performance, governance, and corporate social responsibility disclosures. *Behavioral Research in Accounting* **23**(1): 109-129.
Conrad J, Cornell B, Landsman WR., Rountree BR. 2006. How do analyst recommendations respond to major news? *Journal of Financial and Quantitative Analysis* **41**(1): 25-49.
Coombs WT. 1998. The Internet as potential equalizer: new leverage for confronting social irresponsibility. *Public Relations Review* **24**(3): 289-303.
David P, Bloom M, Hillman AJ. 2007. Investor activism, managerial responsiveness, and corporate social performance. *Strategic Management Journal* **28**(1): 91-100.
Delmas M, Russo MV, Montes-Sancho MJ. 2007. Deregulation and environmental differentiation in the electric utility industry. *Strategic Management Journal* **28**(2): 189-209.
Desarbo WS, Grewal R. 2008. Hybrid strategic groups. *Strategic Management Journal* **29**(3)**:** 293-317.
Dhaliwal DS, Li OZ, Tsang A, Yang YG. 2011. Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. *The Accounting Review* **86**(1): 59-100.
Eesley C, Lenox MJ. 2006. Firm responses to secondary stakeholder action. *Strategic Management Journal* **27**(8): 765-781.
Fama EF, French KR. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* **33**(1): 3–56.
Flammer C. 2015. Does product market competition foster corporate social responsibility? Evidence from trade liberalization. *Strategic Management Journal* **36**(10):1469-1485.
Fornell C, Mithas S, Morgeson FV, Krishnan MS. 2006. Customer satisfaction and stock prices: high returns, low risk. *Journal of Marketing* **70**(1): 3-14.
Francis J, Soffer L. 1997. The relative informativeness of analysts' stock recommendations and earnings forecast revisions. *Journal of Accounting Research* **35**(2): 193-211.
Freeman RE. 1984. *Strategic management: A stakeholder approach*. Boston, MA: Pitman.
Fremeth AR, Holburn GLF, Spiller PT. 2014. The impact of consumer advocates on regulatory policy in the electric utility sector. *Public Choice* **161**(1): 157-181.
Gleason CA, Lee CM. 2003. Analyst forecast revisions and market price discovery. *The Accounting Review* **78**(1): 193-225.
Graves SB, Waddock SA. 1994. Institutional owners and corporate social performance. *Academy of Management Journal* **37**(4): 1034-1046.
Greene WH. 2003. *Econometric analysis*. Prentice Hall: Upper Saddle River, NJ.
Harrison JS, Bosse DA, Phillips RA. 2010. Managing for stakeholders, stakeholder utility functions, and competitive advantage. *Strategic Management Journal* **31**(1): 58-74.
Henisz WJ, Dorobantu S, Nartey LJ. 2013. Spinning gold: the financial returns to stakeholder engagement. *Strategic Management Journal* **35**(12): 1727-1748.
Hennig-ThurauT, Malthouse EC, Friege C, Gensler S, Lobschat L, Rangaswamy A, Skiera B. 2010. The impact of new media on customer relationships. *Journal of Service Research* **13**(3): 311-330.
Hillman AJ, Keim GD. 2001. Shareholder value, stakeholder management, and social issues: what’s the bottom line? *Strategic Management Journal* **22**(2): 125-139.

Iacus SM, King G, Porro G. 2012. Causal Inference without Balance Checking: Coarsened Exact Matching. *Political Analysis* 20:1-24
Illinois Commerce Division. http://www.pluginillinois.org/MunicipalAggregationList.aspx
Ittner CD, Larcker DF. 1998. Are nonfinancial measures leading indicators of financial performance?An analysis of customer satisfaction. *Journal of Accounting Research* **36**:1-35.
Imbens G, Wooldridge J. 2007. *What's New in Econometrics: Difference-in-Differences Estimation*. Lecture Notes 10. Cambridge, MA: National Bureau of Economic Research.
Jansen BJ, Zhang M, Sobel K, Chowdury A. 2009. Twitter power. *Journal of the American Society for Information Science and Technology* **60**(11): 2169-2188.
Jegadeesh N, Kim J, Krische SD, Lee C. 2004. Analyzing the analysts: When do recommendations add value? *The Journal of Finance* **59**(3): 1083-1124.
Jegadeesh N, Kim W. 2010. Do analysts herd? An analysis of recommendations and market reactions. *Review of Financial Studies* **23**(2): 901–937.
J.D. Power and Associates. 2012. How customer satisfaction drives return on equity for regulated electric utilities. *J.D. Power and Associates, The McGraw-Hill Companies, Inc.*
Joskow PL. 2005. The Difficult Transition to Competitive Electricity Markets in the United States. In Electricity Deregulation, Griffin JM, Puller SL (eds.). Chicago, IL: 31-98.
Kim EH. 2013. Deregulation and differentiation: incumbent investment in green technologies. *Strategic Management Journal* **34**(10): 1162-1185.
King BG. 2008. A political mediation model of corporate response to social movement activism. *Administrative Science Quarterly* **53**(3): 395-421.
Kvalseth TO. 1989. Note of Cohen's Kappa. *Psychological Reports* **65**(1): 223-226.
Kwak H, Lee C, Park H, Moon S. 2010. What is Twitter, a social network or a news media? In *Proceedings of the 19th international conference on World Wide Web*, Raleigh, NC.
La Porta R. 1996. Expectations and the cross-section of stock returns. *The Journal of Finance* **51**(5): 1715-1742.
Lee WE, Sweeney JT. 2015. Use of discretionary environmental accounting narratives to influence stakeholders. *Journal of Business Ethics* **129**(3): 673-688.
Lev B, Nissim D. 2004. Taxable income, future earnings, and equity values. *The Accounting Review* **79**(4), 1039-1074.
Lotan G, Graeff E, Ananny M, Gaffney D, Pearce I, Boyd D. 2011. The revolutions were tweeted: information flows during the 2011 Tunisian and Egyptian Revolutions. *International Journal of Communication* **5**: 1375-1405.
Luo X, Wang H, Raithel S, Zheng Q. 2015. Corporate social performance, analyst stock recommendations, and firm future returns. *Strategic Management Journal* **36**(1): 123-136.
Maine Public Utilities Commission. http://www.maine.gov/mpuc/electricity/choosing_supplier/migration_statistics.shtml
Margolis JD, Walsh JP. 2003. Misery loves companies: rethinking social initiatives by business. *Administrative Science Quarterly* **48**(2): 268-305.
McKinsey Quarterly. 2012. Demystifying social media. April. Issue2: 66-77.
Mitchell RK, Agle BR, Wood DJ. 1997. Toward a theory of stakeholder identification and salience: defining the principle of who and what really counts. *Academy of Management Review* **22**(4): 853-886.
Murillo-Luna JL, Garcés-Ayerbe C, Rivera-Torres P. 2008. Why do patterns of environmental response differ? A stakeholders' pressure approach. *Strategic Management Journal* **29**(11):

