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RESEARCH ARTICLE

WHEN SOCIAL MEDIA DELIVERS CUSTOMER SERVICE: DIFFERENTIAL CUSTOMER TREATMENT IN THE AIRLINE INDUSTRY[1]

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Companies increasingly are providing customer service through social media, helping customers on a real-time basis. Although some traditional call centers might prioritize customers based on their expected business values, the grounds for differential customer service on social media are unclear, since there has been little theoretical or empirical investigation of this new phenomenon. Building on the literature of social psychology and complaint management, we hypothesize two main drivers of differential treatment: the social media influence effect, which refers to the impact of the customer's relative standing on social media, and the bystander effect, which refers to the impact of the presence of other social media users. To test these effects, we analyzed more than three million tweets to seven major U.S. airlines on Twitter from September 2014 to May 2015. The evidence is clear that airlines respond to less than half of the tweets directed at them by complaining customers—in contrast with traditional call centers, which are expected to address all callers. Interestingly, we find that the 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, thus confirming the existence of a concealed (or at least unpublicized) social media influence effect. We also find that airlines are less likely to respond to complaints with multiple parties mentioned, confirming the existence of the bystander effect. To the best of our knowledge, this is the first paper in the literature to study the existence and drivers of differential treatment when customer service is delivered on social media, and we expect our findings will have important implications for companies, customers, and regulators.

Keywords: Social media, social influence, customer service, complaint management, bystander effect

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The appendix for this paper are located in the "Online Supplements" section of the *MIS Quarterly*'s website (http://www.misq.org).

Introduction

On Saturday, February 13, 2010, filmmaker Kevin Smith, after being told by Southwest Airlines to leave a plane he had boarded, angrily sent out a tweet to his 1.6 million Twitter followers claiming that he had been kicked off a Southwest Airlines flight for being "too fat." Sixteen minutes later, Southwest Airlines, which had over 1 million Twitter followers, responded and started to de-escalate the crisis. Southwest's handling of the situation was certainly prompt and commendable. But what if Kevin Smith were not some celebrity with more than a million Twitter followers? Would he have received a response in 16 minutes? Would he have received a response at all?

The answers to such questions may hinge on a company's social media strategy, which is becoming increasingly important for the reputation of a brand. Empowered by the popularization of social media and smart phones, customers are no longer limited to a passive role in their relationships with a brand. They can easily express their endorsements or complaints publicly to a large audience in real time, significantly raising the bar for customer service. United Airlines learned this the hard way when the now-famous protest song "United Breaks Guitars" went viral on YouTube in 2009.[2] Although most customers probably would not bother writing a song to share their experience, more and more people are simply tweeting publicly to corporate Twitter accounts to complain. According to a *New York Times* article, such a public approach may actually work out better for consumers than spending time on the phone.[3] In response, companies are scrambling to monitor and respond to consumer complaints on Twitter, effectively providing customer service on social media. Such a practice is different from traditional customer service at call centers in important ways. First, with a traditional call center, the company can often learn the identity of the customer by looking up the phone number the customer is calling from in its internal customer database, which can enable the company to prioritize its handling of the complaint based on the customer's perceived financial value. On social media, it is typically very hard to determine the customer's financial value before engaging with the customer. Instead, the company immediately learns the "social media identity" and potential influence of that customer. Prioritization based on customer *influence*, however, is fundamentally different from prioritization based on customer *value*, according to theories from social psychology. Second, whenever a company receives a customer complaint on social media, the company is immediately presented with a treasure trove of customer data, such as the customer's social media posting history and current social network connections. Such data, often unstructured, is drastically different from the customer data available in a traditional call center and requires very different methodologies to be effectively used by the company.

Inspired by this growing phenomenon, we investigate how and why customers may receive differential treatment on social media. We propose and test two potential drivers of differential treatment. First, we study *whether a customer's social media influence affects the chance and speed of a brand responding to his or her complaint on social media*, an effect we refer to as the *social media influence effect*. Such an effect could be the result of explicit company policies and the corresponding procedures, implicit incentive mechanisms faced by the social media staff, or stereotypes based on social media popularity. Operationally, prioritizing customers based on their social media influence is also becoming easier. For example, according to forbes.com, in 2012, LiveOps, a cloud call-center company, was implementing ways of prioritizing which customers to contact first, based on the number of Twitter followers the customers had.[4] On the other hand, the very existence of the social media influence effect, regardless of its cause, may lead to a perception of service unfairness. As Air France-KLM's senior vice president for e-commerce states: "The audience we have is very suspicious towards famous people getting treated differently. This is not our policy, because we know it will backfire on us" (Kane 2014, p. 6). More recently, Twitter warned in its guide[5] for the growing number of companies using its platform to provide customer service that

[2]https://www.youtube.com/watch?v=5YGc4zOqozo.

[3]In a General Motors (GM) vehicle recall, Lauren Munhoven, a customer in Ketchikan, Alaska, turned to Twitter after wasting an hour on the phone with GM trying to get help with her 2006 Saturn Ion. After she wrote the public tweet "*@GM your agents keep telling me to take my car to a GM dealer for the recall, after I've explained I live on an island in Alaska! Help!!!!,"* a member of GM's Twitter team helped, and the company agreed to pay the $600 cost of a round-trip ferry to ship Ms. Munhoven's car to the nearest dealer, about 300 miles away in Juneau, and to pay for a rental car for the time she was without the Saturn. For the detailed report, see http://www.nytimes.com/2014/03/24/business/after-huge-recall-gm-speaks-to-customers-through-social-media.html?_r=04.

[4]See http://www.forbes.com/sites/alexknapp/2012/05/30/saving-customer-service-with-social-media-and-a-song/ for details.

[5]The guide, titled "Customer Service on Twitter," published by the Twitter for Customer Service Team in 2015, was last retrieved on December 26, 2017, from the link https://cdn.cms-twdigitalassets.com/content/dam/marketing-twitter/downloads/customerservice-playbook.pdf.

> Whichever prioritization criteria you choose, be sure they pass the "sniff test." If these criteria became public, would they embarrass you? If so, they probably need some reworking. Remember, because of the public nature of Twitter, and the fact that anybody can set up a Twitter account and give it any username, analysts, journalists, bloggers and consumer advocates can test your Twitter customer service response, and "reverse engineer" reconstruct your prioritization policies (p. 101).

Second, we investigate *whether mentioning other users in a complaint affects the chance of receiving a response from the brand*, which can be thought of as the social media equivalent of the well-known *bystander effect* from social psychology. The bystander effect states that an individual's likelihood of responding to requests for help decreases when bystanders are present. Studies of the bystander effect in social psychology were partially motivated by a number of real-world incidents where bystanders did not attempt to help a person in need.[6] The theory has received relatively less attention in marketing and consumer psychology literature. Although there are a few studies that have investigated *cyber bullying* and bystander intervention on social network sites, studies conducted in the context of social media customer service are nonexistent. Customers on social media often have other users in the audience while complaining to companies. For example, on Twitter, whenever a customer mentions a user using the @ symbol followed by the user's Twitter account, the tweet will be pushed to that user, thereby making that user a part of the immediate audience. Hence, we can examine the bystander effect by studying whether mentioning multiple users in a complaint reduces the likelihood of receiving a response from a company, especially when the other users are also responsible for the issue the customer is complaining about.

To address our research questions, we select Twitter as the social media platform and focus on the airline industry because Twitter is one of the most popular social media platforms and the airline industry has extensively leveraged Twitter for real-time customer service. We analyzed all tweets mentioning the official Twitter accounts of seven major U.S. airlines for a period of nine months, using text-mining techniques to extract and process data in a scalable fashion.

The data shows that these airlines respond to less than half of the tweets directed at them by complaining customers—in stark contrast with traditional call centers, which are expected to address all callers. Using a joint model for response choice and response time, our estimation results show that airlines are more likely to respond to complaints from customers with more followers. Moreover, if a complaint does receive a response, we find that customers with more followers are more likely to receive it faster. Both of these findings indicate the existence of preferential customer service based on social media influence. We also find that airlines are more likely to respond to complaints that are directed solely to them, as opposed to those also mentioning other users. Therefore, both the social media influence effect and the bystander effect are supported by the empirical evidence.

To the best of our knowledge, along with two recent papers (Ma et al. 2015; Sreenivasan et al. 2012), our paper is among the first in the literature to study customer service on social media. Sreenivasan et al. (2012) manually analyzed the content of 4,578 user tweets mentioning three airlines and found that microblogs were primarily used by customers to share compliments and by airlines for marketing. Other uses, such as sharing general information, asking questions, and providing personal updates, were also noted. They noticed a large number of attention-seeking tweets that highlighted customer issues and concerns as well. They also found that the airlines being studied did not appear to be as responsive to users' postings as expected. Our study differs from Sreenivasan et al. in many aspects. First, the goal of our research is to examine differential treatment of customer service on social media, while the goal of Sreenivasan et al. was to describe and summarize the content of airline-related tweets. Second, our data set is much more comprehensive and recent. Sreenivasan et al. collected 8,978 user tweets mentioning the names of three airlines (Malaysia Airlines, Jet Blue, and Southwest) during a two-week period and analyzed about half of them. Our data includes more than 3 million user tweets sent specifically to seven major U.S. airlines (i.e., using @) during a nine-month period from 2014 to 2015, among which we identified 173,662 initial complaining tweets. It should also be noted that Sreenivasan et al. collected their data in September 2009, which was probably before many companies started doing customer service on Twitter.

Ma et al. (2015) investigated how customers' compliments and complaints on Twitter are driven by their relationships with the firm and by social factors at the site, and how the firm's service intervention affects customers' voices and relationships. Their data is from an anonymous telecommunication company and covers relevant tweets to that company from February to December 2010. By estimating a structural model using tweets from a sample of 714 customers over 310 days, they found that redress seeking is a major driver of customer complaints, and although service intervention im-

[6] The most extreme case is that of Kitty Genovese, a young woman who was stabbed to death in the middle of a street in a residential section of New York City in 1964. Even though the incident was witnessed by a dozen bystanders, none of them intervened to assist the victim.

proves relationships, it also encourages more complaints later. Although both papers study the phenomenon of customer service on social media, the perspectives are very different. While Ma et al. focus on *customers*' decisions to voice, we focus on *firms*' decisions to respond to customer complaints on social media.

As discussed above, although our study shares certain similarities with Sreenivasan et al. and Ma et al., it differs significantly in terms of research questions and findings as well as data. Influence-based preferential treatment is new in customer service and is also controversial. This is the first study to theoretically analyze this practice from the perspective of social psychology and the first to empirically investigate it. This is also the first study to empirically examine the bystander effect in the context of customer complaint management.

The rest of the paper is organized as follows. We first provide a broader literature review before developing the hypotheses for our research questions. After describing our data and measures, we estimate our main econometric model and present the empirical results. We then conduct a series of robustness checks of our main findings using several alternative specifications and settings. A follow-up research extension investigates the potential link between customer satisfaction with social media customer service and an airline's offline consumer satisfaction ranking. We conclude the paper by discussing some implications of our findings while pointing out the limitations of our research and suggesting future research directions.

Research Background

Our paper is broadly related to the literature on customer complaint management, service-level differentiation, and the industry practice of call-center routing.

Customer Complaint Management

There is a rich literature on customer complaint management and we organize our review of this stream of literature into three topics.

Customer Complaint Behavior

Customer complaint behavior has received a great deal of research attention over the past few decades and has been the focus of many studies in marketing.

From the theoretical perspective, Hirschman's (1970) *Theory of Exit, Voice, and Loyalty* has been the foundation for many studies of customer complaint behavior in economics and marketing. Exit-voice theory pertains to situations in which a customer becomes dissatisfied with the services or products provided by the organization and chooses either to exit or to voice, where *voice* implies making a direct complaint to the firm, expressing the dissatisfaction. Hirschman suggested that customers consider two distinct but somewhat interrelated factors in deciding whether to complain, summarized by Singh (1990, p. 3) as the "perceived probability of successful complaint" and the "worthwhileness of complaint." The former suggests that a dissatisfied customer would tend to choose voice actions if he or she is convinced that such actions would effectively bring the desired outcomes. The latter is about the balance between the costs and the benefits of complaining, where the costs and benefits can be economic or psychological. For example, refunds, exchanged products, satisfaction derived from complaining itself, time invested in creating the complaint, and feelings of embarrassment, stress, and confrontation are some of the benefits and costs of complaining.

From the practical perspective, the value of complaints both as a communication device and as a means of giving the firm a chance to turn a dissatisfied customer into a satisfied and loyal one has long been recognized by researchers (Fornell 1976). Stephens and Gwinner (1998) investigated how many potentially helpful complaints are never received because consumers fail to voice them, preferring instead to quietly discontinue patronage. They concluded that firms must make complaining less costly and even reward consumers if they wish to benefit from the information communicated. Complaints may be generated from a disparity between customers' expectations in the pre-purchase stage and disconfirmation in the post-purchase stage (Cho et al. 2001). The reasons for product failure may influence reactions such as desiring a refund or an exchange for the product, perceiving that an apology is owed to the consumer, and even wanting to hurt the firm's business (Folkes 1984). Post-purchase complaint behavior comprises consumer-initiated communication to marketers, their channel members, or public agencies to obtain remedy or restitution for purchase or usage-related problems (Westbrook 1987).

Complaint Management

Regardless of how good the service a company delivers may be, every company often makes mistakes in meeting the expectations of customers (Nikbin et al. 2011). Previous studies indicate that failures themselves do not necessarily lead to customer dissatisfaction, since most customers accept that things may sometimes go wrong (Del Río-Lanza et al. 2009). Instead, the service provider's response or lack of response to the failure is the most likely cause of dissatisfaction (Smith et al. 1999). Complaint management refers to the strategies used to resolve disputes and to improve ineffective products or services in order to establish a firm's reliability in the eyes of its customers (Tax et al. 1998). Thus, customer complaint management is considered a defensive marketing strategy that firms must adopt to prevent adverse brand switching or exit (Fornell and Wernerfelt 1987).

When customers look for a redress, an apology, or a psychological benefit through direct complaining, it is possible to transform their dissatisfaction into a second, post-complaining level of satisfaction, or secondary satisfaction (Oliver 1987). Effective complaint management has a dramatic impact on customer retention, deflecting potential negative word of mouth and improving profitability (Fornell and Westbrook 1984).

Customer Complaint Management in the Social Media Era

Social media has opened up new opportunities for companies to listen to and engage with their customers and potentially to encourage them to become advocates for their products (Malthouse et al. 2013). For instance, 50% of social media users express complaints regarding brands at least once per month (Nielsen Company 2012), which changes customer complaints from private to public phenomena (Ward and Ostrom 2006). On social media, consumers can voice their dissatisfaction with little cost, easily reach a large audience, and thus effectively harm the brand (Chevalier and Mayzlin 2006). As the effects of social media interactions on customers' upselling behavior and churn depends greatly on customers' previous service experience (Maecker et al. 2016), reacting appropriately to complaints on social media has become a major challenge for companies (Bolton and Saxena-Iyer 2009). If companies respond via social media platforms, the resulting favorable brand evaluations are visible to other customers and have an outreach effect that is nearly equivalent to that of the complaints (Maecker et al. 2016).

Gu and Ye (2014) study the impact of management responses on customer satisfaction and find that online brand responses are highly effective among low-satisfaction customers but have limited influence on other customers. Moreover, they show that the public nature of online brand responses increases the future satisfaction of complaining customers who receive responses, but decreases the future satisfaction of complaining customers who observe but do not receive management responses.

All these studies have provided important insights into the customer complaint management process in organizations, in a variety of contexts. However, there is little understanding of the effects of social media influence and the presence of bystanders on brands' response to complaints on social media. Our paper fills this gap and contributes to the stream of literature on customer complaint management in the social media era.

