Article

Journal of Marketing
2021, Vol. 85(6) 1–23

DOI: 10.1177/00222429211002183
journals.sagepub.com/home/jmx

Complaint Publicization in Social Media

Alireza Golmohammadi, Taha Havakhor, Dinesh K. Gauri, and Joseph Comprix

Abstract

Firms are increasingly turning to social media platforms for complaint handling. Previous research and practitioners' reports highlight the benefits of complaint handling on social media, urging firms to provide prompt and detailed responses to complaints. However, little research has explored the possible drawbacks of such practices, especially when responses inadvertently further publicize complaints. Utilizing two unique data sets in a series of observational and quasiexperimental analyses, this research provides the first evidence of "complaint publicization" in social media, a phenomenon in which firm responses to complaints on popular social media platforms increase the potential public exposure of complaints. This negative effect can outweigh any positive customer care–signaling impact from firm responses. The authors show that a response strategy that engenders a high level of complaint publicization (e.g., providing detailed responses through multiple communication exchanges with a complainant) could negatively impact perceived quality and firm value, diminish the positive impact of a firm's own posts, and increase the volume of future complaints. Additional analyses reveal that these adverse impacts are stronger for firms that are targeted by retail investors. The authors also uncover specific response strategies and styles that could mitigate these effects.

Keywords

complaint handling, complaint publicization, firm value, perceived quality, social media

Online supplement: https://doi.org/10.1177/00222429211002183

Consumers and firms are increasingly using social media platforms such as Twitter for complaining and for responding to complaints (hereinafter, "complaint-response communications"). For example, according to Brandwatch (Smith 2020), complaint-response communications on Twitter have increased 250% in the two years leading to 2018. Further growth in the popularity and use of social media as a complaint channel is expected as younger generations become consumers (Alcántara 2020). Social media is also a major source of information for investors in publicly traded firms (Borah et al. 2020; Colicev et al. 2018; Lee, Hutton, and Shu 2015). Therefore, both complaint-response communications and information seeking about a firm are increasing on major social media platforms. As a result, the dynamics of complaint-response communications on these platforms may impact firm value, an issue that has not yet attracted sufficient scholarly attention. Exploring this relationship has important managerial implications, given that enhancing shareholder value is viewed as the ultimate purpose of marketing (e.g., Srivastava, Shervani, and Fahey 1998).

A rich stream of research has demonstrated the benefits of complaint handling on social media. For example, complaint handling has been found to have a positive impact on word of mouth (WOM) and purchase intentions (Hogreve, Bilstein, and Hoerner 2019), restaurant check-ins (Kumar, Qiu, and Kumar 2018), and subsequent ratings (Wang and Chaudhry 2018). These positive effects stem from the fact that firm responses in the public sphere of social media potentially mitigate the complaint's negative impact (e.g., Chung et al. 2020). For example, Chen et al. (2019, p. 83) call the impact of firm responses a "mitigating effect": "[Because firm responses to complaints] mitigate the impact of negative reviews, they may increase future sales." Similarly, Kumar, Qiu, and Kumar (2018, p. 851) argue that firm responses "can improve, though not completely eliminate, the damage created by the negative review." In light of these findings, academics and practitioners

Alireza Golmohammadi is Assistant Professor, Department of Marketing, Belk College of Business, University of North Carolina-Charlotte, USA (email: golmohammadi@uncc.edu). Taha Havakhor is Assistant Professor, Department of Management Information Systems, Fox School of Business, Temple University, USA (email: tul60818@temple.edu). Dinesh K. Gauri is Professor and Walmart Chair in Marketing, Department of Marketing, Sam M. Walton College of Business, University of Arkansas, USA (email: dkgauri@uark.edu). Joseph Comprix is Professor, Department of Accounting, Martin J. Whitman School of Management, Syracuse University, USA (email: jjcompri@syr.edu).

alike recommend that firms, almost unconditionally, be responsive on social media and urge them to respond to complaints in a prompt and detailed manner (e.g., Hogreve, Bilstein, and Hoerner 2019; Kowalewicz 2019; Maerowitz 2018). Little research, however, has explored the possible pitfalls of complaint handling on social media. More specifically, research has ignored an important boundary condition to prior findings: firm responses to complaints might increase the potential public exposure of complaints, complicating the effects of a firm's complaint handling strategies. Our study strives to shed light on this boundary condition.

While the visibility of complaints can impact perceptions about a firm, some design features in popular social media increase complaints' visibility once the firm responds to those complaints (hereinafter, "complaint-publicizing features"). A notable example is Twitter. First, when a firm responds to a complaint on Twitter, the complaint (which previously had only been visible to the followers of the complainant) will be displayed at the top of the firm's Twitter page, which is the most prime display location on the firm's page, along with the firm's response and the firm's own tweets. This allows the complaint to potentially reach a much larger audience.[1] Second, a firm's response to an existing complaint-response communication (i.e., the firm replying to an existing communication exchange between a complainant and the firm) promotes the whole thread back to the top of the firm's Twitter page. This seemingly trivial design feature of prominent social media platforms such as Twitter may have an important implication. Responding to complaints on such platforms inadvertently increases the complaints' potential public exposure. We call this phenomenon "complaint publicization."

Notably, the findings of prior research may not generalize to contexts like Twitter, given that prior literature has studied platforms where a complaint, once posted, is visible to observers, and the firm's response does not alter its visibility. However, the assumption that a complaint is readily visible does not hold on platforms such as Twitter, where the visibility of complaints changes after a response. Firm responses on such platforms may have a complaint-publicizing effect in addition to a positive, customer care–signaling impact.

Complaint publicization could have adverse consequences for firms. Firms' social media pages are public channels, and visiting them is common among social media users. For example, Twitter reports that one of the top two actions users take after being exposed to a brand name on Twitter is visiting the brand's Twitter page (Midha 2014). A high volume of complaint-response communication, which can happen as a result of a just-in-time and detailed response strategy (e.g., providing detailed responses through multiple communication exchanges with a complainant) in periods of high complaint activity, can turn the top and most visible portion of a firm's page into a complaint arena, facilitating observers' exposure to complaints with minimal effort.[2] Exposing visitors to a social media page replete with consumer complaints could prove harmful to the firm for two reasons. First, exposure to complaints can harm perceptions of brand quality, a prediction that is grounded in the existing literature (e.g., Dellarocas 2006). Second, exposure to complaints may encourage observers to complain too (Hewett et al. 2016), creating a negativity spiral. Complaint publicization can thus influence a firm's value, given that investors' decisions are influenced by factors that can impact attitudes about a firm (Colicev et al. 2018; Mizik and Jacobson 2008) and by the overall sentiment about a firm on social media (e.g., Nguyen, Calantone, and Krishnan 2020).

We integrate various streams of research to predict that firm responses to complaints on social media platforms with complaint-publicizing features can negatively influence firm value and negatively moderate the positive impact of a firm's own posts (e.g., its tweets). Utilizing two unique data sets related to firm pages on Twitter, an observational and a quasiexperimental study provide strong support for our hypotheses and offer several additional insights. Our research provides important contributions to the literature.

First, it reveals an overlooked phenomenon in online complaint handling: complaint publicization by firms and its negative impacts on important outcomes such as perceived quality, daily abnormal returns, Tobin's q, and the volume of future complaints. Our results show that a response strategy that leads to lower complaint publicization is associated with daily abnormal returns that are, on average, as much as 14% higher than daily abnormal returns associated with a response strategy that engenders higher complaint publicization. Our findings add to the existing literature on social media complaint handling, which has so far mostly focused on how firm responses mitigate the adverse impact of complaints. This research also contributes to a stream of literature that explores the contingencies of the effectiveness of a firm's complaint handling efforts (in the offline environment; Morgeson et al. 2020). We caution firms against following one-size-fits-all strategies when responding to complaints on social media. According to our results, employing seemingly effective and well-accepted response strategies (e.g., providing timely and detailed responses) without considering their complaint-publicizing implications could have serious repercussions on some social media platforms. For example, in 2016, Delta airlines decided to shut down its customer service Twitter page (@DeltaAssist) and announced that it would provide customer service using its primary page (@Delta). Our results suggest that such a move could increase the potential public exposure of complaints and have negative consequences, given that users are more likely to visit a firm's primary Twitter page than its customer service page.

[1] In Study 2, we provide model-free evidence that consumer complaints to which the firm responds (and are thus published on the firm's Twitter page) receive significantly more likes than complaints that do not receive a firm response.

[2] As part of Study 2, we provide direct evidence for this: a higher volume of firm responses to complaints leads to a larger portion of the firm's Twitter page being occupied by complaints.

Second, the current research is the first to document how firm responses to complaints can diminish the impact of a firm's own posts (e.g., its tweets). While firms frequently utilize social media platforms for both posting original content (e.g., Borah et al. 2020) and handling complaints (e.g., Wang and Chaudhry 2018), limited research attention has been paid to how these two modes of communication may influence each other. The suppressive effect revealed in this research is opposite to the documented impact of responses on platforms that do not have complaint-publicizing features, such as Facebook (Chung et al. 2020).

Third, this research provides the first evidence of differences in the impact of online complaint handling on the value of firms whose investors are primarily retail versus institutional investors. We find that the relative negative impact of complaint publicization is stronger for firms that are major trading targets for retail (vs. institutional) investors, consistent with these investors being more sensitive to public media information (Peress and Schmidt 2020). According to our results, pursuing a response strategy that leads to lower complaint publicization can lead to around 30% higher daily abnormal returns for firms that are more heavily targeted by retail investors than for those targeted by institutional investors.

Finally, our research contributes to the literature on causal inference from observational data (e.g., Wang and Chaudhry 2018) by introducing product recalls as a context that, along with a matching approach to correct for unparalleled trends, could reasonably isolate the impact of different complaint handling strategies.

Theoretical Background

To understand how complaint publicization (resulting from firm responses) may impact firm value, we draw on and integrate recent research on the online primacy effect, the literature of negativity bias, and research on the differential impact of firm- versus consumer-initiated information.

Online Primacy Effect

Recent research explores the importance of the position of online content items (Abhishek, Hosanagar, and Fader 2015; Ghose, Goldfarb, and Han 2013; Ghose, Ipeirotis, and Li 2014). This research documents a strong online primacy effect. Ceteris paribus, items positioned in prime display locations have a higher impact. For example, in their study of a travel search engine, Ghose, Ipeirotis, and Li (2014) demonstrate that a hotel that ranks higher on a search engine results page and thus appears at a higher screen position receives more clicks. Similarly, Abhishek, Hosanagar, and Fader (2015) find that search ads featured in top positions receive a disproportionately larger number of clicks than ads in lower positions. These effects are attributed to search costs: consumers need to exert more cognitive and physical effort while scrolling down a list of items (Ghose, Goldfarb, and Han 2013).

In line with the online primacy effect, we predict that the promotion of a complaint (or an existing complaint-response communication) to the most prime display location on the firm's page (due to the firm's response to it) should increase the complaint's public exposure and impact. However, the online primacy effect alone cannot explain the impact of firm responses to complaints. This is because firm responses publicize both complaints and firm responses to those complaints and, thus, it is not clear whether the negative, complaint-publicizing impact of firm responses or the positive customer care–signaling effect of the responses will dominate. Next, we discuss underlying theories that may explain which of these two scenarios is more plausible.

Negativity Bias

A rich body of marketing research has documented the asymmetric impacts of negative and positive information (e.g., Herr, Kardes, and Kim 1991; Mittal, Ross, and Baldasare 1998). Negative information (e.g., consumer complaints; Diamond 2015; Hewett et al. 2016) tends to be more impactful than neutral and positive information (e.g., firm responses). This negativity bias stems from humans' tendency toward loss aversion (Kahneman and Tversky 1979), where losses are psychologically weighted more heavily than gains (Mittal, Ross, and Baldasare 1998). In the context of online consumer communications, positive online reviews have been found to be less valued than negative consumer reviews (Chen and Lurie 2013). Similarly, Van Dieijen et al. (2019) show that the impact of a shock to negative WOM on stock return volatility is stronger than the impact of a shock to positive WOM. In line with this literature, we argue that complaints (which tend to be negatively toned) may deliver a stronger impact than firm responses (which tend to be nonnegatively toned). Complementing the negativity-bias literature, the literature on firm- versus consumer-initiated information may further help us understand the overall impact of firm responses to complaints.

