Open Voice or Private Message?

The Hidden Tug-of-War on Social Media Customer Service

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Abstract

Firms use social media as a great marketing tool and a convenient platform to deliver customer service. However, due to its public and social nature, social media tends to amplify a brand's successes as well as failures. Reluctant to subject their customer service to public scrutiny, firms are increasingly turning to private messaging on their social media channels for customer service conversations, which amounts to a reincarnation of traditional customer service in the social media era. Nonetheless, whether customers are willing to relinquish their newfound power is unclear. In this paper, we analyze a natural experiment where the inconvenience of the private channel with the treated firm is suddenly eliminated, and we find evidence that customers prefer to complain through the public channel. A randomized survey experiment further confirms this insight. Overall, firms' and customers' diverging preferences toward public or private channel reveal a hidden tug-of-war between the traditional mode of customer service featuring firm control and the recently emerged mode of customer service featuring shared control. These findings have important implications for firms' customer service operations.

Key words: social media, customer service, communication channel, complaint, natural experiment

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Introduction

The issue of customer communication is at the heart of firms' social media operations. For example, consumers and firms extensively use social media to communicate and share their opinions (e.g., Goh et al., 2013; Gu and Ye, 2014). Activities on these social media platforms can affect firms' offline sales (Cui et al., 2016; Wang et al., 2021). Therefore, understanding customer behavior on social media is vital to managing online communication with customers. In this context, customer complaints on social media are especially important as they generate and spread negative sentiments toward a company, thereby hurting its performance.

Hirschman (1970) theorized customer complaints as a reaction when the perceived quality of a good or service is below a customer's expectation. He called such a reaction, *voice,* in contrast to the other type of reaction, *exit*, which involves discontinuing the business-customer relationship. Conceptually, we can further distinguish two types of voices: the *private voice*, which refers to voices solely communicated with the involved party and not visible to the general public, and the *public voice*, which refers to voices that communicate with the involved party and are visible to the general public.

Traditionally, most customer service interactions in the business context are through private voicing, whether delivered in person, by phone, through email, or, more recently, via chatbots. In contrast, social media customer service is delivered through public voicing, which has changed the dynamics and tilted the balance of power between firms and customers. Indeed, the public nature of social media compels firms to address customer complaints in a public manner on platforms such as Facebook and Twitter (He et al., 2018). For example, on Twitter, a disgruntled customer can publicly complain to a firm with the symbol "@," followed by the firm's official Twitter account name. If the firm chooses to respond, it typically replies to the customer publicly on Twitter. If they need to exchange personal information, they can use direct messaging (i.e., DM), the private communication channel on Twitter.

Unlike traditional customer service, delivering customer service publicly is a delicate business, with both opportunities and potential pitfalls. The public display of adequately handling a customer's service inquiry not only improves the brand perception for that customer, but such a positive effect may also spill over to other customers who witness the interaction on social media—a bonus usually unavailable with traditional customer service. By openly responding to a complaining customer rather than ignoring the grievance, the firm also publicly demonstrates its willingness and responsibility to correct its mistake, which is a positive marketing message.

However, such an amplification effect can easily go in the opposite direction. By putting its customer service under public scrutiny, the firm risks *publicly* failing to appropriately address a complaint, which can result in a "double-deviation"— an initial service failure followed by a failed recovery (Grégoire et al., 2009). Such public double deviation can stir up negative word-of-mouth or customer attrition. Recent research suggests that many customers who received customer service through social media felt the same or even worse after interacting with the firm (Gunarathne et al., 2017). Moreover, some researchers have found that complaint publicization can decrease firm value and increase future complaints (Golmohammadi et al., 2021). Hence, the risk of publicly delivering customer service on social media may outweigh the *immediate* benefit of doing so.

That said, avoiding this new public channel is likely an even worse strategy, as avoidance can signal the firm's lack of confidence or openness, especially if its competitors or firms in other industries are already delivering customer service publicly via social media. Therefore, firms' customer service operations on social media have become a sensitive issue that demands careful academic and managerial investigation. Technology firms like Verint have allowed companies to manage private communications across various social media platforms. This naturally attracts the attention of firms that are more comfortable with the private mode of customer service delivery. Some researchers also recommend that firms provide a brief public response to complaints and then take the handling process privately (Golmohammadi et al., 2021). Ironically, if most customers switch to these private channels for customer service interactions, then social media customer service will essentially become a modern reincarnation of traditional customer service in the social media era. In addition, if disgruntled customers only complained privately through social media platforms, there would be fewer negative posts on public display. Therefore, businesses naturally have a strong incentive to encourage customers to complain through private channels.

However, the development of social media customer service has been driven at least in part by consumers who saw this disruptive technology as a way to shift some power from corporations to consumers, and consumers from the new generation may be reluctant to accept the traditional mode of customer service disguised in modern technology. The current paper aims to shed light on this crucial issue by empirically studying the following research question.

Research Question: Do customers on social media prefer communicating with firms through public or private channels?

Intuitively, customers reaching out to a firm might find the public channel attractive because leaving a public message can pressure the firm to respond more promptly. Moreover, because firms are well aware of the fact that customers' public messages are visible to their followers, customers can use their social media influence to their advantage, which can be particularly effective for those with many followers (Gunarathne et al., 2018). On the other hand, specific issues require personal information, which customers might be reluctant to share publicly. In such a case, customers could find the private channel more appropriate. From a privacy calculus perspective (Dinev and Hart, 2006), when the expected benefit of public communication outweighs the potential cost of privacy loss, customers will prefer communicating through the public channel.

Regarding voicing complaints, customers can utilize the public nature of tweets to exert pressure on firms to respond and provide redress. Such benefits can outweigh the potential privacy loss of posting publicly. Therefore, we expect that customers voicing complaints will prefer the public channel more than those communicating non-complaints. Regarding non-complaints, some may include inquiries involving personal information that entails a higher level of privacy loss. Therefore, this type of inquiry will be less likely to be communicated publicly than those that do not involve personal information.

To answer our research question, we take advantage of a natural experiment where a new technological feature suddenly eliminates the inconvenience of private communication with the treated firm. Accordingly, we show that the increased convenience of using the private channel does not lead to any decrease in the use of the public channel when customers complain to the treated firm, compared with control firms that always had this technological feature enabled throughout the observation period. On the other hand, compared with the control firms, a decrease was observed in the use of the public channel when customers contacted the treated firm on social media for reasons other than complaints. A detailed content analysis[1] suggests that customers are likely to decrease the use of the public channel when the nature of the issue likely involves exchanging personal information. These analyses suggest that complaining customers prefer the public to the private channel, in contrast to firms' desire to take complaints to the private channel. Consistent with these results, we further found evidence through a randomized survey experiment conducted on Amazon Mechanical Turk (MTurk) that customers are more likely to engage in public voice when communicating complaints compared with inquiries and other non-complaints.

Overall, firms' and customers' diverging preferences toward the open voice and private message reveal a hidden tug-of-war between the traditional mode of customer service featuring firm control and the disruptive mode of customer service featuring shared control. Since customer communication is an essential aspect of service operations and service recovery is a key operational issue (Craighead et al., 2004; Miller et al., 2000), our research informs firms looking to improve their customer service operations on social media platforms. We recommend that firms assign a dedicated service failure and complaint management team to monitor the public channel and a separate team for more general inquiries on the private channel. We also recommend that firms embrace social media as a source of competitive advantages by utilizing them for business intelligence operations.