Service-Level Differentiation

Preferential treatment is defined as the practice of selectively giving some customers elevated recognition and/or additional or enhanced products and services above and beyond standard firm value propositions and customer service practices (Lacey et al. 2007, p. 242). It implies that the selected customer is receiving something "extra" that other customers do not receive at all, or do not receive to the same extent (Jiang et al. 2013). In practice, firms often assign each customer to a predefined tier according to their transactional value (Lacey et al. 2007; Zeithaml et al. 2001), and customers in more prestigious tiers may receive preferential treatment, which may include a better price, a better position on a priority list if there is a queue, and more attention or faster service (Söderlund et al. 2014).

Although a controversial and philosophically divisive practice, preferential treatment has potentially substantial economic ramifications for firms (Lacey et al. 2007). Prior studies identify a positive association between receiving preferential treatment and variables such as customer satisfaction, positive word of mouth, and repurchase intentions. Using a cross-industry study with 310 firms from business-to-consumer and business-to-business contexts, Homburg et al. (2008) investigated whether and how customer prioritization pays off. Their findings show that customer prioritization ultimately leads to higher average customer profitability and a higher return on sales, as it affects relationships with top-tier customers positively but does not affect relationships with bottom-tier customers. Lacey et al. (2007) show that higher levels of preferential treatment positively influence relationship commitment, increased purchases, customer share, word of mouth, and customer feedback. Söderlund et al. (2014) examine customer reactions to preferential treatment, particularly in social contexts that allow customers to compare what they receive with what other customers receive. They find that customers who receive preferential treatment and those who do not, equally perceive preferential treatment as relatively unjust. However, customer satisfaction among those who receive preferential treatment is enhanced, thus suggesting that preferential treatment affects perceived justice and satisfaction differently. In addition, receiving preferential treatment alone or in the presence of other customers produces different levels of customer satisfaction.

Most of the prior studies of the link between preferential treatment and consumer response have focused on preferential treatment that has been earned through loyalty (i.e., the customer's transactional value) or effort. Some recent studies have focused on companies' use of unearned preferential treatment (e.g., surprise discounts, surprise seat upgrades on airplane flights, sweepstakes, perks) and investigated how consumer reactions to these types of experiences can differ from their reactions to receiving earned preferential treatment. Jiang et al. (2013) show that, when unearned preferential treatment is received in front of others, the positive feelings of appreciation for the treatment can be accompanied by feelings of social discomfort stemming from concerns about being judged negatively by other customers. They assert that these feelings of discomfort can reduce satisfaction with the shopping experience and affect purchasing behaviors.

Although several studies have extensively examined different aspects of preferential treatment in customer service, to the best of our knowledge, no prior study has investigated the phenomenon in the context of social media customer service, and hence preferential treatment based on social media influence. Our paper therefore offers a unique contribution to this stream of literature.

Call-Center Routing

With advances in information and communication technology, call centers have gone beyond the traditional first-in, first-out (FIFO) call routing to perform a variety of sophisticated call-routing algorithms. When a customer call is received at the call center, the customer's identity is often automatically determined at the first point of contact, either by using the number the customer is calling from, or by using a series of short questions in the form of interactive voice response (IVR), which may also capture the purpose of the call. Because answering different types of customer calls usually requires different training, most call centers perform *skill-based routing* (SBR), using automatic call distributors (ACDs) that assign calls to agents with appropriate skills (Wallace and Whitt 2005). More recently, the concept of *value-based routing* (VBR) has been recognized by the industry and studied in the literature. For example, Genesys (2014) emphasizes the importance of understanding a customer's value and opportunity when evaluating the handling of each customer interaction. Sisselman and Whitt (2007) proposed a modification of SBR to maximize a total value function using a value matrix that assigns a value for each agent handling each type of call.

In summary, differential customer treatment is a known and accepted phenomenon in call-center customer service, and the basis for differential treatment is either operational efficiency or customer valuation. This is in contrast to influence-based differentiation, which is a unique feature of customer service on social media and is related to fundamentally different concepts of fairness in social psychology.

Hypotheses

Social Media Influence Effect

The concepts of service-level differentiation and prioritized customer service have existed from the early days of service provision with evidence dating back to the dawn of civilization (Allon and Zhang 2015), and 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). Like it or not, customers live with preferential treatment as firms strive to maximize their profits by redefining the service levels to treat their best customers better. For example, frequent flyer programs publicly offer priority boarding and first-class/business-class upgrades to airlines' frequent travelers. Such a service strategy can clearly enhance customers' loyalty to the company and bring in more value from customers.

With the convergence of social media and customer service, it is not only the value that customers bring in that matters to a company, but also the ability of those customers to influence others in the social network (Allon and Zhang 2015). The traditional view of influence diffusion assumes that a minority of members in a society possess qualities that make them exceptionally persuasive in spreading ideas to others (Cha et al. 2010). They are called *opinion leaders* in the two-step flow theory (Katz and Lazarsfeld 1955), *innovators* in the diffusion of innovations theory (Rogers 1962), and *hubs*, *connectors*, or *mavens* in other work (Gladwell 2000). By targeting the influential individuals in a network, a chain reaction of influence driven by word of mouth can be activated such that a large portion of the network can be reached with a small marketing cost (Bonchi et al. 2011). The influence of well-connected customers in a popular social network is further amplified in the digital age thanks to the Internet and social media.

Firms are starting to tap into social network information to refine their customer service strategies. For example, for limited periods in recent years, American Airlines and Cathay

Pacific Airways granted high Klout[7] scorers access to their exclusive airport lounges, which would have been otherwise available only to their first-class or business-class passengers.[8] Recently, Genesys, a global omni-channel customer experience and contact center solution provider for business clients including major airlines, banks, and telecommunications companies, integrated Klout score into its solutions.[9] This could enable companies that use the Genesys platform to recognize their customers with high Klout scores and route them to specialized customer service agents, if they wish to do so. However, little is known beyond anecdotal evidence regarding the prevalence and magnitude of preferential customer treatment based on social media influence.

There are at least three potential drivers of the social media influence effect. First, a company policy of service-level differentiation could strategically allocate more resources to handle more influential customers in order to minimize the risk of a social media flub or to maximize the reach of positive word of mouth as the result of a successful complaint resolution. The underlying argument is essentially a scaling effect tying social media influence to the marginal utility of responding to a complaining tweet: the risk of a complaining customer causing large damage to the brand or the potential benefit of a complaining customer spreading positive word of mouth upon satisfactory resolution is higher if the customer is more influential on social media. This is illustrated in a recent case, where a customer with more than 1.5 million followers published angry tweets about Maytag's poor customer service and caught the attention of the media.[10]

Second, even without an explicit company policy, the social media team may face an internal incentive mechanism that punishes negligence or a slow response that leads to viral spreading of customer complaints on social media. The phenomenon may be explained by the *reinforcement theory of motivation* in psychology, which suggests that an individual's behavior is a function of its consequences (Ferster and Skinner 1957; Skinner 1953). The theory is based on the psychological principle of the law of effect (Thorndike 1911), which states that behaviors that produce positive consequences are more likely to be repeated, and behaviors that produce negative consequences are less likely to be repeated. Reinforcement theory and the associated principles of behavior modification have been widely studied in the literature and applied in organizational contexts to encourage desired employee behavior (e.g., productivity) and to discourage unwanted behaviors (e.g., absenteeism, tardiness). Reinforcement theory provides two methods of increasing desirable behaviors: *positive reinforcement* (i.e., providing what individuals like when they have performed the desired behavior) and *negative reinforcement* (i.e., removing what individuals do not like when they have performed the desired behavior) (Griggs 2010). Similarly, it provides two methods of eliminating undesirable behaviors: *negative punishment* (i.e., providing what individuals do not like when they have performed the unwanted behavior) and *positive punishment* (i.e., removing what individuals like when they have performed the unwanted behavior) (Griggs 2010). Hence, assuming complaints from customers who are more influential on social media are more likely to cause a public relations debacle on social media, companies' internal reward and punishment mechanisms would encourage social media teams to triage complaints based on customers' social media influence even without having such a policy in place.

The third potential driver is customer stereotyping based on social media influence. Goffman (1959) proposed that human beings try to control others' impressions of them through performances within spatially defined social establishments. Goffman suggested that these performances enable individuals to create and tailor their social identities (i.e., stereotyping) for particular audiences. For example, when an individual enters the presence of several other people, these people tend to seek information about the person who just entered, or recall information about the person what they already know, such as his or her general socioeconomic status, competence, trustworthiness, etc. Goffman saw practical reasons for acquiring such information, as it helps others define the situation, enabling them to know in advance what that person will expect of them and what they may expect of him or her so that they will know how best to act in that particular situation. Goffman's seminal work was written in 1959, well before the age of social media; physical location no longer presents the same barriers to perceptions about individuals. In other words, social media has enabled individuals to publicly reveal multiple facets of themselves, including their private lives, social lives, and opinions (Sánchez Abril et al. 2012). In light of these insights about

[7] The Klout score is a measure of an individual's social influence based on his or her social network information on platforms such as Facebook and Twitter.

[8] See http://mashable.com/2013/05/07/klout-american-airlines/#6R8a8hY3ksqZ and https://www.cathaypacific.com/cx/en_US/about-us/press-room/press-release/2012/cathay-pacific-and-klout-announce-exclusive-partnership.html for more details.

[9] For more details of the report "A High Klout Score Can Lead to Better Customer Service," see http://www.forbes.com/sites/alexknapp/2012/06/12/a-high-klout-score-can-lead-to-better-customer-service/.

[10] https://www.technologyreview.com/s/423924/figuring-out-whom-to-please-first.

human nature, complemented by the abundance of information on social media, it is possible that the social media team has highly positive perceptions of socially popular customers and thus serves them better than others, even in the absence of an explicit company policy or an implicit incentive mechanism.

Regardless of its cause, however, the practice of preferential customer treatment based on social media influence may antagonize less-influential customers and even trigger a public outcry, thus eventually hurting the brand. Customers may perceive such a practice as unfair, and the importance of service fairness for customer satisfaction and long-term customer loyalty is well documented, although little studied in the economics literature. As Kahneman et al. (1986, p. S285) pointed out,

> the absence of considerations of fairness and loyalty from standard economic theory is one of the most striking contrasts between this body of theory and other social sciences—and also between economic theory and lay intuitions about human behavior.

According to Kahneman et al., firms might sometimes forgo exploiting a legal but "unfair" profit opportunity either because their owners and managers prefer acting fairly or because customers may be willing to punish an offending firm by reducing business transactions with that firm, which, despite contradicting the standard economic theory, has been supported by experiments. Therefore, it is important for firms to understand how customers, or society as a whole, would perceive the fairness of prioritizing customers based on their social media influence.

At its root, service fairness is a customer's perception of the degree of *justice* in a firm's behavior (Seiders and Berry 1998). A three-dimensional view of the concept of justice has evolved over time to include distributive justice (dealing with decision outcomes), procedural justice (dealing with decision-making procedures), and interactional justice (dealing with interpersonal behavior in the enactment of procedures and delivery of outcomes) (Tax et al. 1998). In the current context, distributive justice is particularly relevant because differential customer treatment involves the distribution of a social media team's attention and time among customers. Broadly viewed, distributive justice is concerned with the distribution of the conditions and goods that affect individual well-being (Deutsch 1985). Researchers in social psychology have identified a variety of principles or values that can be used as a basis for distributing outcomes. According to social psychologist Deutsch (1985, p. 38), the following three principles are often used in most societies:

- In cooperative relations in which economic productivity is a primary goal, equity rather than equality or need will be the dominant principle of distributive justice.

- In cooperative relations in which the fostering or maintenance of enjoyable social relations is the common goal, equality will be the dominant principle of distributive justice.

- In cooperative relations in which the fostering of personal development and personal welfare is the common goal, need will be the dominant principle of distributive justice.

We argue that differential customer treatment based on social media influence violates all three principles. The violation of the second and the third principles is quite clear. The equity principle is also violated because high influence on social media is not equivalent to greater contribution to the firm.[11] Therefore, we argue that the practice of differential customer treatment based on social media influence will be perceived as unfair by customers, and especially by those who are less influential and thus rather disadvantaged.[12] Previous research indicates that perceived service unfairness influences customers' negative emotional reactions, such as feelings of betrayal and anger, as well as their behavioral responses, such as venting and revenge (Gregoire and Fisher 2008; Gregoire et al. 2010; Gregoire et al. 2009). On social media, these reactions may also lead to immediate discontinuation of patronage, while the negative word of mouth across the social network can prove detrimental to the company in the long term. Indeed, no company has publicly acknowledged that its social media customer service prioritizes customers based on their social media influence. Therefore, whether and to what extent companies are following this practice remains unclear.

Based on our theoretical arguments, unless a company's effort to intentionally reduce the risk of being perceived as providing unfair customer service on social media outweighs the forces that induce the prioritization of customers based on social media influence, companies will engage in such a practice. We propose the following hypothesis for empirical testing.

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[11]We surveyed a randomly selected group of customers who complained on Twitter about their spending on the airlines. We find no evidence that customers more influential on Twitter also spend more on the airline they complain about.

[12]A survey study done by one of the authors in an MBA class also confirms this theoretical prediction.

H1: *An airline is more likely to respond to a complaint sent to it by a customer with a higher number of followers.*

The speed of responding is another important dimension in social media customer service. As customer complaints may be a result of perceived shortcomings of the organization, a delay in responding can create a negative perception of the organization and may result in aggravated dissatisfaction (Bitner et al. 1990). Conlon and Murray (1996) find that response speed for complaints has a positive effect on satisfaction and intentions to repurchase. The findings of Davidow (2000) suggest that timeliness has a positive effect on satisfaction and word-of-mouth valence, but no effect on repurchase intentions or the likelihood of word of mouth.

The varying effects of response times have been investigated in other domains as well. In studies of e-commerce (McKinney et al. 2002; Rose et al. 1999; Rose et al. 2001; Rose and Straub 2001; Torkzadeh and Dillon 2002), response time has been shown to be a major determinant in overall usability. Previous studies on computer response times indicate an inverse relationship between response time and user performance (Barber and Lucas 1983) as well as productivity (Dannenbring 1983; Martin and Corl 1986). Long delays on the Internet are known to be associated with dissatisfaction (Lee and MacGregor 1985), feelings of being lost (Sears et al. 2000), and giving up (Nah 2004). Some studies also investigate the maximum tolerable delay and the specific effects of that delay on users in the context of response times on the Internet. For instance, as the delay exceeds 8 seconds, users suffer from psychological and performance concerns (Kuhmann 1989); at 10 seconds, users lose interest (Ramsay et al. 1998); at 12 seconds, users lose patience (Hoxmeier and DiCesare 2000); and at 38 seconds, users will abandon the task (Nah 2004). These findings suggest that with longer delays users become more impatient and tend to display this in various ways.

Building upon these results, we argue that companies may respond faster to complaints from customers who are more influential on social media because of the same mechanisms driving our first hypothesis. This can be especially evident in a very time-sensitive business like aviation. Therefore, we propose the following hypothesis for empirical testing:

H2: *An airline is more likely to respond faster to a complaint sent to it by a customer with a higher number of followers.*

We summarize the arguments for or against influence-based preferential treatment in Figure 1.

Bystander Effect

The behavior of individuals in critical situations where bystanders are present has long been studied in social psychology. The *bystander effect* refers to the fact that an individual's likelihood of helping a victim in a critical situation decreases when bystanders are present (Darley and Latané 1968; Latané and Darley 1968, 1970). Over the years, several different explanations for the bystander effect have been derived from social and evolutionary psychology and from game theory (e.g., *the volunteer's dilemma,* Krueger and Massey 2009).