Firm- Versus Consumer-Initiated Information

Consumers' communications and firms' communications differ in their perceived credibility, which has important ramifications for the impact of each type of content. Consumer-initiated communications tend to be perceived as more credible than firm-initiated communications and claims (Campbell and Kirmani 2008; Colicev et al. 2018; Friestad and Wright 1994). Consumers tend to look with suspicion at firm-initiated communications (which are often intended to positively influence consumers and to persuade them to make a purchase). By contrast, consumer-initiated communications (e.g., complaints) tend to be perceived as more credible accounts of the quality of a firm and its products (You, Vadakkepatt, and Joshi 2015). Consumer-initiated communications also are perceived as more diagnostic. For example, a consumer's complaint generally has more informational content than a firm's response, which mainly contains follow-up questions or apologies (Einwiller and Steilen 2015; Goh, Heng, and Lin 2013).

Hypothesis Development

Studies across disciplines demonstrate that social media is an important source of information to investors (e.g., Blankespoor, Miller, and White 2013; Borah et al. 2020; Lee, Hutton, and Shu 2015), impacting both retail and institutional investors (e.g., Nguyen, Calantone, and Krishnan 2020). Accordingly, complaint publicization on social media can potentially impact investors' views of a firm and, as a result, a firm's value. As explained previously, complaint publicization results from firm responses to complaints conceding the prime display location on a firm's social media page to the complaints. This happens through (1) displaying the complaint-response communication at the top of the firm's social media page when the firm responds to a new complaint and (2) promoting an existing complaint-response communication back to the top of the page when the firm responds again to it. We predict that the negative, complaint-publicizing impact of firm responses outweighs their positive, customer care–signaling impact, leading to an overall negative impact on firm value, for two reasons.

First, in line with the literature on the online primacy effect, conceding the top of a firm's social media page to complaint-response communications could substantially increase their public exposure, negatively impacting perceived quality. Even though nonnegative firm responses accompany the publicized complaints, negativity bias suggests that the overall impact will still be negative. Moreover, because the negative content (i.e., the complaint) is generated by consumers, whereas the accompanying nonnegative content (i.e., the response) is generated by the firm, the overall impact (e.g., on perceived quality) is likely to be negative, given the higher perceived credibility and diagnosticity of consumer-initiated information. Given that a negative impact on perceived quality can then influence the firm's future profitability and success (Colicev et al. 2018; Mizik and Jacobson 2008; Tirunillai and Tellis 2014), we expect firm responses to complaints to negatively impact firm value. Consistent with this idea, previous research has shown that exposure to consumer complaints negatively impacts other consumers' attitudes about a firm (Colicev et al. 2018; Culotta and Cutler 2016; Dellarocas 2006; Ho, Wu, and Tan 2017). Moreover, anecdotal evidence indicates that firms try to decrease observers' exposure to complaints out of concern that these complaints can damage observers' attitudes (Einwiller and Steilen 2015).

Second, according to the "negativity spiral" effect, complaints lead to more complaints (Hewett et al. 2016). As such, the complaints displayed at the top of a firm's social media page can ignite additional complaints. A firm's reaction (i.e., responsiveness) to this increasing volume of complaints can turn the firm's social media page into a perpetual complaint arena, which encourages further complaints, leading to a vicious cycle. As a result, the negativity spiral could create an "echo chamber for complaints" that becomes loud enough to grab investors' attention, especially due to the virality of negative content. Moreover, investors increasingly monitor firm-related social media conversations and consumer sentiments through social media aggregator services, such as Dataminr and Infegy (Nguyen, Calantone, and Krishnan 2020), which are likely to pick up on the increasingly negative social media sentiment about a firm. Drawing on these two reasons, we hypothesize:

> **H_1:** Firm responses to complaints on platforms with complaint-publicizing features negatively impact firm value.

Given the potential for complaint publicization, we expect firm responses to complaints to moderate the impact of a firm's own posts (e.g., its tweets) too. This is because when a firm responds to a complaint—on Twitter, for example—the complaint-response communication is displayed on the firm's Twitter page, along with the firm's own tweets. This collocation may influence the effectiveness of the firm's tweets because, according to the literature on integrated marketing communication, the effectiveness of a given communication content is influenced by the presence of other content (Batra and Keller 2016). The negative content of a complaint about a firm can, in fact, conflict with the content of the firm's own tweets, especially because many firm tweets use promotional language to build a positive image (Borah et al. 2020; Hewett et al. 2016).[3] For example, a firm's tweet highlighting a product's quality could be displayed adjacent to a consumer complaint about the same product. The literature streams on negativity bias and firm- versus customer-initiated information suggest that the collocation of consumer complaints with firm tweets may suppress the positive impact of firm tweets on perceived quality and, as a result, on firm value. Drawing on the preceding discussion, we hypothesize:

> **H_2:** Firm responses to complaints on platforms with complaint-publicizing features diminish the positive impact of the firm's posts on firm value.

Moreover, given that we argued that complaint publicization underlies the negative impacts of firm responses to complaints, we hypothesize:

> **H_3:** Compared with a response strategy that engenders a lower level of complaint publicization, a response strategy that engenders a higher level of complaint publicization more negatively impacts firm value.

[3] Not all firm tweets are persuasive. However, given that the majority of a firm's tweets are positive and persuasive, on average, the content of complaints may interfere with the content of firm tweets. In our data set, the standardized average valence of firm tweets and consumer complaints are .43 and $-.62$, respectively. Given the possible range for standardized valence scores (i.e., $[-1, 1]$), this indicates a large difference between the valence of firm tweets and consumer complaints.

Table 1. Overview of Studies.

	Study 1	Study 2
Sample	S&P 500 firms	Recall-stricken firms
Sample size	375 firms	107 firms
Context	General	Product recalls
	Industries include manufacturing, finance, communication, wholesale and retail, and others	Focused on the following industries: auto, food and drugs, manufacturing
Focal independent variable	Volume of firm responses	Response strategy
Dependent variables	Tobin's q, perceived brand quality	Daily abnormal returns, volume of future complaints
Nature of the study	Observational	Quasiexperimental
Time period	2014–2015	2014–2018
Hypotheses tested	H_1 and H_2	H_3 and H_4
Evidence of underlying mechanism	—	Complaint publicization
Moderators	Volume of firm tweets	Volume of firm tweets, thread size, retail/institutional target, response styles
Characteristic	Higher external validity	Higher internal validity

> **H_4:** Compared with a response strategy that engenders a lower level of complaint publicization, a response strategy that engenders a higher level of complaint publicization more strongly diminishes the positive impact of the firm's posts on firm value.

We begin with Study 1, an observational study that explores the impact of firm responses to complaints on firm value (Tobin's q), perceived brand quality, and the effectiveness of the firm's own posts. This study tests H_1 and H_2. Study 2, which utilizes a quasiexperimental approach, explores the underlying mechanism that drives the first study's observed associations. Study 2 employs a more controlled setting than Study 1, allowing for better identification of the impact of complaint publicization as the proposed mechanism and allows for tests of H_3 and H_4. Moreover, this study provides additional support for H_1 and H_2 (as reported in the Web Appendix). The two studies are mutually informing. The first provides higher external validity through employing an inclusive sample (375 S&P 500 firms), while the second provides better experimental control, albeit in a smaller set of 107 firms in a more limited set of industries. Table 1 and Figure 1 provide an overview of the two studies.

Study 1

Study 1 utilizes a unique data set of S&P 500 firms' Twitter communications, brand equity, financial, and accounting data to test H_1 and H_2. Specifically, this study explores whether the volume of firm responses on Twitter negatively impacts perceived quality and Tobin's q, and whether it diminishes the impact of the firm's own tweets. Twitter is an appropriate context for at least three reasons: First, it is a platform with complaint-publicizing features, so it allows us to test our hypotheses. Second, investors react more strongly to communications on Twitter than on other social media platforms (Bilinski 2019). Third, Twitter is one of the main social media outlets for complaining and complaint handling. In addition to platforms that provide analytics about communications on Twitter, such as Dataminr and Infegy, many websites provide real-time views of complaints about firms on Twitter (e.g., onholdwith.com).

Sample and Data

The S&P 500 is a popular index because the included firms form a representative sample of established firms across a diverse set of industries. We started with the firms listed on the S&P 500 index in 2014. We examined each firm's website to identify its official Twitter page (if it had one) to ensure that each page belonged to and was managed by the sample firms. We identified 375 firms with a Twitter page at the time of data collection. We then developed a Python engine for web scraping to collect information from Twitter. We downloaded all of the communications on each firm's Twitter page during 2014 and 2015.[4] We then categorized these communications into two groups: tweets and firm responses.

The independent variables are the volume of firm tweets and the volume of firm responses, aggregated into quarterly counts. The dependent variable is quarterly Tobin's q. Tobin's q is a forward-looking market value measure that captures both the short-term performance and the long-term prospects of a firm (Germann, Ebbes, and Grewal 2015). Importantly, Tobin's q is the most widely used measure for capturing changes in the value of a firm's intangible assets (Dotzel, Shankar, and Berry 2013), such as the equity that can be derived from the firm's social media communications. Using Tobin's q is appropriate for a sample like ours that includes firms from different industries (Montgomery and Wernerfelt 1988).

[4] Data collection took place in June 2016. Some sample firms had multiple Twitter accounts. In those cases, we focused on the firm's main Twitter account. Dropping these firms from the sample does not change the results.

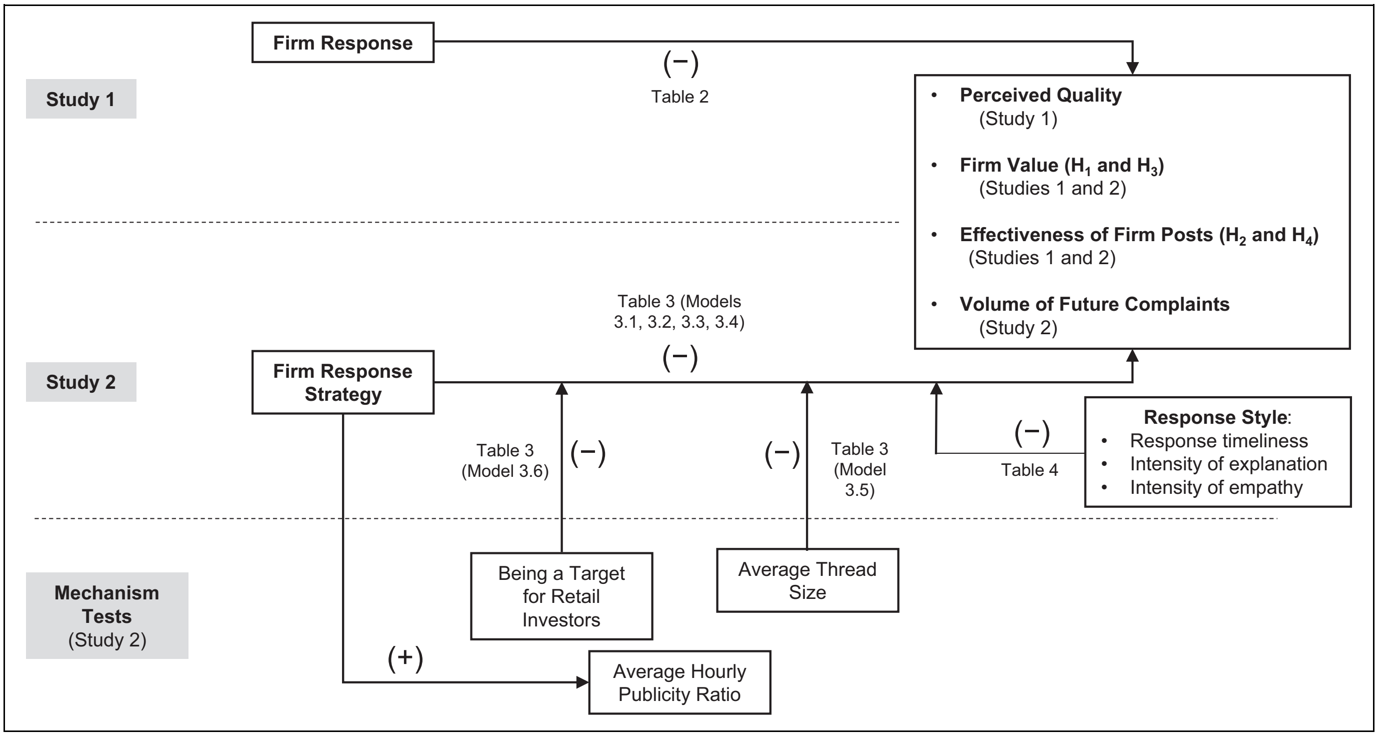


Figure 1. Overview of Studies 1 and 2.

We also followed extant research (Dotzel, Shankar, and Berry 2013; Feng, Morgan, and Rego 2015; Josephson, Johnson, and Mariadoss 2016; Tirunillai and Tellis 2012) and controlled for a comprehensive set of potentially confounding factors (for operationalizations, see Appendix A). Specifically, we controlled for volume of WOM, average length of firm tweets, advertising intensity, research and development (R&D) intensity, competitive intensity, industry size, return on assets, financial leverage, organizational slack, cost of goods sold, and quarter dummies. Our final data set included 2,948 observations over eight quarters (for sample characteristics, see the Web Appendix).