1225-1240.
Neu D, Warsame H, Pedwell K. 1998. Managing public impressions: environmental disclosures in annual reports. *Accounting, Organizations and Society* **23**(3): 265-282.
New York State Department of Public Service. http://www3.dps.ny.gov/W/PSCWeb.nsf/All/441D4686DF065C5585257687006F396D?OpenDocument
Newey WK, West KD. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* **55**(3): 703-708.
O'Connell V, O'Sullivan D. 2014. The influence of lead indicator strength on the use of nonfinancial measures in performance management: evidence from CEO compensation schemes. *Strategic Management Journal* **35**(6), 826-844.
Pandher G, Currie R, 2013. CEO compensation: A resource advantage and stakeholder-bargaining perspective. *Strategic Management Journal*,**34**(1), pp.22-41.
Patten DM. 1991. Exposure, legitimacy, and social disclosure. *Journal of Accounting and Public Policy* **10**(4): 297-308.
Patten DM. 1992. Intra-industry environmental disclosures in response to the Alaskan oil spill: a note on legitimacy theory. *Accounting, Organizations and Society* **17**(5): 471-475.
Perrault E, Quinn MA. 2016. What Have Firms Been Doing? Exploring What KLD Data Report About Firms' Corporate Social Performance in the Period 2000-2010. *Business & Society* DOI: 0007650316648671.
Reid EM, Toffel MW. 2009. Responding to public and private politics: corporate disclosure of climate change strategies. *Strategic Management Journal* **30**(11): 1157-1178.
Rowley TJ. 1997. Moving beyond dyadic ties: a network theory of stakeholder influences. *Academy of Management Review* **22**(4): 887-910.
Schipper K. 1991. Analysts' forecasts. *Accounting Horizons* **5**(4): 105-121.
Sharfman MP, Fernando CS. 2008. Environmental risk management and the cost of capital. *Strategic Management Journal* **29**(6): 569-592.
Sharpe SA. 2005. How does the market interpret analysts' long-term growth forecasts? *Journal of Accounting, Auditing & Finance* **20**(2): 147-166.
Skinner DJ, Sloan RG. 2002. Earnings surprises, growth expectations, and stock returns or don't let an earnings torpedo sink your portfolio. *Review of accounting studies* **7**(2-3):289-312.
Starbird K, Palen L, Hughes AL, Vieweg S. 2010. Chatter on the red: what hazards threat reveals about the social life of microblogged information. In *Proceedings of the 2010 ACM conference on Computer supported cooperative work (pp. 241-250),* Savannah, GA.
Stevens R, Moray N, Bruneel J, & Clarysse B. 2015. Attention allocation to multiple goals: The case of for-profit social enterprises. *Strategic Management Journal* **36**(7), 1006-1016.
Stickel SE. 1985. The effect of Value Line investment survey rank changes on common stock prices. *Journal of Financial Economics* **14**(1):121-143.
Treem JW, Leonardi PM. 2012. Social media use in organizations: exploring the affordances of visibility, editability, persistence, and association. In *Communication Yearbook 36*, Salmon CT (eds). Routledge: New York, N.Y.: 143-189.
Van Liere D. 2010. How far does a tweet travel?: Information brokers in the twitterverse. *Proceedings of the International Workshop on Modeling Social Media. ACM, 2010.*
Verrecchia RE. 1983. Discretionary disclosure. *Journal of Accounting and Economics* **5**:179-194.
Womack KL. 1996. Do brokerage analysts' recommendations have investment value*? The Journal of Finance* **51**(1): 137-167.

Table 1. Customer satisfaction and firm performance: sample responses from 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 7 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 NY. 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 fifty states we contacted for interviews, thirty-two responded to our request. Interviews were conducted via phone and/or email for the following thirty-two 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 between 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.

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	
Firms	*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 vs. OLS		OLS vs. ARIMA		ARIMA vs. GLS	
Firms	*t*-statistic	*p*-value	*t*-statistic	*p*-value	*t*-statistic	*p*-value
Ameren	0.742	0.458	0	1	-0.265	0.791
American Electric Power	0.060	0.952	0	1	-0.083	0.934
Consolidated Edison	0.149	0.882	0	1	-0.092	0.927
DTE Energy	-0.105	0.916	0	1	0.089	0.929
Duke Energy	-0.084	0.933	0	1	0.114	0.909
Edison International	-0.179	0.858	0	1	0.056	0.955
Entergy	-0.033	0.974	0	1	0.039	0.969
FirstEnergy	-0.144	0.886	-0.015	0.988	0.050	0.960
NextEra Energy	-0.130	0.897	0	1	0.041	0.967
Northeast Utilities	-0.013	0.990	0	1	0.006	0.995
PPL	-0.008	0.994	0	1	0.002	0.998
Progress Energy	0.166	0.868	0	1	-0.058	0.954
Public Service Enterprise Group	0.620	0.535	0	1	-0.120	0.904
Sempra Energy	-0.116	0.908	0	1	0.052	0.959
Southern Company	0	1	-0.080	0.936	0.080	0.936
Xcel Energy	-0.408	0.683	0	1	0.346	0.729

[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). (see pp. 20-21 for more details). [b] See p. 21 for more details on the *t*-test.

Table 3. Summary of variables

Variables	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 (*Change in employment retweets)*. In firm-month units.
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 (*Changes in customer retweets*), and 2) the changes in retweets of firm-initiated customer, CSR, and rapport-building tweets (*Changes in customer/CSR/rapport-building retweets*). In firm-month units.
Customer satisfaction sensitivity	The extent to which customer satisfaction affects firm financial performance. This is calculated as the coefficient for *Customer satisfaction* in the following regression. $One - period - ahead\ ROA = \alpha_0 + \alpha_1 Customer\ satisfaction + \alpha_2 ROA + \alpha_3 One - period - lagged\ ROA + \alpha_4 Stock\ Returns + \alpha_5 One - period - lagged\ Stock\ Returns$. Refer to pp.20-21 for more details.
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.
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). Refer to p.19 for more details. In firm-month units.
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 (*Change in investor retweets*, *Change in CSR retweets*, *Change in rapport-building retweets*). In firm-month units.
Deregulation	A greater number reflects a greater degree of deregulation. In firm-year units, and lagged by one year. Refer to p.23 for more details on the construction of the variable.
Growth in total revenue[c]	Growth in terms of total revenue. In firm-quarter units.
Momentum factor[d]	Monthly momentum factor obtained from the Kenneth French Data Library. In firm-month units.
Firm size: assets[c]	Quarterly firm assets (in thousands). In firm-quarter units.
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 units.
Residential sales/total sales[f]	The ratio of residential sales (MWh) over total sales (MWh). In firm-month units.
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 units.
Seasonal dummy variables	Dummy variables for summer (months 6, 7, and 8), fall (months 9, 10 and 11) and winter (months 12, 1, and 2) (baseline is spring for month 3, 4, and 5).
Change in stock price[c]	Change in stock price. In firm-month units.
Earnings surprise[a]	Actual quarterly earnings minus the analyst forecast adjusted by stock price. Refer to p.22 for more details on the construction of the variable. In firm-quarter units.
Change in current year earnings forecast[a]	Change in current year earnings forecast. In firm-month units.
Change in long-term earnings forecast[a]	Change in long-term earnings forecast. In firm-month units.

Sources:
[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"