Latané and Darley (1970) identified three different psychological processes that might explain the bystander effect. The first process is *diffusion of responsibility*, which refers to the phenomenon where a person is less likely to take responsibility for action during a critical situation when others are present, as the responsibility for intervention is shared among all the onlookers and is not unique to any one of them. Consequently, an individual will only feel responsible for a fraction of the cost to the victim associated with nonintervention. The second process is *evaluation apprehension*, which refers to the fear of being judged by others for mistakes or inappropriate actions and of the feeling of being observed, which could make an individual reluctant to intervene in a critical situation. The third process is *pluralistic ignorance*, which results from the tendency to trust the open reactions of others in defining an ambiguous situation. In this case, the maximum bystander effect occurs when no one intervenes because everyone believes that no one else perceives an emergency (Latané and Nida 1981). Several other studies (Fischer et al. 2006; Fischer et al. 2011; Kalafat et al. 1993; Latané and Nida 1981) have also investigated various characteristics of the situation and the bystanders to explain the effect, such as the competence of the bystanders, the age and similarity of the bystanders, social relationships among the bystanders, the possibility of communication among the bystanders, the perceived dangerousness of the situation, and the ambiguity of the situation.

More recently, several studies have explored the bystander effect in the Internet era. Barron and Yechiam (2002) examined whether the probability of receiving a helpful e-mail response is an inverse function of the number of simultaneous e-mail recipients used. They found that there are more responses to e-mails addressed to a single recipient than to multiple recipients, and these responses are more helpful and lengthier. Markey (2000) observed online chat groups to explain and predict bystander intervention in the context of computer-mediated communication. Two interesting findings emerged from this study. First, as the number of people pre-

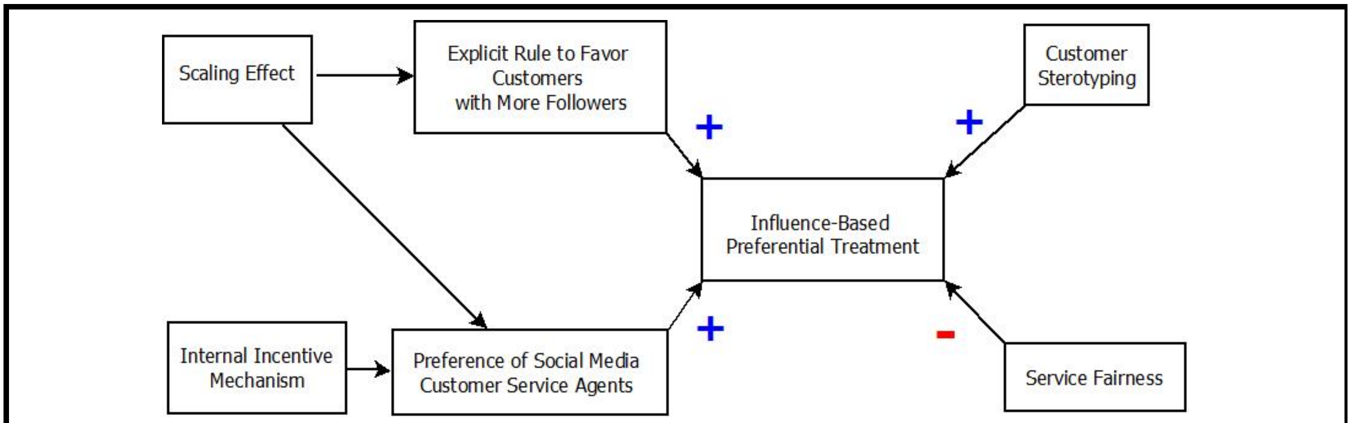

Figure 1. Social Media Influence-Based Preferential Treatment

sent in a computer-mediated chat group increased, it took longer for an individual to receive help. Second, the bystander effect was virtually eliminated and help was received much more quickly when help was requested by specifying a bystander's name. Voelpel et al. (2008) studied the bystander effect in the context of knowledge-sharing in online groups. They found that the bystander effect is present in virtual knowledge-sharing environments and that the group size influences the quality of the response. Brody and Vangelisti (2015) studied the bystander effect in the context of cyber bullying and found that a higher number of bystanders is negatively associated with bystander intervention on social media. Drawing upon the literature from social psychology as well as from the limited yet significant recent studies on bystanders' behavior in cyberspace, we focus on how the presence of bystanders affects customer–firm interactions on social media.

On Twitter, by using the @ symbol immediately followed by a username, people can mention other users in their tweets, and these users will receive those tweets instantaneously once they are posted. This introduces a unique structure into the phenomenon of customer service on social media. To capture this, we classify complaining tweets into two categories: *dialogue* and *multilogue*. Dialogue tweets are complaining tweets in which only the company concerned is mentioned. They can be considered as a direct and more personal communication between the customer and the company. For example, "***@airline*** *Trapped in San Juan trying to get home to Seattle on thrice cancelled flight 1393. No help, no compensation, no apologies!"* is a dialogue tweet. Multilogue tweets are those in which other users (i.e., bystanders) are mentioned, in addition to the company. For example, "*Hey* ***@airline****, I wish your $22 in-flight* ***@Gogo*** *wifi service wasn't so slow... this is definitely not a case of you get what you pay for*" is a multilogue tweet.

Although multiple explanations exist for the bystander effect in social psychology, the psychological process of diffusion of responsibility seems most relevant in our context. A company may be less keen to reply to a multilogue complaint in the presence of other companies that are also held accountable in the complaint (e.g., an in-flight Wi-Fi provider mentioned in addition to the focal airline). Based on these arguments, we propose the following hypothesis for empirical testing:

> H3: *An airline is less likely to respond to a complaint in the presence of a bystander.*

Data and Measures

Our data is constructed from all tweets mentioning the official Twitter accounts of seven major U.S. airlines from September 2014 to May 2015. These airlines carried 739,595,869 passengers in the U.S. in 2015, accounting for over 95% of enplaned passengers among the U.S. passenger airlines according to Wikipedia.[13] For ease of illustration, we refer to these tweets mentioning airline accounts simply as *tweets*.

Tweets vary from complaints and compliments to those seeking or sharing information. As our primary focus is on customer complaints through social media, we followed a lexicon-based approach to build a classifier to distinguish complaints from all other types of tweets. The lexicon was developed based on our reading of about 2,000 random tweets sent by customers to airlines. The lexicon contains 326 n-grams for complaint tweets and 354 n-grams for compliment tweets. We developed a program to process all the tweets

[13] See https://en.wikipedia.org/wiki/List_of_largest_airlines_in_North_America for details.

collected in order to determine whether each tweet was a complaint. A customer tweet was selected for our sample if it matched at least one term in the negative lexicon and none in the compliment lexicon. In order to assess the precision of our classifier, we randomly selected 8,700 complaint tweets from our final data set, and two of the authors independently evaluated these tweets to determine whether each tweet was indeed a complaint.[14] Whenever there was a disagreement, we sought a third person's opinion and used the majority rule to break the tie. In the end, 7,351 tweets out of this randomly selected sample were considered actual complaints. Based on this analysis, we report 84.5% precision for our lexicon-based complaint classifier.

Although a complaint starts with a single tweet posted by the customer, the lifetime of that complaint is not necessarily limited to that tweet but rather continues in a series of tweets exchanged between the customer and the airline in the form of a conversation. Tweets that follow the initial complaining tweet may include more complaining tweets that are essentially related to and part of the same complaint. Clearly, to evaluate an airline's tendency to respond to a customer's complaint and its speed in doing so, it makes more sense to restrict attention only to the initial complaining tweet posted by the customer. To operationalize this, a tweet was considered an initial complaint if the customer had not communicated with the respective airline on Twitter for 8 hours before the creation of the complaining tweet under consideration. Furthermore, a retweet of another customer's complaint, which rarely occurs, is not treated as an independent complaint, and therefore is excluded from our data set. Using this criteria, we identified 173,662 initial complaining tweets in our original sample. Figure 2 presents the distribution of complaints among the seven airlines.

Dependent Variables: Our empirical strategy uses two different dependent variables. In evaluating the hypotheses regarding the probability of receiving a response from the airline, we use a dichotomous measure equal to one if the complaint receives a response from the airline and zero otherwise. In order to determine whether an airline responded to a particular complaining tweet, we used Twitter metadata to match the user tweet with respective airline tweets, and when the tweet was matched with one or more replies from the airline, it was considered to have received a response.[15] In evaluating our hypothesis regarding a customer's waiting time until an airline responds, we use as the dependent variable the time elapsed in seconds from the creation of the complaining tweet to the creation of the first reply tweet from the airline, if there is any.

Independent Variables: The primary independent variables of interest are the number of followers a customer had at the creation of the complaining tweet, and whether the bystander effect is present for the complaining tweet, which is derived from its multilogue status.

There are different types of multilogue tweets. Extensive reading of such tweets suggests that there are three major types of Twitter handles (i.e., usernames) present in the multilogue tweets sent to airlines: *competing companies, collaborating organizations* (e.g., other brands/organizations that enable flight operations, such as in-flight Wi-Fi providers, in-flight entertainment service providers, air ticket reservation websites, the Transportation Security Administration, etc.), and *other individual users* (e.g., friends and family). Table 1 provides examples of multilogue tweets of different types.

Based on manual analysis of 5,000 multilogue tweets, we constructed a list of Twitter handles for commonly occurring brands and organizations. We then labeled each tweet based on the presence of a competing airline, a collaborating organization, or other individual users only. With all the multilogue tweets labeled, we introduced three binary variables corresponding to whether a competing airline was among bystanders, whether a collaborating organization was among the bystanders, and whether all bystanders were individual users. We interpret the binary variable corresponding to whether a collaborating organization is among the bystanders as our main variable for the bystander effect because it fits with the definition of the bystander effect the best in our context. The other two binary variables are treated as control variables.

Control Variables: Thanks to the public nature of social media, we can observe almost all information related to each complaint that is available to the social media customer service agent who handles it, that is, the decision maker. Hence, with appropriate control variables and multiple robustness checks, omitted variable bias is unlikely to be a major issue. We include control variables both at the customer level and at the tweet level, and we also include airline fixed effects and day-of-the-week fixed effects.

Control variables at the customer level include characteristics specific to the user, such as the number of tweets ever posted by the customer (i.e., updates) and whether the customer shares his or her location, website, or profile description (i.e., Twitter bio). Control variables at the tweet level include characteristics specific to the complaining tweet, such as the

[14]The training protocol for identifying complaint tweets is described in the Appendix.

[15]To further ensure the accuracy of this important dependent variable, we also wrote a program to download the relevant Twitter page of those tweets to double-check whether it received a response, and, if it did, when it received a response. We did our last check in January 2016, which was at least 7 months after the original complaining tweet was posted.

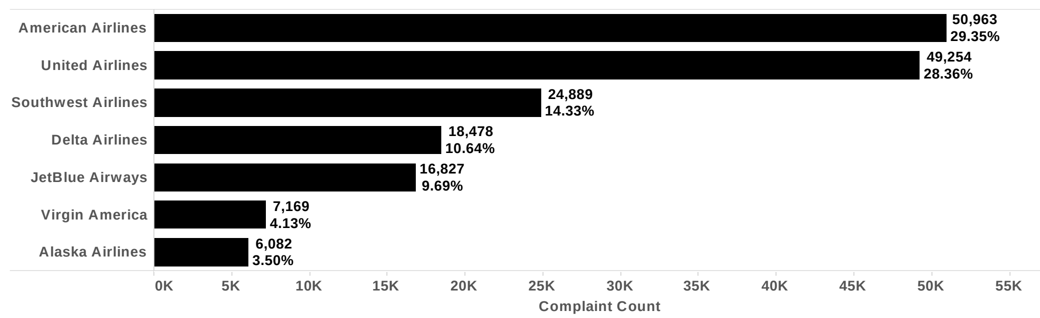

Figure 2. Distribution of Complaints Among Airlines

Table 1. Multilogue Tweet Types

Type	Sample Tweets	Complaining To	Bystanders
Competing Airline	Waiting for bags to arrive from @SouthwestAir is like waiting for grass to grow. I miss @AlaskaAir and #20minutesORless #want2gohome	@SouthwestAir	@AlaskaAir
	Sad to see @United has forgotten how to treat its customers. 60%full plane and they won't let you switch seats. Back to @AmericanAir	@United	@AmericanAir
Collaborating Organization	Hey @VirginAmerica, I wish your $22 in-flight @Gogo wifi service wasn't so slow... this is definitely not a case of "you get what you pay for"	@VirginAmerica	@Gogo
	FRUSTRATED w/ @united & @Expedia now cannot return home for Christmas b/c they decided to change their price after I've selected my flight	@United	@Expedia
Individual Users	@VirginAmerica @Matt sitting on runway for two hours for Virgin flight out of JFK. Brutal.	@VirginAmerica	@Matt
	Not cool, @VirginAmerica. Last week, u break my friend @Fred 's package. Now u rip not one but 2 primary handles on our luggage.	@VirginAmerica	@Fred

number of complaints received by the airline within the previous hour, the position of the airline Twitter handle in the tweet, whether the tweet contains any offensive words, whether the tweet contains a URL, and whether the tweet contains hashtags.

For each original user tweet, we keep track of the number of times it was retweeted. This is potentially important because retweets of a customer's complaint might influence the airline's response decisions and failing to account for the number of retweets a complaining tweet receives might bias the estimation results, given that the number of retweets is likely correlated with the number of followers a customer has. Therefore, we control for the number of times each tweet was retweeted by the time of the first response from the airline (if there was a response) or before the end of our observation period (if there was no response).

Although we have controlled for some text characteristics, such as the use of offensive words, hashtags, and URLs, one may be concerned that customers of different levels of social media influence may complain about different types of problems (e.g., delays and cancellations, mishandled baggage, unprofessional employees), and airline social media teams may respond to different types of problems differently. Customers of different social media influence levels may also write tweets in different styles. Although unlikely, it is not entirely inconceivable for airline social media teams to respond differently to complaints in different writing styles. If the text content written by customers of different social media

Table 2. Sample Tweets from Some Dominant Clusters

Cluster – Suggested Title	Tweets
Cancellations	• @airline Trapped in San Juan trying to get home to Seattle on thrice cancelled flight 1393. No help, no compensation, no apologies! • @airline you CANCELLED my DFW TO MLI flight? Any way I can get there tonight? Have 7:30 am interview.... • A lot of angry people @airline! Canceling yet another flight and not providing us anyway of feasibly getting home #BadService
Baggage Issues	• @airline I'm so mad! 1st u delay my bags and then you deliver my new brand Perry Ellis bag w/ one wheel torn off! • Really @airline?!? "your bag is lost/we found it/come pick it up/oh yeah our office is closed, sorry. @ airline I've never been so disappointed • @airline got a call that my bag is in London but I am in Miami. My friends bag still missing. No one wants to make this better. Fed up!
Waiting	• Sitting on an @airline S80 at the gate for 1 hr 20 min so far, waiting for a part. EDT now 2:30, another hour. What? • @airline been ON the plane for over an hour here in Dallas just wait to fix a light.. Pilot said it would be 20 minutes. Still waiting • Another frustrating morning at the #jfk @airline terminal where you can expect to wait no less than a half hour 2 get through security.
Never Again	• Never in a million years will I fly with them again, @airline how can your employees get away with stealing a dslr from my bag? • Shout out to @airline for ruining my whole entire Friday. YOU WILL NEVER GET BUSINESS FROM ME AGAIN. • I'm never flying with @airline ever. I will take a bus before I fly with y'all..
Failure	• @airline has completely failed a full flight of passengers trying to get out of Jackson today. Horrible job by your airline. • I shoulda taken @Amtrak. @airline y'all playing games today! I shoulda been in NYC by now. #fail • @airline #epic fail again. They gave my seat away because the reservation system don't talk. What should platinum to do?

influence levels systematically differs and this difference leads to differences in response rate and speed, then our estimation will be biased. To alleviate this concern, we use text-clustering techniques to group similar complaining tweets and introduce cluster fixed effects into our model. Details of our clustering method can be found in the Appendix. We manually evaluated each of the 40 clusters obtained and found the grouping of tweets satisfactory. Most of the clusters demonstrated an easily distinguishable tweet type based on either the problem or the writing style of the tweets. We present sample tweets from some of the dominant clusters in Table 2.

