Please Don't Feed the Trolls: The Role of Customer Politeness in Customer Service Engagement on Social Media

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Abstract

Customers are increasingly turning to social media for help. According to a recent report by Twitter, over 5.5M customer service-related tweets are generated per month. In this work, we aim to explore firms' strategy when engaging complaining customers on Twitter. Specifically, we consider how firms' customer engagement strategy is influenced by their expectations for how their customer-service interactions will lead to sentiment broadcast about the firm. We particularly focus on how politeness, a linguistic factor indicating how a customer is questioning or complaining rather than the content of a query, affects firms' customer service engagement strategy. We develop a novel machine-learning methodology to measure politeness from tweets. Using this approach, our estimation results show several interesting results, including that firms are more likely to respond to more polite customers, and that this effect is augmented for customers with high social status. However, firms are more likely to engage impolite customers with a high social status in a private channel such as through direct messaging. This behavior is justified by evidence that customer politeness predicts the nature of sentiment customers broadcast about the firm.

Keywords: social media, politeness, customer service, customer complaints

1. Introduction

Customers are increasingly contacting firms on social media like Twitter and Facebook when they have issues with their products or services. Compared to traditional private channels such as the toll-free (1-800) number, social media has a transparent and open format where the public can view a customer's complaint and the firm's response. Thus, firms strive to publicly engage with and satisfy their customers because such engagement can not only clear up complaints, but can foster positive sentiment and stem potential negative sentiment that could otherwise fester on social media towards the firm (e.g., Zeithaml et al. 1993; Bendapudi and Leonard 1997; Mithas et al. 2005; Maxham and Richard 2002).

However, publicly engaging with customers on social media also bears risks for firms, as some customers might become even more inflamed if their complaints cannot be properly resolved (as they expected), or they might have new complaints stemming from the firm's engagement (Ma et al. 2015). The risks are even greater if the customer's social influence is high, such as if the customer has a lot of followers on Twitter, since the negative word-of-mouth can be more quickly disseminated to reach a large audience (Watts and Dodds 2007; Trusov et al. 2009; Chevalier and Mayzlin 2006).

Such a dilemma poses tremendous challenges to firms' complaint management strategy on social media. Despite the increasing importance and popularity of using social media for customer service for both firms and customers, thus far, little research has focused on this phenomenon, let alone on how firms strategically manage customer complaints. A notable exception is a recent paper by Gunarathne et al. (2017) that shows that firms are more likely to respond to customers with more followers on Twitter. This work, however, has not focused on the potentially negative implications of openly engaging with highly visible customers, and the dilemma it poses to firms' complaint-management strategy on social media. Thus, many critical questions remain unaddressed, such as *should a firm engage with every complaining customer on social media?* If not, *which customers should the firm engage with?* Furthermore, *when engaging with a customer complaint on social media, what form should the engagement take?* Since complaint-management is vital for customer engagement, customer satisfaction, and a firm's brand image, these unanswered questions motivate the present work.

This work aims to answer these important questions by investigating how firms strategically engage with complaining customers on Twitter. We first propose that, on social media, firms not only aim at customer satisfaction but also at amplifying the broadcast of positive sentiment about them and attenuating the broadcast of negative word-of-mouth towards them. Thus, firms may choose to publicly engage with customers if the firm can sense that these customers are more likely to express satisfaction or positive sentiment at the end of the engagement. Conversely, firms may choose to privately engage with customers —especially those with many followers and high social influence who express negativity towards the firm — by directing them to private channels on social media such as direct messaging on Twitter, or by avoiding to engage with them altogether. The latter option may appeal to the firm if it can sense that the customer is likely to remain negative, dissatisfied or hostile.

The proposition that firms engage customers strategically to manage sentiment is premised on the idea that firms can predict a customer's likelihood of being satisfied by a response from the firm, and thereby of spreading positive sentiment about the firm. While little research has directly focused on this idea, past research in the service literature has shed some light on signals that a firm may use to predict customer satisfaction before the actual engagement; these signals include what the complaint is about, who is making the complaint, and, crucially, the manner or tone of the complaint (Mitra and Gilbert 2014; Mollick 2014; Althoff et al. 2014; Burke and Kraut 2008). Building on this research, we focus on one of the most fundamental aspects of tone, namely the politeness of a complaint, as a potential driver of a firm's complaint management strategy on Twitter. Our key hypothesis is that politeness, as an indicator of the level of appreciation and respect a customer directs towards a firm (Brown and Levinson, 1987; Clark and Schunk 1980; Lakoff, 1973; Laplante and Ambady 2003), is likely to reflect the customer's attitude towards the firm independent of the actual content of the complaint, and might additionally reflect the tendency of a customer to respond positive or negatively to a firm's attempt to resolve the complaint. Thus, complaints made using a more polite (vs. less polite) tone will reflect a more positive attitude to the firm and will predict a more positive change in sentiment on the part of the customer subsequent to management of the complaint. In other words, in a social media context, the politeness of a customer is likely to have important implications for the downstream sentiment that is propagated about the firm.

Based on this theorizing, in this work, we examine the effect of customer politeness on the firm's complaint management strategy by addressing the following questions: 1) How does the politeness of a customer complaint on Twitter affect the likelihood that a firm will respond to the complaint publicly? 2) How does the politeness of a customer complaint affect the likelihood that a firm will direct a customer towards a private channel of communication? 3) Does the politeness of a customer complaint predict the likelihood that a customer will express satisfaction and/or a change in sentiment subsequent to a firm's response to the complaint?

To address these research questions, we conduct our analyses based on tweets collected using Twitter's public API. We monitored tweets sent to (i.e., via mention of user-handles) customer service-related accounts of 80 firms. We collected these accounts by searching Twitter with keywords like "customer care", "customer service", etc. As expected, not all tweets sent to firms received a response; the average response rate was only 55%. For those responded tweets, more than 27% were redirected to Twitter's private channel of direct messaging. The time it takes to receive a response also varies by linguistic features of the tweets and social status of the customers, and it differs by firms, supporting the idea that firms have social media strategies for engaging with customer complaints.

Next, we developed a novel machine-learning approach to measuring customers' politeness using linguistic features extracted from the textual content of customer complaining tweets. Based on comprehensive evaluations comparing our machine-learning approach to human assessments of politeness in the text, our approach obtained over 83.5% accuracy, representing a 15% greater accuracy than current state-of-the-art approaches. We then applied this approach to the threads we collected to study how customers' politeness drives firms' complaint management strategy on Twitter.

Our analyses show several interesting results. First, firms are indeed more likely to respond to polite customers in the public channel of communication, indicating that firms tend to engage those who appear more reasonable and respectful, and who behave pro-socially towards firm. Second, firms are more likely to respond to complaints sent by customers with more followers on Twitter, suggesting that firms do take consumers' social influence on Twitter into account in determining whether or not to respond. Third, when considering the interaction between politeness and social influence of the customer, we find, counter-intuitively (albeit consistent with our theorizing), that the more followers that customers have, the *less* likely firms are to engage them publicly when their complaints are impolite. Instead, firms are more likely to direct those impolite customers with more followers to a private channel such as to direct messaging. These findings are consistent with the notion that firms recognize the higher risk in publicly engaging impolite yet influential customers (i.e., doing so can exacerbate the likelihood of broadcasting negative sentiment or word-of-mouth towards the firm). Supporting this view, we find that when firms engage impolite customers publicly, the sentiment of their tweets actually becomes even more negative. This is in contrast to polite customers, where engagement leads to improved sentiment. Therefore, directing impolite customers to private channels of communication (i.e. direct messaging) can be considered a risk-averse strategy for firms. Such a strategy often corresponds to a fundamental precept of the modern social media age: *don't feed the trolls*; in other words, don't inflame or encourage negative commentators by engaging them publicly.