The paper is organized as follows: we first review related literature before proposing our hypothesis. Next, we analyze the results of the natural experiment and present a randomized survey experiment. Finally, we summarize this research's contributions and limitations and discuss its managerial implications.

Literature Review

Social Media's Impact on Operations Efficiency

Social media has been identified in the operations management (OM) literature (Kumar et al., 2018) as a key feature that can influence operational efficiency. Devi et al. (2021) argued that social media platforms can facilitate information sharing and exchange among individuals within an organization, among customers, and with other institutions, which may contribute to more efficient operations. Existing studies have investigated the operational value of consumers' data on social media by understanding companies' and users' behaviors on social media (Lee et al., 2018). In a review article, Kumar et al. (2018) summarized recent research progress on the impact of information systems interface on operations management, and they considered social media as an essential domain based on a review of many important studies that analyzed user activities on social media. Additionally, researchers have also explored the relationships between social media and certain operational measures. For example, Chan et al. (2016) proposed a new approach with an application to identify important business factors from unstructured social media data. In

[1] Due to the page limit, the content analysis is reported in E-Companion B.

addition, social media data are extensively used in sales forecasting (Cui et al., 2018, Lau et al., 2018) to improve prediction accuracy, presumably because social media data provide open information about consumers' preferences. Firms can even analyze consumer activities on crowdsourcing communities for new product ideas (Bayus, 2013) or exploit the volume and sentiment of tweets to alleviate the negative impact of operational glitches on stock market performance (Schmidt et al., 2020). Our paper contributes to this broad stream of OM literature by investigating customers' channel preferences on social media, which helps firms gain a deeper understanding of the distinction between public and private channels, thereby better managing their operations.

Staffing Decision and Service Operations

The current research is specifically related to the literature on service operations management (SOM) regarding how organizations utilize information and communication technologies to provide technology-mediated customer service (Froehle and Roth, 2004; Roth and Menor, 2003). Among other themes, recent studies have examined how firms respond to customers' comments on social media (Gu and Ye, 2014), ways to systematically conduct social media data analysis (Chan et al., 2016), and how live chats can help online retailers improve customer service (Sun et al., 2021). Our work is also related to research on staffing and routing in the context of customer contact centers, where companies train employees to provide customer service (Wallace and Whitt, 2005). Contact center operations have been an important area of OM research, among which the staffing issue is a critical component. Gans et al. (2003) and Aksin et al. (2007) provided reviews and tutorials of traditional and emerging challenges associated with call centers.

Modern contact centers often have an infrastructure that implements skill-based routing so that employees with appropriate skills are assigned to handle related customer issues (Sisselman and Whitt, 2009). More recently, Ilk et al. (2020) proposed an ML-based text analytics approach to route incoming customer communications to appropriate agents based on skills and expertise in online live chats. As customers increasingly use social media for customer service, these social media platforms also function as customer contact centers. To better serve customers on different channels, it is essential to have a thorough understanding of customers' channel preferences under various circumstances. To the best of our knowledge, our work is the first to study customers' public and private channel preferences on social media.

Consumer Complaint Behavior

Complaints often result from a disparity between consumers' expectations in the pre-purchase stage and disconfirmation in the post-purchase stage. Different causes of product failure may lead to varying complaints, such as requesting a refund or exchange or demanding an apology from the firm. When deciding whether to complain, customers consider two distinct but related factors (Hirschman, 1970): the perceived probability of a successful complaint and the worthwhileness of a complaint. The former suggests that dissatisfied customers are more likely to voice their complaints when they believe such actions would effectively produce the desired outcomes. The latter refers to the balance between the costs and benefits of complaining, which could be economic (e.g., refunds, exchanged products, time invested in creating the complaint) or psychological (e.g., the satisfaction derived from the act of complaining itself, feelings of embarrassment, stress, and confrontation).

Researchers have long recognized the value of complaints as a means of giving the firm a chance to turn a dissatisfied customer into a satisfied one (Fornell, 1976). However, studies have also investigated the number of potentially helpful complaints that were never received because consumers either did not voice them or quietly discontinued patronage (Stephens and Gwinner, 1998). These studies suggest that firms should make complaining less costly to benefit from the information communicated. Nowadays, firms regularly provide services to address complaints and dissatisfaction, and firms' successful remedial actions, such as giving a refund, exchange, or repair, may be able to help retain customers (e.g., Bolfing 1989). Meanwhile, firms' inappropriate handling of customers' redress requests can lead to negative word-of-mouth and damage businesses (e.g., Blodgett et al., 1995).

Using data from the airline industry, Anderson et al. (2009) found that the effect of service failure on customer satisfaction depends on the origin of failure (i.e., internal or external to the service provider), and Lapré (2011) argued that reducing customers' propensity to complain is a more effective approach to maintaining a competitive advantage than reducing service failure. Moreover, in the social media era, the perceived probability and worthwhileness of a successful complaint are likely to be influenced by the number of potential readers that will read the complaint. Our study contributes to this stream of research and investigates customers' complaint propensity across the public and private channels on social media.

Customer Complaint Channel

At the beginning of this article, we conceptualized two types of consumer voicing: public and private. Communication is categorized depending on whether it is publicly accessible. This dichotomy is distinct from most of the literature. We believe the root cause of our different conceptualizations is the new context of social media customer service. Figure 1 illustrates the conceptual differences. In this figure, the outer circle (i.e., set **C**) includes voices visible to the complainers (i.e., customers), which consists of all customer complaints almost by definition. The middle circle (i.e., set **B**) includes all voices visible to the firm, whether delivered in person, over the phone, or by email. The inner circle (i.e., set **P**) includes all voices visible to the general public (e.g., on the firm's Facebook page or to the firm's official Twitter account) instead of those only visible to the firm or family members and friends.

Our definition of voices over public channels corresponds to set **P** (i.e., the inner circle). In contrast, our definition of voices over private channels corresponds to the set difference **B-P** (i.e., the horizontally shaded area). The set difference **C-B** is excluded from this discussion because they are generally unobservable to researchers. In the literature, Day and Landon (1977) categorized actions by dissatisfied consumers into public actions, e.g., contacting the business to seek redress or pursuing legal actions, and private actions, e.g., boycotting the business or warning friends and family members. Hence, Day and