To examine whether complaints from more-influential customers are very different from the complaints from less-influential customers, we plot in Figure 3 the distributions of cluster labels for the top and bottom 25,000 complaints in our data set, based on the number of followers. The plots indicate that the distributions of cluster labels for the two groups are actually quite similar to each other in terms of content and style. This is not surprising. First, customers of different levels of social media influence are largely using the same service (flight, airport, etc.) and are vulnerable to similar types of travel problems. Second, unlike traditional media, the length of a tweet is limited to 140 characters, thereby making it unlikely that language styles will vary much between customers of different levels of social media influence. Nevertheless, it is still prudent to include content fixed effects to minimize the potential bias due to customers of different influence levels complaining in different ways and about different problems.

Table 3 explains the key variables in our empirical analysis. The summary statistics are presented in Table 4. The correlation matrix is presented in Table A1 in the Appendix.

Table 5 presents the response rates and the average response times for each airline in our data set. The response rate ranged from 35.99% (Southwest Airlines) to 57.06% (American Airlines). The average response time varied from 9.46 minutes (JetBlue Airways) to 3.68 hours (Southwest Airlines).

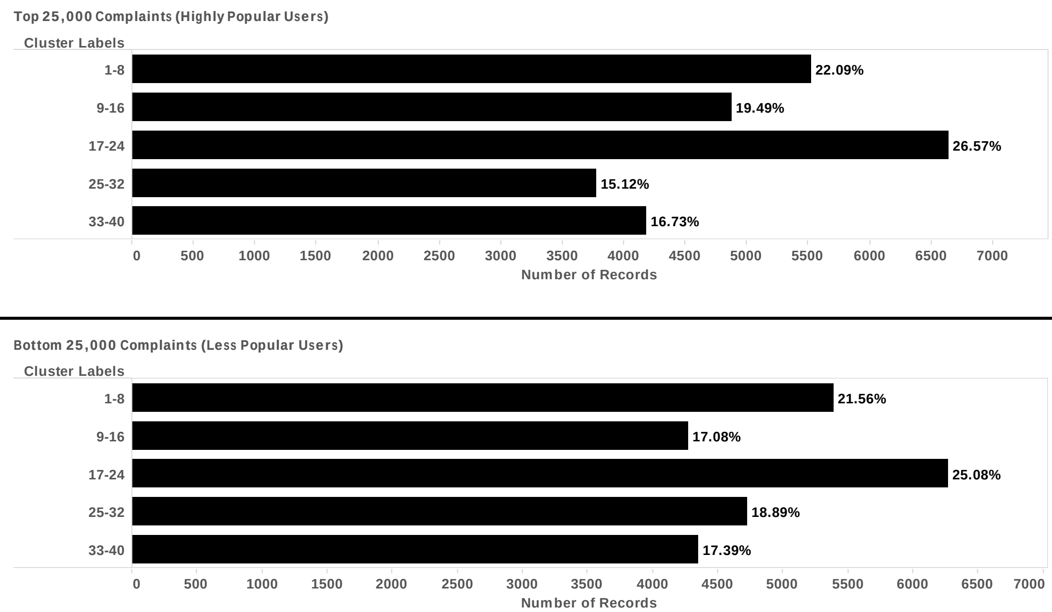

Figure 3. Cluster Distribution of the Top and Bottom 25,000 Complaints, Based on the Number of Followers

Table 3. Definitions of Variables

Variable	Definition
Responded	Binary variable equal to 1 if the airline responded to the complaining tweet, 0 otherwise.
Response Time	Time elapsed in seconds from the creation of the complaining tweet to the creation of the first reply tweet from the airline
Followers	Number of followers the user had, at the creation of the complaining tweet
Competing Airline Mentioned	Binary variable equal to 1 if a competing airline is mentioned in the complaining tweet, 0 otherwise
Collaborating Organization Mentioned	Binary variable equal to 1 if a collaborating organization is mentioned in the complaining tweet, 0 otherwise
Only Individual Users Mentioned	Binary variable equal to 1 if only individual users are mentioned in the complaining tweet, 0 otherwise
Complaints within the Previous Hour	Number of complaining tweets received by the airline during the hour prior to receiving the current complaining tweet
Retweets	Number of times the tweet was retweeted, before the first response from the airline (if the airline responded), or before the end of the observation period (if the airline did not respond)
Hashtag	Number of hashtags contained in the complaining tweet
Offensive	Binary variable equal to 1 if the complaining tweet contains offensive words, 0 otherwise
URL	Binary variable equal to 1 if the complaining tweet contains web URLs, 0 otherwise
@Order	The position of the airline Twitter handle in the complaining tweet, relative to other username mentions, if any
Updates	Number of tweets ever posted by the user
Profile	Binary variable equal to 1 if the user's location, website, or profile description (i.e., Twitter bio) is publicly available, 0 otherwise
Day of Week	Categorical variable indicating the day of the week
Airline	Categorical variable indicating the airline
Cluster	Categorical variable indicating the cluster ID assigned to the complaining tweet

Table 4. Summary Statistics

Variable	Observations	Mean	Std. Dev.
Responded	173,662	0.4619	0.4985
Log of Followers	173,662	5.2020	2.0605
Competing Airline Mentioned	173,662	0.0692	0.2538
Collaborating Organization Mentioned	173,662	0.0060	0.0769
Only Individual Users Mentioned	173,662	0.2188	0.4134
Log of Complaints within the Previous Hour	173,662	2.4221	0.9973
Log of Retweets	173,662	0.0476	0.2426
Hashtag	173,662	0.3436	0.7575
Offensive	173,662	0.0349	0.1836
URL	173,662	0.0806	0.2723
@Order	173,662	2.0758	0.8607
Log of Updates	173,662	6.9705	2.4205
Profile	173,662	0.8458	0.3611
Response Time (seconds)	80,209	4,426.175	14,658.35

For brevity, statistics for Day of Week, Airline, and Cluster dummies are not reported.

Table 5. Response Rates and Average Response Times

Airline	Response Rate (%)	Average Response Time (Minutes)
American Airlines	57.06	34.69
United Airlines	40.10	101.81
Southwest Airlines	35.99	221.03
Delta Airlines	46.70	17.52
JetBlue Airways	46.95	9.46
Virgin America	37.73	159.66
Alaska Airlines	52.42	81.48

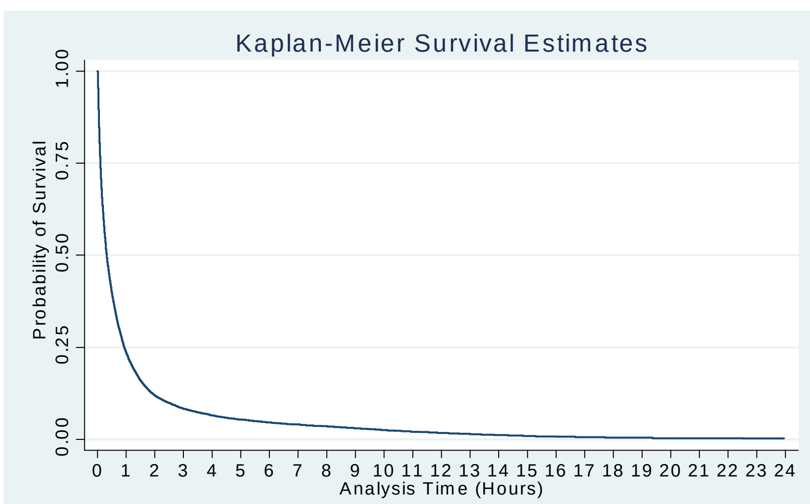

Figure 4. Kaplan-Meier Survival Curve for the Response Times

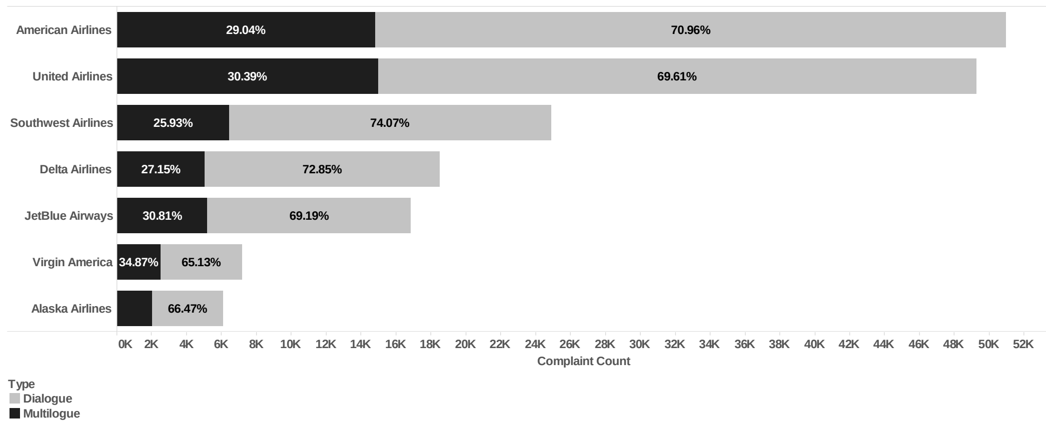

Figure 5. Distribution of Dialogue and Multilogue Complaints for Each Airline

In Figure 4, we present the Kaplan-Meier Survival Curve for our airline response times. The curve indicates a drastic drop in the fraction of complaining tweets yet to receive a response from the airline, approximately around 2 hours. Clearly, the tweets that were to receive a response had received their response from the airline fairly quickly.

The number of followers for the complaining customers varied from 0 to more than 15.6 million across all airlines. On average, *multilogue* complaints comprised about 29.4% of all complaints, although there was some variation across airlines. Figure 5 presents the distribution of *dialogue* and *multilogue* complaints for each airline.

Econometric Analysis and Results

We assume that for airline k, the perceived (latent) value of responding to complaining tweet i created by customer j is y^*_{ijk}, where

$$y^*_{ijk} = \beta_0 + C_{ij}\beta_1 + T_i\beta_2 + \alpha_k\beta_3 + D_t\beta_4 + S_i\beta_5 + \varepsilon_{ijk}$$

Here C_{ij} refers to the vector of observable characteristics of customer j at the creation of complaining tweet i and T_i refers to the vector of observable characteristics related to complaining tweet i. D_t is the day-of-the-week fixed effect, α_k is the airline fixed effect, and S_i is the content fixed effect. ε_{ijk} is the error term. The airline chooses to respond to the tweet if the perceived value of responding is positive, that is, $y^*_{ijk} > 0$. For simplicity, we refer to the vector of all explanatory variables by X and the vector of all coefficients by β. Hence, for a generic complaining tweet, the airline response variable can be written as

$$y = \begin{cases} 1 \quad (responded), & if \;\; y^* = X\beta + \varepsilon > 0 \\ 0 \quad (not\ responded), & if \;\; y^* = X\beta + \varepsilon \le 0 \end{cases}$$

We refer to the equation above as the *response-choice* equation.

If the airline decides to respond to the complaining tweet, there will be a delay between the complaining tweet and the response, which we refer to as the response time and denote by z. We model the log-transformed response time as the following where η is the disturbance term

$$\ln z = \begin{cases} X\gamma + \eta, & if \;\; y = 1 \\ Unobserved, & if \;\; y = 0 \end{cases}$$

We refer to the equation above as the *response-time* equation.

Because whether to respond and when to respond are two decisions that are highly dependent on each other, it is likely that η and ε are correlated with each other. To model this feature, we assume that η and ε follow a bivariate normal distribution specified as the following:

$$\begin{pmatrix} \eta \\ \varepsilon \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{pmatrix} \right)$$

Table 6. Joint Model of Choice and Response-Time: Estimation Results

Variable	(1) Response-Choice Equation	(2) Response-Time Equation
Log of Followers	0.0537***	-0.0313***
	(0.0027)	(0.0039)
Collaborating Organization Mentioned	-0.1547***	0.0549
	(0.0451)	(0.0754)
Competing Airline Mentioned	-0.1809***	0.0385
	(0.0192)	(0.0315)
Only Individual Users Mentioned	-0.5477***	0.1244***
	(0.0141)	(0.0262)
Log of Complaints within the Previous Hour	-0.0156***	0.0312***
	(0.0002)	(0.0004)
Log of Retweets	-0.3617***	0.3988***
	(0.0158)	(0.0275)
Hashtag	0.0080*	0.0077
	(0.0043)	(0.0062)
Offensive	-0.2509***	0.0480
	(0.0262)	(0.0430)
URL	-0.3717***	0.1025***
	(0.0126)	(0.0212)
@Order	-0.4131***	0.0284
	(0.0107)	(0.0211)
Log of Updates	-0.0523***	0.0052
	(0.0023)	(0.0034)
Profile	0.0229**	0.0277*
	(0.0105)	(0.0144)
Error Correlation	-0.1287***	
	(0.0192)	
Constant	1.4149***	6.0823***
	(0.0390)	(0.0594)
Observations	173,662	173,662
Log Likelihood	-234568.5	-234568.5

For brevity, results of Day of Week and Airline dummies are not reported.
Please refer to Table A2 in the Appendix for the estimates of text content fixed effects.
***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parentheses.

Note that if we define the *time at risk* as the interval between the creation of the complaining tweet and the receipt of the first reply from the airline, the *failure time* would be the response time z in our response-time equation. Hence, with the normality assumption of η, the response-time equation can be interpreted as a log-normal accelerated failure time (AFT) survival model. Later in the paper we also explore alternative survival analysis models for the response-time equation.

To jointly estimate the response-choice equation and the response-time equation, we use Heckman's method (Heckman 1979) which is described in the Appendix. The estimation results are reported in Table 6.

From Table 6, column (1), *Log of Followers* is positive and statistically significant ($p < 0.01$). In terms of magnitude, for a one-unit increase in *Log of Followers*, the odds of receiving a response from the airline increase by a factor of 1.0552 (5.52%). Our findings suggest that as the number of followers increases, there is a corresponding increase in the probability of receiving a response from the airline, thereby providing support for H1.

From Table 6, column (2), log-normal specification reports negative and statistically significant ($p < 0.01$) results for *Log of Followers*. The higher the number of followers a customer has, the smaller the response time is. Therefore, our findings suggest that airlines are more likely to respond faster to complaints from customers with a higher number of followers, thereby providing support for H2.

As noted above, social psychologists Darley and Latané (1968) proposed a *diffusion of responsibility* explanation for the bystander effect, asserting that individuals are less obligated to help in the presence of bystanders, as the responsibility to intervene is not directed to any one of the onlookers but rather shared among them. Hence, in testing H3, we think that multilogue tweets with a collaborating organization mentioned provide a better test of the bystander effect. From Table 6, column (1), the variable *Collaborating Organization Mentioned* is negative and statistically significant ($p < 0.01$). In particular, mentioning a collaborating organization in the complaining tweet reduces the odds of getting a response by 14.33%, thereby providing support for H3. It seems that social media teams are highly vulnerable to the bystander effect, which could severely hurt the effectiveness of their mission. In addition, the other two multilogue-related variables are also negative and statistically significant ($p < 0.01$). In fact, mentioning a competing airline reduces the odds of receiving a response from the focal airline by 16.55%, while mentioning only individual users reduces the chance of receiving a response by as much as 42.17%. If direct competitors (e.g., competing airlines) are present among the bystanders, the fear of being judged in public (i.e., *evaluation apprehension*) could make the focal company reluctant to respond.