Model Development and Estimation

We estimated the following equation to test the impact of firm responses on Tobin's q:

$$Y_{it} = \alpha_0 + \alpha_1 \cdot tweet_{it} + \alpha_2 \cdot response_{it} + \alpha_3 \cdot tweet_{it} \times response_{it} + \alpha_4 \cdot X_{it} + \epsilon_{it}. \quad (1)$$

In this equation, subscript i represents the firm, and subscript t represents the quarter. Y is Tobin's q; α_1 and α_2 represent the main effects of the volume of firm tweets and the volume of firm responses, respectively. The interaction between the volume of firm tweets and the volume of firm responses is represented by α_3, while α_4 captures the effects of the vector of control variables. Finally, ϵ is an error term.

Before estimating the model, we conducted an augmented Dickey–Fuller unit root test to determine whether any variable exhibited nonstationary behavior and thus should enter the model in differences. The test identified only R&D intensity as evolving, so we included the first-difference of this variable in the model. We also standardized variables to help in interpretation and to reduce possible multicollinearity (e.g., Josephson, Johnson, and Mariadoss 2016).

A firm's behavior on social media may be influenced by unobserved factors, raising concerns of endogeneity. Although we have controlled for important variables that can impact firm value, other variables may simultaneously influence a firm's behavior on social media and impact the firm's value, rendering our independent variables endogenous. To address endogeneity concerns, we estimated our model using a control function approach (Petrin and Train 2010), which has been widely applied in previous marketing research (e.g., Eilert et al. 2017; Saboo, Kumar, and Anand 2017). We utilized this approach to account for the possible endogeneity of the volume of firm tweets, volume of firm responses, volume of WOM, and advertising intensity. In this approach, a control variable for unobserved variables is included in the regression model to decrease the correlation between the potentially endogenous variables and the error term (Petrin and Train 2010). First, a separate estimation is made for each endogenous variable. In our case, this means four estimations for the four potentially endogenous variables. In each of the four estimations, the endogenous variable is regressed on the set of control variables of Equation 1, as well as a variable that correlates with the endogenous variable (i.e., a relevant instrument) but does not directly correlate with the unobserved drivers of firm value (i.e., it satisfies the exclusion restriction criterion). Second, the predicted residuals from these four estimations are included in the main regression model. This approach enables us to estimate unbiased coefficients and mitigate endogeneity concerns (Eilert et al. 2017).

To identify variables that satisfy these conditions, we followed prior research and used industry-based excluded variables (Germann, Ebbes, and Grewal 2015; Saboo, Kumar, and Anand 2017). Specifically, for the volume of firm tweets (responses), we used the average volume of tweets (responses) by peer firms as the instrumental variables. Peer firms are those in the same two-digit Standard Industrial Classification code as the focal firm (Germann, Ebbes, and Grewal 2015). For firm i in industry j (which includes N_j firms), we calculated this variable as the sum of the volume of firm tweets (responses) by the firms in industry j, other than firm i, divided by $N_j - 1$.

We believe the industry's average communication is a good instrumental variable for two reasons. First, peer firms' behavior can have a normative effect, especially because peer firms face similar market conditions (Germann, Ebbes, and Grewal 2015). In addition, given the lack of clear guidelines regarding the appropriate volume of firm tweets (responses), firms are likely to imitate their peers, a prediction that is supported by previous marketing strategy research (e.g., Saboo, Kumar, and Anand 2017) and is consistent with institutional isomorphism theory (DiMaggio and Powell 1983). Thus, an industry-based instrumental variable is relevant. Moreover, in our analysis, a large number of firms are peer firms for a focal firm. As such, it is unlikely that the average behavior (e.g., tweets and responses) of these firms correlates with firm-level omitted variables that can impact a focal firm's value (e.g., organizational culture; Germann, Ebbes, and Grewal 2015; Saboo, Kumar, and Anand 2017), and thus, the proposed instruments should meet the exclusion restriction criterion. Similarly, we used the average volume of WOM and the average advertising intensity in a firm's industry as instruments for the volume of WOM and advertising intensity, respectively.

In the first stage of the control function approach, we estimated the following four equations:

$$\text{tweet}_{it} = \beta_{01i} + \beta_{11} \cdot \text{Ave\_Ind\_tweet}_{it} + \beta_{21} \cdot X_{it} + \mu_{1it}, \quad (2)$$

$$\text{response}_{it} = \beta_{02i} + \beta_{12} \cdot \text{Ave\_Ind\_response}_{it} + \beta_{22} \cdot X_{it} + \mu_{2it}, \quad (3)$$

$$\text{Adv}_{it} = \beta_{03i} + \beta_{13} \cdot \text{Ave\_Ind\_Adv}_{it} + \beta_{23} \cdot X_{it} + \mu_{3it}, \quad (4)$$

$$\text{WOM}_{it} = \beta_{04i} + \beta_{14} \cdot \text{Ave\_Ind\_WOM}_{it} + \beta_{24} \cdot X_{it} + \mu_{4it}. \quad (5)$$

In these equations, β_{01i}, β_{02i}, β_{03i}, and β_{04i} represent firm-specific heterogeneity with regard to the volume of firm tweets, the volume of firm responses, advertising intensity, and volume of WOM, respectively. β_{11}, β_{12}, β_{13}, and β_{14} capture the impact of the industry's average volume of firm tweets, volume of firm responses, advertising intensity, and volume of WOM, respectively. β_{21}, β_{22}, β_{23}, and β_{24} capture the effects of a vector of control variables. Finally, μ_{1it}, μ_{2it}, μ_{3it}, and μ_{4it} are random error terms. After estimating these four models, we estimated Equation 6. This equation is identical to Equation 1, except that it includes the four predicted residuals from Equations 2, 3, 4, and 5 (the vector δ captures the effect of these four predicted residuals).

$$Y_{it} = \alpha_0 + \alpha_1 \cdot \text{tweet}_{it} + \alpha_2 \cdot \text{response}_{it} + \alpha_3 \cdot \text{tweet}_{it} \times \text{response}_{it} + \alpha_4 \cdot X_{it} + \delta \cdot \mu_{it} + \epsilon_{it}. \quad (6)$$

Study 1 Results

Variance inflation factors (VIFs) were all below 1.5, indicating no issues with collinearity. The results presented in Panel A of Table 2 confirm our predictions. Specifically, the results show a positive association between the volume of firm tweets and firm value, while the volume of firm responses is negatively associated with firm value. This provides support for H_1. Importantly, the results also reveal a tension between firm tweets and firm responses. In support of H_2, we find that the volume of firm responses diminishes the positive impact that the volume of firm tweets has on firm value. Web Appendix reports an analysis that demonstrates the robustness of these findings to the correction for possible sample selection bias and the inclusion of additional control variables. We also conducted an additional analysis to explore the impact of firm responses on perceived quality (for details, see the Web Appendix). The results are reported in Panel B of Table 2 and are consistent with the findings from the previous analysis: a firm's volume of responses to complaints negatively impacts perceived quality and diminishes the impact of firm tweets on perceived quality.

These findings provide indirect evidence of the complaint publicization phenomenon and its impacts. Specifically, these novel findings are consistent with our prediction that the negative complaint-publicizing impact of firm responses can outweigh their positive customer care–signaling impact, leading to an overall negative effect of firm responses on firm value. This points to the asymmetric impact of complaints relative to responses and is in line with our integration of insights from research on negativity bias (Mittal, Ross, and Baldasare 1998) and on the influence of consumer-initiated information (Colicev et al. 2018; Friestad and Wright 1994). These effects are in contrast to findings from previous research that mostly document a positive impact of firm responses to complaints (on platforms such as TripAdvisor and Facebook; Chung et al. 2020; Wang and Chaudhry 2018). Thus, the effects identified here highlight the complex and multifaceted nature of firm responses to complaints, especially on social media platforms with complaint-publicizing features.

Study 2: Role of Complaint Publicization

Study 1 provides evidence of the negative impact of firm responses on perceived quality, firm value, and the effectiveness of a firm's own posts, providing support for H_1 and H_2. That study, however, has several shortcomings. First, although we controlled for an extensive list of variables, one might argue that the observed negative impact on firm value is driven

Table 2. The Impact of Firm Responses on Tobin's q (Panel A), Perceived Brand Quality (Panel B), and the Effectiveness of Firm Tweets (Panels A and B).

A: Firm Responses on Tobin's q and the Effectiveness of Firm Tweets						B: Firm Responses on Perceived Brand Quality and the Effectiveness of Firm Tweets	
Dependent Variable	**Volume of Firm Tweets**	**Volume of Firm Responses**	**Volume of WOM**	**Advertising Intensity**	**Tobin's q**	**Perceived Quality**	
Industry average	.20*** (.03)	.25*** (.03)	.23*** (.03)	.19*** (.01)			
Volume of firm tweets					.1** (.03)	Volume of firm tweets	.08 (.10)
Volume of firm responses (H_1)					−.12*** (.02)	Volume of firm responses to complaints (H_1)	−.20* (.09)
Volume of firm tweets × Volume of firm responses (H_2)					−.01*** (.00)	Volume of firm tweets × Volume of firm responses to complaints (H_2)	−.16* (.06)
Advertising intensity					.44*** (.05)	Advertising expenditures	.20*** (.03)
Volume of WOM					1.89*** (.36)	Volume of WOM	.12*** (.04)
Average length of firm tweets	−.08*** (.03)	.24*** (.03)	−.04 (.02)	.05*** (.01)	.08*** (.02)	Volume of firm response to noncomplaint tweets	−.02 (.03)
Cost of goods sold	.02 (.03)	.06 (.03)	.07** (.02)	−.02** (.01)	−.09*** (.01)	Volume of firm tweets × Volume of firm responses to noncomplaint tweets	.03 (.07)
Competitive intensity	.02 (.03)	.00 (.03)	.02 (.03)	−.01 (.01)	−.01 (.01)	Volume of firm responses to complaints × Volume of responses to noncomplaint tweets	.49*** (.09)
Financial leverage	−.20*** (.03)	−.10** (.03)	−.17*** (.03)	.03* (.01)	.00 (.01)		
Organizational slack	−.01 (.04)	.02 (.04)	.06 (.03)	.06*** (.02)	.09*** (.03)		
R&D intensity	−.02 (.03)	−.04 (.04)	−.02 (.03)	.02 (.01)	.01 (.01)		
Return on assets	.02 (.03)	.02 (.04)	−.03 (.03)	.01 (.01)	.12*** (.01)		
Industry size	.00 (.03)	−.03 (.03)	−.01 (.03)	.00 (.01)	−.11*** (.01)		
Wald's chi					3,822.70		1,402.40
N	2,948	2,948	2,948	2,948	2,948		8,700

*$p < .05$.
**$p < .01$.
***$p < .001$.
Notes: Standard errors are in parentheses. We exclude the coefficients of dummy variables and predicted residuals for brevity.

by other factors for which the study did not control. Firm fundamentals could be such confounding factors. A higher volume of complaints (and complaint handling activity) might result from an underlying issue, which could also decrease firm value.

Second, Study 1 did not provide direct evidence of the role of complaint publicization as the proposed underlying mechanism behind the negative impact of firm responses. This is due to the observational setting of the study, where causal confounders can hardly be controlled. We thus cannot draw any strong causal inferences about the role of complaint publicization from Study 1. Third, our preliminary findings give rise to important questions: Do firm responses to complaints harm firm value more for certain types of firms? In addition, how can a firm mitigate complaint publicization and its adverse effects? Finally, the use of Tobin's q, the main dependent variable of Study 1, has been criticized by recent research (Bendle and Butt 2018). Therefore, employing an alternative dependent variable can increase confidence in the findings. Study 2 is designed to address these issues. Perhaps most importantly, it rules out the confounding impact of firm fundamentals and captures the nature and the impact of complaint publicization. Our identification strategy in Study 2 entails a quasiexperiment in which we employ a strict regimen of matching (see Appendix B) to directly compare the impacts of two response strategies that lead to differential levels of complaint publicization. As such, this study provides tests of H_3 and H_4.

Identification Settings: Product Recalls

One of the best settings to study firm responses to complaints is in the context of product recalls. Recalls occur when a product is defective or dangerous, causing the manufacturer to retrieve it from end consumers and distribution channels (Chen, Ganesan, and Liu 2009). Importantly, a product recall could lead to a spike in the volume of complaints (Hsu and Lawrence 2016). Appendix C illustrates how such incidents cause a spike in the volume of WOM (Panel A) and in the volume of complaints (Panel B) about the firms in our data set. As we describe subsequently, we utilized these complaint-inducing events as opportunities to conduct several difference-in-differences (DID), as well as difference-in-difference-in-differences (DIDID) analyses.