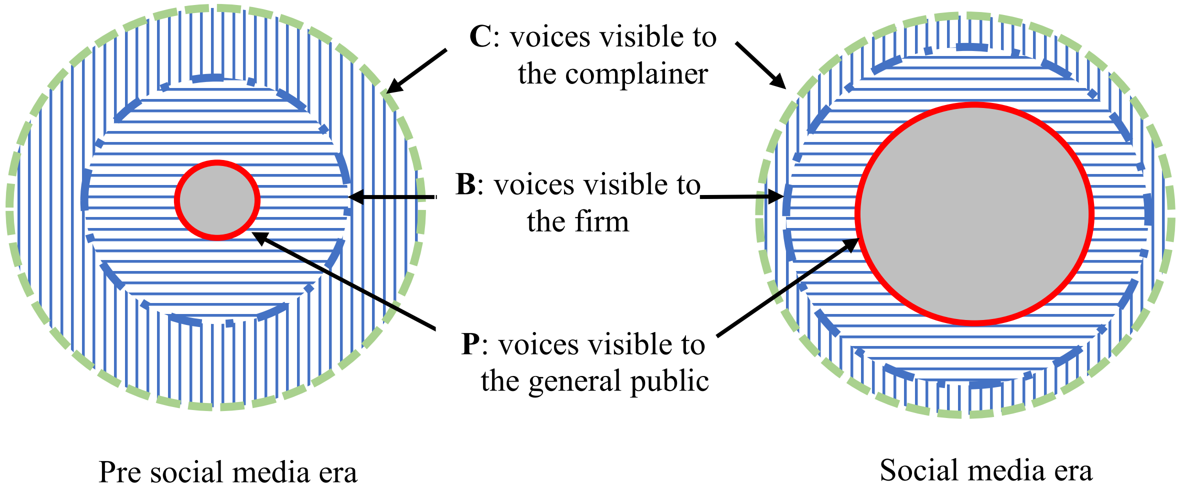

Figure 1: Different Definitions of Public vs. Private Channels

Landon (1977) defined the public voice as set **B** (i.e., the middle circle) and the private voice as the set difference **C-B** (i.e., the vertically shaded area). This taxonomy regarding the definition of public and private complaints is largely followed in later literature (e.g., Balaji et al., 2015; Harrison-Walker, 2001; Mattila and Wirtz, 2004; Singh, 1988). As is succinctly summarized by Balaji et al. (2015), "under these definitions, public complaints are complaints visible for the service provider to see, while private complaints largely remain undetected by the service provider." The only exceptions we found were Grégoire et al. (2009) and Breitsohl et al. (2014). In Grégoire et al. (2009), private complaining is implicitly defined as customers' voicing their concerns only to firms, and public complaining is implicitly defined as customers' going beyond firms' borders to alert the public about a service failure episode. In Breitsohl et al. (2014), three types of electronic complaint channels are distinguished based on their corresponding degrees of communication publicity: forums and websites are considered channels of high publicity; Facebook walls and login blogs are regarded as channels of limited publicity; and emails are considered a channel of no publicity.

To a large extent, the difference between our definitions and most existing definitions in the literature reflects the changing landscape of how customers complain and where firms deliver customer service. For example, before the social media age, most dissatisfied customers would either complain to family or friends in an offline environment or complain to the firm privately, either in person, by phone, or through email or websites. Hence, a dichotomy between sets **B** and **C-B** would be an intuitive way of defining public and private complaints.

With the rise of social media, aggrieved customers increasingly turn to social media sites (e.g., Facebook, Twitter) to voice their frustration and anger, which firms closely monitor. This trend implies the shrinkage of set **C-B** along with the expansion of set **P**. Our definitions of public and private complaints are in line with and motivated by this new reality. Therefore, to minimize confusion while discussing the extant literature, the terms "*public complaint*" and "*private complaint*" are avoided in the current section. Instead, we use more specific and less ambiguous characterizations of the complaining channels discussed in the literature.

The literature on customers' complaint channel choice is sparse. Mattila and Wirtz (2004) found that customers seeking tangible compensation prefer interactive face-to-face communication and phone calls, while those seeking to vent their frustration prefer remote channels, such as letters and emails. Ward and Ostrom (2006) used the protest-framing theory to understand how consumers use rhetorical tactics (injustice, identity, and agency framing) to mobilize mass audiences against a firm. They also analyzed protest sites constructed by dissatisfied consumers and found that consumers "frame" their corporate betrayal to the public to demonstrate their power to influence others and gain revenge. Kietzmann and Canhoto (2013) compared the semi-public nature of Facebook with the public nature of Twitter. They found that customers prefer Twitter for expressing lower-than-expected product and service quality (i.e., negative disconfirmation). Balaji et al. (2015) studied customers' complaining behaviors on social media sites. Applying the justice theory, the researchers argued that customers tend to complain publicly if they feel they are treated unjustly. Such a public action serves as a way to retaliate and seek justice. They also argued that customers might complain publicly if the service failure appears to be permanent and is likely to occur again, as such a public action can help warn fellow customers of similar future service failure. Grégoire et al. (2015) recommended that companies respond to publicly expressed and complicated complaints privately to address issues in detail, while also responding publicly to signal to the public that they are actively working on resolving the issue. Our research contributes to this line of literature by explaining customers' channel choices from a cost-and-benefit perspective.

Social Media Customer Service

There is an increasing number of papers studying the delivery of customer service on social media which can be broadly categorized as those examining firm behavior (e.g., Hu et al. 2019, Gunarathne et al. 2022) and those examining customer behavior. Our paper falls in the latter among which review Berry et al. (2018) is particularly relevant. They studied the effect of customers' personalities on their complaint channel choices, categorizing complaint channels into three levels: active, passive, and delayed. The specific channels considered include face-to-face, offline communication with friends, social media sites, online review platforms, and emails. Most other papers in this category examined customers' voicing decisions without focusing on voicing channels. For example, Chevalier et al. (2018) argued that a customer is motivated to write reviews not only because reviews may impact other customers, but also because reviews may impact the management and the quality of the service. Therefore, the managerial response will stimulate negative reviews that are seen as more impactful in the eyes of customers. However, in the context of customer service on Twitter, Sun et al. (2021) found that although service interventions cause more complaints, such an increase seems to be driven mostly by service awareness. In another study focusing on hotels' management responses, Wang and Chaudhry (2018) found that management responses to users' negative reviews positively impact subsequent user opinion, while management responses to users' positive reviews negatively impact subsequent user opinion. Another interesting perspective is the role of identity information. For example, Chen et al. (2019) argued that the availability of user identity information on review platforms could affect users' motivation to post reviews following hotels' management response adoptions, while Gao et al. (2023) found that the availability of agent identity information can also affect customers' motivation to continue their engagements on social media. Although these papers studied consumers' voicing decisions following firm interventions, they focused only on the public communication channel. In contrast, the present study focuses on customers' communication channel choices instead of the effect of firms' management responses on subsequent reviews.

In a recent study, Golmohammadi et al. (2021) found that firms' public responses to public complaints on Twitter can lead to further complaint publicization and negatively impact the perceived quality and firm value. They provided a normative recommendation that firms limit their public response to one message and continue handling the complaint privately. A key takeaway from their paper is that firms should prioritize taking customers' complaining conversations in a private mode. Therefore, Twitter's direct message functionality should be of great interest to firms as direct messages are private and unobservable to the public. That said, it is unclear whether customers prefer public tweets or private messages when communicating with firms. The answer to this question will play an essential role in understanding the effectiveness of the proposed policy. Our paper explores customers' channel preferences and fills this gap in the literature.

Hypothesis and Empirical Strategy

From the customers' perspective, the new option of publicly complaining to a firm can be empowering, especially for those with a significant social media influence. Indeed, there have been reports suggesting that dissatisfied customers only had their issues resolved after they switched from traditional customer service via telephone to social media customer service.[2] Intuitively, the more people who can potentially see a customer's complaint, the higher the perceived pressure is for the firm to respond. For

[2] Source: http://time.com/3916355/social-media-customer-service/ (Last access: Sept. 4, 2022)

example, Gunarathne et al. (2018) found that firms prioritize complaining customers with a large social media audience. For customers, resorting to the private channel effectively sets the audience size to one instead of their actual number of followers had they used the public channel. Hence, from a strategic point of view, a complaining customer may prefer public voicing to private voicing.