Results for the content fixed effects (refer to Table A2 in the Appendix for details) also reveal some interesting facts about social media customer service. For instance, for cluster 9, the response-choice model coefficient is negative and statistically significant ($p < 0.01$), while the response-time model coefficient is positive and statistically significant ($p < 0.05$). In particular, being in cluster 9 decreases the odds of receiving a reply from the airline by about 45%, while reporting longer delays to respond, compared with being in cluster 0, the benchmark cluster. Manual reading of tweets in cluster 9 shows that it is the cluster with tweets written in extreme language (e.g., *F**k @airline! Always delays flights and f**k up my schedules! Last time I fly @airline*). So certain features of the text seem to discourage a social media customer service agent from responding to such tweets, or responding to such tweets promptly. On the other hand, for cluster 6, the response-choice model coefficient is positive and statistically significant ($p < 0.01$), while the response-time model coefficient is negative but not statistically significant. Specifically, being in cluster 6 increases the odds of receiving a response from the airline by about 14%, compared with cluster 0, the benchmark cluster. Manual reading of the tweets in cluster 6 reveals that this is the cluster of tweets that reports hardships due to flight delays (e.g., *@airline I've been waiting for my flight and you've delayed it numerous times...4hrs delay and you r calling for a 6hr delay...unbelievable*). These two examples suggest the importance and effectiveness of using text clustering to control for content heterogeneity, both in terms of substance and in terms of style.

It is also interesting to note that the correlation between the error term from the response-choice equation and the error term from the response-time equation is negative and statistically significant. This suggests that the unobserved factors that increase the chance of a customer tweet receiving a response also reduce the delay, which is consistent with our intuition.

Surprisingly, we find the coefficient of *retweets* negative. A close look at the data reveals that the majority (98.44%) of the complaint tweets receive zero (95.06%) or only 1 retweet (3.38%), probably because customer complaints often involve very specific issues and are unlikely to generate broad public interest on social media. Further inspection of the small sample of tweets that received retweets suggests that there might be some subtle difference between these tweets and most of the others. For example, 44.4% of the tweets that received retweets are multilogue tweets while the percentage is 28.6% for tweets that did not receive retweets. Similarly, 4% of the tweets that received retweets contain very offensive words (e.g., f**k, sh*t), compared with 3% of those that were not retweeted. Hence, we suspect that certain features of a tweet that encourage retweeting (e.g., mentioning many others, being provocative) might in turn discourage a customer service agent from responding to it. On the other hand, having one or two retweets is unlikely to have much effect in prompting the company to respond. In summary, the observed negative coefficient of retweet is probably driven more by the content of the complaining tweets than by the retweeting. Given that most complaint tweets received no retweet at all, we caution readers not to misinterpret the negative coefficient of *retweets* as the effect of retweets on airline response.

Another interesting finding is the positive and significant effect of the variable *Profile*, which is defined as 1 if the complaining customer shared his or her location, provided a website, or wrote a profile description on Twitter. Providing such personal information increases the odds of receiving a response from the airline by a factor of 1.0232 (2.32%). This finding seems to be in line with the *mechanistic* metaphor (Haslam 2006) of the *dehumanization theory* (Allport 1954;

Bandura et al. 1975; Kelman 1973; Opotow 1990) from social psychology. In mechanistic dehumanization, some individuals are perceived as machines lacking the human qualities of being emotional or disclosing to others such that they are judged as indifferent, inert, cold, rigid, and passive (Haslam 2006). As a result, *depersonalization* may occur, which could wear away the richness of interpersonal interactions. In the present study, a plausible explanation for the effect of *Profile* is that customers who do not disclose any personal information on social media are more likely to be perceived by the social media team as lacking human characteristics and thus are less likely to be treated to a normal social interaction than those who do disclose their personal information.

Robustness Checks

In this section, we conduct five major robustness checks and report the estimation results. We have also conducted a robustness check using each of the seven individual airlines, the results of which are available in the Appendix.

Robustness Check: Seasonality

In our main model, we used day-of-the-week dummies to control for within-week seasonality. More important, we also controlled for the traffic volume in the previous hour (i.e., the number of complaining tweets received by the airline within the hour before the receipt of the focal complaining tweet), which we believe is a better way to control for a potential surge of complaints due to disruptions (e.g., bad weather). In order to further control for seasonality, we augment our benchmark model with *week of year* and *day of year* dummies, which essentially allows us to compare the complaining tweets posted in the same week, and on the same day, respectively. The results, presented in Table 7, are qualitatively similar to our benchmark model.

Robustness Check: Linear Splines

To further examine the relationship between airline responses and number of followers, we reestimate our benchmark model, incorporating linear splines on *Log of Followers*. Splines create a piecewise specification where functions are spliced together at predefined intervals based on the distribution of the variable in question. Although the number of followers in our data set ranged from 0 to more than 15.6 million, the distribution is skewed to the right. Roughly 82% of the users have fewer than 1,000 followers. This is not surprising considering the actual follower distribution on Twitter. According to one study,[16] Twitter accounts that have 1,000 followers are in the 96th percentile of active Twitter users. We therefore consider a quartile-based knot specification for the linear spline model. We place knots at the 25th and 75th percentiles of *Log of Followers,* representing 52 and 608 followers respectively**.** Benchmark model estimation results for this specification are presented in Table 8.

Spline regression generates separate parameter estimates for *Log of Followers* for each of the segments defined by the knots. From Table 8, column (1), all the spline variable coefficients are positive and statistically significant ($p < 0.01$), thereby providing strong evidence of the existence of the *social media influence effect* across the full distribution of followers.

Furthermore, it is apparent that the magnitude of the preferential treatment effect based on the number of followers varies significantly across each segment. Based on the spline regression model estimates, in Figure 6, we also plot the average predicted probabilities of airline response against *Log of Followers*, which provides visual evidence of the existence of differential customer treatment based on customers' social media influence.

Robustness Check: Classifier Accuracy

In constructing our data set, we employed a lexicon-based classifier to separate complaints from other types of tweets sent to airlines. One may be concerned about the inevitable inaccuracy due to machine classification, and its impact on our empirical findings. We performed two robustness checks to address this concern.

First, we used the sample of 7,351 tweets that were manually identified as actual complaints to reestimate our benchmark model. The results, presented in column (1) and (2) of Table 9, are qualitatively the same as the benchmark model.

Second, we used the 8,700 manually labeled tweets to train an SVM classifier and a maximum entropy classifier. The precision for the maximum entropy classifier is about 89.3%, and the precision for the SVM classifier is about 85%. We then used these supervised classifiers to relabel all 173,662 tweets and reestimated the benchmark model using those tweets classified as complaints. The results, presented in columns (3)–(6) of Table 9, are qualitatively the same as the benchmark model.

[16] http://www.entrepreneur.com/article/230487.

Table 7. Robustness: Controlling for Seasonality

Variable	Week of Year		Day of Year	
	(1) Response-Choice	(2) Response-Time	(3) Response-Choice	(4) Response-Time
Log of Followers	0.0527***	-0.0298***	0.0532***	-0.0283***
	(0.0027)	(0.0038)	(0.0027)	(0.0038)
Collaborating Organization Mentioned	-0.1493***	0.0643	-0.1493***	0.0600
	(0.0453)	(0.0745)	(0.0455)	(0.0735)
Competing Airline Mentioned	-0.1851***	0.0490	-0.1850***	0.0485
	(0.0192)	(0.0311)	(0.0193)	(0.0307)
Only Individual Users Mentioned	-0.5528***	0.1262***	-0.5549***	0.1201***
	(0.0141)	(0.0259)	(0.0142)	(0.0256)
Log of Complaints within the Previous Hour	-0.0140***	0.0272***	-0.0126***	0.0244***
	(0.0002)	(0.0004)	(0.0003)	(0.0005)
Log of Retweets	-0.3576***	0.3719***	-0.3546***	0.3474***
	(0.0159)	(0.0272)	(0.0160)	(0.0268)
Hashtag	0.0075*	0.0090	0.0078*	0.0115*
	(0.0043)	(0.0062)	(0.0043)	(0.0061)
Offensive	-0.2487***	0.0349	-0.2518***	0.0343
	(0.0263)	(0.0425)	(0.0264)	(0.0420)
URL	-0.3711***	0.1011***	-0.3706***	0.0998***
	(0.0127)	(0.0209)	(0.0127)	(0.0207)
@Order	-0.4152***	0.0168	-0.4181***	0.0124
	(0.0107)	(0.0209)	(0.0108)	(0.0207)
Log of Updates	-0.0518***	0.0041	-0.0524***	0.0035
	(0.0023)	(0.0033)	(0.0023)	(0.0033)
Profile	0.0228**	0.0310**	0.0214**	0.0308**
	(0.0105)	(0.0143)	(0.0106)	(0.0141)
Error Correlation	-0.1103***		-0.0924***	
	(0.0192)		(0.0197)	
Constant	1.2082***	6.4220***	1.4707***	5.4842***
	(0.0428)	(0.0645)	(0.0750)	(0.1052)
Observations	173,662	173,662	173,662	173,662
Log Likelihood	-233143.4	-233143.4	-231434.4	-231434.4

For brevity, results of Day of Week, Airline, Cluster, and Seasonality dummies are not reported.
***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parentheses.

Robustness Check: Alternative Error Distributions

In our benchmark model, we assumed normal distributions of the errors. To investigate whether our results are driven by this specific distribution, we reevaluate our hypotheses with alternative distributions. To simplify the computation, we estimate the response-choice model and the response-time model separately. In particular, we estimate a logistic regression on the response-choice model and perform log-logistic and Weibull parametric survival analysis on the response-time model. The results, presented in Table 10, are again qualitatively the same as the benchmark model.

Robustness Check: Alternative Measure of Social Media Influence

According to Aral and Walker (2012), the number of followers a Twitter user has may be a weak indicator of the per-

Table 8. Robustness: Linear Splines on Log of Followers

Variable	(1) Response-Choice	(2) Response-Time
Spline Variable 1 (followers < Q1 = 52)	0.0960***	0.0058
	(0.0058)	(0.0082)
Spline Variable 2 (Q1 ≤ followers < Q2 = 608)	0.0299***	0.0075
	(0.0054)	(0.0075)
Spline Variable 3 (followers ≥ Q2)	0.0575***	-0.0757***
	(0.0045)	(0.0063)
Collaborating Organization Mentioned	-0.1548***	0.0531
	(0.0451)	(0.0754)
Competing Airline Mentioned	-0.1827***	0.0381
	(0.0192)	(0.0314)
Only Individual Users Mentioned	-0.5478***	0.1236***
	(0.0141)	(0.0262)
Log of Complaints within the Previous Hour	-0.0156***	0.0311***
	(0.0002)	(0.0004)
Log of Retweets	-0.3582***	0.4486***
	(0.0161)	(0.0280)
Hashtag	0.0067	0.0050
	(0.0043)	(0.0062)
Offensive	-0.2511***	0.0505
	(0.0262)	(0.0430)
URL	-0.3701***	0.1037***
	(0.0126)	(0.0212)
@Order	-0.4128***	0.0290
	(0.0107)	(0.0211)
Log of Updates	-0.0535***	-0.0069*
	(0.0025)	(0.0036)
Profile	0.0028	-0.0063
	(0.0110)	(0.0150)
Error Correlation	-0.1285***	
	(0.0192)	
Constant	1.3164***	6.0261***
	(0.0407)	(0.0614)
Observations	173,662	173,662
Log Likelihood	-234484.5	-234484.5

For brevity, results of Day of Week, Airline, and Cluster dummies are not reported.
***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parentheses.

son's *true* social influence. In our context, the key variable of interest is the *perceived* social influence in the mind of a social media customer service agent. The number of Twitter followers a customer has stands out as the most natural candidate for this measure of perceived social influence in our context. Nevertheless, it will be a useful robustness check if we use an alternative measure of social influence. One such measure is the Klout score, which is a numerical value between 1 and 100 used by the company Klout to measure someone's online social influence.

We randomly selected 5% of complaints from our sample and used the Klout API to obtain the Klout scores of the complaining customers as of March 9, 2017. We are able to obtain the Klout score for 6,537 of the 7,351 customers in this subsample.

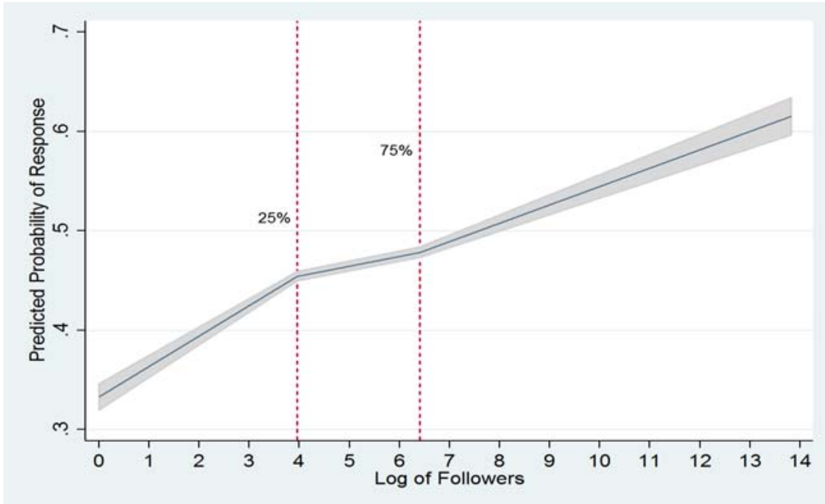

Figure 6. Average Predicted Probabilities of Airline Response with 95% Confidence Intervals

Replacing followers by Klout score in our main model, we estimated the joint model again and the results are reported in Table 11. The coefficient for the Klout score is significantly positive in the response-choice equation and significantly negative in the response-time equation, thereby supporting hypotheses H1 and H2. We recognize that the Klout score is also not a perfect measure of social media influence. Moreover, the scores we retrieved using the Klout API reflect users' social media influence as of March 2017, while our main sample was collected from 2014 to 2015. Therefore, the results reported in Table 11 have limitations. Nevertheless, this robustness check does provide some additional evidence for our hypotheses.

Extension

As there is public data on consumer satisfaction with the U.S. airlines in our sample, it would be interesting to compare the rankings based on such traditional satisfaction data with the rankings based on their social media customer service. To do this, we did a survey of customer satisfaction with their complaining experience on social media.

The survey data is constructed from complaint-based conversations on Twitter between customers and the airlines in our sample, where a conversation is defined as all the tweets exchanged between a customer and an airline about a particular complaint. We randomly selected conversations with at least two replies from the airline. To learn how these customers felt at the end of their interactions with the airlines on Twitter, we first created a dedicated Twitter account and started following each customer; the instantaneous Twitter notification this created was likely to capture the customer's immediate attention. The next step was to immediately send out a tweet to the customer asking him or her to follow us back, so we could communicate via direct messages (DM), keeping the conversation private and confidential. This tweet took the following form: "*Hi Amy, we are studying how airlines treat customers on Twitter. Could you follow us so we can DM you 2 short questions? Thanks!*" If the customer followed us back indicating a willingness to interact, we sent a couple of direct messages asking two short questions: "*Thx Amy. We are collecting voices on @airline to monitor their service. We want to learn your Twitter experience with them on December 7th*" and then "*(Q1) Did @airline solve your problem? (Q2) Did your conversation with @airline make you feel better, worse, or the same?*" Upon receiving responses from the customer, we ended the conversation with a thank-you note.

We offered the survey to 2,500 different customers of the 7 airlines in our study, and heard back from 559 customers, a response rate of 22.4%. Surprisingly, 53.3% of the customers reported that they felt worse at the end of the complaining encounter on social media, while only 20% of the customers felt better, and the rest felt the same. Just 11.45% of the customers perceived that the airline's social media team had resolved their problem. Moreover, 31.84% of the customers reported handoffs, instead of having their complaint resolved by the airline on Twitter. The airline had apologized to 73.52% of the complainants, and 31.48% received explanations from the airline regarding the complaint.