Table 4. Descriptive statistics and correlations

	Mean	*S.D.*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1)	0.04	0.74																					
(2)	0.08	0.20	0.10																				
(3)	0.75	0.27	0.08	0.23																			
(4)	4.73	158.43	0.00	0.05	0.03																		
(5)	1.35	29.01	-0.02	0.02	0.00	0.14																	
(6)	0.25	21.08	-0.01	-0.01	-0.03	0.14	0.30																
(7)	-0.02	2.93	0.26	-0.01	0.01	-0.27	-0.20	-0.21															
(8)	0.22	10.88	-0.14	-0.01	-0.01	0.25	-0.02	0.15	-0.18														
(9)	6.33	170.28	0.00	0.05	0.02	0.97	0.34	0.31	-0.31	0.25													
(10)	0.22	0.41	0.04	0.10	-0.18	0.18	0.07	0.09	0.03	-0.12	0.19												
(11)	0.24	0.43	-0.03	-0.05	-0.12	0.28	0.10	0.25	-0.08	0.17	0.31	0.35											
(12)	0.37	1.16	-0.18	0.01	0.03	-0.21	-0.03	-0.02	-0.15	0.08	-0.20	-0.22	-0.09										
(13)	0.12	0.33	0.04	0.18	-0.14	0.06	0.02	-0.02	-0.05	-0.03	0.06	-0.02	-0.03	-0.02									
(14)	0.00	0.12	0.04	-0.09	-0.05	-0.01	0.01	-0.04	-0.01	0.09	-0.02	-0.05	0.01	0.13	-0.02								
(15)	-0.03	1.64	0.03	0.07	0.00	-0.08	-0.04	-0.04	0.05	-0.03	-0.09	-0.02	-0.04	-0.07	-0.06	-0.15							
(16)	0.37	0.36	-0.07	0.16	-0.20	-0.03	-0.01	0.02	-0.01	0.00	-0.02	0.09	0.01	-0.08	0.03	-0.03	0.01						
(17)	0.01	0.18	0.04	0.03	-0.19	0.01	0.02	0.08	0.07	0.04	0.02	0.05	0.12	-0.22	-0.01	-0.14	0.05	-0.01					
(18)	33.22	18.37	-0.05	0.00	-0.40	-0.05	-0.03	0.00	-0.01	0.03	-0.05	0.08	0.21	-0.02	0.11	0.08	0.05	0.24	0.14				
(19)	0.47	0.15	-0.01	0.32	0.27	-0.03	-0.01	0.00	0.03	-0.01	-0.03	-0.09	-0.14	-0.02	0.07	-0.08	0.09	0.42	0.26	-0.10			
(20)	2.47	0.94	-0.05	0.26	-0.18	0.03	0.03	0.01	-0.01	-0.02	0.04	0.06	-0.06	-0.02	0.12	-0.09	0.05	0.33	0.15	-0.42	0.51		
(21)	0.54	2.01	0.02	0.02	0.03	0.08	-0.07	-0.01	-0.03	0.02	0.07	0.03	-0.02	-0.16	0.03	-0.14	0.00	0.00	0.05	0.01	-0.01	-0.01	
(22)	38.61	13.14	0.04	-0.01	-0.05	0.01	0.01	-0.01	0.00	0.00	0.01	-0.06	0.03	-0.03	0.08	0.00	0.04	-0.66	0.03	0.02	-0.43	-0.16	0.01

N = 153; (1) Change in analyst stock recommendations (2) Customer satisfaction sensitivity (3) Public consumer advocates (4) Change in customer retweets (5) Change in CSR retweets (6) Change in rapport-building retweets (7) Change in employment retweets (8) Change in investor retweets (9) Change in customer/CSR/rapport-building retweets (10) Unusually high volume of customer-initiated negative tweets (85th percentile) (11) Unusually high volume of customer-initiated positive tweets (85th percentile) (12) Change in stock price (13) Earnings surprise (14) Change in current year earnings forecast (15) Change in long-term earnings forecast (16) Deregulation (17) Growth in total revenue (18) Market share (19) Residential sales/total sales (20) Number of competitors (21) Momentum factor (22) Firm size

Table 5. GLS regression results for change in analyst recommendations[a]

DV: Change in analyst stock recommendations Variable	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8
Customer satisfaction sensitivity	0.319	0.292	0.452*	0.472**	0.331	0.298	0.401	0.418*
	(0.254)	(0.246)	(0.248)	(0.237)	(0.253)	(0.247)	(0.245)	(0.239)
Public consumer advocates	0.061	0.173	0.214	0.338	0.063	0.174	0.149	0.230
	(0.288)	(0.282)	(0.288)	(0.284)	(0.286)	(0.277)	(0.284)	(0.272)
Change in customer retweets	0.0001	0.0005	-0.0009**	-0.0005				
	(0.0004)	(0.0004)	(0.0004)	(0.0005)				
Change in customer retweets × Customer satisfaction sensitivity			0.010***	0.008***				
			(0.003)	(0.003)				
Change in customer/CSR/rapport-building retweets					-0.0001	0.0004	-0.0004	0.0001
					(0.0003)	(0.0003)	(0.0003)	(0.0003)
Change in customer/CSR/rapport retweets × Customer satisfaction sensitivity							0.006***	0.004**
							(0.002)	(0.002)
Change in employment retweets		0.040***		0.072***		0.041***		0.065**
		(0.014)		(0.027)		(0.013)		(0.026)
Change in employment retweets × Customer satisfaction sensitivity				0.313*				0.241
				(0.185)				(0.179)
Change in investor retweets		-0.006		-0.003		-0.006		-0.002
		(0.006)		(0.006)		(0.006)		(0.006)
Change in investor retweets × Customer satisfaction sensitivity				-0.017				-0.024
				(0.026)				(0.026)
Change in CSR retweets		-0.001		0.004				
		(0.001)		(0.004)				
Change in CSR retweets × Customer satisfaction sensitivity				0.031				
				(0.020)				
Change in rapport-building retweets		0.0008		0.0003				
		(0.0025)		(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	-0.243*	-0.255*	-0.284*	-0.221	-0.251*	-0.251*	-0.267*
	(0.141)	(0.140)	(0.142)	(0.145)	(0.140)	(0.138)	(0.141)	(0.143)
Unusually high volume of customer-initiated negative tweets (85th percentile)	-1.486***	-1.416***	-1.545***	-1.567***	-1.503***	-1.423***	-1.520***	-1.419***
× Public consumer advocates	(0.334)	(0.345)	(0.320)	(0.341)	(0.325)	(0.336)	(0.311)	(0.300)
Unusually high volume of customer-initiated positive tweets (85th percentile)	0.098	0.080	0.042	-0.011	0.118	0.093	0.055	0.042
	(0.140)	(0.138)	(0.141)	(0.146)	(0.139)	(0.135)	(0.140)	(0.144)
Unusually high volume of customer-initiated positive tweets (85th percentile)	0.986***	0.588	0.677**	0.367	0.993***	0.569	0.802**	0.489
× Public consumer advocates	(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

[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 in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6. Summary results for H3: alternative percentiles for an unusually high volume of customer-initiated negative (positive) tweets[a]