This work makes several contributions to the literature: First, we provide empirical evidence on how firms strategically balance the need to address customer complaints with the need to manage customer sentiment being broadcast about the firm. To the best of our knowledge, along with three recent papers (Sreenivasan et al. 2012; Ma et al. 2015; Gunarathne et al. 2017), our paper is among the first in the literature to study customer service on social media. There are significant differences between our work and these prior works. For example, Ma et al. (2015) focused on customers' decisions to complain whereas we focus on firms' strategy in responding to customer complaints on social media. On the other hand, while Gunarathne et al. (2017) examined the effect of customers' social status on firm's strategy, we go further by examining how the tone of customers' complaints affects firm social media engagement strategy as well as how customers' social status moderates the effect on tone. Besides differences in the type of questions addressed, Gunarathne et al. (2017) and Sreenivasan et al. (2012) are based solely on data from airlines, whereas our dataset is much more comprehensive and recent. Thus, our findings extend the current, nascent literature on customer engagement on social media by providing newer and richer perspectives on firm's complaint management strategy. Second, prior research has examined the question of how service providers' politeness affects customer satisfaction (e.g., Goodwin and Smith 1990; Tax et al. 1998; Szymanski and Henard, 2001). However, relatively little research has examined the implications of politeness expressed by a customer. Thus, we contribute to the literature by first developing a novel machine learning approach to automatically measure the politeness of a text document. After applying it to the context of social media-based customer service, we show that a customer's politeness has a significant and direct impact on firms' complaint management strategy.

2. Customer Service and Social Media

Researchers have long recognized the importance of appropriately addressing customer complaints (Zeithaml et al. 1993, Bendapudi and Leonard. 1997, Rust and Chung. 2006, Fornell and Wernerfelt. 1987, Blodgett et al. 1993, Maxham and Richard. 2002, Fornell 1976). Prior research shows that failures and mistakes do not necessarily lead to customer dissatisfaction, since most customers expect product and service failures (Del Río-Lanza et al., 2009). Rather, the service provider's response to the failure (or lack of response) is the most likely cause of dissatisfaction and abandonment of the firm (Smith et al., 1999).

Social media has recently emerged as an important channel through which customers communicate complaints to firms. A recent report found that over 65% of firms are using social media for customer service (The CRM magazine 2012). Moreover, over 30% of customers prefer complaining on social media than through more traditional channels such as telephone and email (The Nielsen Company 2012). Despite its increasing popularity and importance for firms and customers, social media-based customer service and complaint management has received relatively little attention in the academic literature. Sreenivasan et. al. (2012) analyzed tweets that mention firms and identified common types of customer complaining behaviors on social media, such as customers complaining to the firm online immediately after a first-service failure, publicizing extraordinary recoveries, spreading negative word-of-mouth, and reaching out to third-party complaint intercessors. Gunarathne et al. (2017) analyzed tweets exchanged between customers and three major airlines in North America and found that airlines are more likely to respond to complaints from customers with more followers, and customers with more followers are more likely to receive faster responses. On the other hand, Ma et al. (2015) found that although customer service intervention improves customer relationships, it also encourages more complaints later. As a result, firms are likely to overestimate the returns to service interventions.

All these studies have provided important insights into the customer complaint management process on social media. However, there is little understanding of the importance of the tone of customer communications for firms' complaint-management strategy on social media. Our paper fills this gap and contributes to the stream of literature on customer complaint management in the social media era.

3. Hypotheses Development

The basic thesis of the present research is that firms' social media customer service strategy is focused not only on customer satisfaction, but also on promoting the spread of positive sentiment and limiting the spread of negative sentiment towards the firm. Moreover, we posit that politeness of a customer's complaint is a key factor, representing the customer's sentiment towards the firm as well as helping firms predict the sentiment that a complaining customer is liable to spread about the firm, subsequent to the firm's response. Below, we first discuss the politeness construct. Next, we develop our hypotheses on the effect of politeness.

3.1 Background of Politeness Theory

Politeness is an important element of communications. It has been recognized as a decisive factor in whether social interactions go well or poorly, affecting problem solving, relationship building, and task accomplishment, inter alia (Obeng. 1997, Andersson and Pearson. 1999, Laplante and Ambady 2003). According to theories of politeness, politeness is defined as an interaction style used by a speaker to phrase communications in a way that maintains the "face" of the addressee (Brown and Levinson, 1987, Clark and Schunk, 1980; Lakoff, 1973). Goffman (1967) defines face as "the positive social value a person effectively claims for himself." As such, it recognizes that we each have a self-image and hope that other people see us as we see ourselves. According to Brown and Levinson (1987), there are two kinds of face: positive and negative. Positive face concerns the desire to be liked, appreciated, and approved. Negative face concerns the desire not to be imposed upon, intruded upon, or otherwise put upon.

The core idea of politeness theory is that some acts such as direct expressions of complaint, request, and command are intrinsically threatening to face and thus require "softening" (Brown and Levinson, 1987). Thus, a speaker may seek to maintain or enhance the addressee's positive face and/or negative face by using positive or negative politeness strategies respectively. Positive politeness strategies involve expressing an appreciation of the addressee's wants and in doing so convey a sense of similarity and solidarity, making the addressee feel good about herself, her interests or her possessions. On the other hand, negative politeness strategies are characterized by self-effacement, formality, and restraint to avoid the appearance of imposing on the addressee. To illustrate the varieties of complaints from a speaker (e.g., a customer) to an addressee (a service agent), consider the following examples: 1) without any politeness (e.g., "*help me*."), 2) with positive politeness (e.g., "*please help me*."), 3) with negative politeness (e.g., "*I know you're very busy but I would appreciate it if you can help me*").

Politeness in complaint management has been well researched, but exclusively from a firm's perspective (e.g., McColl-Kennedy and Sparks 2003; Blodgett et al., 1997; Goodwin and Smith 1990; Tax et al. 1998). Firm's politeness is found to be important to customer complaint evaluation, repurchase intention, and satisfaction (Blodgett et al., 1997; Szymanski and Henard, 2001). Compared to the research on firm's politeness, little work has focused on the flip side – customer's politeness. A notable exception is Lerman (2006), which found that a customer's politeness affects her choice of complaining behavior. In particular, impolite consumers are more likely than polite consumers to directly complain toward the offending party. However, the prior work does not examine the effect of customers' politeness on firms' complaint management strategy, which is the main focus of the current study.

3.2 Customer Politeness and Customer Satisfaction

In the present research, our central thesis is that the politeness of a customer complaint both reflects a customer's attitude towards the firm and predicts the type of sentiment that a customer is likely to spread about the firm subsequent to a response from the firm to the complaint. The idea that politeness reflects the customer's attitude towards the firm is consistent with politeness theory (Brown and Levinson, 1987), which holds that the level of politeness that a speaker (e.g., a customer) uses with an addressee (e.g., a firm's service agent on Twitter) reflects the level of respect of the speaker towards the addressee.

It is well accepted that a customer's attitude towards a firm can impact customer satisfaction (Halstead and Droge. 1991; Sivadas and Baker-Prewitt 2000). As Bolton and Drew (1994) point out "customer satisfaction ... depends on preexisting or contemporaneous attitudes". There are several reasons to expect that a customer's attitude towards the firm will influence customer satisfaction. First, attitudes influence how ambiguous information is processed. Yi (1993) defines ambiguity as information that can be interpreted in various ways. Ambiguity can arise when experience with the service does not in and of itself lead to a clear and unanimous interpretation (Hoch and Deighton, 1989). In the context of complaining management on social media, a firm's response to a customer can be ambiguous in many ways, especially given the length limit of social media messages. Individuals may interpret the same interaction as informative and helpful, or as confrontational. Previous research has demonstrated that individuals tend to process ambiguous information in a manner that is consistent with their pre-existing attitudes (Judd et al., 1983). As such, we expect greater customer satisfaction to be associated with more positive attitudes towards the firm, since customers are expected to interpret the situation in a more positive light. Moreover, customer satisfaction is often based upon confirmation or disconfirmation of expectations (Anderson and Sullivan. 1993). If one holds a negative attitude toward the firm, then one is also likely to interpret the firm's subsequent actions negatively.