Table 9. Robustness: Adjusting for Classifier Accuracy						
	Manual Labeling		Maximum Entropy Classifier		SVM Classifier	
Variable	(1) Response-Choice	(2) Response-Time	(3) Response-Choice	(4) Response-Time	(5) Response-Choice	(6) Response-Time
Log of Followers	0.0747***	-0.0468***	0.0529***	-0.0310***	0.0513***	-0.0309***
	(0.0122)	(0.0170)	(0.0029)	(0.0042)	(0.0029)	(0.0040)
Collaborating Organization Mentioned	-0.4045**	0.0748	-0.1577***	0.0712	-0.1704***	0.0617
	(0.1801)	(0.3281)	(0.0488)	(0.0800)	(0.0484)	(0.0799)
Competing Airline Mentioned	-0.1620*	-0.1358	-0.1689***	0.0393	-0.1611***	0.0216
	(0.0926)	(0.1503)	(0.0211)	(0.0339)	(0.0205)	(0.0331)
Only Individual Users Mentioned	-0.4725***	0.0339	-0.5313***	0.1413***	-0.5312***	0.1338***
	(0.0684)	(0.1208)	(0.0156)	(0.0283)	(0.0152)	(0.0275)
Log of Complaints Within the Previous Hour	-0.0175***	0.0324***	-0.0158***	0.0318***	-0.0155***	0.0311***
	(0.0011)	(0.0023)	(0.0002)	(0.0005)	(0.0002)	(0.0005)
Log of Retweets	-0.2847***	0.3517***	-0.3442***	0.3863***	-0.3455***	0.3908***
	(0.0709)	(0.1103)	(0.0172)	(0.0289)	(0.0170)	(0.0286)
Hashtag	0.0432**	0.0176	0.0117**	0.0095	0.0142***	0.0081
	(0.0218)	(0.0305)	(0.0047)	(0.0067)	(0.0046)	(0.0066)
Offensive	-0.3194***	0.0040	-0.2718***	0.0368	-0.2664***	0.0544
	(0.1212)	(0.2074)	(0.0272)	(0.0439)	(0.0267)	(0.0434)
URL	-0.2982***	0.2342**	-0.3551***	0.1019***	-0.3481***	0.1090***
	(0.0629)	(0.0996)	(0.0143)	(0.0234)	(0.0139)	(0.0226)
@Order	-0.4499***	0.2004*	-0.4150***	0.0201	-0.4149***	0.0400*
	(0.0543)	(0.1057)	(0.0121)	(0.0232)	(0.0117)	(0.0226)
Log of Updates	-0.0549***	0.0147	-0.0501***	0.0037	-0.0482***	0.0042
	(0.0111)	(0.0159)	(0.0025)	(0.0036)	(0.0024)	(0.0035)
Profile	-0.0468	0.0120	0.0187*	0.0356**	0.0167	0.0305**
	(0.0527)	(0.0719)	(0.0113)	(0.0153)	(0.0110)	(0.0149)
Constant	1.4092***	5.6539***	1.4051***	6.1572***	1.3936***	6.1098***
	(0.1879)	(0.2831)	(0.0434)	(0.0648)	(0.0418)	(0.0628)
Error Correlation	-0.1327		-0.1267***		-0.1427***	
	(0.0964)		(0.0214)		(0.0204)	
Observations	7,351	7,351	144,800	144,800	152,922	152,922
Log Likelihood	-10215.18	-10215.18	-199036.5	-199036.5	-210251.9	-210251.9

For brevity, results of Day of Week, Airline, Cluster, and Seasonality dummies are not reported.
***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parentheses.

The dependent variable of the survey analysis is *Customer Satisfaction*, which equals 1 if the customer felt better, -1 if the customer felt worse, and 0 if the customer felt the same, at the end of the conversation with the airline. We are interested in the airline-specific fixed effects. We include a set of control variables to account for unobserved heterogeneity at the conversation level and the customer level. Controlling for the customer's personality is also important as personality traits are likely to influence a customer's satisfaction at the end of the encounter on social media. Therefore, for each customer, we derived the "big five" personality traits (i.e., openness, conscientiousness, extraversion, agreeableness, neuroticism), which have long been shown to affect various human behaviors (Goldberg 1993). Please refer to the Appendix for details on deriving the personality traits.

Table 12 explains the main variables in the empirical analysis. Nonresponse bias was assessed by using Heckman selection model. Error correlation was not statistically significant at the p < .05 level, suggesting that nonresponse bias is not likely a

Table 10. Robustness: Alternative Error Distributions

Variable	(1) Response-Choice (Logit)	(2) Response-Time (Log-Logistic)	(3) Response-Time (Weibull)
Log of Followers	0.0878***	-0.0246***	-0.0243***
	(0.0045)	(0.0036)	(0.0039)
Collaborating Organization Mentioned	-0.1733**	0.0966	-0.0199
	(0.0757)	(0.0702)	(0.0757)
Competing Airline Mentioned	-0.2080***	0.0359	0.0406
	(0.0331)	(0.0296)	(0.0318)
Only Individual Users Mentioned	-0.8402***	0.0721***	0.1572***
	(0.0251)	(0.0234)	(0.0255)
Log of Complaints within the Previous Hour	-0.0281***	0.0363***	0.0341***
	(0.0004)	(0.0004)	(0.0005)
Log of Retweets	-0.6224***	0.3250***	0.4692***
	(0.0276)	(0.0255)	(0.0288)
Hashtag	0.0103	0.0084	0.0108*
	(0.0072)	(0.0059)	(0.0063)
Offensive	-0.4243***	0.0008	0.0436
	(0.0440)	(0.0409)	(0.0433)
URL	-0.6248***	0.0585***	0.0688***
	(0.0212)	(0.0192)	(0.0205)
@Order	-0.7613***	-0.0285	-0.0035
	(0.0202)	(0.0187)	(0.0204)
Log of Updates	-0.0852***	0.0022	-0.0057*
	(0.0038)	(0.0031)	(0.0033)
Profile	0.0373**	0.0277**	-0.0027
	(0.0174)	(0.0138)	(0.0146)
Constant	2.4907***	5.6538***	8.1692***
	(0.0674)	(0.0570)	(0.0603)
Observations	173,662	80,209	80,209
Log Likelihood	-100815.08	-132506.6	-140967.1

For brevity, results of Day of Week, Airline, and Cluster dummies are not reported.
***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parentheses.

major concern of this study. We estimate an ordered logit model, and the results are presented in Table 13.

From columns (1) and (2) of Table 13, carrier fixed effects show statistically significant results only for Alaska Airlines and Southwest Airlines. In particular, complaining to Alaska Airlines on Twitter increases the odds of feeling better at the end, as compared to complaining to United Airlines, the benchmark carrier. On the other hand, complaining to Southwest Airlines on Twitter decreases the odds of feeling better at the end. In terms of magnitude, Alaska Airlines ranks highest, followed by American Airlines, Delta Airlines, JetBlue, Virgin America, and Southwest Airlines. According to the J. D. Power 2016 North America Airline Satisfaction Study,[17] rankings are provided separately for traditional (e.g., American Airlines, United Airlines, Alaska Airlines, Delta Airlines) and low-cost (e.g., JetBlue, Southwest Airlines) segments of air carriers. Since approximately 91.7% of our data contains conversations involving traditional carriers, we perform a subsample analysis for these airlines to compare the traditional customer satisfaction rankings with our social media customer satisfaction rankings. The results are presented in columns (3) and (4) of Table 13. Only Alaska Airlines shows positive and statistically significant effects on

[17] J. D. Power 2016 North America Airline Satisfaction Study (http://www.jdpower.com/press-releases/2016-north-america-airline-satisfaction-study).

Table 11. Alternative Measure of Social Media Influence

Variable	(1) Response-Choice Equation	(2) Response-Time Equation
Klout Score	0.0049***	-0.0040**
	(0.0014)	(0.0020)
Collaborating Organization Mentioned	-0.3940**	0.3268
	(0.1918)	(0.3363)
Competing Airline Mentioned	-0.1683*	-0.1016
	(0.0963)	(0.1498)
Only Individual Users Mentioned	-0.4538***	0.0523
	(0.0708)	(0.1195)
Log of Complaints within the Previous Hour	-0.0182***	0.0329***
	(0.0012)	(0.0024)
Log of Retweets	-0.2136***	0.3093***
	(0.0712)	(0.1063)
Hashtag	0.0350	0.0026
	(0.0228)	(0.0310)
Offensive	-0.3125**	0.0104
	(0.1313)	(0.2142)
URL	-0.3249***	0.2336**
	(0.0666)	(0.1033)
@Order	-0.4406***	0.1957*
	(0.0560)	(0.1041)
Log of Updates	-0.0218**	-0.0078
	(0.0099)	(0.0136)
Profile	-0.0252	-0.0317
	(0.0543)	(0.0718)
Error Correlation	-0.1315	
	(0.1016)	
Constant	1.3519***	5.7602***
	(0.1943)	(0.2830)
Observations	6,611	6,611

For brevity, results of Cluster dummies, Day of Week dummies, and Airline dummies are not reported.
***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parentheses.

customers' complaint-satisfaction, compared to United Airlines, the benchmark carrier. Also, Alaska Airlines ranks highest in complaint-satisfaction, followed by Delta Airlines, and American Airlines. Interestingly, this ranking is in fact consistent with the customer satisfaction rankings of the traditional-carrier segment of the J. D. Power study. Thus, it seems that the airlines that excel in traditional customer service show equivalent competency in social media customer service as well.

Discussion and Conclusion

Key Results and Contributions

Drawing upon the literature in information systems, management, and social psychology, we have developed the theoretical foundation for two important effects that lead to differential customer treatment on social media: the social media influence effect and the bystander effect. Using a uni-

Table 12. Extension Study: Definitions of Variables

Variable	Description
Customer Satisfaction	Customer's feeling of satisfaction at the end of the conversation (obtained from Q1 of the survey) (-1 = worse, 0 = the same, 1 = better).
Followers	Number of followers for the customer at the start of the conversation.
Complaint Type	Binary variable indicating the complaint type (1 = outcome/operations – e.g., flight delay/cancellation, mishandled baggage, in-flight service, non-employee-related issues at airports, etc.). 0 = process/employees/dedicated customer service-related – e.g., rude flight attendants, longer than usual holding times in contacting customer service, response delays from customer service, etc.)
Average Airline Response Time	Average of response times between a complaint tweet and the airline response tweet, in seconds.
Handoff	Binary variable equal to 1 if the social media team handed the customer off to some other department, 0 otherwise.
Problem Solved	Binary variable equal to 1 if the airline resolved the complaint on social media (obtained from Q2 of the survey), 0 otherwise.
Apology	Binary variable equal to 1 if the airline apologized, 0 otherwise.
Explanation	Binary variable equal to 1 if the airline provided an explanation, 0 otherwise.
Thanking	Binary variable equal to 1 if the airline thanked the customer, 0 otherwise.
Total Tweets Exchanged	Total number of tweets exchanged during the conversation.
DM	Binary variable equal to 1 if the customer or the airline mentioned direct messaging, 0 otherwise.
Customer at the End	Binary variable equal to 1 if it was the customer who ended the conversation, 0 otherwise.
Brand Switch Warning	Binary variable equal to 1 if the customer warned the airline about possible brand switching in the future, 0 otherwise.
Consecutive User Tweets	Binary variable equal to 1 if consecutive user tweets exist in the conversation, 0 otherwise.
Consecutive Airline Tweets	Binary variable equal to 1 if consecutive airline tweets exist in the conversation, 0 otherwise.
Customer Account Age	Number of days since the creation of the customer's Twitter account.
Profile	Binary variable equal to 1 if the user's location, website, or profile description is publicly available, 0 otherwise.
Agreeableness	Person's tendency to be compassionate and cooperative towards others (altruism, cooperation, trustworthiness, empathy).
Conscientiousness	Person's tendency to be organized and dependable (organization, persistence, self-assurance).
Extraversion	Person's tendency to seek stimulation in the company of others (outgoingness, sociability, energy, positive emotions, assertiveness, sociability, talkativeness).
Neuroticism	Person's tendency to experience unpleasant emotions easily, such as anger, anxiety, and depression.
Openness	The extent to which a person is open to experiencing a variety of activities (creativity, intellect, preference for novelty).

que data set of customer complaints on Twitter to seven major U.S. airlines over a nine-month period, and using machine-learning techniques, we investigate whether a customer's social media influence and the presence of bystanders to the complaint have any effect on the customer's receiving a response from the airline. We further examine the effect of a customer's social media influence on the response time. We have two notable results.

First, airlines are more likely to respond to complaints from customers with more followers. Moreover, if the complaint does receive a response, airlines are more likely to respond faster to customers with more followers. These results suggest the existence of preferential customer service on social media based on a customer's social media influence. The phenomenon could be the result of an explicit company policy that prioritizes customers based on their social media

Table 13. Ordered Logistic Regression of Customer Satisfaction				
	All Carriers		**Traditional Carriers**	
Variable	**(1) Ordered Logit Coefficient**	**(2) Ordered Logit Odds Ratio**	**(3) Ordered Logit Coefficient**	**(4) Ordered Logit Odds Ratio**
Alaska Airlines	1.4744**	4.3683**	1.5034**	4.4970**
	(0.6338)	(2.7687)	(0.6299)	(2.8328)
American Airlines	1.4322	4.1878	0.8176	2.2651
	(1.4408)	(6.0338)	(1.5022)	(3.4028)
Delta Airlines	1.3162	3.7294	0.8879	2.4301
	(0.9424)	(3.5147)	(1.0117)	(2.4586)
JetBlue Airways	-0.7410	0.4766		
	(0.7371)	(0.3513)		
Southwest Airlines	-1.2797*	0.2781*		
	(0.6629)	(0.1844)		
Virgin America	-1.1314	0.3226		
	(0.9479)	(0.3058)		
Complaint Type	0.4525**	1.5722**	0.4620**	1.5873**
	(0.2120)	(0.3332)	(0.2144)	(0.3403)
Handoff	-0.4201**	0.6570**	-0.4376**	0.6456**
	(0.2063)	(0.1355)	(0.2049)	(0.1323)
Problem Solved	2.1760***	8.8113***	1.7047***	5.4996***
	(0.3015)	(2.6562)	(0.3112)	(1.7114)
Apology	0.1543	1.1669	0.2174	1.2428
	(0.2089)	(0.2438)	(0.2139)	(0.2659)
Explanation	-0.0310	0.9695	-0.1033	0.9018
	(0.2016)	(0.1954)	(0.2018)	(0.1820)
Thanking	0.6855***	1.9847***	0.6738***	1.9617***
	(0.2053)	(0.4076)	(0.2083)	(0.4087)
Total Tweets Exchanged	-0.0758*	0.9270*	-0.0712*	0.9313*
	(0.0407)	(0.0377)	(0.0408)	(0.0380)
Log of Average Response Time	0.0229	1.0231	0.0175	1.0177
	(0.0955)	(0.0977)	(0.0974)	(0.0991)
DM	0.1331	1.1424	0.1918	1.2115
	(0.2486)	(0.2840)	(0.2587)	(0.3134)
Customer at the End	-0.3299	0.7190	-0.3599	0.6977
	(0.2157)	(0.1551)	(0.2231)	(0.1556)
Brand Switch Warning	-0.7135***	0.4899***	-0.6996***	0.4968***
	(0.2559)	(0.1254)	(0.2534)	(0.1259)
Consecutive User Tweets	0.1096	1.1158	0.0408	1.0416
	(0.2157)	(0.2407)	(0.2214)	(0.2306)
Consecutive Airline Tweets	-0.3641	0.6948	0.1932	1.2131
	(0.7404)	(0.5144)	(0.8503)	(1.0315)
Customer Account Age	-0.0002	0.9998	-0.0002	0.9998
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Profile	-0.3946	0.6739	-0.3688	0.6915
	(0.3263)	(0.2199)	(0.3290)	(0.2275)

Table 13. Ordered Logistic Regression of Customer Satisfaction (Continued)				
	All Carriers		**Traditional Carriers**	
Variable	**(1) Ordered Logit Coefficient**	**(2) Ordered Logit Odds Ratio**	**(3) Ordered Logit Coefficient**	**(4) Ordered Logit Odds Ratio**
Log of Followers	0.1683***	1.1833***	0.1859***	1.2043***
	(0.0605)	(0.0716)	(0.0627)	(0.0755)
Agreeableness	-0.0627	0.9392	-0.0164	0.9837
	(0.1205)	(0.1131)	(0.1230)	(0.1210)
Conscientiousness	0.5927**	1.8088**	0.5346**	1.7067**
	(0.2533)	(0.4581)	(0.2553)	(0.4357)
Extraversion	0.0066	1.0066	-0.0421	0.9587
	(0.1557)	(0.1567)	(0.1641)	(0.1574)
Neuroticism	0.1421	1.1527	0.1419	1.1525
	(0.3035)	(0.3499)	(0.3064)	(0.3532)
Openness	-0.0984	0.9063	-0.0919	0.9122
	(0.0917)	(0.0831)	(0.0916)	(0.0836)
Cut 1 Constant	1.4376	4.2106	1.0559	2.8745
	(1.4069)	(5.9237)	(1.4471)	(4.1596)
Cut 2 Constant	2.9425**	18.9634**	2.5648*	12.9985*
	(1.4116)	(26.7687)	(1.4513)	(18.8650)
Observations	559	559	513	513
Log Likelihood	-491.3137		-467.8096	

***p < 0.01, **p < 0.05, *p < 0.1 (standard errors in parentheses).

influence, an internal reward-punishment mechanism that incentivizes the social media team to minimize the risk of negative word of mouth going viral, or stereotyping of customers based on their social media influence.