DV: Change in analyst stock recommendations Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
70th Percentile								
Unusually high volume of customer-initiated negative tweets (70th percentile)	0.178	0.128	0.121	0.039	0.176	0.132	0.130	0.070
	(0.153)	(0.151)	(0.156)	(0.156)	(0.153)	(0.149)	(0.154)	(0.155)
Unusually high volume of customer-initiated negative tweets (70th percentile)	-0.331	-0.385	-0.436	-0.550	-0.341	-0.365	-0.392	-0.527
× Public consumer advocates	(0.406)	(0.381)	(0.393)	(0.388)	(0.404)	(0.376)	(0.394)	(0.360)
Unusually high volume of customer-initiated positive tweets (70th percentile)	-0.054	-0.038	-0.087	-0.113	-0.052	-0.038	-0.075	-0.099
	(0.140)	(0.138)	(0.142)	(0.142)	(0.140)	(0.135)	(0.141)	(0.140)
Unusually high volume of customer-initiated positive tweets (70th percentile)	-0.056	-0.373	-0.153	-0.467	-0.053	-0.387	-0.094	-0.309
× Public consumer advocates	(0.396)	(0.385)	(0.387)	(0.386)	(0.394)	(0.378)	(0.385)	(0.356)
75th Percentile								
Unusually high volume of customer-initiated negative tweets (75th percentile)	0.178	0.128	0.121	0.039	0.176	0.132	0.130	0.070
	(0.153)	(0.151)	(0.156)	(0.156)	(0.153)	(0.149)	(0.154)	(0.155)
Unusually high volume of customer-initiated negative tweets (75th percentile)	-0.331	-0.385	-0.436	-0.550	-0.341	-0.365	-0.392	-0.527
× Public consumer advocates	(0.406)	(0.381)	(0.393)	(0.388)	(0.404)	(0.376)	(0.394)	(0.360)
Unusually high volume of customer-initiated positive tweets (75th percentile)	-0.054	-0.038	-0.087	-0.113	-0.052	-0.038	-0.075	-0.099
	(0.140)	(0.138)	(0.142)	(0.142)	(0.140)	(0.135)	(0.141)	(0.140)
Unusually high volume of customer-initiated positive tweets (75th percentile)	-0.056	-0.373	-0.153	-0.467	-0.053	-0.387	-0.094	-0.309
× Public consumer advocates	(0.396)	(0.385)	(0.387)	(0.386)	(0.394)	(0.378)	(0.385)	(0.356)
80th Percentile								
Unusually high volume of customer-initiated negative tweets (80th percentile)	0.141	0.117	0.089	0.009	0.139	0.117	0.099	0.033
	(0.144)	(0.142)	(0.146)	(0.148)	(0.144)	(0.140)	(0.144)	(0.146)
Unusually high volume of customer-initiated negative tweets (80th percentile)	-0.515	-0.583*	-0.626*	-0.795**	-0.536	-0.581*	-0.584*	-0.732**
× Public consumer advocates	(0.352)	(0.345)	(0.345)	(0.350)	(0.348)	(0.337)	(0.341)	(0.312)
Unusually high volume of customer-initiated positive tweets (80th percentile)	-0.001	-0.023	-0.068	-0.119	0.014	-0.012	-0.055	-0.067
	(0.138)	(0.136)	(0.141)	(0.144)	(0.138)	(0.134)	(0.140)	(0.143)
Unusually high volume of customer-initiated positive tweets (80th percentile)	0.465	0.102	0.226	-0.110	0.478	0.092	0.312	0.070
× Public consumer advocates	(0.358)	(0.365)	(0.357)	(0.359)	(0.352)	(0.357)	(0.348)	(0.315)
85th Percentile								
Unusually high volume of customer-initiated negative tweets (85th percentile)	-0.216	-0.243*	-0.255*	-0.284*	-0.221	-0.251*	-0.251*	-0.267*
	(0.141)	(0.140)	(0.142)	(0.145)	(0.140)	(0.138)	(0.141)	(0.143)
Unusually high volume of customer-initiated negative tweets (85th percentile)	-1.486***	-1.416***	-1.545***	-1.567***	-1.503***	-1.423***	-1.520***	-1.419***
× Public consumer advocates	(0.334)	(0.345)	(0.320)	(0.341)	(0.325)	(0.336)	(0.311)	(0.300)
Unusually high volume of customer-initiated positive tweets (85th percentile)	0.098	0.080	0.042	-0.011	0.118	0.093	0.055	0.042
	(0.140)	(0.138)	(0.141)	(0.146)	(0.139)	(0.135)	(0.140)	(0.144)
Unusually high volume of customer-initiated positive tweets (85th percentile)	0.986***	0.588	0.677**	0.367	0.993***	0.569	0.802**	0.489
× Public consumer advocates	(0.340)	(0.372)	(0.337)	(0.349)	(0.330)	(0.361)	(0.320)	(0.301)
90thPercentile								
Unusually high volume of customer-initiated negative tweets (90th percentile)	-0.190	-0.222	-0.232	-0.258*	-0.195	-0.229	-0.224	-0.241*
	(0.143)	(0.143)	(0.145)	(0.147)	(0.143)	(0.140)	(0.144)	(0.145)
Unusually high volume of customer-initiated negative tweets (90th percentile)	-1.557***	-1.488***	-1.591***	-1.601***	-1.563***	-1.483***	-1.564***	-1.433***
× Public consumer advocates	(0.331)	(0.352)	(0.318)	(0.339)	(0.324)	(0.343)	(0.309)	(0.300)
Unusually high volume of customer-initiated positive tweets (90th percentile)	0.031	0.022	-0.014	-0.077	0.050	0.031	-0.010	-0.023
	(0.157)	(0.153)	(0.159)	(0.161)	(0.157)	(0.150)	(0.158)	(0.159)
Unusually high volume of customer-initiated positive tweets (90th percentile)	1.104***	0.729*	0.757**	0.417	1.094***	0.695*	0.869***	0.513
× Public consumer advocates	(0.350)	(0.396)	(0.347)	(0.358)	(0.341)	(0.385)	(0.330)	(0.314)

[a] This table is obtained by using alternative threshold percentiles for unusually high volumes of customer-initiated negative (positive) tweets in Table 5. We only show relevant coefficients and standard deviations.
Standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7. Robustness checks: subsample analysis based on financial measures (ROA and PE Ratio)[a]

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel A: Subsample analysis based on ROA – (1) Without top 2 firms (about 10%)								
Change in customer retweets × Customer satisfaction sensitivity			0.009***	0.009***				
			(0.003)	(0.003)				
Change in customer/CSR/rapport retweets × Customer satisfaction sensitivity							0.006***	0.004**
							(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 negative tweets × Public consumer advocates	-1.100***	-1.078***	-1.146***	-1.149***	-1.093***	-0.994**	-1.128***	-0.970**
	(0.383)	(0.417)	(0.375)	(0.420)	(0.374)	(0.400)	(0.383)	(0.386)
Unusually high volume of customer-initiated positive tweets × Public consumer advocates	1.107***	0.725	0.726*	0.518	1.122***	0.697	0.883**	0.614
	(0.394)	(0.450)	(0.394)	(0.438)	(0.384)	(0.437)	(0.400)	(0.401)
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 satisfaction sensitivity			0.009***	0.008***				
			(0.003)	(0.003)				
Change in customer/CSR/rapport retweets × Customer satisfaction sensitivity							0.006***	0.005**
							(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 negative tweets × Public consumer advocates	-1.043***	-0.989**	-1.107***	-1.003**	-1.029***	-0.940**	-1.068***	-0.957**
	(0.396)	(0.419)	(0.389)	(0.417)	(0.390)	(0.411)	(0.407)	(0.409)
Unusually high volume of customer-initiated positive tweets × Public consumer advocates	1.189***	0.822*	0.847**	0.564	1.204***	0.792*	0.962**	0.722*
	(0.409)	(0.451)	(0.410)	(0.424)	(0.401)	(0.449)	(0.427)	(0.435)
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 satisfaction sensitivity			0.010***	0.009***				
			(0.003)	(0.003)				
Change in customer/CSR/rapport retweets × Customer satisfaction sensitivity							0.006***	0.004**
							(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 negative tweets × Public consumer advocates	-1.465***	-1.301***	-1.497***	-1.360***	-1.478***	-1.329***	-1.454***	-1.232***
	(0.387)	(0.405)	(0.363)	(0.389)	(0.373)	(0.391)	(0.372)	(0.350)
Unusually high volume of customer-initiated positive tweets × Public consumer advocates	0.962**	0.570	0.558	0.351	0.971***	0.566	0.770**	0.484
	(0.378)	(0.410)	(0.366)	(0.377)	(0.362)	(0.397)	(0.364)	(0.334)
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 satisfaction sensitivity			0.009***	0.008**				
			(0.003)	(0.003)				
Change in customer/CSR/rapport retweets × Customer satisfaction sensitivity							0.006***	0.005**
							(0.002)	(0.002)
Change in employment retweets		0.037**		0.092***		0.038***		0.084***
		(0.015)		(0.030)		(0.013)		(0.030)
Unusually high volume of customer-initiated negative tweets × 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 × 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 5. We only show relevant coefficients and standard deviations.
Standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 8. Robustness checks: subsample analysis based on non-financial measures (KLD & CSRI)[a]