On the basis of this discussion, the following hypotheses are advanced:

Hypothesis 1a: *When a firm engages a customer (by replying in a public forum) in response to a complaint, the politeness of the complaint will be positively correlated with sentiment change.*

Stated differently, the less polite the complaint the more negative will be the change in customer sentiment following firm engagement.

Hypothesis 1b: *When the firm engages a customer (by replying in a public forum) in response to a complaint, the politeness of the complaint will be positively correlated with the likelihood that the customer publicly expresses satisfaction at the end of the engagement. Stated differently, the less polite the complaint, the lower the likelihood that the customer expresses satisfaction after the firm's engagement.*

3.3 Customer Politeness and Firm's Preference in Complaint Management

The concepts of service-level differentiation and prioritized customer service have existed from the early days of service provision (Gurvich et al. 2008). It is widely accepted that companies should set clear priorities among their customers and allocate resources that correspond to these priorities (Zeithaml et al. 2001).

In the context of customer complaint management on social media, as noted, the firm's customer service strategy may be focused not only on customer satisfaction, but also on broadcasting positive sentiment (and not broadcasting negative sentiment) about the firm. Thus, the firm's policy of service-level differentiation could strategically allocate more resources to handle customers who are more likely to spread positive sentiment about the firm. Given our proposition that the politeness of a customer's complaint is both a manifestation of sentiment towards the firm and a predictor of future sentiment, we surmise the following hypothesis:

Hypothesis 2*: A firm is more likely to reply (in the public forum) to a polite tweet than an impolite tweet sent by a customer.*

3.3 Customer Politeness and Customer Social Influence

The study of influence diffusion through social networks has a long history in the social sciences and has recently attracted much attention across many fields, including marketing science and information systems (e.g., Chen et al., 2010; Bakshy et al., 2012; Trusov et al., 2009). On social media, the number of followers of a user directly represents the size of the audience that particular user has, thereby serving as proxy for the user's social influence (Bakshy et al., 2011). For firms, the social influence of a user affects both the degree of risk to the firm's image stemming from an unsatisfied customer and the degree of potential benefit stemming from a satisfied customer.

The risk and rewards associated with social influence leads us to the following hypothesis:

> ***Hypothesis 3:*** *There will be a positive interaction between a customer's politeness and social influence on the likelihood of firm response to a complaint. In other words, politeness will have a positive influence on the effect of a customer's Twitter social influence on the likelihood that a firm will reply (in the public forum) to a customer; or conversely, impoliteness will have a negative influence on effect of a customer's Twitter social influence on the likelihood that a firm will reply to a customer.*

At first blush, an aspect of Hypothesis 3 appears counterintuitive. Specifically, we expect firms to attend more diligently to high-influence customers, and therefore we might also expect firms to be particularly likely to respond to such customers when they are being impolite so as to dampen their negative sentiment towards the firm and prevent this sentiment from reaching the customer's followers. However, we have theorized that impolite customers will be predisposed to react negatively to firm engagement. This implies that impolite customers will be likely to spread negative sentiment about the firm in response to attempts to address their complaint publicly, which is a risk firms will try to avoid or minimize. However, the notion that impoliteness portends the tendency to spread negative sentiment leads us to the following additional hypothesis:

Hypothesis 4: *There will be a positive interaction between social influence and customer impoliteness (i.e., the opposite of politeness) on the likelihood of being directed by the firm towards a private channel such as direct messaging. In other words, impoliteness will increase the likelihood of being directed to a private channel more for customers with high social influence than for customers with low social influence.*

In the following sections, we first describe our approach to compute a politeness score from the textual content of tweets. We then present our data collection methodology, empirical models and results.

4. Measuring Politeness of Customer Complaints

4.1 Identifying and Extracting Politeness Strategies with Bootstrapping

Building on prior work on politeness, we develop a novel machine-learning model for measuring politeness of tweets automatically. Our model is built on 16 politeness strategies identified in Brown and Levinson (1987). Table 1 lists the details of these politeness strategies. Specifically, gratitude and deference (lines 1–2) are ways for the speaker to balance out the social cost of the request, question, or complaint on the addressee. Greetings (line 3) are another way to build a positive relationship with the addressee. Group identity (line 4) and presupposition (line 5) are also tools for positive politeness by claiming common ground between speaker and addressee. The remaining cues in Table 1 are negative politeness strategies, serving the purpose of minimizing the imposition on the addressee. Apologizing (line 8) deflects the social threat of the request/question/complaint by attuning to the imposition itself. Indirect (line 9) is another way to minimize social threat. Conversely, being direct or using second-person forms such as "you" as a form of direct address is less polite (lines 10–11). Hedges (line 12) provide the addressee with a face-saving way to deny the request. Similarly, disagreement avoidance (line 13) indicates the speaker is vague about the opinions so as not to disagree explicitly. By being pessimistic (line 14) the speaker signals the absence of an intention to coerce the addressee. Finally, we also include terms from the sentiment lexicon (Liu et al., 2005). The positive terms are useful markers for positive politeness emphasizing a positive relationship with the addressee (line 4), while the avoidance of negative sentiment can potentially minimize the imposition as well. It is worth noting that many of these features are correlated with each other, but this is reasonable as Brown and Levinson point out that politeness markers are often combined to create a cumulative effect of politeness (Brown and Levinson, 1978).

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To extract these politeness strategies, a common approach is to use lexicons (e.g., Hedges lexicon in Hyland, (2005)). However, those static lexicons may not be able to capture domain-specific cues and idiosyncratic expressions on social media. Therefore, we developed a bootstrapping approach to build lexicons from tweets. Specifically, we first obtain the part of speech (POS) tags for each tweet in using TweetNLP, a natural language processing toolbox designed for Twitter data.[1] Based on these POS tags, we use regular expressions to extract the top 250 most frequently used politeness-bearing words (e.g., adjectives, adverbs, nouns, and verbs; so RT, @mention were ignored). Using these words as seeds, we use WordNet to search their synonyms to further expand the lexicon. Finally, we construct a lexicon of 504 words that represent all 16 politeness strategies (e.g., hedges, deference, greetings, etc). Finally, based on this bootstrapped lexicon, we build a politeness feature vector for each tweet, indicating whether the tweet exhibits words that present the politeness strategies.

4.1. Predicting Politeness

To measure politeness of tweets between customers and firms, we build our machine-learning model based on three supervised classifiers with two different feature sets for automatically classifying tweets according to politeness – an SVM classifier with unigram feature only (SVM-BOW), an SVM classifier with unigram feature as well as politeness features (SVM-Ling); a logistic regression model with classifier with unigram feature (LR-BOW); a logistic regression model with unigram feature as well

[1] TweetNLP: http://www.cs.cmu.edu/~ark/TweetNLP/

as politeness features (LR-Ling); a decision tree classifier with unigram feature only (DT-BOW), a decision tree classifier with unigram feature as well as politeness features (DT-Ling).

Next, to get the training and testing data to train our models, we follow a popular approach in text mining and label a large portion of over 2,000 tweets randomly sampled from our dataset using Amazon Mechanical Turk (AMT). For each tweet, the annotator had to indicate how polite she perceived it to be by using a slider with values ranging from “very impolite (-3)” to “very polite (3)”. Each request was labeled by three different annotators. We selected annotators by restricting their residence to be in the U.S. and by conducting a linguistic background questionnaire. Since politeness is highly subjective and annotators may have inconsistent scales, we applied the standard *z*-score normalization to each worker’s scores. Finally, we define the politeness score of a tweet by averaging the scores from the annotators, and a positive score corresponds to the polite class where as a negative score corresponds to the impolite class. The classes are relatively balanced, with politeness class consisting of 989 requests and 1,011 for impoliteness class (e.g., a positive score corresponds to the polite class). We then train, test, and evaluate the performance of our classifiers with a standard leave-one-out cross-validation procedure. Table 2 shows the results against the manually labeled ground truth. The linguistically informed politeness features give an average of 7.7% improvement over the unigram features. This confirms that our politeness theory-inspired features are indeed effective in practice. Moreover, we find logistic regression performs better than SVM and decision tree. Therefore, in the next section we apply the trained LR-Ling model to automatically annotate a much larger set of Twitter conversations with predicted politeness score, enabling us to relate customer politeness to firm behaviors.