On the other hand, if complaining customers do not anticipate any response or resolution from the firm, then the act of complaining could be explained by the customers' desire for retaliation, which refers to actions intended to punish the firm for violating the norm of fairness. According to the theory of distributive justice (Deutsch, 1985), one of the fundamental principles of fairness is the equity principle, which states that individuals compare their inputs and outputs with others to determine the perceived fairness. When there is an imbalance, an individual will experience distress that will lead to actions to restore equity. Therefore, retaliation against a firm can be interpreted as an act to restore equity in the minds of dissatisfied customers. If the goal is to penalize the firm, voicing publicly is a much more effective way to retaliate than voicing privately only to the firm. Given these two lines of arguments, we propose the following hypothesis for empirical testing:

Hypothesis: *A dissatisfied customer using social media customer service prefers engaging with the firm publicly to doing so privately.*

To test the hypothesis, we utilized a natural experiment from the customers' perspective in 2016 when Delta Air Lines adopted a new Twitter feature. This new feature, referred to in this paper as OpenDM, was first introduced by Twitter in April 2015.[3] It allows a Twitter user to opt-in to receive direct messages from anyone even if the user is not following the potential sender.[4] Once a firm adopts OpenDM, the overhead of private communication for its customers is effectively eliminated, making direct messaging an attractive customer service and communication channel. Indeed, after the adoption of OpenDM, there is no material difference in customers' convenience between complaining publicly on Twitter or privately through direct messaging. If our hypothesis is valid, there should be no statistically significant difference in the number of public complaints before and after the adoption of OpenDM. A statistically significant decrease in the number of public complaints would suggest that some complaining customers who would

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[3] Date source: https://techcrunch.com/2015/04/20/twitter-now-lets-you-opt-in-to-receive-direct-messages-from-anyone/ (Last access: Sept. 4, 2022)

[4] Twitter's direct messaging function is created to prevent unsolicited messages (i.e., spam). Our identification strategy relies on a firm's adoption of a new feature that significantly eases such restrictions. However, because users can send direct messages to their followers, there should be minimal adoption effect for those social media customers the firm followed before the adoption. Hence, our findings do not necessarily apply to those customers. In addition, outlets reported that Twitter granted some accounts the option to receive direct messages from followers without following them back first. (https://mashable.com/2013/10/15/twitter-direct-messages). Because there is limited information about this option, our findings may not necessarily apply to a firm's followers to be more conservative. While it is important to study the channel preference of these customers, it is unclear how to causally identify their preferences in the absence of certain significant policy shocks similar to the one exploited in the current paper. We acknowledge this as a limitation of the current study.

have otherwise complained publicly had chosen to complain privately through direct messaging, which would reject the hypothesis.

To articulate the informal argument above in a rigorous manner, we may consider a Hotelling model (Hotelling 1990). First, we introduce the notion of *voice type*. On social media, customer voices toward a brand can be of different types. For example, at the coarsest level, voices can be categorized as complaints or non-complaints. If we further distinguish between different types of non-complaints, the set of voice types can be as follows: {*complaints, compliments, informational*}. Similarly, we can also distinguish between different types of complaints, either by the severity level or in terms of reasons (e.g., delay, baggage issue), thereby obtaining an even finer set of voice types. We interpret the Hotelling model with a generic voice type in mind so that each empirical test in this section can be perceived as an application of the Hotelling model when a specific voice type is considered. Second, the population of customers in this study consists of all customers who were using the public channel to initiate their conversations with firms *before* the OpenDM policy shock. A small group of customers[5] who firms already followed before the policy shock generally faced less inconvenience in starting a private conversation with firms, hence, were excluded from the population in the current study.

Customers are distributed along the line segment between 0 and 1 based on their preferences over the two options of communication channels, private and public, which are located at the two ends of the interval. The cumulative distribution function of customer location is a strictly increasing function $G: [0,1] \to [0,1]$. Without any cost, a customer's utility from voicing through the public (private) channel is U_{public} ($U_{private}$). There are two types of costs: the mismatch cost and the technical cost. The mismatch cost of a customer choosing a communication channel depends on the customer's location and the unit distance cost $t \geq 0$. Specifically, for a customer located at $x \in [0,1]$, the mismatch cost of using the public channel is tx and the mismatch cost of using the private channel is $t(1-x)$. The technical cost of the public channel is normalized to 0, and the technical cost of the private channel is $c > 0$ before OpenDM and 0 after OpenDM.[6] The total number of customers using the public channel is 1 before the OpenDM policy. After the OpenDM policy, the customer who is indifferent between choosing the public and private channels, if exists, is located at x^*, which is determined by the following condition:

$$U_{public} - x^* t = U_{private} - (1 - x^*)t.$$

Hence, the number of customers who choose the public channel after the OpenDM policy is as follows:

[5] The number of accounts followed by Delta Air Line's official account was fewer than 10,000 in 2016.

[6] Note that c is implicitly used in the equilibrium calculation before OpenDM, leading to the market share of public voice to 1. However, it is not used in our calculation for the equilibrium after OpenDM because the OpenDM policy eliminates it.

$$D = \begin{cases} 0 & \text{if } U_{public} < U_{private} - t \\ 1 & \text{if } U_{public} > U_{private} + t \\ G\left(\frac{U_{public} - U_{private} + t}{2t}\right) & \text{otherwise} \end{cases}.$$

Because the cumulative distribution function is assumed to be strictly increasing,[7] we have $G\left(\frac{U_{public} - U_{private} + t}{2t}\right) < 1$ if and only if $U_{public} < U_{private} + t$. Hence, there are two possible scenarios as explained below and illustrated in Figure 2.

- If D decreases after OpenDM, i.e., $D < 1$, then $U_{public} < U_{private} + t$, suggesting that some customers strictly prefer the private channel to the public channel.
- If D remains unchanged after OpenDM, i.e., $D = 1$, then $U_{public} \geq U_{private} + t$, suggesting that all customers prefer the public channel to the private channel.

Therefore, to infer customer channel preference, the key is to test whether the adoption of the OpenDM policy causes a decrease in the number of customers using the public channel.[8]

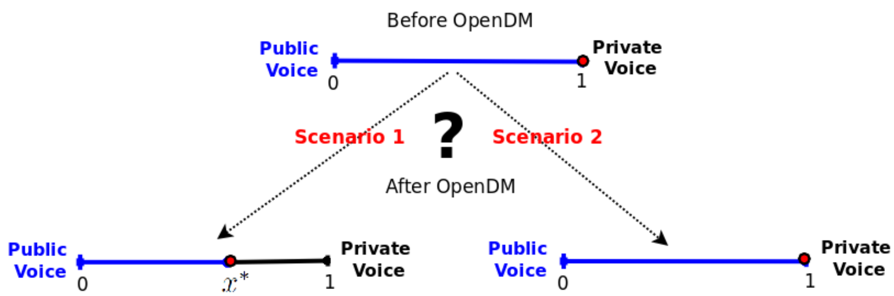

Figure 2: The Hotelling Model

Data and Analyses

The data used for the current empirical testing comes from the U.S. airlines industry, which was chosen as our context because it is one of the leaders in social media customer service. In comparison to other sectors, the airline industry stands out because of its much greater volume and the nature of its social media interactions in real time.[9] According to the SimpliFlying Airline Social Media Outlook Survey[10],

[7] If the cumulative distribution function is not strictly increasing, then it is theoretically possible that the equilibrium has an interior solution (i.e., $U_{public} < U_{private} + t$). Still, there is no decrease in the market share of public voice after OpenDM. However, this does not affect our conclusion in any practical sense because, with such a pathological situation, the total measure of customers located between x^* and 1 (i.e., the black segment) is necessarily zero.