Utilizing product recalls allows for clearer identification of the impact of complaint publicization because it allows us to account for the source of complaints (i.e., the recall) and to objectively control for its severity. Specifically, using automatic textual analysis of the complaints to identify the nature and severity of the issue causing the complaints would be challenging, subjective, and likely prone to errors. A benefit of employing product recalls as a complaint-inducing shock is that we can reasonably attribute complaints in the days following the shock to a known source (i.e., a product recall with known severity). Regulatory agencies such as the Consumer Product Safety Commission (CPSC), Food and Drug Administration (FDA), and the National Highway Traffic Safety Administration (NHTSA) provide measures of the severity of a recall. We utilize these measures in our preanalysis matching to control for the severity of the underlying issue causing the complaints. Moreover, the impact of the type of recall is absorbed by removing fixed effects in a DID (or DIDID) estimation.

Quasiexperimental Design

We first collected a sample of product recalls of U.S. publicly traded firms from three major sources that report product recalls for the automobile, manufacturing, and food and drug industries: the NHTSA, CPSC, and FDA, respectively. Overall, we found 318 product recalls from 2014 to 2018 that were not accompanied by other confounding events within a ten-day window [−5d, +5d] around the recall announcement.[5] These data were supplemented with a proprietary data set that included daily social media communications of publicly traded firms in the United States for the same period. A critical consideration in building an appropriate sample was that the firms use Twitter as their main social media platform for handling complaints. We identified a firm as "mainly using Twitter for complaint handling" if more than 70% of the total complaints directed at the firm in the quarter leading to the recall were communicated through Twitter. In our sample, 172 recalls belonged to firms in this group. Therefore, the focus of the study is on these 172 recalls belonging to 111 firms. We focused on tweets and responses to complaints of these firms in a ten-day window surrounding the recall.

When faced with a complaint, firms normally employ one of two types of response strategies. Some firms respond to complaints using a "closed-exchange" strategy, where a firm's response is limited to one public message that invites the complainant to continue the complaint handling process in a private mode (e.g., through direct message or email). Other firms employ an "open-exchange" response strategy, where the complainant and the firm engage in multiple exchanges (i.e., back-and-forth messaging) on Twitter.[6]

This natural distinction in response strategies across the firms in our sample provides an identification opportunity to test the impact of complaint publicization in a quasiexperimental fashion. Specifically, on Twitter, whenever a firm responds to a user's tweet (or to an existing complaint-response thread), the complaint-response communication appears at the top of the firm's page as the firm's most recent communication. Thus, using an open-exchange strategy leads to a given complaint-response communication appearing *multiple times* at the top of the firm's Twitter page; every time the firm responds to the existing thread, the communication reappears as the firm's

[5] We obtained confounding events from the *Wall Street Journal*, consistent with prior literature (e.g., Chen, Ganesan, and Liu 2009).

[6] In our final sample, a complaint on the Twitter page of firms utilizing an open-exchange (vs. closed-exchange) response strategy entailed an average of 3.032 (vs. 1) exchanges between the firm and the customer (i.e., 3 [vs. 1] firm responses).

most recent communication. For example, suppose a firm employs an open-exchange response strategy, and three communication exchanges happen between the firm and a complainant. In this case, the complaint-response thread appears three times at the top of the firm's Twitter page. By contrast, if a firm employs a closed-exchange response strategy, the complaint and the firm's response appear only once at the top of the firm's Twitter page. Consequently, the proportion of the space of a firm's Twitter page that is conceded to complaint-response communications should be higher for firms utilizing an open-exchange strategy than for firms utilizing a closed-exchange strategy. In other words, an open (vs. closed) exchange response strategy induces higher (vs. lower) complaint publicization in our quasiexperimental design. As we discuss subsequently, we test this assertion using a novel measure that directly captures the publicity of complaints on a firm's Twitter page.

The main independent variable is firm response strategy. In our analyses, we compare firms that addressed more than 75% of consumer complaints using an open-exchange response strategy (treatment group) against a matched group of firms that received the same volume of complaints but addressed more than 75% of them using a closed-exchange response strategy (control group). Moreover, we explore the interaction between response strategy and a firm's tweets. Finally, we explore the interaction between response strategy and three response-style variables, namely, response timeliness, the intensity of explanation, and the intensity of empathy in firm responses. The main dependent variable is daily abnormal returns. In a subsequent analysis, we utilize the volume of future complaints as an alternative dependent variable.

Identification Strategy

Several aspects of our analyses serve to remove the impacts of extraneous variables. First, we employed a strict regimen of matching, which, at the cost of losing observations and power, enabled us to better isolate the impact of response strategy and to ensure that extraneous variables do not drive the observed effects. Specifically, firms in the treatment and control groups were matched on the basis of the preshock value of a wide range of variables (Appendix B details the variables used for matched-sample construction, as well as the rationale for their inclusion). A matching with replacement was done using the nearest neighbor following a propensity score matching approach. Out of the 172 recalls in our sample, we could match (with replacement) 107 recalls, and we eliminated the rest.[7]

Second, we controlled for an extensive list of variables at the firm-, complaint-, and response-levels during the event window (for details, see Appendix A). Third, by removing preshock differences, the DID estimation significantly attenuates any baseline differences between the control and treatment groups. Fourth, the DID estimation removes the fixed effects of any firm-specific variable that does not change during the narrow temporal window of the analysis (i.e., [−5d, +5d] around the event). Fifth, we dropped observations with other major news within the event window.[8] Finally, the impact of the type of product recall event is absorbed by removing fixed effects in our model. Taken together, our identification strategy reduces the likelihood that the key elements attributable to daily returns (e.g., product quality, firm fundamentals) become causal confounders and ensures that observed differences between the treatment and control groups can be reasonably attributed to differential response strategies (which create different levels of complaint publicization). As we show subsequently, the treatment and control groups have parallel daily return trends prior to the shock.

Model Specification

Our specification is as follows:

$$Y_{it} = \beta \cdot Open_i \times Post_t + \gamma \cdot X_{it} + \alpha_i + \theta_t + \epsilon_{it}, \quad (7)$$

where Y is the daily abnormal returns for brand i at day t; $Open_i$ identifies whether brand i employs an open- or a closed-exchange response strategy; and $Post_t$ is an indicator variable that is equal to 1 for day t after the recall and 0 otherwise. The coefficient of interest, β, measures the difference between differences (the DID term) in daily abnormal returns before and after product recalls between the treatment and control groups. We also include α_i and θ_t to control for brand and day fixed effects, respectively (which absorb the direct effects of $Open_i$ and $Post_t$). X_{it} is the vector of time-varying control variables.

Study 2 Results

Main effects. VIFs in all models were below 1.5 (the highest VIF was 1.384), indicating no issues with collinearity. Before reporting the main results, we present the estimates from a relative-time DID estimation in Table 3 to better examine the validity of our parallel-trends assumption (Model 3.1). As the estimates show, the DID coefficients (i.e., [t − m] × Open) are insignificant in all but one of the days before the recall event, while, for the four consecutive days after the recall event, the coefficients (i.e., [t + m] × Open) are significantly and negatively associated with abnormal returns. This pattern shows that the parallel-trends assumption reasonably holds. The Web Appendix presents the interval plot for Model 3.1 to illustrate this point. Table 3 (Model 3.2) summarizes our parameter estimates for Equation 7. All significance levels are determined using firm-clustered standard errors. We observe that firms that address complaints using an open-exchange response strategy

[7] A propensity score difference cutoff to keep a nearest neighbor was determined as the highest acceptable distance based on which the statistical difference between matching variables in the treatment and control groups is insignificant ($p > .10$).

[8] We found matches for 15 of the observations that were originally dropped due to having other major news in their event windows. Including these observations produced results that were qualitatively similar to our main findings. These results are available upon request.

Table 3. The Impact of Response Strategy on Daily Abnormal Returns (Models 3.1 and 3.2), the Volume of Future Complaints (Model 3.3), the Effectiveness of Firm Tweets (Model 3.4), and Causal Mechanism Tests (Models 3.5 and 3.6).

	Model					
Dependent Variable	**3.1 Daily Abnormal Returns**	**3.2 Daily Abnormal Returns**	**3.3 Volume of Future Complaints**	**3.4 Daily Abnormal Returns**	**3.5 Daily Abnormal Returns**	**3.6 Daily Abnormal Returns**
Post × Open (DID, H_3)		−.084** (.026)	.114*** (.028)	−.091** (.032)	−.078** (.029)	−.081** (.029)
(t − 5) × Open	.006 (.004)					
(t − 4) × Open	−.012† (.007)					
(t − 3) × Open	.005 (.004)					
(t − 2) × Open	−.010 (.006)					
(t − 1) × Open	.004 (.003)					
Event Day	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
(t + 1) × Open	−.081* (.04)					
(t + 2) × Open	−.093** (.032)					
(t + 3) × Open	−.046* (.019)					
(t + 4) × Open	−.021† (.011)					
(t + 5) × Open	.005 (.004)					
Firm tweets				.028* (.012)		
Open × Post × Firm tweets (H_4)				−.022* (.009)		
Open × Post × Thread_size					−.029** (.010)	
Open × Post × Retail						−.108* (.048)
Window-time controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	No	Yes	Yes
Wald's χ	6,712.56	5,823.32	3,815.77	7,498.85	5,644.82	5,158.94
N	1,177	1,177	214	1,177	1,177	968

†$p < .1$.
*$p < .05$.
**$p < .01$.
***$p < .001$.
Notes: Standard errors are in parentheses. Window-time controls: number of followers of the firm's Twitter account, volume of complaint tweets, valence of complaint tweets, volume of noncomplaint tweets, valence of noncomplaint tweets, intensity of high arousal emotions (disgust, fear/anxiety, anger) in complaints, intensity of low arousal emotion (sadness) in complaints, complaint complexity, complaint length, engagement with a complaint prior to firm response, time of day when the complaint was tweeted, complaint-related firm responsiveness, non-complaint-related firm responsiveness, response timeliness, intensity of explanation in firm response, intensity of empathy in firm response, intensity of apology in firm response, compensation in firm response, variation in response sequence, and firm's newsworthiness.
For brevity, we have excluded the coefficients for Firm tweets × Post and Firm tweets × Open from Model 3.4, the coefficients for Thread_size, Thread_size × Open, and Thread_size × post from Model 3.5, and the coefficients for Retail, Retail × Open, and Retail × post for Model 3.6.

have significantly lower abnormal stock returns in the days following the event compared with firms that employ a closed-exchange response strategy, in support of H_3. We posit that this negative impact is due to the higher level of complaint publicization that results from an open-exchange response strategy. Collectively, these estimates provide robust evidence about the complaint publicization phenomenon and its impact. These findings have important theoretical and managerial implications that we detail in a subsequent section.

As discussed in the "Conceptual Development" section, complaint publicization may also have a long-lasting impact by igniting more complaints. This can create a vicious cycle that can linger for extended periods, impacting more stationary indices of performance, such as quarterly Tobin's q (as revealed in Study 1). To test this idea, we conducted an analysis similar to our main analysis, but with the volume of future complaints (in a window of 30 business days following the event window) as the dependent variable (details are provided in the Web Appendix). The results of this DID estimation are presented in Table 3 (Model 3.3). Consistent with our predictions, we find that an open-exchange response strategy (which engenders higher complaint publicization) leads to a significantly higher volume of future complaints when compared with a closed-exchange response strategy. A firm's responsiveness to this increasing volume of complaints can turn the firm's page into a perpetual complaint arena, which would itself encourage further complaints, leading to a vicious cycle. This negativity spiral could adversely impact the overall sentiment about the firm on the social media platform. Overall, these results indicate that complaint publicization could have a lasting impact on the firm. Additional analyses (reported in the Web Appendix) demonstrate the robustness of our results and provide additional insights.

Interaction effect. Study 1 indicates that firm responses to complaints may diminish the positive impacts of a firm's own tweets. We argue that this suppressive effect may stem from the collocation of firm tweets with consumer complaints on the firm's Twitter page. If this argument holds, an open-exchange response strategy should lead to a stronger suppressive effect, because this strategy engenders higher complaint publicization when compared with a closed-exchange response strategy. This should increase the frequency of firm tweets being collocated with consumer complaints on the firm's Twitter page. To test this idea, we conducted a difference-in-difference-in-differences (DIDID) analysis, which evaluates whether the impact of a firm's tweets is contingent on the DID term. This DIDID term (Open $\times$ Post $\times$ Firm tweets) is similar to the (firm tweets $\times$ firm responses to complaints) term in Study 1. The results are reported in Table 3 (Model 3.4). We find a positive main effect of firm tweets on firm value, similar to Study 1. Consistent with H_4 and in line with our previous findings, we also find a negative three-way interaction indicating that, when compared with a closed-exchange strategy, an open-exchange response strategy more strongly diminishes the positive impact of a firm's tweets. This provides additional evidence of the suppressive impact of complaint publicization.