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5. Data, Econometric Model, and Results

5.1 Data Collection

We used Twitter public API to collect tweets mentioning the official account or customer service-specific account of 80 firms from May 2017 until September 2017. We obtained these accounts by searching Twitter with keywords like "customer care" and "customer service".

Customers may engage with firms on social media for complaints or compliments. Since our primary focus is on firms' customer complaint management strategy, we developed and trained a logistic regression model with standard linguistic and lexicon features (e.g., n-grams, TF-IDF, punctuations, LIWC, etc) to classify a tweet as a complaint or a compliment. In order to evaluate the precision of our classifier, we randomly selected 1,000 complaint tweets from our dataset, and two graduate students independently evaluated these tweets to determine whether each tweet was indeed a complaint. Whenever there was a disagreement, we sought a third person's opinion and used the majority rule to break the tie. Based on this analysis, we report 82.8% precision for our complaint classifier.

Typically, a complaint starts with a single tweet posted by the customer. After that, a firm may decide whether to respond and in which way, i.e., publicly or privately, depending on the firm's complaint management strategy. This may lead to a series of tweets exchanged between the customer and the firm, forming a conversation. To characterize the firm's initial response strategy with a binary response/no response classification, we restrict attention only to the initial complaining tweet posted by the customer. To operationalize this, we reconstruct conversation threads between customers and firms based on the metadata of their tweets. We identified 488,926 conversation threads containing at least one complaining tweet by the customer and zero or more tweets responded to by the firm.

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5.2 Variables in Empirical Analysis

Below we present the variables used in our empirical analysis. The summary statistics are presented in Table 3 and Table 4 shows the correlation matrix. Table 5 also shows the firms in our study.

Dependent Variables: The following dependent variables are used for testing our hypotheses 1) ***SentimentChange*** (H1a): We measure the sentiment change between a customer's first and last tweet in a conversation thread that involves firm's response. We use VADER (Hutto and Gilbert 2014), a popular dictionary and rule-based sentiment tool to compute sentiment scores ranging from -1 to 1 from the tweets. 2) ***Satisfaction*** (H1b): We check if a customer at the end of the conversation made an indication to *like* the firm's response (via Twitter's built-in feature), or expressed their satisfaction using language such as "Thank you for the help", "Great, appreciate that", etc. of course, it is possible that a customer who does not explicitly express appreciation may still be satisfied. However, in the context of the complaint management strategy on social media, when a customer culminates a public conversation with an explicit and publicly viewable expression of having been satisfied, this provides a positive tangible outcome to the firm because it helps amplify the positive sentiment about the firm. 3) ***Response*** (H2, H3): We check whether or not a firm responded to a customer complaint. 4) *Direct customer to private* ***DirectMessaging*** *channel* ***(DM)*** (H4): We check whether a firm directed a customer towards a private channel on Twitter using direct messages, which allow firms to have private conversations with customers to address their concerns and complaints without the risk of escalating the situation publicly. This practice is highly recommended by many industrial experts.[2,3,4] Typically, when a firm decides to redirect a customer to direct messages, the firm can respond to the customer's complaint by replying "*please DM us*" or "*Please send us a direct message with your customer ID"* or send a direct messaging link to start the private conversation. Therefore, to construct this variable, we use regular expressions to detect if a firm's response contains keywords related to direct messaging such as "DM", "direct message", "direct msg", etc.

Independent Variables: The primary independent variables of interest are the politeness score of a customer's initial complaining tweet, derived using the model described in Section 4, and the number of followers the customer had when posting the initial complaining tweet.

Control Variables: We include control variables both at the customer level and at the tweet level, and we also include firm fixed effects and weekend (whether the complaint is sent during a week day or

[2] http://www.socialmediaexaminer.com/how-to-better-serve-customers-with-twitter-direct-messages/
[3] https://www.zoho.com/social/blog/5-ways-to-use-direct-messages-for-better-customer-service-and-engagement-on-twitter.html
[4] https://blog.twitter.com/marketing/en_us/a/2016/making-customer-service-even-better-on-twitter.html

weekend) fixed effects. Control variables at the customer level includes characteristics of the customer, such as the number of people the customer is following, number of tweets ever posted by the customer, the number of tweets liked by the customer, and whether the customer is a verified Twitter user (indicating that the customer is of public interest such as users from music, fashion, government, politics, sports, business areas[5]). Control variables at the tweet level include characteristics of the complaining tweet, such as the length of the tweet, how many mentions in the tweet, and whether the tweet contains hashtags.

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5.3 Model and Estimation Method

We use two econometric models: 1) logit regression and 2) linear probability model (LPM) to test our hypotheses. Our benchmark econometric specification is as follows:

$$Y_{ij} = \beta_0 + \beta_1 C_i + \beta_2 T_i + \beta_3 F_j + \beta_{M-S} D_{M-S} + \epsilon_{ij} \quad (1)$$

C_i refers to the vector of observable characteristics of the customer at the creation of the complaining tweet that initiates conversation i, and T_i refers to the vector of observable characteristics related to complaining tweet that initiates conversation i, F_j is the firm fixed effect, D_{M-S} is the vector representing fixed-effects for each day of the week except one (Monday-Saturday), and ϵ_{ij} is the error term.

It is worth noting that three dependent variables, namely DM, SentimentChange, and Satisfaction are only observable after the firm decides to respond to the customer's complaining tweet. In other words, the outcome of these variables is conditioned on $Y_{ij} = 1$ for firm's response ($Y_{ij} = 0$ means the firm does

[5] https://help.twitter.com/en/managing-your-account/about-twitter-verified-accounts

not respond). Therefore, below, we first report the empirical results on firm's response choice. After that, we use Heckman's method to solve the potential selection bias issue and jointly estimate the firm's response and other dependent variables.

-- INSERT TABLE 6 HERE –

5.3.1 Basic Results on Firm's Response

We begin by reporting the main effects in Table 6. Since our dependent variable, firm's response is a binary variable, we first use the conditional fixed effects logit model. However, interaction variables are hard to interpret in nonlinear models such as the logit model (Hoetker 2007). Besides, the coefficient of the interaction term may not be a reliable estimator of the true estimation (Ai and Norton 2003). Therefore, we also use the linear probability model (LPM), which typically results in quantitatively similar results as in limited dependent variables models (Angrist and Pischke 2008). The major concern for using the LPM, however, is that the predicted probability from the linear probability model may lie out of the range between 0 and 1, compared with OLS using the probability estimates. So we performed a post-estimation inspection, which showed that 99.81% predicted probabilities remain within the [0,1] bound. Thus our LPM model is justified.

The variation inflation factor (VIF) of our regression result is around 1 implying that multicollinearity is not a concern here. From Table 6, for all models, customer's politeness has positive and significant effects ($p<0.01$) on a firm's probability to respond. In terms of magnitude, for the logit model, from column (3), we compute the odds ratio. The results show that for a one-unit increase in customer politeness, the odds of receiving a response from the firm increase by a factor of 1.478 (48.7%). Similarly, from the results of LPM model in column (3), being polite increases the likelihood of receiving the firm's responses by 35.6%. Our findings suggest that holding other factors fixed, higher customer politeness is associated with a much higher chance of receiving responses from the firm, thereby providing support for H2.