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel A: KLD - Corporate Governance[b]								
Change in customer retweets × Customer satisfaction sensitivity			0.010***	0.008***				
			(0.003)	(0.003)				
Change in customer/CSR/rapport retweets × Customer satisfaction sensitivity							0.005***	0.004**
							(0.002)	(0.002)
Change in employment retweets		0.036***		0.066**		0.038***		0.062**
		(0.013)		(0.027)		(0.013)		(0.026)
Unusually high volume of customer-initiated negative tweets × Public consumer advocates	-1.602***	-1.494***	-1.642***	-1.481***	-1.619***	-1.498***	-1.626***	-1.275***
	(0.326)	(0.350)	(0.308)	(0.330)	(0.310)	(0.343)	(0.295)	(0.289)
Unusually high volume of customer-initiated positive tweets × Public consumer advocates	1.159***	0.763**	0.803**	0.578*	1.175***	0.734**	0.989***	0.692**
	(0.334)	(0.375)	(0.335)	(0.324)	(0.318)	(0.367)	(0.311)	(0.273)
Constant	0.688**	0.633*	0.857**	0.898***	0.725**	0.629*	0.830**	0.847***
	(0.347)	(0.343)	(0.344)	(0.326)	(0.344)	(0.342)	(0.342)	(0.327)
Observations	142	142	142	142	142	142	142	142
Panel B: KLD - Environment[c]								
Change in customer retweets × Customer satisfaction sensitivity			0.010***	0.010***				
			(0.003)	(0.003)				
Change in customer/CSR/rapport retweets × Customer satisfaction sensitivity							0.007***	0.005**
							(0.002)	(0.002)
Change in employment retweets		0.040***		0.064**		0.041***		0.063**
		(0.014)		(0.027)		(0.013)		(0.026)
Unusually high volume of customer-initiated negative tweets × Public consumer advocates	-1.428***	-1.342***	-1.514***	-1.619***	-1.449***	-1.354***	-1.478***	-1.416***
	(0.357)	(0.375)	(0.343)	(0.383)	(0.348)	(0.360)	(0.333)	(0.326)
Unusually high volume of customer-initiated positive tweets × Public consumer advocates	1.077***	0.683*	0.745**	0.537	1.082***	0.657*	0.874***	0.550*
	(0.349)	(0.385)	(0.345)	(0.387)	(0.338)	(0.370)	(0.326)	(0.311)
Constant	0.532	0.514	0.739**	0.847**	0.560	0.515	0.694*	0.791**
	(0.359)	(0.355)	(0.361)	(0.350)	(0.356)	(0.354)	(0.357)	(0.347)
Observations	142	142	142	142	142	142	142	142
Panel C: KLD - Community[d]								
Change in customer retweets × Customer satisfaction sensitivity			0.010***	0.010***				
			(0.003)	(0.003)				
Change in customer/CSR/rapport retweets × Customer satisfaction sensitivity							0.007***	0.005**
							(0.002)	(0.002)
Change in employment retweets		0.040***		0.063**		0.043***		0.062**
		(0.015)		(0.027)		(0.014)		(0.026)
Unusually high volume of customer-initiated negative tweets × Public consumer advocates	-1.608***	-1.422***	-1.654***	-1.831***	-1.617***	-1.422***	-1.598***	-1.481***
	(0.386)	(0.431)	(0.356)	(0.427)	(0.369)	(0.406)	(0.341)	(0.335)
Unusually high volume of customer-initiated positive tweets × Public consumer advocates	1.116***	0.559	0.686*	0.450	1.097***	0.476	0.867**	0.450
	(0.380)	(0.456)	(0.369)	(0.428)	(0.361)	(0.433)	(0.338)	(0.323)
Constant	0.016	-0.184	0.130	0.153	0.019	-0.232	0.136	-0.012
	(0.512)	(0.509)	(0.515)	(0.498)	(0.508)	(0.503)	(0.509)	(0.505)
Observations	131	131	131	131	131	131	131	131
Panel D: The Corporate Social Responsibility Index[e]								
Change in customer retweets × Customer satisfaction sensitivity			0.009***	0.008**				
			(0.003)	(0.003)				
Change in customer/CSR/rapport retweets × Customer satisfaction sensitivity							0.007***	0.005**
							(0.002)	(0.002)
Change in employment retweets		0.038**		0.070***		0.041***		0.063**
		(0.015)		(0.026)		(0.013)		(0.026)
Unusually high volume of customer-initiated negative tweets × Public consumer advocates	-1.429***	-1.367***	-1.491***	-1.479***	-1.453***	-1.380***	-1.475***	-1.421***
	(0.341)	(0.348)	(0.332)	(0.339)	(0.332)	(0.341)	(0.324)	(0.324)
Unusually high volume of customer-initiated positive tweets × Public consumer advocates	0.983***	0.626*	0.722**	0.413	1.003***	0.581	0.805**	0.529
	(0.350)	(0.377)	(0.349)	(0.348)	(0.339)	(0.369)	(0.334)	(0.336)
Constant	0.696**	0.648*	0.858**	0.907***	0.734**	0.657*	0.864***	0.867***
	(0.339)	(0.339)	(0.336)	(0.321)	(0.335)	(0.339)	(0.328)	(0.321)
Observations	142	142	142	142	142	142	142	142

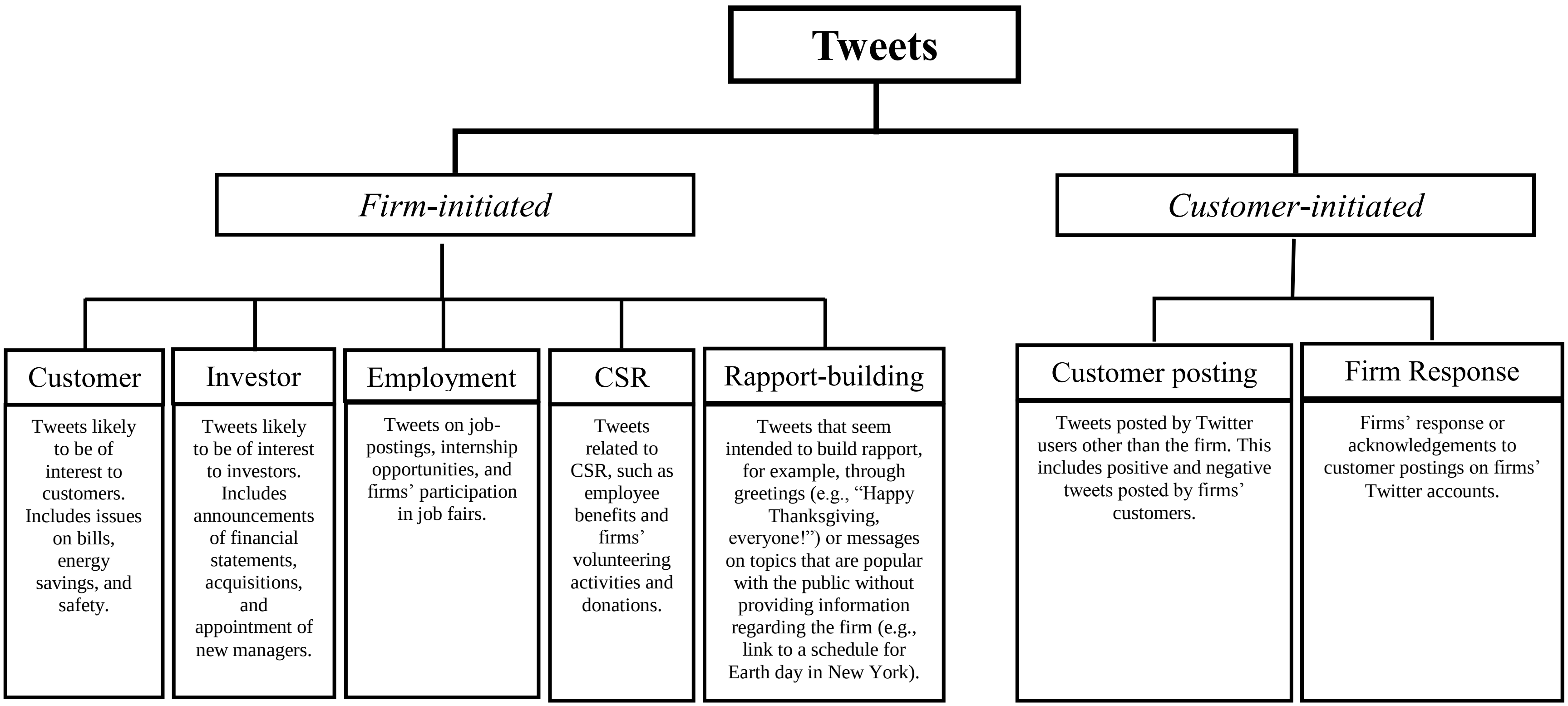
[a] Subsample analyses of the models in Table 5. We only show relevant coefficients and standard deviations.
[b] Subsample analysis excluding the firm with the greatest number of strengths (Entergy with a total of 2 strength). Following Entergy there are 11 firms with 1 strength and additionally excluding them would result in too few observations for analysis; [c] Subsample analysis without the firm with the greatest number of strengths (Duke with a total of 4 strengths). Following Duke there are 7 firms with a total of 3 strengths and additionally excluding them would result in too few observations for analysis; [d] Subsample analysis without firms with the greatest number of strengths (Xcel and Duke with a total of 3 strengths). Additionally excluding firms with 2 strengths (Progress and AEP) have similar results; [e] Sub-sample analysis excluding the firm on the *CSRI Top 50* list (Southern).
Standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 9. Robustness checks: summary of Difference-in-Difference-in-Differences (DDD) models[a]