[8] Note that the Hotelling model does not consider customers who use both channels simultaneously because such customers are not part of the Hotelling line.

[9] Source: https://www.kambr.com/articles/how-airlines-embrace-of-social-media-is-evolving-after (Last access: Sept. 4, 2022)

[10] Source: https://genylabs.io/how-social-media-analytics-helps-the-airline-industry/ (Last access: Sept. 4, 2022)

approximately 87% of airline executives used social media analytics to understand their customers. Therefore, analyzing the airline industry's social media data may provide essential insights.

By monitoring the OpenDM status of several business Twitter accounts, we detected that Delta Air Lines adopted OpenDM on March 31, 2016. We obtained tweets received and posted by Delta Air Line, as well as tweets received and posted by three other large U.S. airlines (i.e., American Airlines, United Airlines, and Southwest Airlines) that served as the control group as they adopted OpenDM during the entire observational period from December 1, 2015 to July 31, 2016. The challenge associated with using always-adopters as the control group is analyzed in E-Companion C of the paper.

As customers and airlines sometimes engage in back-and-forth conversations over multiple tweets regarding a single issue, we first organized the tweets into distinct *dialogues.* Specifically, for each tweet in the data set, its metadata was used to determine whether the tweet is a response to another tweet and, if so, the ID and content of the previous tweet. We used this information to trace and construct sequences of tweets that belong to the same dialogue between an airline and a customer. In total, our data set contains 2,392,980 customer-initiated dialogues.[11]

We adopted a supervised learning approach to classify whether a given tweet is a complaint or a non-complaint.[12] Operationally, three annotators were hired to label approximately 3,700 randomly selected customer tweets independently. The inter-rater reliability measure suggested a high level of agreement between the three annotators (Fleiss' Kappa = 0.721). Subsequently, we used the labeled data to train a support vector machine (SVM) classifier.[13] The performance of the SVM classifier is satisfactory and reported in Table A1 in E-Companion A.

Empirical Model

The *treatment group* consists of Delta Air Lines customers while customers of the other three largest U.S. airlines serve as the *control group*. As discussed in E-Companion C, we can identify the pre-treatment ATE instead of the commonly identified post-treatment ATE in a standard DID. Moreover, the pre-treatment ATE can still be estimated using regression DID but with time reversed. Specifically, we estimated the following regression model:

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[11] Note that airlines sometimes post tweets aiming to engage with customers. For example, an airline might ask customers to tweet their favorite vacation destinations, and customers might tweet their replies to the airline. For these dialogues, we treat the customer's first reply as the beginning of each dialogue.

[12] Example complaint and non-complaint tweets are listed in E-Companion A.

[13] We used the SVM model as it achieved the highest f-score based on a 10-fold cross-validation of various machine learning models. Specifically, we trained five machine learning models: SVM, classification tree, random forest, boosting, and bagging. We report the classification performance of these five models in Table A2 of E-Companion A. Note the trained SVM model only classifies a tweet as either a complaint or a non-complaint. It does not classify whether a tweet contains a question or issue.

$$y_{it} = \alpha_0 + \alpha_1 * Treatment_i \times Before_t + \delta_i + Week_t + DayOfWeek_t + \epsilon_{it}.$$

The dependent variable y_{it} is the variable of interest, which, depending on the specific analysis, is either the logarithm of the daily number of complaint or non-complaint dialogues for airline *i* on day *t*, or the dialogue-level averaged logarithm of the number of followers of customers engaging with airline *i* on day *t*. The main independent variable of interest is the interaction term between $Treatment_i$, a dummy variable equal to 1 if airline i is Delta, and $Before_t$, a dummy variable indicating whether day t is before the adoption of OpenDM because we recorded time in reverse and aimed to estimate the pre-treatment ATE. To control for seasonality, the model includes the week of the year fixed effects ($Week_t$) and the day of the week fixed effects ($DayOfWeek_t$). To control for time-invariant airline-specific factors, airline fixed effects (δ_i) are included. Note that as we show in E-Companion C, we need to flip the sign of the estimated coefficient $\widehat{\alpha_1}$ from the regression to obtain the estimate of the pre-treatment ATE.

As our control group consists of three airlines, we also conducted an additional analysis based on a synthetic control method (SCM) in which we constructed a synthetic comparison airline for the treated airline using a weighted average of the outcomes of the three control airlines (Abadie et al., 2010). Again, because all donors are always-adopters, we estimated the pre-treatment ATE by recording time in reverse and flipping the sign of the obtained estimate. We used a data-driven procedure to choose the weights so that the counterfactual outcome values are closest to those of the treated unit after the intervention. The SCM is sometimes considered a generalization of the DID method. We used the same dependent variables in the DID model for the SCM analysis.

We constructed samples using data from four months before and after Delta's OpenDM policy change. Table 1 reports the summary statistics of the main variables, where the values are reported separately for the periods before and after Delta adopts the OpenDM functionality.

Main Results

Table 2 reports the estimation results of the DID model and the SCM. From the coefficient estimates of the interaction term $Treatment_j \times Before_t$ in column 1, after flipping the sign, we found that the number of public non-complaints sent by treated customers reduced significantly after the OpenDM adoption, compared with the control group. This suggests that some non-complaining customers switched to the private channel after the OpenDM feature became available.

In contrast, from column 2, the number of public complaints sent by treated customers did not seem to be significantly affected by the OpenDM adoption. Specifically, the magnitude of the treatment effect (0.00608) is close to zero. In other words, after introducing the OpenDM feature that significantly improved customers' convenience to communicate privately with a firm, complaining customers continued

Table 1: Summary Statistics

		Number of Observations = 972				
Variables	Description		mean	s.d.	max	min
num_tweets	Daily number of tweets received	before	1106.308	737.667	7196	305
		after	1303.574	1062.788	14762	317
log_followers	Daily average log(number of followers for customers that initiated a dialogue)	before	5.622	0.207	6.384	4.864
		after	5.596	0.250	6.319	3.820
num_complaint	Daily number of complaint tweets received	before	653.585	595.282	5899	103
		after	741.080	646.387	9125	134
num_noncomplaint	Daily number of non-complaint tweets received	before	452.723	203.915	2028	176
		after	562.494	558.971	7466	182
avg_followers_complaint	Daily average log(number of followers for customers that initiated a complaint dialogue)	before	5.432	0.204	6.023	4.729
		after	5.428	0.185	6.088	4.847
avg_followers_noncomplaint	Daily average log(number of followers for customers that initiated a non-complaint dialogue)	before	5.865	0.263	6.805	5.058
		after	5.813	0.376	6.649	3.571

to engage with the firm publicly. To statistically reject the null hypothesis that complaining customers switch from the public to the private channel upon introducing the OpenDM feature, we operationalized the null hypothesis with various thresholds of customer switching. Specifically, we hypothesized the null hypothesis with four thresholds, which state that at least 2.5%, 5%, 7.5%, or 10% of the complaining customers switched to the private channel in response to OpenDM, respectively; these four thresholds translate to the statement that the coefficient of the interaction term *Treatment* * *Before* as reported in column 2 of Table 2 is greater than or equal to 2.5%, 5%, 7.5%, and 10%, respectively. These hypothesis tests allow us to operationalize the rejection of the null hypothesis and to statistically establish an upper bound of the size of the potential treatment effect. Based on the test results reported in Table 3, we conclude that the reduction of complaint tweets, if any, could not be larger than 7.5%.