In addition, from Table 6 for all models, the number of followers of a customer and whether the customer is a verified Twitter user have significant and positive effects. Specifically, as the number of followers increases or the customer becomes a verified user, there is a corresponding increase in the probability of receiving a response from the firm. This implies that firms do take customer popularity and status on social media into account in determining whether or not to respond, thus confirming prior findings (Gunarathne et al., 2017).

Finally, we observe that the coefficient on the interaction term between the politeness of his/her complaint and the customer's number of followers on Twitter is statistically significant and positive ($p<0.01$). This finding indicates that politeness has a more positive impact on the likelihood of receiving a firm's response when the customer has more followers. In conclusion, these results provide strong support for H3.

5.3 Heckman Analysis

As mentioned earlier, the dependent variables in H1a, H1b, and H4, namely, *SentimentChange*, *Satisfaction*, and *DirectMessaging* are all conditioned on the situation that the firm has already responded to the customer's complaint. Such dependence has to be considered in the interpretation and analysis of the results, because the population of customers that the firm responded to may be different from the overall population that originated the complaint. For more insight into this potential source of selection bias, we apply a two-step Heckman correction in the following analyses. The basic econometric specification is in Equation 2:

$$Y_{ij} \,|(Response_i = 1) = \beta_0 + \beta_1 C_i + \beta_2 T_i + \beta_3 F_j + \beta_{M-S} D_{M-S} + \beta_4' X_{ij}' + \rho\lambda + \epsilon_{ij} \quad (2)$$

where λ denotes the inverse Mill's ratio, which is calculated from first-stage regression results, and is utilized to control for selection bias. The selection stage of Heckman model is a probit model for whether tweet i is responded by the firm j. We use the same variables used in the previous response model for the selection stage. In the second stage, we use a LPM model with explanatory variables X'_{ij} that may affect the dependent variables (*DM, SentimentChange, Satisfaction*), including the politeness of the customer's tweet, the number of followers of a customer, and other variables. For *SentimentChange* and *Satisfaction* models, we further include control variables such as the total number of a firm's tweets in the conversation thread, the firm response time, and the length of the firm's responding tweets (since these measures of how a firm responded to the customer might also affect customer's sentiment or satisfaction at the end of the customer service engagement). It is worth noting that variables that may affect the first selection stage such as the weekend dummy are not in the main regression, thus satisfying the exclusion restriction.

-- INSERT TABLE 7 HERE –

Table 7 shows the results. Before estimating our main model, we conducted an analysis of collinearity. The variance inflation factors (VIFs) associated with all variables were below 1, indicating no issue of multicollinearity. First, we find from Table 7 that politeness has a positive and significant effect on customers' sentiment change and satisfaction ($p<0.01$). In other words, although complaining on social media naturally is inevitably negative, a more polite customer is more like to be satisfied or at least have a more positive change in sentiment after a firms' engagement to address their concerns. In terms of magnitude, at the end of the firm's engagement, the odds of customer satisfaction increases by 64.5% for a more polite customer (based on the coefficient of politeness in the second stage of the Satisfaction model, $\exp(0.498) = 1.645$). On the other hand, the odds of positive sentiment change also increases as much as 53.6% (based on the coefficient of politeness in the second stage of the SentimentChange model, $\exp(0.429) = 1.536$). Furthermore, shorter firm response times, and more detailed firm responses (indicated by tweet length) show positive and significant effects in our *SentimentChange* and *Satisfaction* models. In sum, these results provide strong and clear support of H1a and H1b, that a customer's politeness is likely to portend the customer's predisposition to being satisfied with the firm's response and, in turn, the customer's predisposition to express positive sentiment subsequent to the firm's response.

Next, for the *DirectMessaging* model, we first observe that politeness alone has no significant effect on the firm's tendency to direct a customer to Twitter's private messaging channel. As hypothesized, we find a negative and significant interaction between the indicator of customer politeness and the number of followers of the customer ($p<0.01$) or conversely, a positive and significant interaction between the customer impoliteness and the number of followers of the customer (as politeness score is binary). This indicates that the odds of being redirected to a private channel on Twitter increases with increasing followers for customers low in politeness. These two findings suggest that once a firm decides to respond to a customer, the firm is more likely to redirect its impolite customers with higher social influence to private channels to address their complaints, as compared to impolite customers with lower social influence who perhaps are less risky to engage with publicly. This is consistent with our theorizing that firms aim to avoid the risk of negative word-of-mouth being broadcast by customers with high social influence. Our results suggest that firms have a risk-averse strategy when engaging such impolite and unhappy customers, thereby supporting H4.

6 Robustness Tests

In this section, we report additional analyses intended to test the robustness of our main findings. We begin by providing convergent evidence for our main findings by measuring politeness in a different way. Our second set of analyses examine the robustness of our results with respect to additional controls for day-of-the-week effects.

6.1 Alternative Measurement for Politeness

We look to verify our primary measure of politeness, which was truncated as a binary (polite or impolite). Here, we re-estimate our model specifications using the numeric politeness score (between 0 and 1, indicting the probability of a text being polite) from the machine-learning model we developed. The results are reported in Table 8 and Table 9. We continue to observe the same pattern of results; that is, customer's politeness has a positive and significant effect on the firm's tendency to respond publicly to customer complaints. Customer's politeness also has a positive and significant relationship to their eventual change in sentiment and publicly expressed satisfaction. Moreover, when interacting with customer's social popularity on Twitter, customers' *impoliteness* has a positive influence on the relationship between customers' social influence (number of followers) and likelihood of being redirected by firms to private channels. In sum, these additional results indicate that our findings are not dependent upon our choice of measures.

-- INSERT TABLE 8 HERE –

-- INSERT TABLE 9 HERE –

6.1 Control for Within-week Seasonality

In our main model, we used weekend dummies to control for whether the complaint is sent during a weekday or weekend. In order to further control for seasonality, we augment our benchmark model with day-of-the-week dummies to control for within-week seasonality. The results, presented in Table 10 and 11, are qualitatively similar to our benchmark model.

-- INSERT TABLE 10 HERE –

-- INSERT TABLE 11 HERE –

7. General Discussion

Social media has fundamentally changed the relation between customers and firms. In particular, with the rise of social media, customers are no longer limited to a passive role. Instead, thanks to social media's transparency and openness, they now can voice their dissatisfaction with little cost, easily reach a large audience, and thus potentially boost or harm the brand through the broadcast of positive or negative sentiment respectively (Chevalier and Mayzlin 2006). As customer-firm interactions proliferate on social media, reacting appropriately to complaints on social media has become a major challenge for companies (Bolton and Saxena-Iyer 2009; Einwiller and Steilen 2015; Grégoire et al., 2015).

In the present research, we analyzed tweets sent to and by 80 firms on Twitter to examine how the tone of a customer's complaint influenced the firm's customer engagement strategy. Our basic proposition was that the politeness of a complaining tweet reflects the attitude of a customer towards the firm, and thereby also the customer's predisposition to being satisfied with the firm's response. Moreover, we anticipated that firms would strategically adapt their response according to the politeness of customer complaints in order to manage the sentiment being broadcast on social media about the firm.

Our findings supported these hypotheses. Specifically, we found that companies are more likely to respond to more polite customers, effectively discriminating based on customers' politeness on social media. More interestingly, we also found that firms are less likely to publicly engage impolite customers with high social status; instead, firms prefer to resolve the complaints of these customers in a private channel such as through direct messaging. Furthermore, we found that linguistic tokens indicating politeness, which appear in a customer's initial message to a firm's customer service account on social media, strongly predict the nature of the sentiment the customer will broadcast about the firm at the end of the interaction. A more polite customer is more likely to express positive changes in sentiment between the time of the customer's first message complaining or requesting help from a firm's customer service account, to the last message in a thread of Twitter messages exchanged between the firm and the customer.

6.1 Theoretical Implications

Our research provides important theoretical contributions to the stream of consumer correspondence-handling literature. Although several previous studies examined organizational responsiveness to consumer complaints and compliments, to the best of our knowledge, they were mostly conducted within the frame of traditional customer service. Research in social media-based customer relationship management (CRM) is still in its infancy. Thus, our research reveals the importance of a new dimension of CRM arising from social media that firms need consider, namely the importance of the power of social media to broadcast sentiment.