The second important result emerging from our empirical analysis is that companies are less likely to respond to a complaining tweet when some bystander is present. In other words, airlines are less likely to respond to complaints directed not just to them but also to other collaborating firms. This confirms the existence of the "bystander effect" in social media customer service.

The contribution of this study to the field of information systems research is twofold. First, despite the controversy about preferential customer service based on social media influence, to the best of our knowledge, this is the first study to theoretically explain and analyze the drivers and risks of such a practice. In particular, our proposed theoretical framework, which draws upon the principles of distributive justice to analyze the perceived fairness of influence-based preferential treatment, not only allows managers to place their evaluation of this practice on a sound theoretical footing, but also contributes to existing theories on service-level differentiation and relationship marketing. In fact, implicit in the concept of relationship marketing are a consumer focus and selectivity that do not serve all customers the same way, as it may not be feasible or worthwhile to develop the same level of long-term relationships with all customers (Sheth and Parvatiyar 1995). Our study validates and extends this traditional notion of relationship marketing by providing analysis of the differential customer service unique to social media. Furthermore, in contrast with traditional preferential service practices based on customer value, we show that preferential customer service based on social media influence violates all principles of distributive justice and thus is more prone to be perceived as unfair. Moreover, the empirical part of our study validates for the first time the existence of this unique type of customer preferential treatment, which has important practical implications for customers and managers. In light of some recent public relation failures,[18] managers in the social media era

[18]For example, the forced removal of a passenger from a United Airlines flight on April 9, 2017, triggered a public outcry and resulted in severe damage to the carrier although some legal experts claim that the airline has the legal right to remove passengers from planes for many reasons. Clearly, whether a policy is legal is a different question from whether the policy is fair or whether the policy is enforced correctly.

probably should forgo exploiting some legal but unfair gains despite what they have learned from standard economic theory.

Second, our analysis of the bystander effect not only enriches the existing theories on customer complaint management, but also demonstrates the uniqueness of customer service on social media. It points to the importance of researching this traditional topic with the specifics of the technology-driven new business environment.

Implications for Policy and Practice

Our findings have important implications, especially for companies that are trying to harness the power of social media to provide customer service.

First, our empirical tests of H1 and H2 provide strong evidence of the practice of preferential customer treatment based on levels of social media influence. Given its controversial nature and our theoretical analysis of its effect on customers' perceptions of fairness, companies should carefully examine the drivers of this practice within their social media teams and act accordingly. For example, if there is an internal policy or procedure that enables this practice, it is time to evaluate its benefits and risks. Although customers generally have limited information, as more studies like the present one are made public, customers will become more aware of differential treatment on social media, and the risk of a backfire may outweigh the benefits of the policy. Just as Twitter warned in its playbook for providing customer service on social media, it is important to pass the "sniff test."

On the other hand, if the main drivers of the practice are implicit incentive mechanisms or stereotyping, then companies should consider establishing policies to minimize the actual driving force. For example, companies might want to design mandatory training programs for their social media teams to address the problem.

Second, our empirical test of H3 clearly indicates the significant impact of the bystander effect in the context of social media customer service. The finding suggests that social media teams are vulnerable to this social psychological force, and companies should properly train them to avoid this pitfall. We believe that both implications are important for companies that are exploring customer service on social media, and the theoretical framework provided in this study could be their guide. By doing customer service on social media, companies can further segment customers by mining the unstructured and real-time social media data of those customers. Such a strategy may trigger a revolution in how companies manage customer relationships and even portend a new stream of research on the interface of information systems and service management.

In the long run, companies may offer their customers the option of linking their social media identity with other "identities" such as a frequent flyer number or some membership ID. By doing so, they can reduce the number of interactions with each customer and track the customer's social activities and preferences. It would also help companies to associate the current or potential economic value of each customer with other social media activity characteristics. Ultimately, companies can excel by providing truly *customized* customer service.

Our findings also provide some practical guidance for customers when they complain to companies on social media. For example, it is clearly better to use dialogue to complain to companies on Twitter, considering the bystander effect. Families and friends can still be notified of a dialogue complaining tweet as long as they are following the user, which is likely the case. Also, disclosing some personal information on social media, such as writing a short bio or posting a location, can significantly increase the chance of a response from a company, as well as the speed of the response.

Our study also has implications for policy makers. With the vast amount of social media data about each individual and the development of big data technologies, companies are increasingly capable of measuring and tracking each person's social media influence. Should companies be encouraged to use influence scores to differentiate customers while providing service or to differentiate employees or potential employees while evaluating them, or should the practice be discouraged? We hope this study can stimulate careful attention to the risks and rewards of acknowledging social media influence, whether explicitly or implicitly, in organization–individual relationships. At a broader level, we believe an important way to regulate firms in the age of big data is to promote data-analytics-based journalism and we hope our study can inspire more research to bridge the gap between journalism and data analytics.

Limitations and Future Work

There are several limitations of our study. First, due to the limitation of the data, we are unable to control for each customer's transactional value as perceived by the social media customer agents. Hence, it is possible that our estimate of the prevalence of influence-based preferential treatment is larger or smaller than it actually is due to the potential correlation between a customer's transactional value and social media influence. Second, our findings are based on the data from seven major airlines in the U.S. on a major social media platform. One should be careful in generalizing the findings to other industries or to other social media platforms. Although Twitter stands out among social media platforms in terms of simplicity and the ability to facilitate viral spread of messages (Campo-Ávila et al. 2013), other social media platforms are also starting to create channels through which consumers can seek customer service. Conducting a similar study on a platform such as Facebook would provide further insights. Extending this study to industries such as financial services and retailing would enrich the insights as well.

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RESEARCH ARTICLE

WHEN SOCIAL MEDIA DELIVERS CUSTOMER SERVICE: DIFFERENTIAL CUSTOMER TREATMENT IN THE AIRLINE INDUSTRY

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Appendix

Correlation Matrix

Table A1. Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12
1	Log of Followers												
2	Collaborating Organization Mentioned	0.0183											
3	Log of Complaints Within the Previous Hour	0.0024	-0.0095										
4	Log of Retweets	0.1899	0.002	0.0258									
5	Competing Airline Mentioned	0.0279	0.0028	-0.0212	0.0195								
6	Only Users Mentioned	0.0977	-0.041	0.0847	0.0581	-0.1443							
7	Log of Updates	0.7931	0.0179	0.0141	0.0936	0.0225	0.1427						
8	@Order	0.0729	0.0848	-0.0307	0.03	0.3807	0.4597	0.1028					
9	Profile	0.4901	0.0163	0.0027	0.0472	0.0277	0.0682	0.5112	0.049				
10	Hashtag	0.0003	0.0091	-0.0099	0.0546	0.0039	-0.027	-0.0289	-0.0279	0.0263			
11	Offensive	0.0386	-0.0078	0.0442	0.0082	-0.0041	0.0793	0.0794	0.0324	0.0285	-0.0319		
12	URL	0.0825	0.0136	0.023	0.0991	-0.0135	0.0367	0.0619	-0.0166	0.0503	0.0876	-0.0128	

Clustering Complaining Tweets

We follow a bag-of-words approach to group similar tweets into clusters using the K-Means algorithm. Considering the inherently noisy nature of text in tweets, first, we preprocess and clean the data set. For example, we process hashtags, Internet slang words, user names, and repetitive characters before any transformation. We also remove stop words and use stemming techniques to structure the data further. Next, we implement the term frequency-inverse document frequency (TF-IDF) approach to map the most frequent words to feature indices and to reweight them over the entire corpus. As the dimensionality of text data can be very high, we employ latent semantic analysis (LSA) techniques to reduce the high dimensionality of the data.

One limitation of the K-Means algorithm is that it may converge to a local minimum, which is highly dependent on the initialization of the centroids. To overcome this problem, we run the computation several times with different initializations of the centroids distant from each other in general rather than random initialization, as recommended by previous researchers (Han et al. 2012). Another limitation is that K-Means requires the number of clusters to be specified at the beginning. As there are no pre-identified absolute class labels available for our tweets to match against the clustering outcome, we use the silhouette coefficient (Rousseeuw 1987) to assess the appropriate number of clusters suitable for our data. However, since this measure is known to suffer from the "curse of dimensionality" for high dimensional datasets such as text data, we use it as a baseline measure to make a reasonable choice for the number of clusters. The best silhouette coefficient score was obtained for 40 clusters. Therefore, 40 clusters were obtained. Accordingly, we introduce cluster fixed effects into our benchmark model and the results are presented in Table A2.

Table A2. Benchmark Model: Content Fixed Effects

Cluster ID	Response-Time	Response-Choice	Cluster ID	Response-Time	Response-Choice
1	-0.0388	-0.1337***	21	0.0355	0.0506*
	(0.0471)	(0.0334)		(0.0410)	(0.0302)
2	-0.0259	-0.0619*	22	-0.0361	0.0569
	(0.0474)	(0.0341)		(0.0473)	(0.0359)
3	0.0032	0.0749**	23	-0.1000**	-0.1164***
	(0.0450)	(0.0334)		(0.0446)	(0.0321)
4	0.0750	-0.1375***	24	0.0179	-0.1085***
	(0.0478)	(0.0333)		(0.0517)	(0.0366)
5	-0.0381	-0.0242	25	0.0555	-0.0341
	(0.0428)	(0.0313)		(0.0447)	(0.0326)
6	-0.0379	0.1323***	26	0.0084	-0.0622*
	(0.0363)	(0.0268)		(0.0461)	(0.0333)
7	-0.0899**	0.0290	27	0.0305	-0.3690***
	(0.0389)	(0.0285)		(0.0759)	(0.0464)
8	0.0691	-0.4064***	28	0.0233	-0.0302
	(0.0528)	(0.0344)		(0.0463)	(0.0340)
9	0.1707**	-0.5960***	29	0.1233***	-0.0295
	(0.0688)	(0.0410)		(0.0416)	(0.0299)
10	-0.0295	-0.0742**	30	0.0109	0.0202
	(0.0403)	(0.0289)		(0.0436)	(0.0324)
11	-0.0152	-0.2016***	31	-0.0773**	0.0272
	(0.0473)	(0.0325)		(0.0391)	(0.0287)
12	-0.0120	-0.0338	32	0.0316	0.1039***
	(0.0428)	(0.0312)		(0.0382)	(0.0282)
13	-0.0262	0.0995***	33	0.0440	0.0166
	(0.0448)	(0.0335)		(0.0451)	(0.0332)
14	0.0070	-0.1397***	34	-0.0467	-0.0184
	(0.0411)	(0.0294)		(0.0424)	(0.0309)
15	-0.0422	-0.6096***	35	0.0242	-0.1386***
	(0.0719)	(0.0423)		(0.0557)	(0.0389)
16	-0.0209	-0.1825***	36	-0.0305	0.0390
	(0.0364)	(0.0259)		(0.0459)	(0.0341)
17	0.0778*	0.0555*	37	-0.0257	0.0091
	(0.0416)	(0.0308)		(0.0427)	(0.0316)
18	-0.0193	-0.0035	38	-0.0626	-0.3381***
	(0.0478)	(0.0353)		(0.0590)	(0.0383)
19	-0.0039	0.0079	39	-0.0168	-0.1718***
	(0.0444)	(0.0322)		(0.0474)	(0.0329)
20	0.0586	-0.1636***			
	(0.0430)	(0.0301)			

Individual Airlines

To investigate whether our results are driven by a single airline, we estimate the joint model of response-choice and response-time with the same set of independent variables for each airline. The results, presented in Table A3, suggest that the *follower-based preferential treatment effect* (H1) is evident for all seven airlines. For American Airlines, United Airlines, Delta Airlines, and Southwest Airlines, a higher number of followers is associated with a faster response. Surprisingly, for Alaska Airlines and Virgin America, having more followers seems to result in a slower response. One possible explanation is that both airlines share a similar strategy of intentionally trading off response speed with more deliberation time while preparing their responses. It is interesting to note that the two airlines have become sister airlines following the 2016 acquisition of Virgin America by Alaska Air Group.[1]

The estimates of error correlation between the response-choice model and the response-time model are negative and significant for United Airlines and American Airlines, and are insignificant for Delta Airlines, JetBlue Airways, and Southwest Airlines. The positive and significant estimates of the error correlations of Alaska Airlines and Virgin America are consistent with the fact that, for these two airlines, having more followers leads to higher probability of being responded to but longer delay in receiving the responses. Overall, the pattern of the size of error correlations seems to suggest that the workflow of managing customer complaints on Twitter at Delta Airlines, JetBlue Airways, and Southwest Airlines, might be different from that of the other four airlines in our sample. For example, for the three airlines with negligible error correlations between the response-choice model and the response-time model, the two decisions might have been made by two different groups of agents (including possibly machine algorithm), while for the other four airlines, the two decisions might have been made by the same group of agents.

The coefficients of the bystander effect remain negative for six out of the seven airlines in our sample, although some coefficients are statistically insignificant. The one with a positive sign is not statistically significant.

Overall, we find the results of individual airline analysis largely consistent with the results from the main analysis.

Table A3. Robustness: Individual Airlines

	Log of Followers		Collaborating Organization Mentioned	
Airline	Response-Choice	Response-Time	Response-Choice	Response-Time
American Airlines	0.0560***	-0.0645***	0.0956	-0.0788
	(0.0047)	(0.0058)	(0.0867)	(0.1110)
United Airlines	0.0458***	-0.0326***	-0.3203***	0.2617*
	(0.0051)	(0.0069)	(0.0869)	(0.1390)
Delta Airlines	0.0463***	-0.0212*	-0.0091	0.3471
	(0.0082)	(0.0114)	(0.1662)	(0.3163)
Southwest Airlines	0.0335***	-0.0783***	-0.2057	0.0140
	(0.0076)	(0.0189)	(0.1676)	(0.5238)
JetBlue Airways	0.0640***	0.0082	-0.4022***	0.0672
	(0.0089)	(0.0091)	(0.1409)	(0.1766)
Alaska Airlines	0.0597***	0.0976***	-0.2515*	-0.7050*
	(0.0131)	(0.0345)	(0.1495)	(0.4090)
Virgin America	0.0723***	0.1684***	-0.2198	-0.8535
	(0.0112)	(0.0331)	(0.1734)	(0.5198)

***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parentheses. Refer to Tables A4 and A5 for detailed estimation results.