We ran another regression by including complaints and non-complaints in the analysis with a three-way interaction of the *Treatment* dummy, *Before* dummy, and another dummy representing *whether an observation corresponds to non-complaints.* The estimation result is reported in column 3 of Table 2. The result shows that, compared with complaints, there is a larger quantity reduction for non-complaints after the OpenDM shock. Specifically, the treated airline received about 19 percent more reductions in non-complaints than complaints. In addition, the estimated treatment effect on complaints is insignificant, and the magnitude is close to zero.

We also found qualitatively similar results from the SCM analysis with time recorded in reverse as shown in columns 4–5 of Table 2. Based on the average treatment effect on the treated (ATT) estimators, we found that only the number of non-complaints decreased significantly after OpenDM. We visualized the estimated ATT using data aggregated at the weekly level, as well as compared the actual and estimated counterfactual outcomes in Figure 3.[14]

Overall, our empirical evidence suggests that most complaining customers prefer to complain publicly.

Table 2: Effect of OpenDM on Channel Choice

	Channel choice				
	DID			SCM	
	Non-complaint	Complaint	All	Non-complaint	Complaint
	(1)	(2)	(3)	(4)	(5)
Treatment*Before	0.186***	-0.00608	-0.00608	0.188*	-0.0589
	(0.0499)	(0.0488)	(0.0614)	(0.100)	(0.0510)
Treatment*Before *Non-complaint			0.192**		
			(0.0868)		
Two-way interactions			Yes		
Airline fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
# observations	972	972	1,944	972	972
R-squared	0.304	0.486	0.311		

Note: This table reports the main results using the DID model and SCM. All regressions include day of week fixed effects, week fixed effects, and airline fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: One-sided Tests for the Effect of OpenDM on Complaints

	Complaint			
Threshold	2.5%	5%	7.5%	10%
	(1)	(2)	(3)	(4)
Corresponding Null hypothesis	α_1>2.5%	α_1>5%	α_1>7.5%	α_1>10%
p-value	0.262	0.126	0.049**	0.015**
Reject H0	No	No	Yes	Yes

Note: This table reports the one-sided tests of the treatment effect on complaint tweets. α_1 is the coefficient associated with the interaction term *Treatment * Before.* *** p<0.01, ** p<0.05, * p<0.1.

[14] Figure 3 visualizes SCM's actual and counterfactual outcomes with the weekly data as it is visually more illustrative due to the smoothness of the curve. The figure using daily data has similar patterns.

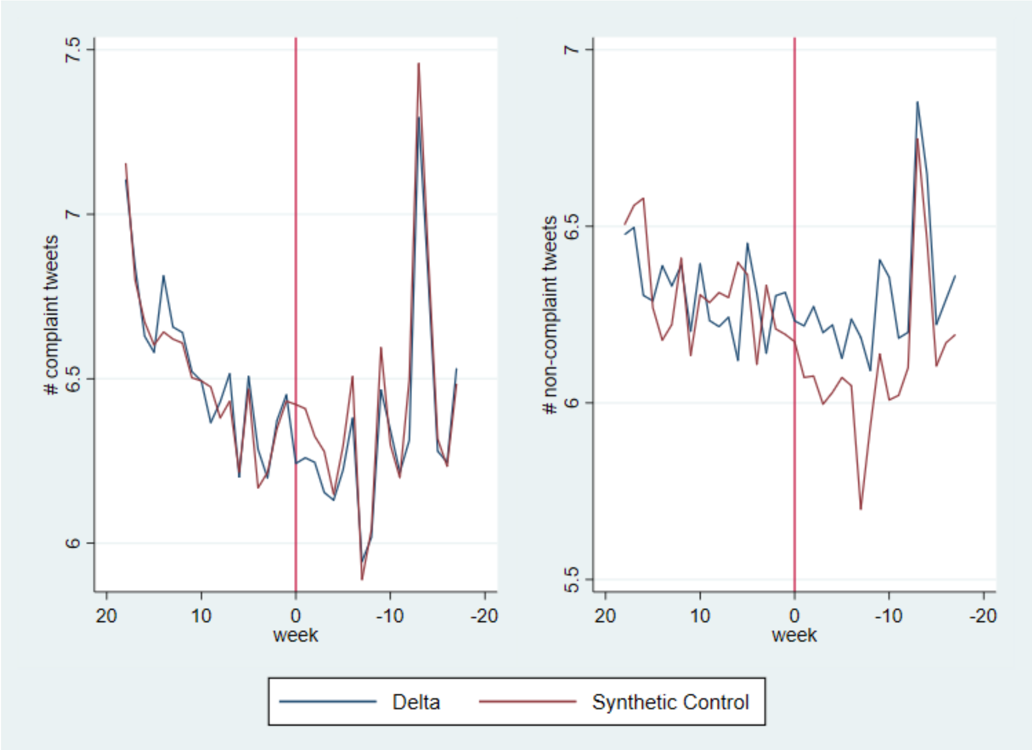

Figure 3 Treated and Counterfactual Averages using SCM

Robustness Checks

Four-class classification. In the main analysis, we classified all dialogues as complaints or non-complaints based on an SVM classifier. The output binary class could be sensitive to the threshold used in SVM, and one may be concerned about misclassification that could lead to measurement errors. Therefore, we categorized all dialogues into four groups based on the predicted (complaint) score to alleviate this concern. Specifically, we assigned a *complaint score* to each dialogue based on the output of the SVM classifier, which reflects the probability that a given dialogue is a complaint.[15] We then categorized the dialogues into four groups based on their complaint scores: dialogues categorized into group 1 are least likely to be complaints (with scores between 0 to 0.25), while those in group 4 are most likely to be complaints (with scores between 0.75 to 1). We replicated the DID and SCM analyses using this four-class classification, and we reported the results in Table 4. All results are qualitatively the same as those based on the two-class classification.

Parallel trend. With always-adopters as the control group, the parallel-trend assumption requires the treated and control groups to exhibit similar temporal trends *after* the treatment. To test this, we

[15] The probability estimate of the SVM classifier is generated through Platt scaling, as SVM does not output probability estimates by default.

examined the time-varying changes in the number of dialogues separately for complaint and non-complaint dialogues. We used Delta's data after the OpenDM shock and analyzed them in consecutive two-week periods. Table 5 reports the estimation results where we used the bi-week period that follows the OpenDM adoption date as the baseline period. The results show that there were no statistically significant changes in each of the bi-week periods after the OpenDM adoption, indicating our data supports the parallel trend assumption required for our specific econometric model.