Specifically, this work makes contributions to the marketing and service intervention literature in four important respects: First, we extend the current literature on complaint-management and CRM. Prior studies mostly looked at the causes and the sources of the customers' complaints and the procedural determinants of the complaint management process, with specific focus on repurchase intentions, or potential word of mouth and customer satisfaction with the resolution outcomes. We offer a new perspective by focusing on the relationship between customers' politeness, i.e., the tone of communication, and how firms engage customers on social media. Second, our work contributes to the nascent literature on customer complaint-management on social media, by providing new evidence of how firms strategically engage with customers regarding their complaints on the publicly broadcast platform Twitter. Third, we develop a novel machine-learning approach to algorithmically measure customer's politeness from their tweets. Politeness has been found to be an important factor in marketing with many applications in service intervention, market communication, etc. Prior studies mostly used manual approaches such as labeling or surveys which are costly, time consuming, and error-prone. Therefore, our automated approach can help significantly reduce the cost and improve the accuracy for future studies that involve examining the role of politeness (or tone more generally). To the best of our knowledge, this study is among the first to analyze the tone of communication and its effect on the firm's customer service engagement strategy on social media platforms.

Finally, we show that the tone of a customer's communication predicts how customers will react to future communications by the firm. This suggests that tone is an important indicator of the receptivity of a customer to attempts by the firm to resolve a complaint. More broadly, it suggests that tone signals a bias in how individuals process subsequent information, a finding that bears potential implications for multiple research questions. For example, future research on tone might examine how differences in the language used by a marketer can interact with the tone of the customer to affect satisfaction. Likewise, future research can examine how tone influences receptivity to recommendations and other customer behaviors.

6.2 Managerial Implications

This research also has important business implications for companies practicing various strategies of customer service on social media. We argue that firms need to consider cost and utility in customer service, especially social media-based customer service, so customer service agents can strategically deal with customers when prioritizing what tweets seeking service and help to respond to. To this end, our research provides several insights that can be useful for industry practitioners and social media strategists in investigating the optimal mix of strategies towards effective customer correspondence on social media. In particular, firms should consider how linguistic tokens associated with politeness could serve as reliable predictors for deciding which customers to engage publicly, and how to engage them, in order to amplify positive sentiment on social media and to attenuate negative sentiment. Although our data suggests firms already do this to some degree, it is likely that their approach can be further optimized by systematically examining the effect of politeness, and perhaps other features of a complaining tweet, on the nature of sentiment likely to be broadcast about the firm.

8. Conclusion

Understanding the dynamics and factors associated with successful customer service engagement on social media has the potential to substantially improve customer-firm relationships, the customer experience, and brand image management, among other outcomes. In addition to these practical benefits, understanding the factors that influence customer-service interactions has implications for research in online communications, social psychology, information systems, marketing, and related areas. The present research contributes to understanding customer service interactions on social media by highlighting the important role of tone, and specifically of politeness, in predicting the nature of sentiment customers are likely to broadcast about the firm. Likewise, it contributes to understanding of firms' customer-service engagement strategies as a function of the tone of social media complaints. Our hope is that our research fosters additional research on customer service engagement strategies on social media.

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Table 1 Politeness Strategies.

	Strategy	**Example**
1	Gratitude	**Thanks** in advance!/I really **appreciate** your help!
2	Deference	You did an **amazing job**…
3	Greeting	**Hi** @attacares…/**Hey**, I just tried to…
4	Group identity	Help me please, **guys**…/Help me with this bag here, will you **pal**?
5	Presuppose	Ok, **let's** stop that problem…/**We** should do this…
6	Please	**Please** help…/Could you **please** explain?...
7	1st person	**I** have a problem with.../**I** cannot do it…
8	Apologizing	**Sorry** to bother you…
9	Indirect	**By the way**, I also want to…
10	Direct question/start	**Why** does this happen?/**So** can you solve it or not?
11	2nd person	**You** come here…/**You** should not do this to me…
12	Hedges	I **assume** this is reason…/**I'm not** an expert **but**
13	Disagreement avoidance	I **sort of** think…/I **kind of** want…
14	Pessimistic	**Could**/**Can**/**Would**/**Will** you help me?
15	Positive lexicon	**Awesome**!/This is **great** …
16	Negative lexicon	I **dislike** your design…/Really **bad** service…

Table 2 Classification Accuracy against ground truth

	Unigram	Linguistic + Unigram
SVM	70.12%	72.67%
Logistic Regression (LR)	74.51%	83.54%
Decision Tree (DT)	68.54%	71.37%

Table 3. Descriptive Statistics of Key Variables

Variable	Mean	Std
Response	0.55	0.49
DirectMessaging (DM)	0.27	0.41
SentimentChange	0.11	0.12
Satisfaction	0.08	0.28
Politeness	0.54	0.11
#Followers	182.2	5,2336
#Followings	764.5	8,437.5
#Tweets	1,898	1,025
#Likes	458	412
isVerified	0.01	0.14
TweetLength	18.0	19.5
retweets	1.27	1.83
#hashtags	0.25	0.75
#mentions	1.4	1.2
Weekend	0.54	0.11

Table 4. Correlation Matrix for Key Variables

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Response	1													
2	DM	**.03**	1												
3	SentimentChange	**.05**	**-.12**	1											
4	Satisfaction	**.11**	**-.10**	**.16**	1										
5	Politeness	**.14**	**-.07**	**.02**	**.03**	1									
6	# Follower	**.15**	**.14**	**.16**	**-.10**	**.14**	1								
7	#Following	**.15**	**.25**	**.20**	**-.14**	**.03**	**.02**	1							
8	#Tweets	**-.11**	**-.06**	**-.13**	**.05**	**.11**	.01	**.02**	1						
9	#Likes	**.03**	**.04**	**.07**	**.12**	**-.02**	-.01	**-.01**	**.02**	1					
10	isVerified	**.12**	**.03**	**.12**	**.11**	**.02**	**.01**	**.02**	**.01**	**.02**	1				
11	TweetLength	**-.11**	**.14**	**.12**	**.11**	**.02**	**.02**	**.02**	.00	.00	**.05**	1			
12	#hashtags	**-.05**	**-.25**	**-.25**	**.51**	**.25**	**.36**	**.49**	**.47**	**.14**	**.01**	**.02**	1		
13	#mentions	**-.25**	**-.22**	**-.04**	**-.03**	**.00**	**.01**	**-.25**	**-.21**	**-.06**	**-.04**	.00	**.02**	1	
14	Weekend	**.11**	**.11**	**.12**	**.04**	**.03**	**.05**	**.07**	**.01**	**.22**	**.01**	.00	.01	.00	1

* Significant numbers (p<.05) are in bold

Table 5. Firms used in the present study

Firm Name	Twitter handle	#complaints
2K	2ksupport	25,543
Acura	acuraclientcare	91
Airbnb	airbnbhelp	3,204
Allstate	allstatecares	146
Amazon	amazonhelp	27,501
AOL	aolsupporthelp	213
Welsfargo	ask_wellsfargo	529
American express	askamex	5,203
Citi bank	askciti	1,045
Dyson	askdyson	253
Ebay	askebay	2,462
Lyft	asklyft	3,034
Papa johns	askpapajohns	458
Playstation	askplaystation	30,243
Suntrust	asksuntrust	263
Target	asktarget	1,422
US bank	askusbank	126
Visa	askvisa	196
At&t	attcares	9,891
Azure	azuresupport	1,731
Beats	beatssupport	329
Belkin	belkincares	458
Bestby	bestbuysupport	1,999
Barnes & Noble	bn_care	307
Bank of America	bofa_help	2,023
British airlines	british_airways	28,904
Chase banks	chasesupport	2,876
Chevrolet	chevycustcare	117
Comcast	comcastcares	13,556
Dell	dellcares	2,564
Delta airline	delta	142,107
Dropbox	dropboxsupport	1,280
Emirate airline	emiratessupport	2,789
Enterprise rental	enterprisecares	875
Etsy	etsyhelp	406