Unfolding the Underlying Mechanism

Study 2's quasiexperimental design provides evidence that complaint publicization underlies the effect of firm responses to complaints on daily abnormal returns and the volume of future complaints. In this section, we provide additional evidence consistent with this proposed mechanism.

Do firm responses impact the composition of a firm's Twitter page real estate? We developed a novel measure that directly captures the publicization of complaints on a firm's Twitter page, as displayed on both desktop computers and mobile devices. Specifically, we measured the "average hourly publicity ratio of complaints on a firm's Twitter page" as the average ratio of the firm's Twitter page space (within three mouse scrolls on a 16-inch monitor with 100% zoom, and three screen-wide scrolls on a 6-inch smartphone) that is occupied by complaints in a given hour. We explored whether the average hourly publicity ratio of complaints is significantly higher for the treatment (open-exchange) group versus the control (closed-exchange) group (for details, see the Web Appendix). Consistent with our expectation, we find that firm responses to complaints do affect the composition of a firm's Twitter page real estate. The results of two t-tests indicate that, compared with a closed-exchange strategy, an open-exchange response strategy leads to a significantly higher average hourly publicity ratio of complaints on a 16-inch monitor ($M_{open} = .58$; $M_{closed} = .33$; $t = 10.61$; $p < .001$) and on a 6-inch smartphone ($M_{open} = .82$; $M_{closed} = .38$; $t = 13.85$; $p < .01$).

As we noted previously, the back and forth between a complainant and the firm, and the subsequent promotion of the complaint-response thread to the top of the firm's page, should be the reason that the open-exchange response strategy results in lower daily stock returns. Consistent with this, the DID must be stronger (more negative) as the daily average (complaint-response) thread sizes increase. This is because a larger thread (i.e., more back and forth between a firm and complainants), leads to a given thread appearing at the top of the firm's Twitter page a greater number of times.[9] This should lead to complaints occupying a larger portion of a firm's Twitter page at a given time. Consistent with this idea, we find that the average hourly publicity ratio of complaints for firms that employ an open-exchange strategy, but with small average thread sizes (i.e., close to 1; [1, 1.25]), is not different from that for the firms that employ a closed-exchange strategy ($M_{open} = .37$; $M_{closed} = .33$; $t = 1.15$; $p > .1$). Nonetheless, firms that employ an open-exchange strategy, but with larger average thread sizes, have an average hourly publicity ratio that is significantly higher than that for the firms that employ a closed-exchange strategy ($M_{open} = .66$; $M_{closed} = .33$; $t = 16.37$; $p < .001$).

Moreover, Table 3 (Model 3.5) presents a DIDID estimate, which shows that the impact on abnormal returns becomes larger as the daily average thread size increases. These findings further confirm that complaint publicization is the mechanism through which the open-exchange strategy leads to lower daily returns. The findings reported in this section are also consistent with the literature on the online primacy effect (Abhishek, Hosanagar, and Fader 2015; Ghose, Ipeirotis, and Li 2014; Ghose, Goldfarb, and Han 2013), which suggests that items positioned at the most prime display locations enjoy a higher impact. Extending this literature, our findings indicate that firm responses to complaints negatively impact firm value because firm responses concede the most prime display location on the firm's Twitter page to complaints, with a larger thread size amplifying this pattern.

Does being displayed on a firm's Twitter page increase the potential public exposure of complaints? Given that it is almost impossible to directly measure users' exposure to the complaints displayed on a firm's Twitter page, we looked at a downstream consequence of exposure: the number of "likes" a complaint receives. If a firm's Twitter page matters, in the sense that observers pay attention to it, complaints that receive a firm response (and are thus displayed on the firm's Twitter page) should receive, on average, more likes than complaints that never receive a firm response (and thus are not displayed on the firm's Twitter page). Consistent with this conjecture, we find that the average number of likes for complaints that never received a firm's response was .13, whereas this number was

[9] The volume of complaints, a control variable in our model, partials out the effect of the number of unique complaint-response communications.

4.53 for complaints to which a firm responded. This pattern is consistent with our implicit assumption that a complaint displayed on a firm's Twitter page has a higher level of public exposure.[10]

Another underlying assumption in the current research is that the space of a firm's social media page gives valuation clues to investors, and that is why complaint publicization may impact daily returns. While a direct test of such an underlying mechanism may not be feasible, indirect evidence can be obtained if the observed negative impacts are stronger for a subset of firms whose investors rely more on informational clues found on public media. According to the existing literature on stock trading, retail investors are more heavily influenced by publicly available sources of information given their limited access to professional means, such as Bloomberg terminals (Bukovina 2016). By contrast, institutional investors are less influenced by individual pieces of information in public media. Given their better access to information (e.g., professional databases, private information; Bukovina 2016) and their higher level of sophistication, institutional investors' decisions are mostly driven by fundamental information about a firm.

Accordingly, we argue that if the observed effect on firm value stems from differential levels of complaint publicization across the two groups (i.e., open-exchange and closed-exchange) and not from firm fundamentals, the effect should be stronger for a subsample of firms targeted by retail investors. To test this idea, we created a dummy variable (Retail) indicating whether the firm is primarily a target of retail or institutional investors and estimated a model that includes this dummy and its interaction with the DID term (the Web Appendix provides details). The results, reported in Table 3 (Model 3.6), confirm our predictions. Specifically, we find that the negative effect on firm value of a response strategy that engenders higher complaint publicization is stronger in the subsample of retail-target firms. This finding provides further evidence that complaint publicization impacts daily returns as the space of a firm's page gives valuation clues to investors.

Additional Insights

Moderating impact of firm response style. So far, we have provided strong evidence of the negative impacts of complaint publicization resulting from a firm's responses to complaints. Furthermore, we have demonstrated that limiting public complaint-response communications with a complainant (for example, through a closed-exchange response strategy) leads to lower levels of complaint publicization. To provide managers with additional practical insights, we explore whether certain response styles—namely, response timeliness and the level of content customization of the response—can further mitigate the negative impacts of complaint publicization. The former is important, given the synchronous nature of social media and consumers' expectations of faster responses from firms on social media (Amaresan 2019). The latter is important because consumers react negatively to canned firm responses (Fehr, Gelfand, and Nag 2010). That said, tailoring a response to a specific complaint (e.g., by providing explanations and showing empathy) is resource intensive and time consuming (Kumar, Qiu, and Kumar 2018). Evidence of the role of these response styles in mitigating the negative effect of complaint publicization provides justification for a firm's investment in them.

To explore these boundary conditions, we conduct several DIDID analyses to explore the moderating impact of response timeliness, intensity of explanation, and intensity of empathy in firm responses (for operationalizations, see Appendix A). The results, reported in Table 4 (Models 4.1, 4.2, 4.3, and 4.4), indicate that responding promptly and with greater empathy and explanations benefits firms that utilize a closed-exchange response strategy more than firms that employ an open-exchange strategy. This indicates that, even though the outcome of the complaint handling effort is unclear to observers when a closed-exchange response strategy is employed (due to the switch to a private mode), timely and substantive responses demonstrate the firm's seriousness in effectively handling the complaint.

Subsample comparison of open versus closed exchange strategies. While our DID and DIDID analyses provide evidence of significant differences between open- and closed-exchange strategies, it is imperative to explore separately the impact of firm responses for firms following each strategy. To do so, we broke down our sample into firms that addressed more than 75% of consumer complaints using a closed-exchange response strategy and those that addressed more than 75% of consumer complaints using an open-exchange response strategy. We then conducted two subsample analyses based on Study 1's Equation 1, where the daily abnormal return for a period of 30 business days before the recall is the dependent variable.[11] These analyses provide more tangible insights about the effectiveness of each strategy.

The results are presented in Table 5. We find that for firms that employ an open-exchange response strategy (Model 5.1), the volume of responses to complaints negatively impacts firm value and diminishes the impact of the firms' tweets. Interestingly, the impact of firm responses is markedly different for firms that employ a closed-exchange strategy (Model 5.2). In this case, the volume of responses to complaints positively impacts firm value and reinforces the impact of the firms' own tweets. Thus, while a response strategy that overpopulates a firm's page with complaints (through multiple exchanges with

[10] We acknowledge that being displayed on a firm's Twitter page is not the only factor that could impact the number of likes a complaint receives. In addition, we do not claim that these complaints are similar in terms of their characteristics.

[11] We focus on a time period outside of the recall window because it enables us to compare the results with those of Study 1, which was a not an event study. Moreover, although the context of product recalls enabled us to study complaint publicization in the previous analyses, focusing on another time period can improve the generalizability of our analyses.

Table 4. The Moderating Impact of the Intensity of Explanation in Firm Responses (Models 4.1 and 4.4), the Intensity of Empathy in Firm Responses (Models 4.2 and 4.4), and Response Timeliness (Models 4.3 and 4.4).

	Model			
Dependent Variable	4.1 Daily Abnormal Returns	4.2 Daily Abnormal Returns	4.3 Daily Abnormal Returns	4.4 Daily Abnormal Returns
Open × Post (DID, H_3)	−.087*** (.023)	−.084*** (.019)	−.081** (.025)	−.082* (.033)
Explanation	.009 (.007)			.009 (.007)
Explanation × Open	.004 (.003)			.004 (.003)
Explanation × Post	.030** (.010)			.031** (.010)
Open × Post × Explanation	−.021* (.01)			−.020* (.010)
Empathy		.011† (.006)		.011† (.006)
Empathy × Open		.008 (.005)		.008 (.005)
Empathy × Post		.027** (.010)		.027* (.011)
Open × Post × Empathy		−.019† (.01)		−.010 (.010)
Timeliness			.013* (.006)	.013* (.006)
Timeliness × Open			.003 (.002)	.003 (.002)
Timeliness × Post			.005 (.005)	−.003 (.005)
Open × Post × Timeliness			−.03† (.018)	−.03† (.017)
Window-Time controls	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Wald's χ	7,233.15	7,154.89	7,268.69	7,053.20
N	1,177	1,177	1,177	1,177

†$p < .1$.
*$p < .05$.
**$p < .01$.
***$p < .001$.
Notes: Standard errors are in parentheses. See Table 3 for controls.

each complainant) harms the firm, the firm benefits from a response strategy that signals customer care, without allowing complaints to dominate the firm's Twitter page.

Discussion

This research shows how seemingly trivial design features on popular social media, such as Twitter, can complicate complaint handling. We use two unique data sets and conduct an observational and a quasiexperimental study to show how firm responses to complaints on a platform with complaint-publicizing features can potentially lead to a host of adverse effects, ranging from diminished perceived quality, Tobin's q, and daily abnormal returns to suppressed effectiveness of the firm's own posts and increased volume of future complaints. Notably, we find that these effects are stronger for firms that are trading targets for retail investors, given these investors' reliance on public information.

Moreover, this research sheds light on the mechanism behind these effects. It reveals the role of a unique phenomenon—complaint publicization—where firm responses to complaints increase the potential public exposure of complaints by conceding the real estate of the firm's social media page to the complaints. Complaint publicization can influence investors in two important ways. First, it can negatively impact investors' expectations of a firm's future profitability and success, given its negative effect on consumers' perceived quality. Second, it may engender a negativity spiral by encouraging more complaints, which can adversely impact the overall sentiment about the firm on the social media platform. Social media aggregator services, which provide social media analytics to investors, are likely to pick up on this increasingly negative social media sentiment about a firm.

In our experimental approach, we rely on an identification strategy that capitalizes on the natural distribution of open- and closed-exchange response strategies, which result in differential levels of complaint publicization. We show that a closed-exchange response strategy may mitigate complaint publicization and its negative impacts. Specifically, employing a closed- (open-) exchange strategy leads to firm responses to complaints positively (negatively) impacting daily abnormal returns and reinforcing (diminishing) the positive impact of firm posts. Furthermore, when responses are timely and substantive, a closed-exchange response strategy becomes even more effective.

Contributions to Research

By exploring the complex nature of complaint handling on social media, the current research makes several theoretical contributions (see Table 6). First, the current work contributes to the literature about online complaint handling by revealing how firm responses to complaints can negatively impact firm value and perceived quality and increase the volume of

Table 5. The Impact of Firm Responses to Complaints on Daily Abnormal Returns and on the Effectiveness of Firm Tweets Under Each Response Strategy (Subsample Analysis).