DV: Change in analyst stock recommendation Variable	Only DDD variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Treatment	-0.319	-0.407	-0.595	-0.557	-1.014**	-0.485	-0.587	-0.573	-0.964**
	(0.506)	(0.494)	(0.496)	(0.469)	(0.447)	(0.488)	(0.488)	(0.456)	(0.445)
Public consumer advocates	0.157	0.196	0.221	0.256	0.328	0.180	0.265	0.194	0.260
	(0.198)	(0.290)	(0.296)	(0.293)	(0.302)	(0.289)	(0.283)	(0.287)	(0.286)
Unusually high volume of customer-initiated negative tweets	-0.198	-0.233	-0.222	-0.262*	-0.268*	-0.250*	-0.235*	-0.272*	-0.269**
(*Customer negative tweets*)	(0.134)	(0.149)	(0.141)	(0.150)	(0.139)	(0.148)	(0.140)	(0.148)	(0.136)
Unusually high volume of customer-initiated positive tweets	-0.008	-0.025	-0.059	-0.058	-0.156	0.001	-0.040	-0.056	-0.109
(*Customer positive tweets*)	(0.135)	(0.155)	(0.151)	(0.158)	(0.153)	(0.156)	(0.148)	(0.157)	(0.149)
Treatment × Public consumer advocates	-1.584	-1.177	-0.961	0.214	3.517	-0.118	-0.518	0.455	2.795
	(2.742)	(3.297)	(3.311)	(3.307)	(3.152)	(3.212)	(3.071)	(3.133)	(3.049)
Treatment × Customer negative tweets	0.094	0.147	-0.162	-0.063	-0.749	0.305	-0.135	0.036	-0.660
	(0.541)	(0.606)	(0.564)	(0.615)	(0.590)	(0.608)	(0.579)	(0.608)	(0.590)
Treatment × Customer positive tweets	0.039	0.167	0.271	0.277	0.612	0.227	0.269	0.312	0.546
	(0.601)	(0.606)	(0.586)	(0.590)	(0.554)	(0.602)	(0.589)	(0.575)	(0.558)
Customer negative tweets × Public consumer advocates	-0.988***	-1.122***	-0.895**	-1.114***	-1.016***	-1.166***	-0.990***	-1.069***	-0.973***
	(0.370)	(0.376)	(0.369)	(0.370)	(0.367)	(0.366)	(0.357)	(0.339)	(0.312)
Customer positive tweets × Public consumer advocates	0.678*	0.556	0.295	0.344	0.052	0.599	0.165	0.657*	0.381
	(0.406)	(0.407)	(0.429)	(0.404)	(0.430)	(0.395)	(0.400)	(0.355)	(0.345)
Treatment × Customer negative tweets × Public consumer advocates	-5.197**	-5.496**	-6.220***	-5.724**	-6.899***	-5.391**	-5.800**	-6.342**	-7.127***
	(2.287)	(2.547)	(2.291)	(2.542)	(2.318)	(2.537)	(2.317)	(2.504)	(2.313)
Treatment × Customer positive tweets × Public consumer advocates	6.810*	6.860*	6.313	5.227	1.925	5.813	6.051	4.804	2.469
	(3.509)	(4.087)	(3.953)	(4.086)	(3.793)	(4.031)	(3.803)	(3.931)	(3.758)
Constant	0.048	0.218	0.157	0.506	0.355	0.225	0.128	0.453	0.440
	(0.131)	(0.372)	(0.372)	(0.373)	(0.366)	(0.369)	(0.368)	(0.360)	(0.353)
Observations	153	153	153	153	153	153	153	153	153

[a] The first model (column 1) includes variables necessary for the Difference-in-Difference-in-Differences (DDD) analysis only. Models 1 – 8 are identical to those in Table 5 and additionally include variables for the DDD analysis. All models include a group indicator (i.e., firms affected by Irene) and month indicators. We only show relevant coefficients and standard deviations.
Standard errors are in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

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. Firm responses to Twitter users' postings fall under this category.

Appendix S1. Tweets and Retweets: Variance Across and Within Firms

Table S1-1 displays the monthly mean and standard deviation of tweets (company-initiated), retweets (of company-initiated tweets), and retweets over tweets by firm.

[Insert Table S1-1 about here]

There are significant differences in the number of tweets and retweets across firms. For example, the monthly mean number of tweets ranges from 1.75 (Sempra Energy) to 161.80 (DTE Energy) and retweets from 0.5 (FirstEnergy and Sempra) to 296.20 (DTE Energy). The number of retweets is generally positively correlated with the number of tweets, but the correlation is not perfect. For example, while Consolidated Edison and FirstEnergy have similar numbers of tweets, 6.73 and 7, respectively, Consolidated Edison has far more retweets (7.91) than First Energy (0.5). The ratio of retweets over tweets shown in the last column provides a convenient metric to compare firms in terms of the extent of retweets. The monthly mean ratio of retweets over tweets ranges from 0.18 (Sempra) to 2.65 (Edison International), which means that on average tweets by Edison International receive approximately 15 times more retweets than Sempra. This evidence illustrates that the number of tweets does not necessarily reflect the extent of the retweets.

In addition, Table S1-1 shows variations even within firms in the extent to which tweets are retweeted and heterogeneity in such within-firm variations. For example, the standard deviation of the monthly mean ratio of retweets over tweets for PESG is 3.16, while for Sempra it is 0.17. Overall, these examples illustrate variance in tweets and retweets across and within firms. Thus, we make use of monthly data at the firm level.