Fedex	fedexhelp	4,174
Finishline	finishlinehelp	747
Geoco	geico_service	445
HBO	hbonowhelp	136
Homedepot	homedepot_care	210
Honda	hondacustsvc	793
Hulu	hulu_support	2,289
Ikea	ikeausahelp	202
Jawbone	jawbonesupport	1,099
Jcrew	jcrew_help	803
Lowes'	lowescares	86
Lufthasa	lufthansa_usa	305
Louis Vuitton	lvservices	608
Megabus	megabushelp	179
Microsoft	microsofthelps	2,098
National	nationalcares	266
Nest	nestsupport	1,036
Netflix	netflixhelps	7,802
Newegg	neweggservice	123
Nike	nikesupport	1,419
Nissan	nissansupport	162
Optimum	optimumhelp	1,015
Orbitz	orbitzcareteam	78
Samsung	samsungsupport	1,896
Skype	skypesupport	1,440
Sleepnuber	sleepnumberhelp	36
Son	sonysupportusa	268
Southwest	southwestair	30,603
Spotify	spotifycares	9,901
Starhub	starhubcares	275
Surface	surfacesupport	567
TacoBell	tacobellteam	977
Turbox	teamturbotax	135
Toshiba	toshibausahelp	25
Uber	uber_support	17,299
Ubisoft	ubisoftsupport	5,992
United	united	31,025
UPS	upshelp	7,333
USAA	usaa_help	520

US cellular	uscellularcares	94
USPS	uspshelp	8,162
Virgin Atlantic	virginatlantic	6,040
VMware	vmwarecares	42
Windows	windowssupport	689
Xbox	xboxsupport	25,434

Table 6. Estimation of Main Effect. Dependent variable is a binary indicator, 1=firm responded within 7 days of a customer complaint, otherwise 0.

Model	Logit				LPM			
Specification	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
log(following)	0.476*** (0.065)		0.480*** (0.065)	0.571*** (0.016)	0.388*** (0.055)		0.446*** (0.012)	0.475*** (0.013)
log(follower)	0.250*** (0.015)		0.221*** (0.015)	0.643*** (0.016)	0.201*** (0.005)		0.213*** (0.044)	0.553*** (0.016)
Politeness		0.375*** (0.014)	0.391*** (0.013)	0.252*** (0.003)		0.295*** (0.002)	0.353*** (0.004)	0.355*** (0.002)
log(follower)* Politeness				0.156*** (0.001)				0.301*** (0.001)
#Tweets	-0.117*** (0.015)	-0.208*** (0.013)	-0.118*** (0.015)	-0.217*** (0.015)	-0.321*** (0.015)	-0.317*** (0.015)	-0.304*** (0.011)	-0.258*** (0.015)
#Likes	0.087*** (0.011)	0.107*** (0.013)	0.117*** (0.015)	0.217*** (0.015)	0.305*** (0.015)	0.371*** (0.015)	0.267*** (0.008)	0.299** (0.015)
isVerified	0.188** (0.013)	0.108** (0.011)	0.101** (0.015)	0.148** (0.015)	0.618** (0.015)	0.571** (0.015)	0.408** (0.005)	0.418** (0.016)
TweetLength	0.519*** (0.013)	0.500*** (0.015)	0.447*** (0.015)	0.566*** (0.015)	0.297*** (0.011)	0.257*** (0.015)	0.212*** (0.019)	0.212*** (0.010)
#hashtags	-0.222*** (0.015)	0.214*** (0.015)	0.207*** (0.015)	-0.298*** (0.015)	-0.220*** (0.011)	-0.255*** (0.019)	-0.117*** (0.015)	-0.117*** (0.010)
#mentions	-0.074*** (0.005)	-0.223*** (0.005)	-0.252*** (0.015)	-0.210*** (0.015)	-0.218*** (0.015)	-0.355*** (0.010)	-0.447** (0.014)	-0.465* (0.010)
Weekend	-0.079** (0.002)	-0.022*** (0.001)	-0.015*** (0.005)	-0.011*** (0.005)	-0.021*** (0.005)	-0.020*** (0.002)	-0.027*** (0.003)	-0.024*** (0.003)
Constant	1.849*** (0.005)	1.049*** (0.002)	1.909*** (0.005)	1.909*** (0.005)	1.449*** (0.003)	1.549*** (0.003)	1.941*** (0.004)	2.541*** (0.005)
Observations	488,926	488,926	488,926	488,926	488,926	488,926	488,926	488,926
Within R-squared	0.2494	0.2425	0.2405	0.2472	0.2306	0.2228	0.2404	0.2484
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. Estimation of Main Effect. Column 1: Dependent variable is a binary indicator, 1=firm redirected the conversation to private channel, otherwise 0. Column 2: Dependent variable is a continuous measure, indicating the sentiment changes between the customer's first and last tweets. Column 3: Dependent variable is a binary indicator, 1=customer expressed satisfaction at the end of the conversation, otherwise 0. Dependent variable of the first-stage model is the binary indicator of firm's response.

	DV=DM, with Heckman Correction		DV=SentimentChange, with Heckman Correction		DV=Satisfaction, with Heckman Correction	
Stage	First	Second	First	Second	First	Second
log(following)	0.106** (0.008)	-0.406*** (0.008)	-0.209** (0.009)	0.219 (0.059)	-0.129** (0.009)	0.050** (0.003)
log(follower)	0.113** (0.008)	-0.813*** (0.002)	0.452** (0.112)	-0.182 (0.062)	0.302** (0.009)	-0.400*** (0.062)
Politeness	0.246 (0.138)	0.242 (0.135)	0.229** (0.078)	0.429*** (0.008)	0.102** (0.058)	0.498*** (0.001)
log(follower)*Politeness	-0.107* (0.013)	-0.197** (0.003)	0.124* (0.010)	0.209 (0.107)	0.107 (0.110)	0.295*** (0.034)
#Tweets	-0.270** (0.015)	0.347*** (0.015)	-0.247** (0.075)	-0.057* (0.020)	-0.141** (0.075)	-0.183*** (0.062)
#Likes	0.27 (0.15)	-0.107* (0.015)	-0.347*** (0.005)	0.047** (0.019)	-0.242*** (0.005)	0.305*** (0.047)
isVerified	-0.238 (0.105)	-0.118 (0.075)	0.118** (0.05)	-0.118** (0.075)	0.108** (0.05)	-0.108** (0.075)
CustomerTweetLength	0.279*** (0.015)		-0.519** (0.015)		-0.442** (0.015)	
#hashtags	-0.215*** (0.015)		-0.121 (0.085)		-0.119*** (0.085)	
#mentions	0.317*** (0.015)		0.687 (0.115)		-0.45*** (0.115)	
Weekend	-0.427*** (0.015)		-0.182** (0.055)		-0.229** (0.075)	
FirmReplyTime				0.056* (0.020)		-0.075*** (0.002)
FirmTweetLength				0.260** (0.07)		0.124** (0.017)
Inverse Mill's ratio		-0.058*** (0.002)		-0.038*** (0.001)		0.034*** (0.001)
Observations		89,321		89,321		89,321
Multiple R-squared		0.177		0.118		0.118
Firm Fixed Effect		Yes		Yes		Yes

Table 8. Estimation of Main Effect with numeric politeness score. Dependent variable is a binary indicator, 1=firm responded within 7 days of a customer complaint, otherwise 0.