[1]https://blog.alaskaair.com/alaska-airlines/news/asplusvx-customer-questions/

Table A4. Joint Model of Choice and Response-Time – Estimation Results for Individual Airlines								
	AmericanAir		United		Delta		SouthWest	
Variable	Response-Choice (Probit)	Response-Time (Log-Normal)	Response-Choice (Probit)	Response-Time (Log-Normal)	Response-Choice (Probit)	Response-Time (Log-Normal)	Response-Choice (Probit)	Response-Time (Log-Normal)
Log of Followers	0.0560***	-0.0645***	0.0458***	-0.0326***	0.0463***	-0.0212*	0.0335***	-0.0783***
	(0.0047)	(0.0058)	(0.0051)	(0.0069)	(0.0082)	(0.0114)	(0.0076)	(0.0189)
Collaborating Organization Mentioned	0.0956	-0.0788	-0.3203***	0.2617*	-0.0091	0.3471	-0.2057	0.0140
	(0.0867)	(0.1110)	(0.0869)	(0.1390)	(0.1662)	(0.3163)	(0.1676)	(0.5238)
Competing Airline Mentioned	0.0983***	-0.1703***	-0.0609*	0.1182**	-0.0004	0.2724	-0.9663***	0.1623
	(0.0330)	(0.0449)	(0.0338)	(0.0477)	(0.0979)	(0.1859)	(0.0718)	(0.3155)
Only Individual Users Mentioned	-0.6445***	0.4995***	-0.5228***	0.1186***	0.1067*	0.1042	-0.6247***	0.4102**
	(0.0271)	(0.0408)	(0.0221)	(0.0389)	(0.0564)	(0.1086)	(0.0517)	(0.2067)
Log of Complaints within the Previous Hour	-0.0143***	0.0419***	-0.0183***	0.0228***	-0.0255***	0.0699***	-0.0116***	0.0104***
	(0.0003)	(0.0004)	(0.0005)	(0.0011)	(0.0013)	(0.0027)	(0.0011)	(0.0036)
Log of Retweets	-0.3029***	0.4965***	-0.2913***	0.2505***	-0.7557***	0.7582***	-0.3256***	0.7641***
	(0.0274)	(0.0373)	(0.0268)	(0.0418)	(0.0860)	(0.1706)	(0.0465)	(0.1465)
Hashtag	0.0440***	-0.0368***	-0.0134	0.0262**	-0.1228***	0.0336	0.0051	0.0178
	(0.0075)	(0.0095)	(0.0082)	(0.0107)	(0.0170)	(0.0275)	(0.0114)	(0.0274)
Offensive	-0.1303***	0.1143**	-0.2005***	-0.0277	-0.5237***	0.2381	-0.2383***	0.2942
	(0.0435)	(0.0579)	(0.0465)	(0.0674)	(0.1418)	(0.2879)	(0.0721)	(0.2046)
URL	-0.1653***	0.1408***	-0.4569***	0.2155***	-0.2395***	0.0762	-0.4965***	0.1654
	(0.0237)	(0.0307)	(0.0231)	(0.0400)	(0.0492)	(0.0768)	(0.0366)	(0.1417)
@Order	-0.3637***	0.3358***	-0.7378***	0.1491***	-0.5437***	-0.0070	-0.2330***	-0.2154
	(0.0187)	(0.0285)	(0.0226)	(0.0531)	(0.0439)	(0.1042)	(0.0380)	(0.1446)
Log of Updates	-0.0493***	0.0325***	-0.0494***	0.0114*	-0.0322***	0.0144	-0.0414***	0.0048
	(0.0041)	(0.0051)	(0.0045)	(0.0061)	(0.0069)	(0.0095)	(0.0062)	(0.0165)
Profile	0.0046	0.0338	0.0390*	0.0445*	-0.0221	0.0269	0.0019	0.0496
	(0.0181)	(0.0222)	(0.0203)	(0.0254)	(0.0290)	(0.0387)	(0.0284)	(0.0654)
Error Correlation	-0.8891***		-0.2165***		-0.0757		0.0010	
	(0.0043)		(0.0584)		(0.0866)		(0.1435)	
Observations	50,963	50,963	49,254	49,254	18,478	18,478	24,889	24,889
Log - Likelihood	-71168.67	-71168.67	-57141.77	-57141.77	-25314.76	-25314.76	-32852.23	-32852.23

For brevity, the constant and coefficients for Day of Week dummies, Airline dummies, and Cluster dummies are not reported.
***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parentheses.

Table A5. Joint Model of Choice and Response-Time – Estimation Results for Individual Airlines						
	JetBlue		AlaskaAir		VirginAmerica	
Variable	Response-Choice(Probit)	Response-Time (Log-Normal)	Response-Choice(Probit)	Response-Time (Log-Normal)	Response-Choice (Probit)	Response-Time (Log-Normal)
Log of Followers	0.0640***	0.0082	0.0597***	0.0976***	0.0723***	0.1684***
	(0.0089)	(0.0091)	(0.0131)	(0.0345)	(0.0112)	(0.0331)
Collaborating Organization Mentioned	-0.4022***	0.0672	-0.2515*	-0.7050*	-0.2198	-0.8535
	(0.1409)	(0.1766)	(0.1495)	(0.4090)	(0.1734)	(0.5198)
Competing Airline Mentioned	-0.8322***	-0.0986	-0.5463***	-1.3717***	-0.8138***	-2.4338***
	(0.0739)	(0.1155)	(0.0952)	(0.2682)	(0.1086)	(0.3467)
Only Individual Users Mentioned	-0.6634***	0.0702	-0.6908***	-1.7170***	-0.4846***	-1.2500***
	(0.0532)	(0.0829)	(0.0733)	(0.2091)	(0.0825)	(0.2557)
Log of Complaints within the Previous Hour	-0.0146***	0.0279***	-0.0401***	-0.1148***	-0.0254***	-0.0445***
	(0.0008)	(0.0013)	(0.0050)	(0.0145)	(0.0034)	(0.0104)
Log of Retweets	-0.9134***	0.6906***	-0.5548***	-0.4112	-0.1908***	-0.2006
	(0.0694)	(0.1104)	(0.0953)	(0.2773)	(0.0619)	(0.1869)
Hashtag	-0.0096	-0.0012	0.0293	0.0659	0.0000	0.0251
	(0.0129)	(0.0123)	(0.0202)	(0.0528)	(0.0202)	(0.0591)
Offensive	-0.4948***	-0.0442	-0.4899***	-0.9366**	-0.6434***	-1.3318***
	(0.0914)	(0.1154)	(0.1506)	(0.4320)	(0.1474)	(0.4571)
URL	-0.5034***	-0.0154	-0.4046***	-0.8325***	-0.3241***	-0.8085***
	(0.0361)	(0.0499)	(0.0559)	(0.1532)	(0.0541)	(0.1608)
@Order	-0.3363***	0.0409	-0.2477***	-0.4711***	-0.3665***	-0.8811***
	(0.0375)	(0.0623)	(0.0473)	(0.1372)	(0.0594)	(0.1888)
Log of Updates	-0.0577***	-0.0059	-0.0820***	-0.1847***	-0.0712***	-0.1577***
	(0.0076)	(0.0079)	(0.0117)	(0.0306)	(0.0106)	(0.0311)
Profile	-0.0062	-0.0766**	0.1030*	0.3463**	-0.0116	-0.1752
	(0.0366)	(0.0337)	(0.0552)	(0.1432)	(0.0605)	(0.1752)
Error Correlation	-0.0627		0.9879***		0.9960***	
	(0.1011)		(0.0019)		(0.0008)	
Observations	16,827	16,827	6,082	6,082	7,169	7,169
Log -Likelihood	-19556.26	-19556.26	-9643.521	-9643.521	-9008.531	-9008.531

For brevity, the constant and coefficients for Day of Week dummies, Airline dummies, and Cluster dummies are not reported.
***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parentheses.

Deriving Big Five Personality Traits

For each customer, we derive the "big five" personality traits (i.e., openness, conscientiousness, extraversion, agreeableness, neuroticism), which have long been shown to affect various human behaviors (Goldberg 1993). Traditionally, these personality traits have been measured with the use of personality questionnaires. However, on social media, most people are not willing to spend the extra effort in responding to such questionnaires, making the measurement of personality difficult (Chen et al. 2015). Therefore, deriving personality from people's writings on social media has become an attractive option for the researchers.

Several previous studies successfully derived personality traits from people's writings based on the already established relationship between word use and personality (Fast and Funder 2008; Hirsh and Peterson 2009). Yarkoni (2010) examined web blogs and showed that people's word use reliably correlates with their personality. Several recent research studies focused on people's writings on Twitter and/or Facebook to predict their personality (Golbeck et al. 2011; Golbeck, Robles, and Turner 2011; Gou et al. 2014; Sumner et al. 2012). Almost all of these previous studies used lexicons such as the Linguistic Inquiry and Word Count (LIWC) dictionary to extract word features from text. Although the findings on the accuracy of such lexicon-based personality predictions are mixed, the predicted personality values from some studies have shown moderate correlations with the personality measurements from the questionnaires (Golbeck, Robles, and Turner 2011).

We derived all five traits for each customer in a lexicon-based approach, using the customer's past tweets as input to the LIWC dictionary (Pennebaker et al. 2015). Each trait is computed using the number of words that correspond to the words in a LIWC word category that is known to correlate with the trait. Given a vector containing the correlation coefficients, and a vector containing word counts of corresponding word categories, the trait is computed as the dot product of the two vectors (i.e., a linear combination of the word counts weighted by the correlation coefficients; Chen et al. 2015). For this study, we adopt the significant correlations from Yarkoni, as the correlations are based on a substantially larger corpus in comparison to other similar work (Golbeck et al. 2011; Golbeck, Robles, and Turner 2011; Sumner et al. 2012), and also because their effectiveness of deriving personality traits has been independently validated and used by other researchers (Chen et al. 2015; Gou et al. 2014). We augment our empirical model with the derived big five personality traits, accounting for the likely omitted variable bias due to differences in customer personality.

Training Protocol for Identifying Complaint Tweets

The Merriam Webster dictionary defines a *complaint* as an expression of grief, pain, or dissatisfaction. Accordingly, in this study, any user tweet that expresses a user's grief, pain, or dissatisfaction toward the airline under consideration is categorized as a complaint. In other words, we consider a user tweet as a complaint if it carries negative sentiment toward the airline. This is in line with prior research (Ma et al. 2015) that treated negative messages from customers on Twitter as complaints.

Customer complaints to an airline come in a variety of forms such as expressions of dissatisfaction regarding the following issues:

- **Operational issues**: mishandled baggage, flights delays, flight cancellations, long queues in airports, over-sold flights, in-flight entertainment issues, unsatisfactory meals in-flight, broken seats in-flight, computer system delays, seat change without notification, unfair service charges

- **Employee-related issues**: rude flight attendants, unprofessional gate agents, incompetent workers

- **Issues related to airline's dedicated customer service**: longer than usual on-hold times, calls hung-up by customer care agents, complaints unresolved for a long time, unsatisfactory compensation

- **Disgust toward the airline**: tweets with extreme language, tweets with warnings of potential brand switching

Some sample complaint tweets are listed in Table A6.

Table A6. Sample Complaint Tweets

- @airline Trapped in San Juan trying to get home to Seattle on thrice cancelled flight 1393. No help, no compensation, no apologies!
- @airline I'm so mad! 1st u delay my bags and then you deliver my new brand Perry Ellis bag w/ one wheel torn off!
- The joys of flying @airline! Leave the gate, back to the gate, get off the plane, back on the plane. I'll only be 7.5hrs late...
- @airline told me yesterday they knew where my baggage was and I should have it by noon. Now they are saying they can't locate it. #awful
- @airline been ON the plane for over an hour here in Dallas just wait to fix a light.. Pilot said it would be 20 minutes. Still waiting
- I shoulda taken @Amtrak. @airline y'all playing games today! I shoulda been in NYC by now. #fail
- @airline fail again!! FL1678 BOS-SFO on old 757-300 with NO power, personal ent sys or wifi. Gonna be a long 6 hours. You can do better!
- My arrival into LA gets delayed by 12+ hrs but yet my bags still don't fucking make it here?! Never again @airline, never again.
- Frustration @airline: I was early yet you would charge $75 to grab early flight even with open seats...now my flight delayed #fail cust svc
- Why would you change my seat @airline? Now I'm going to get very airsick stuck by the window. Certainly not the seat I had at check-in.
- disheartened by @airline Cancelled our reservation not once but twice, never informing us...and now it's our problem not theirs...
- Was just hung up on by reservations for @airline who claims my reservation never existed. Astounded at the poor customer service.
- NEVER flying @airline again. Booked window & aisle seats in the same row, was given two middle seats 10 rows apart. Lots more. Avoid – awful
- @airline LAS-EWR First class is a joke. Better get a refund ASAP. Awful!!!
- At this point I have to assume that @airline just loves keeping us waiting on runways until we reach past our boiling point.
- @airline computers go down twice while boarding flight 310 and we aren't even done with the B group. Waiting to reboot
- @airline too disappointed in your service. Left LAX on our honeymoon last Thursday on first class, was treated disgustingly horrible.
- @AmericanAir How is it that you refuse to refund the change fee for moving to a flight that YOU subsequently CANCELLED? #smh #poorservice
- It's not irony that a trip using a voucher from a cancelled @airline flight results in a cancelled flight. That's @airline!
- @airline1 have tried since June to get a refund, still no response. Will start flying @airline2 due very poor customer service from @airline1.
- Hate @airline it's been over a month no response from their "customer service" department as promised. Never fly them!
- Just had the worst customer service call with "Lu" from @airline - borderline aggressive to SkyMiles members - is it time to switch?
- Very disappointed by the lack of professionalism displayed by the @airline gate agent today. His condescension made a bad situation worse
- @airline very unpleasant flight (#2580). Disrespectful flight attendant because my 2y boy not wanting to sit alone but me to hold him.

Using Heckman's Method to Estimate the Joint Model

The response-time model, the response-choice model, and the error correlation structure are summarized below.

$$\ln z = \begin{cases} X\gamma + \eta, & \text{if } y = 1 \\ \text{Unobserved}, & \text{if } y = 0 \end{cases}$$

$$y = \begin{cases} 1 \text{ (responded)}, & \text{if } y^* = X\beta + \varepsilon > 0 \\ 0 \text{ (did not respond)}, & \text{if } y^* = X\beta + \varepsilon \le 0 \end{cases}$$

$$\begin{pmatrix} \eta \\ \varepsilon \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{pmatrix} \right)$$

From the above model specification, we have

$$E[\ln z \mid y = 1] = X\gamma + E[\eta \mid \varepsilon > -X\beta]$$

Using standard results on truncated bivariate normal distribution (e.g., Johnson and Kotz 1972), we know

$$E[\eta \mid \varepsilon > -X\beta] = \rho\sigma \frac{\phi(X\beta)}{\Phi(X\beta)} = \rho\sigma\lambda(X\beta)$$

where $\lambda(\cdot)$ is the inverse Mills ratio for the Normal distribution. Hence,

$$E[\ln z \mid y = 1] = X\gamma + \rho\sigma\lambda(X\beta)$$

To estimate the response-time model, we can use the following procedure which was suggested by Heckman (1979):

1. Estimate β consistently using a Probit model where the dependent variable is the response decision (i.e., y). The estimate of β from the Probit model, $\hat{\beta}$, would be the coefficients of the response-choice model.

2. Compute the estimated inverse Mills ratio for each observation as $\hat{\lambda}_i = \lambda(X_i\hat{\beta})$ using $\hat{\beta}$.

3. Include $\hat{\lambda}_i$ in a regression of $\ln z$ on X_i to obtain the coefficients of the response-time model. The coefficients of $\hat{\lambda}_i$ will be a measure of $\rho\sigma$, from which we can derive the estimated error correlation ρ using additionally the estimated standard deviation, σ, of the disturbance η.

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