DV = Daily Abnormal Returns (30 Business Days Before the Event Window)	Model	
	5.1 Open-Exchange Response Strategy	**5.2 Closed-Exchange Response Strategy**
Volume of firm responses to complaints (H_3)	−.048*** (.006)	.011* (.005)
Volume of firm tweets	.011* (.005)	.012*** (.003)
Volume of firm tweets × Volume of firm responses to complaints (H_4)	−.078*** (.008)	.019*** (.005)
Volume of WOM	.058*** (.009)	.053*** (.006)
Volume of firm responses to noncomplaint tweets	.015*** (.004)	.018*** (.003)
Firm tweets × responses to noncomplaint tweets	.011 (.009)	.005 (.007)
Responses to complaints × responses to noncomplaint tweets	.018 (.012)	.008 (.011)
Firm fixed effect	Yes	Yes
Wald's χ	3,542.79	3,127.81
N	1,320	1,890

*$p < .05$.
**$p < .01$.
***$p < .001$.
Notes: Standard errors are in parentheses.

complaints. The evidence on the negative impact of firm responses to complaints departs from the existing literature, which has mostly documented the positive impacts of these responses (on platforms such as TripAdvisor, Yelp, and Facebook; Chung et al. 2020; Kumar, Qiu, and Kumar 2018; Wang and Chaudhry 2018). These positive effects stem from the role of firm responses on these platforms in mitigating the negative impact of complaints (which are already visible) without substantially increasing potential public exposure of complaints. We show that firm responses to complaints do not have a mitigating role on platforms such as Twitter, where the visibility of complaints is changed by the firm's response to them.

Second, limited existing evidence of the possible negative impact of firm responses includes the impact of firm responses in encouraging future complaints by the same complainant (Ma, Sun, and Kekre 2015) and the role of offering compensation in increasing complaint virality (Herhausen et al. 2019). The current work adds a new element to the online complaint handling equation by revealing how a design feature of popular social media platforms such as Twitter leads to a hitherto-unknown phenomenon that we call "complaint publicization." We show that firm responses to complaints on such platforms can impact the composition of a firm's social media page, increasing the potential public exposure of complaints. The finding that a platform's design features affect the dynamics of complaint handling indicates that employing a uniform complaint handling strategy across different platforms can have unintended consequences. This finding is relevant to a body of literature that shows that the effectiveness of (offline) complaint handling may be moderated by exogenous factors (e.g., Morgeson et al. 2020). Theoretically, we show that only an integrative view that marries the online primacy effect with negativity bias and the literature on firm- versus consumer-initiated information can explain the overall impact of firm responses to complaints and the underlying role of complaint publicization. The findings also highlight the importance of considering platform-specific characteristics in social media research.

Third, the current work contributes to the literature on social media communications by documenting how firm responses to complaints can diminish the positive impact of a firm's own posts. This finding highlights that the effects of social media communications can be more complicated than separate analyses of firm responses and firm posts would indicate. This is important, given that recent research has documented the impact of a firm's social media posts on its bottom line (e.g., Li et al. 2020). The discovered within-channel suppression effect also adds to the literature on integrated marketing communication, as previous research on suppressive effects mostly focuses on between-channel suppressions (e.g., Sridhar and Sriram 2015).

Finally, this research makes methodological contributions in two ways. First, it develops a novel approach to measure the publicization of complaints on a firm's social media page (for details, see the Web Appendix). Such a measure can be used to investigate how different social media communication strategies impact the composition of a firm's page. Second, our work is the first, to the best of our knowledge, to show that product recalls provide quasiexperimental opportunities to study complaint handling, especially on social media platforms. Prior quasiexperimental research on online complaint handling mostly leverages a multiplatform identification strategy (e.g., comparing platforms that allow [vs. do not allow] firms to respond to users; Kumar, Qiu, and Kumar 2018; Wang and Chaudhry 2018). Our work provides empirical evidence that

Table 6. Summary of Major Findings, Contributions, and Implications.

Key Findings	Related Literature/Gap	Theoretical Contributions	Practical Implications
• Firm responses to complaints increase the public exposure of complaints (complaint publicization), negatively impact perceived quality and firm value (H_1 and H_3) and increase the volume of future complaints.	• Prior research suggests that firm responses to complaints mitigate the negative impact of complaints (e.g., Chung et al. 2020; Wang and Chaudhry 2018). • Prior research has explored how firm-controlled factors, such as firm responsiveness and response style, impact the effectiveness of firm responses to complaints (Herhausen et al. 2019; Kumar, Qiu, and Kumar 2018). • Little research has explored how social media platforms' design features change the dynamics of firm responses to complaints.	• By revealing a possible dark side of complaint handling, this research contributes to the literature of online complaint handling. • By documenting the impact of a social media platform's design features, this research extends the complaint handling literature by adding the role of platform-controlled features. • The findings highlight the importance of considering platform-specific characteristics in social media research.	• Firms should acknowledge the complexity of communication on social media, a complexity stemming from the distinct design features of different platforms. • Firms need to craft their social media communication strategies in light of a platform's idiosyncrasies. • Firms need to incorporate tactics to decrease complaint publicization and its negative impacts when formulating complaint handling strategies.
• Firm responses to complaints diminish the positive impact of that firm's own posts (H_2 and H_4).	• Prior research has shown that communicating inconsistent messages through different channels may lead to suppressive effects among communication efforts (e.g., Sridhar and Sriram 2015). • Chung et al. (2020) show that firm responses to complaints on Facebook, a platform where firm responses do not change the visibility of complaints, reinforce the positive impact of the firm's own posts.	• This research is the first to document a suppressive relationship between firm posts and firm responses to complaints, and thus refines our understanding of the complexities of firm communication on social media.	• Firms should try to minimize the risk of the collocation of their posts and consumer complaints. • Firms can employ a closed-exchange response strategy, which could lead to a reinforcing effect between firm posts and responses.
• Recall events provide (quasi)experimental opportunities to study complaint handling, especially on social media platforms.	• Prior (quasi)experimental research on online-complaint handling mostly leverages a multiplatform identification strategy (e.g., Kumar, Qiu, and Kumar 2018; Wang and Chaudhry 2018).	• Research on online complaint handling can utilize product recalls (as complaint-inducing shocks) along with matching procedures to isolate the impact of firm responses (strategies).	
• Firm responses to complaints impact the composition of a firm's social media page. • The impact of complaint publicization is stronger as the thread size increases.	• Little research has explored the possible complaint-publicizing impact of firm responses to complaints.	• This research is the first to document how more back-and-forth messaging between a firm and a complainant can increase the potential public exposure of complaints	• Firms should actively monitor the real estate of their social media page and prevent complaints from turning it into a complaint arena. • If employing an open-exchange response strategy, firms should try to minimize the amount of back-and-forth messaging with a complainant.

recalls cause a spike in the volume of complaints (Appendix C), and shows how using product recalls, along with sample matching, is a reasonable way to isolate the impact of firm responses to complaints. This approach allows for identifying the source of complaints (i.e., a product recall with known severity), which would otherwise be challenging.

Managerial Implications

Firms are increasingly using multiple social media platforms for online complaint handling. Given our results, firms must craft their online complaint handling strategies in light of each platform's idiosyncrasies and avoid one-size-fits-all strategies in responding to complaints. For example, employing strategies such as transparent complaint handling through multiple communication exchanges with a complainant may not be beneficial in all situations and on all social media platforms. Given the design features of some popular social media platforms, such as Twitter, such practices on these platforms may have the unintended consequence of conceding the real estate of the firms' social media page to complaints. Firms should strive to mitigate the risk of such complaint publicization, given its negative impacts on perceived quality, firm value, and the volume of future complaints. Next, we provide several concrete recommendations.

Actively monitor the real estate of the firm's social media page. A firm's social media page is a public channel, and users frequently visit it. Moreover, the space of a firm's social media page gives valuation clues to investors. In Study 2, we developed a novel measure that directly captures the ratio of the firm's page space occupied by complaints (as displayed on different devices; for details, see the Web Appendix). Firms could use such analytical tools to actively monitor the composition of the real estate of their page. Insight provided by such tools can be utilized to manage the firm's page and to prevent complaints from turning it into a complaint arena, as we discuss next.

Avoid protracted exchanges with complainants. An effective complaint handling strategy on platforms with complaint-publicizing features enables signaling customer care without allowing complaints to dominate the firm's social media page. According to our findings, such a strategy could positively impact firm value and reinforce the positive impact of the firm's own posts by limiting public responses to a complaint to one message that invites the complainant to continue the complaint handling process in a private mode. This strategy enables a firm to reduce complaint publicization, as a given complaint-response communication would appear on the top portion of the firm's page only once. The following is a real complaint-response communication between a major public firm active in the food industry (we call the firm "BeefCo") that is recalling one of its frozen poultry products and a customer who owns a local business. BeefCo, in this case, follows such a strategy.

Customer: Hey @BeefCo! Can you confirm if packages with an expiration date prior to 7/23 also need to be taken down? Have been trying to reach you over the phone for 2 hrs!!

BeefCo: [CustomerName] sorry we have not been able to answer your calls. We recommend taking down all packages with an expiration date in July. You can either discuss the refund process with your distributor or reach me at service@beefco.com.

Firms should avoid handling complaints through multiple communication exchanges with a complainant on the public space of a platform like Twitter. Such a strategy can turn the firm's page into a complaint arena where observers are exposed to consumer complaints. This can lead to decreased firm value, an increased volume of future complaints, and diminished effectiveness of the firm's posts. We present another complaint-response communication that also happens in the context of a food recall, in which a firm (which we call "ChickenCo") uses such a strategy to handle an almost identical inquiry.

Customer: Hey @Chicken Co fr? . . . can someone at least tell me how can I get reimbursed for this? None of the phone lines work.

ChickenCo: Hey sorry we couldn't reach out earlier. Can you tell us more? Date of your order, etc.?

Customer: About a week ago and my O.N. is . . . I should dispose of the whole order and we are a small shop!

ChickenCo: We are very sorry. I have assigned a customer service agent to reach out to you. Ciao!

Customer: still no luck . . .

ChickenCo: I checked and you should receive a call from us in few minutes.

If a firm employs such a response strategy, it should at least try to minimize back-and-forth messaging with a complainant, as larger thread-sizes amplify complaint publicization and its negative impacts.

Leverage appropriate response styles. Drawing on our analyses, we make the following recommendations. First, we find that a closed-exchange response strategy will be even more effective if firms respond promptly and provide substance (e.g., empathy, explanation) in their single public response to a complaint. Interestingly, we find that only 12% of closed-exchange responses in our sample provide substance in the form of an explanation or empathy. Our findings suggest that a closed-exchange strategy can be complemented by adding substance to the response. This will signal the firm's seriousness in handling the complaint, as the ultimate outcome of the complaint handling effort will be unclear to observers (due to the switch to a private communication mode). Second, although timeliness in responding is generally encouraged (e.g., Amaresan 2019), our findings suggest that an open-exchange response strategy, which is more prone to publicizing complaints, may benefit from a slower pace in responding. Thus, if conditions necessitate employing an open-exchange response strategy, the firm should manage response timing judiciously to avoid conceding the space of its social media page to complaints for long periods.

Use platform functionalities. Social media platforms offer functionalities that may be utilized by a firm to mitigate complaint publicization. For example, Twitter allows users to "pin" one of their own tweets on their page. Given that a tweet pinned by a firm will permanently appear at the top of its Twitter page, it can be utilized to reduce the amount of prime space of the firm's Twitter page that is conceded to complaint-response communications.

Avenues for Future Research

Although our study has been conducted in the context of Twitter, we believe that its implications are generalizable and useful in various settings. First, Twitter's distinct capability to broadcast customer messages is a prime reason the platform is heavily used by consumers issuing complaints and firms handling those complaints. Given this, and because social media platforms' design features are constantly evolving, competing platforms may emulate Twitter and its features. Second, even though the precise dynamics of complaint publicization might differ across platforms, we already have seen similar broadcasting algorithms used in comparable platforms. So, insights into the broader phenomenon of complaint publicization and its consequences extend beyond Twitter. That said, replication studies that consider other platforms with complaint-publicizing features can further add to the robustness of our findings.

Second, although we match treatment and control firms on the basis of their recall severity in Study 2, future research must consider field settings that allow for a clearer identification of the impact of firm responses from that of the recall itself. Third, in Study 2, we distinguished between closed-exchange and open-exchange response strategies. While this natural distinction in response strategies provided an identification opportunity to test the impact of complaint publicization in a quasiexperimental fashion, this distinction, in itself, is worth further investigation. How does a firm decide to use a given strategy? Moreover, what are the broader implications of such a decision? Relatedly, while the current research reveals the negative impacts of complaint publicization, future research could explore possible boundary conditions to these effects. For example, are there contexts in which complaint publicization is beneficial or an open-exchange response strategy is more effective than a closed-exchange strategy? Under some circumstances, the benefits of full transparency in complaint handling might outweigh the negative impacts of the increased public exposure of complaints. In such conditions, the effect of complaint publicization might be different from that found in the current study. Exploring boundary conditions to the complaint publicization phenomenon could further enrich our understanding of the impact of complaint handling strategies on social media.