Model	LPM			
Specification	Spec. 1	Spec 2.	Spec 3.	Spec 4.
log(following)	0.388*** (0.055)		0.376*** (0.011)	0.425*** (0.010)
log(follower)	0.201*** (0.005)		0.211*** (0.041)	0.353*** (0.011)
Politeness		0.281*** (0.002)	0.253*** (0.004)	0.325*** (0.002)
log(follower)* Politeness				0.207*** (0.011)
#Tweets	-0.321*** (0.015)	-0.317*** (0.015)	-0.304*** (0.011)	-0.218*** (0.014)
#Likes	0.305*** (0.015)	0.331*** (0.012)	0.267*** (0.008)	0.029** (0.015)
isVerified	0.061** (0.015)	0.051** (0.013)	0.040** (0.005)	0.041** (0.016)
TweetLength	0.297*** (0.011)	0.257*** (0.015)	0.212*** (0.019)	0.212*** (0.010)
#hashtags	-0.220*** (0.011)	-0.155*** (0.019)	-0.111*** (0.011)	-0.117*** (0.010)
#mentions	-0.021*** (0.015)	-0.026*** (0.010)	-0.043*** (0.014)	-0.046*** (0.010)
Weekend	-0.021*** (0.005)	-0.031*** (0.002)	-0.027*** (0.003)	-0.024*** (0.003)
Constant	1.449*** (0.003)	1.529*** (0.003)	1.441*** (0.004)	1.541*** (0.005)
Observations	488,926	488,926	488,926	488,926
Within R-squared	0.2306	0.2108	0.2404	0.2484
Firm Fixed Effect	Yes	Yes	Yes	Yes

Table 9. Estimation of Main Effect with numeric politeness score. Dependent variable of the first-stage model is the binary indicator of firm's response. Dependent variable of the second-stage model is indicated in the table's column heading (as in Table 7).

	DV=DM, with Heckman Correction		DV=SentimentChange, with Heckman Correction		DV=Satisfaction, with Heckman Correction	
Stage	First	Second	First	Second	First	Second
log(following)	0.116** (0.008)	-0.326*** (0.008)	-0.211** (0.019)	0.217 (0.059)	-0.129** (0.009)	0.052** (0.003)
log(follower)	0.111** (0.008)	-0.543*** (0.002)	0.251** (0.112)	-0.172 (0.062)	0.302** (0.009)	-0.411*** (0.062)
Politeness	0.242 (0.138)	0.218 (0.138)	0.248** (0.078)	0.369*** (0.008)	0.124** (0.058)	0.348*** (0.001)
log(follower)*Politeness	-0.107* (0.013)	-0.198*** (0.003)	0.220* (0.010)	0.234 (0.107)	0.101 (0.110)	0.225*** (0.031)
#Tweets	-0.027** (0.015)	0.035*** (0.005)	-0.042** (0.075)	-0.051* (0.020)	-0.141** (0.075)	-0.192*** (0.042)
#Likes	0.027 (0.115)	-0.107* (0.015)	-0.341*** (0.005)	0.044** (0.019)	-0.242*** (0.005)	0.325*** (0.042)
isVerified	-0.024 (0.019)	-0.022 (0.015)	0.128** (0.05)	-0.110** (0.075)	0.108** (0.055)	-0.109** (0.025)
CustomerTweetLength	0.018*** (0.005)		0.052** (0.015)		-0.442** (0.015)	
#hashtags	-0.022*** (0.001)		-0.121 (0.085)		-0.119*** (0.085)	
#mentions	0.032*** (0.005)		0.687 (0.115)		-0.45*** (0.115)	
Weekend	-0.043*** (0.005)		-0.182** (0.055)		-0.229** (0.075)	
FirmReplyTime				0.051* (0.020)		-0.074*** (0.002)
FirmTweetLength				0.262** (0.07)		0.123** (0.011)
Inverse Mill's ratio		-0.053*** (0.002)		-0.034*** (0.001)		0.032*** (0.001)
Observations		89,321		89,321		89,321
Multiple R-squared		0.147		0.130		0.102
Firm Fixed Effect		Yes		Yes		Yes

Table 10. Estimation of Main Effect with Day-of-Week dummy. Dependent variable is a binary indicator, 1=firm responded within 7 days of a customer complaint, otherwise 0. (For brevity, results of Day of Week are not reported)

Model	LPM			
Specification	Spec. 1	Spec 2.	Spec 3.	Spec 4.
log(following)	0.328*** (0.051)		0.376*** (0.011)	0.425*** (0.010)
log(follower)	0.201*** (0.005)		0.211*** (0.041)	0.353*** (0.011)
Politeness		0.281*** (0.002)	0.253*** (0.004)	0.325*** (0.002)
log(follower)*Politeness				0.224*** (0.011)
#Tweets	-0.320*** (0.014)	-0.317*** (0.015)	-0.304*** (0.011)	-0.218*** (0.014)
#Likes	0.310*** (0.012)	0.331*** (0.012)	0.267*** (0.008)	0.029** (0.015)
isVerified	0.062** (0.011)	0.051** (0.013)	0.040** (0.005)	0.041** (0.016)
TweetLength	0.227*** (0.011)	0.257*** (0.015)	0.212*** (0.019)	0.212*** (0.010)
#hashtags	-0.210*** (0.010)	-0.155*** (0.019)	-0.111*** (0.011)	-0.117*** (0.010)
#mentions	-0.034*** (0.011)	-0.026*** (0.010)	-0.043*** (0.014)	-0.046*** (0.010)
Constant	1.449*** (0.003)	1.529*** (0.003)	1.441*** (0.004)	1.541*** (0.005)
Observations	488,926	488,926	488,926	488,926
Within R-squared	0.2326	0.2217	0.2414	0.2463
Firm Fixed Effect	Yes	Yes	Yes	Yes

Table 11. Estimation of Main Effect with Day-of-Week dummy. Dependent variable of the first-stage model is the binary indicator of firm's response. Dependent variable of the second-stage model is indicated in the table's column heading (as in Table 7). (For brevity, results of Day of Week are not reported)

	DV=DM, with Heckman Correction		DV=SentimentChange, with Heckman Correction		DV=Satifaction, with Heckman Correction	
Stage	First	Second	First	Second	First	Second
log(following)	0.116** (0.008)	-0.326*** (0.008)	-0.211** (0.019)	0.217 (0.059)	-0.129** (0.009)	0.062*** (0.003)
log(follower)	0.111** (0.008)	-0.483*** (0.002)	0.251** (0.112)	-0.172 (0.062)	0.302** (0.009)	-0.211*** (0.071)
Politeness	0.242 (0.138)	0.210 (0.138)	0.248** (0.078)	0.369*** (0.008)	0.102** (0.058)	0.248*** (0.002)
log(follower)*Politeness	-0.107* (0.013)	-0.198*** (0.003)	0.220* (0.010)	0.234 (0.107)	0.124 (0.110)	0.204*** (0.031)
#Tweets	-0.027** (0.015)	0.035*** (0.005)	-0.042** (0.075)	-0.051* (0.020)	-0.141** (0.075)	-0.191*** (0.043)
#Likes	0.027 (0.115)	-0.107* (0.015)	-0.341*** (0.005)	0.054** (0.019)	-0.212*** (0.005)	0.254*** (0.042)
isVerified	-0.024 (0.019)	-0.022 (0.015)	0.128** (0.05)	-0.110** (0.075)	0.108** (0.055)	-0.119** (0.025)
CustomerTweetLength	0.018*** (0.005)		0.052** (0.015)		0.432** (0.011)	
#hashtags	-0.022*** (0.001)		-0.121 (0.085)		-0.119*** (0.085)	
#mentions	0.032*** (0.005)		0.687 (0.115)		-0.45*** (0.115)	
FirmReplyTime				0.051* (0.020)		-0.074*** (0.002)
FirmTweetLength				0.262** (0.07)		0.123** (0.011)
Inverse Mill's ratio		-0.064*** (0.002)		-0.031*** (0.001)		0.044*** (0.001)
Observations		89,321		89,321		89,321
Multiple R-squared		0.145		0.124		0.101
Firm Fixed Effect		Yes		Yes		Yes