Channel preference and social media influence. Thus far, we have found statistical evidence that complaining customers prefer the public channel, while some non-complaining customers prefer the private channel. Data limitation precludes a direct test of customers' channel preference for social media customer service. A useful robustness test is to examine further whether and how the composition of customers who choose the public channel changes after the OpenDM shock. In particular, the interest lies in detecting potential composition changes regarding customers' social media influence. Such a test could serve as a robustness check for our main results for two reasons.

First, since we saw no change regarding the complaint volume before and after the OpenDM adoption, a lack of compositional change of complaining customers regarding social media influence could alleviate the concern of time-varying omitted variables.

Second, one of the key arguments leading to our hypothesis is motivated by the firm's perceived urgency and pressure to respond quickly when a customer's complaint is visible to many people. This argument should also apply to a non-complaining customer seeking information, especially if the customer has a large follower base because firms might want to demonstrate that they respond quickly to public inquiries. Therefore, after the OpenDM shock, customers with a large follower base may find it advantageous to continue using the public channel for inquiries more so than customers with a smaller follower base. In other words, customers with a small number of followers are potentially more likely to switch to the private channel after OpenDM.

To implement the test, we replaced the dependent variable in the main analysis with the daily average log-transformed number of followers of customers who chose the public channel. The intuition is that the daily average number of followers would increase (decrease) if customers with a small (large) number of followers are more likely than those with a large (small) number of followers to switch to the private channel when they engage with a firm. The results, reported in columns 1–3 of Table 6, indicate that the coefficient of the interaction term is negative and significant for non-complaint dialogues, which

Table 4: Effect of OpenDM on Channel Choice (4-Class Classification)

	DID				SCM			
DV: log number of dialogues	Group 1 (0-0.25)	Group 2 (0.25-0.50)	Group 3 (0.50-0.75)	Group 4 (0.75-1)	Group 1 (0-0.25)	Group 2 (0.25-0.50)	Group 3 (0.50-0.75)	Group 4 (0.75-1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment *Before	0.173***	0.167***	0.0670*	-0.0597	0.229***	0.251***	-0.0259	-0.0244
	(0.0348)	(0.0433)	(0.0397)	(0.0449)	(0.0494)	(0.0901)	(0.138)	(0.0892)
Airline fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.850***	6.158***	6.459***	7.398***				
	(0.0447)	(0.0479)	(0.0535)	(0.0570)				
# observations	972	972	972	972	972	972	972	972
R-squared	0.805	0.396	0.675	0.791				

Note: This table reports the treatment effects using a 4-class classification. We interact the Treatment dummy with the Before dummy for each group. All regressions include day of week fixed effects, week fixed effects, and airline fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Change in Social Media Followers, Operating Flights, Disrupted Flights, and Mishandled Baggage

	# followers	# flights	# delayed flights	# disrupted flights	#mishandled baggage
	(1)	(2)	(3)	(4)	(5)
Treatment * Before	-0.00894	-0.0123	0.0593	0.0385	-0.00215
	(0.0103)	(0.0194)	(0.141)	(0.133)	(0.0448)
Airline fixed effects	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
# observations	935	72	72	72	72
R-squared	0.914				

Note: This table reports results showing how firms' flight operations changed before and after the OpenDM shock. We interact the Treatment dummy with the Before dummy. All regressions include month fixed effects and airline fixed effects. *** p<0.001, ** p<0.01, * p<0.05.

means that, after the OpenDM shock, the average number of followers *increased* for non-complaining customers. This is consistent with our reasoning that customers with a large follower base are more likely to continue using the public channel. On the other hand, the interaction term coefficient is insignificant for complaint dialogues, suggesting a lack of compositional change in complaining customers.

Table 5: Parallel Trend Analysis

	Channel choice	
DV: daily number of dialogues	Non-Complaint (1)	Complaint (2)
Treatment*Biweek$_{t+1}$	-0.231	-0.136
	(0.154)	(0.174)
Treatment*Biweek$_{t+2}$	-0.0335	-0.267
	(0.154)	(0.174)
Treatment*Biweek$_{t+3}$	0.0703	-0.243
	(0.154)	(0.174)
Treatment*Biweek$_{t+4}$	-0.149	-0.117
	(0.154)	(0.174)
Treatment*Biweek$_{t+5plus}$	-0.126	-0.135
	(0.123)	(0.139)
# observations	488	484
R-squared	0.377	0.180

Note: This table reports the parallel trend test for the DID analysis using always-adopter as the control group. All regressions include day of week fixed effects, week fixed effects, and airline fixed effects.

Negative binomial model. In our main analysis, we used the log-transformed number of dialogues to handle the skewed distribution of the (non-negative) dependent variable in the linear regression model. An alternative approach is to use a count data model. Hence, to check the robustness concerning functional specification, we estimated a negative binomial model where the number of dialogues is the dependent variable. Columns 4–6 of Table 6 report the estimation results. Overall, we found that the results are qualitatively the same as the main results.

Table 6: Main Effect Analysis Using Social Media Influence and Negative Binomial Model Analysis

	Social Media Influence			Negative Binomial		
	Non-complaint	Complaint	All	Non-complaint	Complaint	All
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment *Before	-0.386***	0.00129	0.00129	0.254***	0.0178	0.00765
	(0.0362)	(0.0249)	(0.0262)	(0.0494)	(0.0484)	(0.0565)
Treatment*Before*Non-complaint			-0.387***			0.253***
			(0.0441)			(0.0811)

Two-way interactions			Yes			Yes
Airline fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
# observations	972	972	1,944	972	972	1,944
R-squared	0.259	0.202	0.487			

Note: This table reports the results on social media influence and the main results using a negative binomial model. All regressions include day of week fixed effects, week fixed effects, and airline fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Alternative Explanations. Could it be that some customers who never would have complained publicly decided to do so precisely because of the OpenDM shock, while others who would have complained publicly switched to the private channel because of OpenDM? Or, to put it another way, could it be that these two opposite effects of the same cause (i.e., OpenDM) largely canceled out, leading to the overall result that the total number of complaints did not decrease much despite the shock caused by OpenDM?

While this cancellation explanation might be possible, at least theoretically, we do not think it is plausible because it is unlikely that customers who would not have complained publicly without OpenDM would now do so because of OpenDM. After all, OpenDM only decreased the cost of private but not public communications. Hence, we believe our explanation that customers prefer to complain publicly offers a much more straightforward and plausible mechanism underlying the observation that the number of public complaints did not decrease after the OpenDM shock.

Nevertheless, we examine one potential mechanism for this cancellation explanation. Namely, OpenDM might have increased the popularity of the airline's Twitter account and attracted more customers to complain. To assess this possibility, we first collected the log-transformed number of followers of each airline's official Twitter account at the end of each day to measure the airline account's popularity. We then conducted a DID analysis using this new variable as the dependent variable. The result, reported in column 1 of Table 7, shows that the DID coefficient is not significant, suggesting that the popularity of the airline's Twitter account did not change after the OpenDM shock.