Table S1-1. Monthly Mean and Standard Deviation of *Tweets*, *Retweets*, and *Retweets/Tweets*

	Tweets		**Retweets**		**Retweets/Tweets**	
Company name	*Mean*	*S.D.*	*Mean*	*S.D.*	*Mean*	*S.D.*
Ameren	31.55	7.61	16.73	10.69	0.49	0.30
American Electric Power (AEP)	29.73	4.90	24.45	7.78	0.80	0.25
Consolidated Edison	6.73	4.56	7.91	14.02	0.60	0.90
DTE Energy	161.80	39.97	296.20	128.41	1.70	0.63
Duke Energy	17.36	5.05	31.27	19.25	1.82	1.00
Edison International	61.91	68.98	252.36	386.87	2.65	2.50
Entergy	27.82	27.34	19	20.31	0.61	0.34
FirstEnergy	7	7.07	0.5	0.71	0.19	0.27
NextEra Energy	15.64	16.39	23.36	52.65	1.46	2.66
Northeast Utilities	19.36	25.20	93.18	201.31	2.10	2.50
PPL	111.91	77.15	84.55	119.63	0.44	0.46
Progress Energy	58.27	50.36	123.64	195.89	1.49	0.92
Public Service Enterprise Group	46.70	20.87	149.90	207.22	2.51	3.16
Sempra Energy	1.75	2.87	0.5	1	0.18	0.17
Southern Company	26	10.18	57.91	37.99	2.34	1.16
Xcel Energy	42.82	7.43	20	10.53	0.37	0.21

Appendix S2. Difference-in-Difference-in-Differences (DDD)

The basic triple difference equation in our context is the following (Imbens and Wooldridge, 2007).

$$\begin{aligned} Y_{it} = \ & \lambda_t + \alpha_g + T_{gt} + \beta_1 C_{it} + \beta_2 P_i + \ \beta_3\left(T_{gt} \times C_{it}\right) + \beta_4(C_{it} \times P_i) + \beta_5\left(P_i \times T_{gt}\right) \\ & + \beta_6\left(T_{gt} \times C_{it} \times P_i\right) + \ \varepsilon_{it} \end{aligned}$$

where *i* indexes firm, g indexes group affected by the treatment, and *t* indexes time. This model has a full set of time effects, λ_t, a full set of group effects, α_g, group/time period covariates, T_{gt} (this is the treatment variable), firm-specific covariates, C_{it} and P_i (explained in the next paragraph), and two-way and three-way interactions among T_{gt}, C_{it}, and P_i. Y_{it} is the outcome variable. ε_{it} is firm-specific errors. We are interested in estimating β_6, the coefficient for the three-way interaction variable.

The major weather event we make use of is Hurricane Irene, which caused significant damage during August 2011. Thus, α_g indicates whether the firm is affected by Hurricane Irene and T_{gt} is equal to 1 for the firm-month observation if g is 1 and the month is August. C_{it} indicates whether a firm received an unusually high volume of customer-initiated tweets in a given month. Since customers can be frustrated (negative) or thankful (positive), we include two separate variables for negative tweets and positive tweets. P_i denotes the presence of public consumer advocates in states where firms operate. Y_{it} indicates changes in analyst recommendations.

The coefficient for the three-way interaction variable, β_6, captures the treatment effect of Hurricane Irene, allowing for differences in C_{it} and P_i across firms. More specifically, β_6 can be represented as follows.

$$\beta_6 = (\overline{Y_{C=1,P=1,T=1}} - \overline{Y_{C=1,P=1,T=0}})$$
$$- (\overline{Y_{C=0,P=1,T=1}} - \overline{Y_{C=0,P=1,T=0}})$$
$$- (\overline{Y_{C=1,P=0,T=1}} - \overline{Y_{C=1,P=0,T=0}})$$

where $\overline{Y}$ indicates average changes in analyst recommendations and *C*, *P*, *T* indicates C_{it}, P_i and T_{gt}, respectively. Then, our DDD coefficient captures the effect of Irene on firms with an unusually high volume of customer-initiated tweets in states with public consumer advocates. The second term subtracts the potential trend in analyst recommendations for firms with public consumer advocates but without an unusually high volume of customer-initiated tweets. The third term removes the potential trend in analyst recommendations for firms with an unusually high volume of customer-initiated tweets but without public consumer advocates.

Appendix S3. Robustness Checks for the Difference-in-Difference-in-Differences (DDD) Estimates

In Table S3-1, we further provide robustness checks for our main DDD estimates.

[Insert Table S3-1 about here]

For simplicity, the coefficients are shown only for the DDD variables based on two models in Table 9 (the first column (with only the treatment-related variables) and the fifth column (model 4)). We perform three sets of analyses. The first set of robustness tests additionally controls for interactions between our main variables and time fixed effects (Walker, 2013). This is to take into account the possibility that the effect of our variables of interest may change over time. Specifically, the interaction variable with the group dummy models aggregate shocks common to firms that are affected by Hurricane Irene in a given month (results under (1) Group × Month). The interaction variable with the public consumer advocates controls for unobserved shocks common to firms operating in states with public consumer advocates in a given month ((2) Public consumer advocates × Month). The interaction variables with customer-initiated tweets (separately for negative and positive tweets) allow for shocks common to firms with an unusually high volume of customer-initiated tweets in a given month ((3) Customer negative/positive tweets × Month). The results are similar to those shown in Table 9 in terms of magnitude and significance.

The second set of analyses controls for the possibility that more (less) stakeholder-oriented firms may receive more positive (negative) customer-initiated tweets by additionally controlling for alternative stakeholder orientations variables and their interactions with time dummies. The interaction variables address potentially differential effects of stakeholder orientations across different time periods due to severe weather conditions such as storms, hot or cold weather, etc. Stakeholder orientation is captured by the KLD score for Community and Society, American Customer Satisfaction Index (ACSI), corporate use of social media (total number of firm-initiated tweets, and whether the company uses other types of social media such as Facebook and YouTube). Again, the results are very similar to those shown in Table 9. In addition, in regressions not shown in the table, for each stakeholder orientation measure, we examined the interactions of each measure with time fixed effects. Also, instead of the total number of firm-initiated tweets, we used the total number of firm-initiated tweets targeting customers, i.e., customer tweets and customer/CSR/rapport-building tweets in turn. The results are very similar to those shown in Table S3-1.

The third set of analyses addresses potential differences between the treatment and control groups. We employed Coarsened Exact Matching (CEM) to reduce imbalance in covariates between the treated and control groups, i.e., firms affected by Hurricane Irene and those not affected by Irene. Following Younge, Tong, and Fleming (2015), in matching we use pre-treatment average values of variables that have been shown to affect our outcome variable in prior research. As discussed in the paper, changes in either the price or the value of a company can trigger changes in analysts' recommendations. Thus, ideally we would match based on change in stock price and changes in all the variables that proxy for change in value such as earnings surprises and near-term and long-term earnings forecasts. Due to our small sample size, however, we are not able to use all these variables in matching; we would either end up with too small a sample size, or dropping our three-way interaction variables of interest. Thus, in matching we use two variables—changes in stock price and changes in earnings forecast for current year. In CEM there is a tradeoff between the number of cutoff points used for matching and the number of matched observations. Using the median values of changes in stock price and changes in earnings forecast for current year (thus having four strata for CEM) left us with enough observations after matching to run follow-up regressions. Specifically, the CEM resulted in matches for 12 firms among the 16 firms in our sample, which reduced the sample size from 153 to 131 firm-month observations.

In CEM, the quality of matching is typically expressed in terms of the L_1 statistic (Blackwell, et al., 2009). The L_1 statistic is an overall imbalance measure, ranging from 0 to 1; larger values indicate larger imbalance between the treated and control groups, where $L_1 = 1$ indicates complete separation of the two distributions (Iacus, King and Porro, 2012). Our matching led to a significant decrease in L_1 from 0.8 to 0.22. Also, the two-sample Hotelling's T-squared test shows that the treated and control groups are not significantly different from each other (F-value = 0.12, Probability > F = 0.89). Furthermore, the *t*-test for each variable shows that after matching the means are not significantly different between the treated and control groups at the 5% level (Table S3-2).

[Insert Table S3-2 about here]

As shown in Table S3-2, even before matching, our variables of interest and most control variables do not show significant differences between the two groups. The only variable that was significantly different between the treated and control group before matching was *Residential/total sales*. This variable does not affect our regression results at all when excluded from the analysis (the regression results are available upon request). After matching, the difference between the means of the treated and control group becomes not significant at the 5% level. The results using the matched samples are similar to our main DDD regression results shown in Table 9. The size of the coefficient for *Treatment* × *Customer negative tweets* × *Public consumer advocates* appears larger after matching in model 4 with $\beta = -8.7628$ ($p < 0.01$). The comparable coefficient in model 4 of Table 9 is $\beta = -6.899$ ($p < 0.01$). However, the *t*-test of the two coefficients shows that they are not significantly different from each other (p-value = 0.582). This additional evidence provides further support for our DDD results. Overall, all of our robustness checks corroborate our main findings in further support of our hypotheses.