Appendix A. Summary of Variables, Operationalizations, and Data Sources.

Variable	Operationalization	Source	Study
Tobin's q	(Market value of common stock shares + book value of preferred stock + book value of long-term debt + book value of inventories + book value of current liabilities – book value of current assets)/(book value of total assets)	Compustat	One
Perceived quality	YouGov item: "Is the brand of good or poor quality—irrespective of price?"	YouGov	
Volume of firm tweets	The # of firm tweets	Twitter	
Volume of firm responses	The # of firm responses		
Volume of firm responses to complaints	The # of firm responses to complaint tweets		
Volume of firm responses to noncomplaint tweets	The # of firm responses to noncomplaint tweets		
Average length of firm tweets	Average # of words in the tweets of a firm		
Volume of WOM	The # of user tweets that included the name of a firm or mentioned its Twitter account	Twitter (third-party data)	
Advertising intensity	Advertising expenses scaled by sales	Ad$pender and Compustat	
Cost of goods sold	—		
Competitive intensity	Reciprocal of the Hirschmann–Herfindahl index (sum of the squared market shares for all firms in the same four-digit Standard Industrial Classification code)		
Financial leverage	Long-term debt scaled by total assets		
Organizational slack	Net cash flows from operating activities scaled by total assets		
R&D intensity	Total R&D expenditures scaled by sales		
Return on assets	Income before extraordinary items scaled by total assets		
Industry size	Total sales of all firms in the same industry		

(continued)

Appendix A. (continued)

Variable	Operationalization	Source	Study
Daily abnormal returns	$R_{it} - R_{ft} = \beta_{0i} + \beta_{1i}(R_{mt} - R_{ft}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \epsilon_{it}$	CRSP	Two
Volume of future complaints	The number of complaints directed at a firm in a window of 30 business days following the event window	Twitter (Proprietary data)	
Open-exchange response strategy	Equal to 1 for firms that handle more than 75% of complaints through multiple communication exchanges on Twitter itself		
Closed-exchange response strategy	Equal to 1 for firms that handle more than 75% of complaints through one public message on Twitter, inviting the complainant to continue the complaint handling process in a private mode		
Response timeliness	The reciprocal of the time lag between the consumer complaint and the firm's response (averaged for each day within the event window)		
Intensity of explanation in firm response	Daily avg. # of words in a firm response matching the words in the LIWC dictionary "cogproc" scaled by the # of words		
Intensity of empathy in firm response	Daily avg. # of words in a firm response matching the words in the LIWC dictionary "affect" scaled by the # of words		
Volume of complaint tweets	The daily # of unique complaint threads (back-and-forth) within the event window		
Valence of complaint tweets	Weighted positivity of complaint tweets (using AFINN dictionary; averaged for each day within the event window)		
Volume of noncomplaint tweets	The daily # of unique noncomplaint threads (back-and-forth) within the event window		
Valence of noncomplaint tweets	Weighted positivity of noncomplaint tweets (using AFINN dictionary; averaged for each day within the event window)		
Intensity of high arousal emotions (disgust, fear/anxiety, anger) in complaints	The # of words in a complaint matching the words in the "disgust" dictionary (developed by Herhausen et al. [2019]), and those matching the words in LIWC dictionaries "anx" and "anger" scaled by the total # of words (averaged for each day within the event window)		
Intensity of low arousal emotions in complaints	Daily avg. # of words in a complaint matching the words in the LIWC dictionary "sad" scaled by the total # of words		
Complaint complexity	The # of words in a complaint with more than six letters per sentence (averaged for each day within the event window)		
Complaint length	Average # of words in complaints for each day within the event window		
Engagement with a complaint prior to firm response	Average daily # of likes a complaint received before a firm response		
Time of day when the complaint was tweeted	Night: 12:00 A.M. and 5:59 A.M.; morning 6:00 A.M.–11:59 A.M.; afternoon: 12:00 P.M. and 5:59 P.M.; evening: 6:00 P.M. and 11:59 P.M. (averaged across all of complaints within each day)		
Number of followers of the firm's Twitter account	Natural logarithm of daily # of followers of the account within the event window (measured at the end of the day)		
Complaint-related firm responsiveness	The # of firm responses to complaints scaled by the total # of complaints		
Noncomplaint-related firm responsiveness	The # of firm responses to noncomplaints scaled by the total # of noncomplaint tweets		
Intensity of apology in firm response	Dictionary developed by Herhausen et al. (2019)		
Whether compensation was offered	Dictionary developed by Herhausen et al. (2019)		
Variation in response sequence	Variance in the proportion of empathic and explanatory words across firm responses to different complaints		
Whether the firm is a target of retail investors	Equal to 1 for firms with below-median institutional holdings, and equal to 0 otherwise.	13-f filings	
Firm's newsworthiness	Natural logarithm of one plus the # of daily news articles on the Dow Jones Edition (relevance score above 20)	RavenPack	

Notes: CRSP = Center for Research in Security Prices; LIWC = Linguistic Inquiry and Word Count.

Appendix B. Description of the Variables Used For Matched-Sample Construction in Study 2.

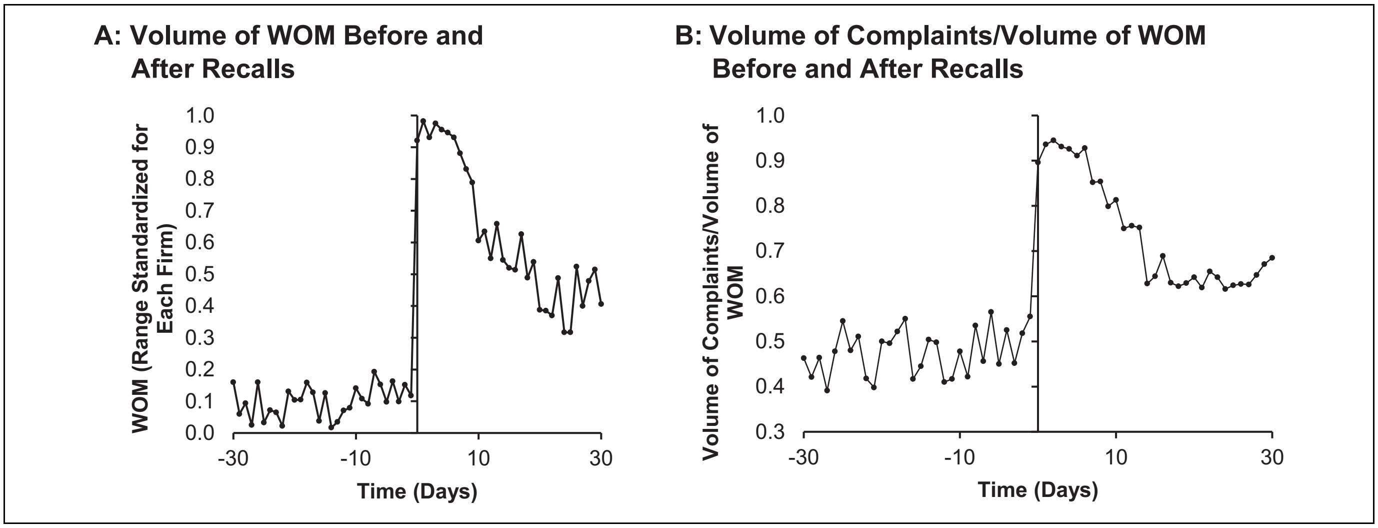
Variable	Operationalization	Source	Identification Notes
Momentum	Average of cumulative stock returns from the 12th month to the 2nd month prior to the event month	CRSP	Ensures that abnormal returns in the [−5d, +5d] window are not different due to different market fundamentals and trends
Market cap	Stock price on the last business day of the month prior to the event month multiplied by the number of shares outstanding		
Book-to-market value	Book value of equity for the fiscal year prior to the event divided by market value of equity at the end of that year	Compustat	
Recall severity	Dummy equal to 1 if the recall involves severe quality defects (NHTSA recalls), or if the recall is in categories A and B (CPSC recalls) or if the recall is in categories I and II (FDA recalls).	CPSC, NHTSA, and FDA	Ensures treatment and control firms are not different in the levels of severity of recall
Number of followers of the firm's Twitter account	Natural logarithm of the daily number of followers of the account averaged across all of the days within the 12 months leading to the event month	Twitter (proprietary data)	Ensures treatment and control firms are not different in terms of the direct audience of their Twitter communications
Volume of complaint tweets	Measured in the 12-month period leading to the event month		Ensures treatment and control firms are not different in preshock levels of complaints and complaint characteristics
Valence of complaint tweets	Weighted positivity of complaint tweets (using AFINN dictionary) measured in the 12-month period leading to the event month		
Intensity of high arousal emotions (disgust, fear/anxiety, anger) in complaints	The number of words in a complaint matching the words in the "disgust" dictionary, and those matching the words in LIWC dictionaries "anx" and "anger" scaled by the total number of words (averaged across all of complaints within the 12-month leading to the event month)		
Intensity of low arousal emotion (sadness) in complaints	The number of words in a complaint matching the words in the LIWC dictionary "sad" scaled by the total number of words (averaged across all of complaints within the 12-month leading to the event month)		
Complaint complexity	The average number of words with more than six letters per sentence in a complaint (averaged across all of complaints within the 12-month leading to the event month)		
Complaint length	The average number of words in a complaint (averaged across all of the complaints within the 12-month leading to the event month)		
Engagement with a complaint prior to firm response	The number of likes a complaint has received before firm response (averaged across all of the complaints within the 12-month leading to the event month)		
Time of day when the complaint was tweeted	Night: 12:00 A.M. and 5:59 A.M.; morning 6:00 A.M.–11:59 A.M.; afternoon: 12:00 P.M. and 5:59 P.M.; evening: 6:00 P.M. and 11:59 P.M. (averaged across all of complaints within the 12 months leading to the event month)		
Volume of noncomplaint tweets	Measured in the 12-month period leading to the event month		Ensures treatment and control firms are not different in preshock levels and characteristics of noncomplaint tweets
Valence of noncomplaint tweets	Weighted positivity of noncomplaint tweets (using AFINN dictionary) averaged across all of the noncomplaint tweets within the 12-month period leading to the event month		
Complaint-related firm responsiveness	The number of firm responses to complaint tweets scaled by the number of complaint tweets		Ensures that preshock differences in perceptions about a firm's responsiveness do not drive the observed effect

(continued)

Appendix B. (continued)

Variable	Operationalization	Source	Identification Notes
Noncomplaint-related firm responsiveness	The number of firm responses to noncomplaint tweets scaled by the number of noncomplaint tweets		
Firm's newsworthiness	Natural logarithm of 1 plus the number of news articles on the Dow Jones Edition of RavenPack with relevance score above 20 in the 12-month leading to the event month	RavenPack	Ensures that treatment and control firms are not different in terms of preshock coverage and characteristics of investors following their news
Whether the firm is a target of retail investors	Equal to 1 for firms with below-median institutional holdings, and equal to 0 for those with above-median institutional holdings.	13-f filings	

Notes: CRSP = Center for Research in Security Prices.



Appendix C. The impact of product recalls on the volume of WOM and complaints.

Notes: WOM = number of complaints + number of noncomplaint tweets; a range-standardized WOM of .15 means that the firm's WOM in that particular day was 15% of the maximum observed daily WOM for that firm in our sample.

Associate Editor

Koen Pauwels

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

ORCID iDs

Dinesh K. Gauri https://orcid.org/0000-0001-6805-7175
Joseph Comprix https://orcid.org/0000-0003-1984-2032

References

Abhishek, Vibhanshu, Kartik Hosanagar, and Peter S. Fader (2015), "Aggregation Bias in Sponsored Search Data: The Curse and the Cure," *Marketing Science*, 34 (1), 59–77.

Alcántara, Ann-Marie (2020), "Customer Complaints, and Their Ways of Complaining, Are on the Rise," *The Wall Street Journal* (June 14), https://www.wsj.com/articles/customer-complaints-and-their-ways-of-complaining-are-on-the-rise-11591998939.

Amaresan, Swetha (2019), "What Are Your Customers' Expectations for Social Media Response Time?" *Hubspot* (January 18), https://blog.hubspot.com/service/social-media-response-time.

Batra, Rajeev and Kevin L. Keller (2016), "Integrating Marketing Communications: New Findings, New Lessons, and New Ideas," *Journal of Marketing*, 80 (6), 122–45.

Bendle, Neil Thomas and Moeen Naseer Butt (2018), "The Misuse of Accounting-Based Approximations of Tobin's Q in a World of Market-Based Assets," *Marketing Science*, 37 (3), 484–504.

Bilinski, Pawel (2019), "The Battle of Social Media Platforms: The Use of Twitter, YouTube and Instagram in Corporate Communication," working paper, Cass Business School, City University of London.

Blankespoor, Elizabeth, Gregory S. Miller, and Hal D. White (2013), "The Role of Dissemination in Market Liquidity: Evidence from Firms' Use of Twitter," *Accounting Review*, 89 (1), 79–112.

Borah, Abhishek, Sourindra Banerjee, Yu-Ting Lin, Apurv Jain, and Andreas B. Eisingerich (2020), "Improvised Marketing Interventions in Social Media," *Journal of Marketing*, 84 (2), 69–91.

Bukovina, Jaroslav (2016), "Social Media Big Data and Capital Markets—An Overview," *Journal of Behavioral and Experimental Finance*, 11, 18–26.

Campbell, Margaret C. and Amna Kirmani (2008), "I Know What You're Doing and Why You're Doing It: The Use of Persuasion Knowledge Model in Consumer Research," in *Handbook of Consumer Psychology*, Curtis Haugvedt, Paul M. Herr, and Frank R. Kardes, eds. Mahwah, NJ: Lawrence Erlbaum Associates, 549–73.

Chen, Wei, Bin Gu, Qiang Ye, and Kevin Xiaoguo Zhu (2019), "Measuring and Managing the Externality of Managerial Responses to Online Customer Reviews," *Information Systems Research*, 30 (1), 81–96.

Chen, Yubo, Shankar Ganesan, and Yong Liu (2009), "Does a Firm's Product-Recall Strategy Affect Its Financial Value? An Examination of Strategic Alternatives During Product-Harm Crises," *Journal of Marketing*, 73 (6), 214–26.

Chen, Zoey and Nicholas H. Lurie (2013), "Temporal Contiguity and Negativity Bias in the Impact of Online Word of Mouth," *Journal of Marketing Research*, 50 (4), 463–76.

Chung, Sunghun, Animesh Animesh, Kunsoo Han, and Alain Pinsonneault (2020), "Financial Returns to Firms' Communication Actions on Firm-Initiated Social Media: Evidence from Facebook Business Pages," *Information Systems Research*, 31 (1), 258–85.

Colicev, Anatoli, Ashwin Malshe, Koen Pauwels, and Peter O'Connor (2018), "Improving Consumer Mindset Metrics and Shareholder Value Through Social Media: The Different Roles of Owned and Earned Media," *Journal of Marketing*, 82 (1), 37–56.

Culotta, Aron and Jennifer Cutler (2016), "Mining Brand Perceptions from Twitter Social Networks," *Marketing Science*, 35 (3), 343–62.

Dellarocas, Chrysanthos (2006), "Strategic Manipulation of Internet Opinion Forums: Implications for Consumers and Firms," *Management Science*, 52 (10), 1577–93.

Diamond, Michael L. (2015), "Viral Power: Negative Social Media Bad for Business," *USA Today* (January 10), https://www.usatoday.com/story/money/business/2015/01/10/viral-power-negative-social-media-bad-for-business/21570851/.

DiMaggio, Paul J. and Walter W. Powell (1983), "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields," *American Sociological Review*, 48 (2), 147–60.

Dotzel, Thomas, Venkatesh Shankar, and Leonard L. Berry (2013), "Service Innovativeness and Firm Value," *Journal of Marketing Research*, 50 (2), 259–76.

Eilert, Meike, Satish Jayachandran, Kartik Kalaignanam, and Tracey A. Swartz (2017), "Does It Pay to Recall Your Product Early? An Empirical Investigation in the Automobile Industry," *Journal of Marketing*, 81 (3), 111–29.

Einwiller, Sabine A. and Sarah Steilen (2015), "Handling Complaints on Social Network Sites: An Analysis of Complaints and Complaint Responses on Facebook and Twitter pages of Large US Companies," *Public Relations Review*, 41 (2), 195–204.

Fehr, Ryan, Michele Gelfand, and Monisha Nag (2010), "The Road to Forgiveness: A Meta-Analytic Synthesis of Its Situational and Dispositional Correlates," *Psychology Bulletin*, 136 (5), 894–914.

Feng, Hui, Neil A. Morgan, and Lopo L. Rego (2015), "Marketing Department Power and Firm Performance," *Journal of Marketing*, 79 (5), 1–20.

Friestad, Marian and Peter Wright (1994), "The Persuasion Knowledge Model: How People Cope with Persuasion Attempts," *Journal of Consumer Research*, 21 (1), 1–31.

Germann, Frank, Peter Ebbes, and Rajdeep Grewal (2015), "The Chief Marketing Officer Matters!" *Journal of Marketing*, 79 (3), 1–22.

Ghose, Anindya, Avi Goldfarb, and Sang Pil Han (2013), "How Is the Mobile Internet Different? Search Costs and Local Activities," *Information Systems Research*, 24 (3), 613–31.

Ghose, Anindya, Panagiotis G. Ipeirotis, and Beibei Li (2014), "Examining the Impact of Ranking on Consumer Behavior and Search Engine Revenue," *Management Science*, 60 (7) 1632–54.

Goh, Khim-Yong, Cheng-Suang Heng, and Zhijie Lin (2013), "Social Media Brand Community and Consumer Behavior: Quantifying the Relative Impact of User- and Marketer-Generated Content," *Information Systems Research*, 24 (1), 88–107.

Herhausen, Dennis, Stephan Ludwig, Dhruv Grewal, Jochen Wulf, and Marcus Schoegel (2019), "Detecting, Preventing, and Mitigating Online Firestorms in Brand Communities," *Journal of Marketing*, 83 (3), 1–21.

Herr, Paul M., Frank R. Kardes, and John Kim (1991), "Effects of Word-of-Mouth and Product-Attribute Information on Persuasion: An Accessibility-Diagnosticity Perspective," *Journal of Consumer Research*, 17 (4), 454–62.

Hewett, Kelly, William Rand, Roland T. Rust, and Harald J. van Heerde (2016), "Brand Buzz in the Echoverse," *Journal of Marketing*, 80 (3), 1–24.

Ho, Yi-Chun, Junjie Wu, and Yong Tan (2017), "Disconfirmation Effect on Online Rating Behavior: A Structural Model," *Information Systems Research*, 28 (3), 626–42.

Hogreve, Jens, Nicola Bilstein, and Kathrin Hoerner (2019), "Service Recovery on Stage: Effects of Social Media Recovery on Virtually Present Others," *Journal of Service Research*, 22 (4), 421–39.

Hsu, Liwu and Benjamin Lawrence (2016), "The Role of Social Media and Brand Equity During a Product Recall Crisis: A Shareholder Value Perspective," *International Journal of Research in Marketing*, 33 (1), 59–77.

Josephson, Brett W., Jean L. Johnson, and Babu John Mariadoss (2016), "Strategic Marketing Ambidexterity: Antecedents and

Financial Consequences," *Journal of the Academy of Marketing Science*, 44 (4), 539–54.

Kahneman, Daniel and Amos Tversky (1979), "Prospect Theory: An Analysis of Decisions Under Risk," *Econometrica*, 47 (2), 263–91.

Kowalewicz, Rebecca (2019), "Best Practices for Customer Service on Social Media," *Forbes* (August 12), https://www.forbes.com/sites/forbesagencycouncil/2019/08/12/best-practices-for-customer-service-on-social-media/.

Kumar, Naveen, Liangfei Qiu, and Subodha Kumar (2018), "Exit, Voice, and Response on Digital Platforms: An Empirical Investigation of Online Management Response Strategies," *Information Systems Research*, 29 (4), 849–70.

Lee, Lian Fen, Amy P. Hutton, and Susan Shu (2015), "The Role of Social Media in the Capital Market: Evidence from Consumer Product Recalls," *Journal of Accounting Research*, 53 (2), 367–404.

Li, Jingjing, Ahmed Abbasi, Amar Cheema, and Linda B. Abraham (2020), "Path to Purpose? How Online Customer Journeys Differ for Hedonic Versus Utilitarian Purchases," *Journal of Marketing*, 84 (4), 127–146.

Ma, Liye, Baohong Sun, and Sunder Kekre (2015), "The Squeaky Wheel Gets the Grease—An Empirical Analysis of Customer Voice and Firm Intervention on Twitter," *Marketing Science*, 34 (5), 627–45.

Maerowitz, Sophie (2018), "5 Tactics Brands Can Learn from Delta's Customer Support on Twitter," *PR News* (May 14), https://www.prnewsonline.com/delta-customer-support-twitter.

Midha, Anjali (2014), "Study: Exposure to Brand Tweets Drives Consumers to Take Action – Both on and Off Twitter," *blog entry*, Twitter (May 1), https://blog.twitter.com/en_us/a/2014/study-exposure-to-brand-tweets-drives-consumers-to-take-action-both-on-and-off-twitter.html.

Mittal, Vikas, William T. Ross Jr., and Patrick M. Baldasare (1998), "The Asymmetric Impact of Negative and Positive Attribute-Level Performance on Overall Satisfaction and Repurchase Intentions," *Journal of Marketing*, 62 (1), 33–47.

Mizik, Natalie and Robert Jacobson (2008), "The Financial Value Impact of Perceptual Brand Attributes," *Journal of Marketing Research*, 45 (1), 15–32.

Montgomery, Cynthia A. and Birger Wernerfelt (1988), "Diversification, Ricardian Rents, and Tobin's Q," *RAND Journal of Economics*, 19 (4), 623–32.

Morgeson, Forrest V. III, G. Tomas M. Hult, Sunil Mithas, Timothy Keiningham, and Claes Fornell (2020), "Turning Complaining Customers into Loyal Customers: Moderators of the Complaint Handling–Customer Loyalty Relationship," *Journal of Marketing*, 84 (5), 79–99.

Nguyen, Hang, Roger Calantone, and Ranjani Krishnan (2020), "Influence of Social Media Emotional Word of Mouth on Institutional Investors' Decisions and Firm Value," *Management Science*, 66 (2), 887–910.

Peress, Joel and Daniel Schmidt (2020), "Glued to the TV: Distracted Noise Traders and Stock Market Liquidity," *Journal of Finance*, 75 (2), 1083–1133.

Petrin, Amil and Kenneth Train (2010), "A Control Function Approach to Endogeneity in Consumer Choice Models," *Journal of Marketing Research*, 47 (1), 3–13.

Saboo, Alok R., V. Kumar, and Ankit Anand (2017), "Assessing the Impact of Customer Concentration on Initial Public Offering and Balance Sheet–Based Outcomes," *Journal of Marketing*, 81 (6), 42–61.

Smith, Kit (2020), "60 Incredible and Interesting Twitter Stats and Statistics," *Brandwatch* (January 2), https://www.brandwatch.com/blog/Twitter-stats-and-statistics/.

Sridhar, Shrihari and Srinivasaraghavan Sriram (2015), "Is Online Newspaper Advertising Cannibalizing Print Advertising?" *Quantitative Marketing and Economics*, 13 (4), 283–318.

Srivastava, Rajendra K., Tasadduq A. Shervani, and Liam Fahey (1998), "Market-Based Assets and Shareholder Value: A Framework for Analysis," *Journal of Marketing*, 62 (1), 2–18.

Tirunillai, Seshadri and Gerard J. Tellis (2012), "Does Chatter Really Matter? Dynamics of User-Generated Content and Stock Performance," *Marketing Science*, 31 (2), 198–215.

Tirunillai, Seshadri and Gerard J. Tellis (2014), "Mining Marketing Meaning from Online Chatter: Strategic Brand Analysis of Big Data Using Latent Dirichlet Allocation," *Journal of Marketing Research*, 51 (4), 463–79.

Van Dieijen, Myrthe, Abhishek Borah, Gerard J. Tellis, and Philip Hans Franses (2019), "Big Data Analysis of Volatility Spillovers of Brands Across Social Media and Stock Markets," *Industrial Marketing Management*, 88, 465–84.

Wang, Yang and Alexander Chaudhry (2018), "When and How Managers' Responses to Online Reviews Affect Subsequent Reviews," *Journal of Marketing Research*, 55 (2), 163–77.

You, Ya, Gautham G. Vadakkepatt, and Amit M. Joshi (2015), "A Meta-Analysis of Electronic Word-of-Mouth Elasticity," *Journal of Marketing*, 79 (2), 19–39.