Table S3-1. Summary of Robustness Checks for the Difference-in-Difference-in-Differences (DDD) Models[a]

	ADDITIONAL CONTROLS: *Main variables * Time fixed effects*						***ADDITIONAL CONTROLS:*** *Alternative stakeholder orientations*	
	(1) Group × Month		(2) Public consumer advocates × Month		(3) Customer negative/positive tweets × Month		(4)[b] KLD (Community)	
	Only DDD variables	Model 4	Only DDD variables	Model 4	Only DDD variables	Model 4	Only DDD variables	Model 4
Treatment × Customer neg. tweets × Public consumer advocates	-5.267**	-7.015***	-5.360**	-6.811***	-5.184**	-7.262***	-5.306**	-6.837***
	(2.298)	(2.303)	(2.181)	(2.122)	(2.153)	(2.179)	(2.292)	(2.324)
Treatment × Customer pos. tweets × Public consumer advocates	6.634*	1.584	6.547*	1.432	6.785*	1.896	6.876*	1.717
	(3.538)	(3.780)	(3.443)	(3.707)	(3.481)	(3.625)	(3.515)	(3.834)
Constant	0.049	0.26	0.144	0.442	0.016	0.308	0.022	0.592
	(0.155)	(0.443)	(0.156)	(0.359)	(0.158)	(0.370)	(0.138)	(0.656)
Observations	153	153	153	153	153	153	153	153

	ADDITIONAL CONTROLS: *Alternative stakeholder orientations (continued)*						***COARSENED EXACT MATCHING (CEM)***	
	(5)[b] American Customer Satisfaction Index (ACSI)		(6)[b,c] Number of firm-initiated tweets		(7)[b] Other types of social media (Facebook & YouTube)			
	Only DDD variables	Model 4	Only DDD variables	Model 4	Only DDD variables	Model 4	Only DDD variables	Model 4
Treatment × Customer neg. tweets × Public consumer advocates	-5.311**	-6.809***	-5.104**	-6.887***	-5.400**	-6.922***	-6.9344***	-8.7628***
	(2.286)	(2.325)	(2.309)	(2.330)	(2.289)	(2.333)	(2.526)	(2.470)
Treatment × Customer pos. tweets × Public consumer advocates	7.272**	1.802	6.774*	1.863	7.089**	1.952	6.9054*	1.246
	(3.580)	(3.817)	(3.488)	(3.806)	(3.523)	(3.807)	(3.594)	(3.992)
Constant	-1.153	-0.392	0.032	0.356	0.099	0.360	-0.083	-0.02
	(0.991)	(1.312)	(0.133)	(0.367)	(0.149)	(0.370)	(0.233)	(0.585)
Observations	153	153	153	153	153	153	131	131

[a] Summary of robustness checks of the models in Table 9. For convenience, the results for two models (the DDD variables (the first column) and model 4 (the fifth column) in Table 9) are displayed. We only show relevant coefficients and standard deviations.
[b] For (4) KLD (Community), (5) American Customer Satisfaction Index (ACSI), (6) Number of firm-initiated tweets, and (7) Other types of social media (Facebook & YouTube), in regressions not shown in the table, we also further controlled for interactions between each measure and time dummies. The results are similar in magnitude and significance with those shown in the table.
[c] Instead of the total number of firm-initiated tweets, we also used the total number of customer tweets and the total number of customer/CSR/rapport-building tweets and their interactions with time dummies. The results are similar in magnitude and significance with those shown in the table.
Standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table S3-2. T-Tests on the Pre-Treatment Average Values between the Control and Treatment Group[a]

Panel A: Control vs. Treatment Group in the "Full Sample" (16 firms)

	Control group		Treatment group		T-test	
Variable	*Mean*	*S.D.*	*Mean*	*S.D.*	*t*-statistic	*p*-value
Customer satisfaction sensitivity	0.016	0.165	0.076	0.227	-0.598	0.563
Public consumer advocates	0.710	0.319	0.757	0.310	-0.277	0.789
Deregulation	0.195	0.274	0.511	0.422	-1.793	0.099
Number of competitors	2.288	1.150	2.827	1.022	-0.899	0.399
Market share	30.313	28.920	32.683	14.681	-0.173	0.869
Residential/total sales	0.358	0.065	0.529	0.143	-3.289	0.005
Firm size	42.550	12.265	36.064	13.400	0.952	0.367
Growth in total revenue	0.000	0.026	0.022	0.075	-0.840	0.415
Change in stock price	0.287	0.163	0.452	0.325	-1.356	0.197
Earnings surprise	0.066	0.075	0.122	0.200	-0.806	0.434
Change in current year earnings forecast	0.007	0.038	-0.002	0.025	0.440	0.676
Change in long-term earnings forecast	-0.036	0.071	0.001	0.235	-0.481	0.639
Unusually high customer negative tweets	0.309	0.189	0.164	0.200	1.395	0.199
Unusually high customer positive tweets	0.291	0.197	0.198	0.214	0.847	0.420
Change in customer retweets	18.164	40.974	-1.549	10.267	1.061	0.346
Change in customer/CSR/rapport building retweets	20.782	46.628	0.075	13.454	0.975	0.381
Change in investor retweets	0.223	0.767	0.183	0.480	0.106	0.920
Change in employment retweets	-0.073	0.163	-0.021	0.221	-0.520	0.614
Change in CSR retweets	2.582	5.727	0.992	3.002	0.585	0.584
Change in rapport-building retweets	0.036	0.350	0.632	1.832	-1.038	0.321
Number of firms:	*5*		*11*			

Panel B: Control vs. Treatment Group in the "CEM Sample" (12 firms)

	Control group		Treatment group		T-test	
Variable	*Mean*	*S.D.*	*Mean*	*S.D.*	*t*-statistic	*p*-value
Customer satisfaction sensitivity	0.109	0.129	0.113	0.236	-0.029	0.978
Public consumer advocates	0.767	0.225	0.830	0.203	-0.457	0.658
Deregulation	0.132	0.229	0.403	0.386	-1.124	0.287
Number of competitors	2.115	1.411	2.532	0.840	-0.638	0.538
Market share	36.183	35.365	31.863	13.463	0.326	0.751
Residential/total sales	0.354	0.028	0.535	0.145	-2.079	0.064
Firm size	50.617	4.544	35.737	13.805	1.784	0.105
Growth in total revenue	0.038	0.085	0.044	0.069	-0.127	0.901
Change in stock price	0.222	0.175	0.341	0.408	-0.478	0.643
Earnings surprise	0.030	0.045	0.163	0.271	-0.816	0.434
Change in current year earnings forecast	-0.031	0.084	-0.024	0.045	-0.196	0.848
Change in long-term earnings forecast	0.026	0.118	-0.305	0.436	1.261	0.236
Unusually high customer negative tweets	0.278	0.096	0.096	0.171	1.712	0.118
Unusually high customer positive tweets	0.278	0.096	0.141	0.209	1.073	0.308
Change in customer retweets	-0.444	0.509	-4.893	19.004	0.393	0.703
Change in customer/CSR/rapport building retweets	-0.611	1.084	-4.396	19.209	0.330	0.748
Change in investor retweets	1.944	1.873	0.652	1.176	1.442	0.180
Change in employment retweets	-0.056	0.585	0.133	0.400	-0.639	0.537
Change in CSR retweets	0.000	0.500	0.256	0.608	-0.652	0.529
Change in rapport-building retweets	-0.167	0.500	0.241	0.672	-0.952	0.363
Number of firms:	*3*		*9*			

[a] When the pre-Irene average values were not available due to the late adoption of Twitter (later than August), we used the post-Irene average values.