A common threat to the validity of DID identification is time-varying confounding factors. In our context, is it possible that Delta Airlines experienced some quality shocks? Or, maybe there is a major change in flight operations. To alleviate such concerns, we collected information about U.S.-based airlines' flight delays[16] and baggage mishandling[17] from the Bureau of Transportation Statistics. The former data

[16] Data source: https://www.transtats.bts.gov/OT_Delay/OT_DelayCause1.asp (Last access: Sept. 4, 2022)
[17] Data source: https://www.transportation.gov/lost-delayed-or-damaged-baggage (Last access: Sept. 4, 2022)

includes each U.S.-based airline's monthly number of flights and the number of flights delayed or canceled for each airport. The latter data represents the numbers of checked bags that are lost, damaged, delayed, or pilfered, as reported by or on behalf of the passengers. The intuition is that if there were no significant changes in the numbers of total and delayed flights and the number of mishandled baggage, then it would be unlikely that unobserved quality shocks drove the observed results.

Given the relatively small number of observations available at the monthly level, we applied the SCM on a prolonged data set that contains twelve months of pre-treatment and six months of post-treatment data. The dependent variable is an airline's monthly total number of flights, delayed flights,[18] disrupted flights (e.g., delayed, canceled, or diverted flights), and mishandled baggage. Following our main analysis, the *Treatment* variable equals 1 for Delta and 0 for United, American, and Southwest airlines. The *Before* variable equals 1 if month *t* is before March 2016. The results are reported in columns 2– 5 of Table 7 and show that the estimated coefficients of the *Treatment* and *Before* interaction are not statistically different from zero across different settings. In other words, we did not find evidence that Delta experienced any significant quality shift around the time it enabled OpenDM.

Content Analysis. Based on our main results, only the number of public non-complaints significantly decreased after Delta adopted OpenDM. We further investigated which types of non-complaints were more likely to shift to the private channel. To this end, we adopted a deep learning approach to analyze which topic(s) of tweets decreased in number after the OpenDM adoption. The results show that the adoption of OpenDM mainly shifted customers' non-complaint tweets on flight delays, cancellations, and flight experiences. Details of the content analysis are presented in E-companion B.

Randomized Survey Experiment

While the OpenDM natural experiment provides us with a real-world setting to study our research question, the inference and evidence are both indirect. To complement that, we conducted a randomized survey experiment to directly elicit customers' channel preferences in hypothetical air travel-related scenarios.

Survey Design

The survey consists of ten scenarios, each corresponding to an air travel-related communication occasion. These ten scenarios contain both complaint-related and inquiry-related occasions. For each scenario, we instructed the survey respondents to compose a message to send to a hypothetical airline. We asked the respondents to decide which channel(s) to send the message by selecting one of the following

[18] We followed the definition of delayed flights from the Bureau of Transportation Statistics. A flight is considered delayed when it arrives 15 or more minutes later than scheduled.

options: (1) tweet publicly, (2) DM privately, and (3) tweet and DM simultaneously. We report the list of scenarios in Table A6 in E-Companion A.

Additionally, each respondent was randomly assigned to have one of three predetermined numbers of followers (50, 250, and 25,000) that reflects their social media influence. These numbers are roughly the 25th, 50th, and 75th percentiles in the distribution of Twitter users' number of followers, respectively. We reminded the respondents of their follower numbers before evaluating each scenario. At the end of the survey, the respondents answered demographic questions including gender, age, income, education level, how long they have been a Twitter user, and how many flight segments they usually take in a typical year.

Results from Survey Data

Following the literature (e.g., Huang et al., 2019; Lee et al., 2019), we conducted the randomized survey experiment on MTurk, where the survey respondents were required to be US-based and have an approval rating of 99% or above to be eligible, resulting in a total of 252 valid responses.[19] As we asked the respondents to construct complaint or inquiry messages based on different scenarios, we conducted between-group t-tests to verify that the messages written in response to the complaint scenarios were more negative than those to the inquiry scenarios. The results, shown in the first row of Table 10, indicate that the messages written in response to the complaint scenarios were significantly more negative than those to the inquiry scenarios, suggesting that the respondents followed the survey instruction.[20]

Next, we examined whether respondents' channel preferences differed based on scenario types. First, based on the numbers reported in the fourth row of Table 10, most respondents chose to use just one channel. Additional t-tests reported in the second and third rows of Table 10 show that the likelihood of choosing the public (private) channel is higher when voicing complaints (inquiries).

To further control for respondent-level characteristics, we conducted linear and logit fixed-effects regressions to estimate the effect of scenario type on channel preference. We constructed a dummy variable, *only_public*, to represent respondents' channel selections as the dependent variable. The main independent variable of interest is the non-complaint dummy. The regression results are reported in columns 1–2 of Table 11. The estimated coefficients of the non-complaint dummy are negative and significant in both specifications, indicating that respondents were more likely to choose the public channel when voicing complaints.

Lastly, we explored whether respondents' hypothetical social media influence moderated their channel preferences. Specifically, we examined whether respondents with more followers were more likely to choose the public channel than respondents with fewer followers. We labeled respondents who were

[19] The survey was published on MTurk through the Cloud Research platform, which monitors response quality through filters including IP address, geocode block, and country location, among others.
[20] The message sentiment was analyzed using Python's VADER package.

randomly assigned to the three different levels of social media influence as small (50), medium (250), and large (25,000), respectively. The results are reported in columns 3–4 of Table 11. Similar to our main findings, we found non-complaint messages to be less likely to be sent publicly, but respondents with larger social media influence had a higher probability of choosing the public channel.

Overall, the randomized survey experiment results are consistent with those from the natural experiment, where we found that customers continued to utilize the public channel for complaints despite the availability of a private channel.

Table 10: T-Test Results of Survey Data

	Complaint group	Inquiry group	Difference in means	t-statistics
Sentiment	-0.138	0.158	-0.296	-18.137***
Only public	0.350	0.241	0.109	6.021***
Only private	0.420	0.637	-0.217	-11.155***
Both channels	0.230	0.122	0.108	7.181***

Note: This table shows the two-sample t-tests on the mean values of sentiment and channel preference for complaint and inquiry messages.

Table 11: Effect of Scenario Type on Channel Preference

	Dependent Variable: Choosing Only the Public Channel			
	Main Specification		Moderation of Social influence	
	(1)	(2)	(3)	(4)
	linear	logit	linear	logit
Non-complaint	-0.109***	-0.690***	-0.173***	-1.101***
	(0.0200)	(0.143)	(0.0356)	(0.265)
Non-complaint*medium			0.0832	0.581**
			(0.0509)	(0.278)
Non-complaint*large			0.107**	0.637**
			(0.0472)	(0.285)
Respondent FE	Yes	Yes	Yes	Yes
# Observations	2,520	2,520	2,520	2,520

Note: This table reports regression results on the effects of complaint and social media influence on survey respondents' channel choice. Standard errors are clustered at the respondent level in columns 1 and 3. Bootstrap standard errors in columns 2 and 4. *** p<0.001, ** p<0. 01, * p<0.05.

Contributions and Limitations

In this paper, we studied consumers' preference between public and private channels for social media customer service. While firms hope to steer customer complaints away from the public space, we found through a natural experiment and a randomized survey experiment that complaining customers prefer to do so publicly. In contrast, some non-complaining customers, especially those without much social media influence, prefer to do so privately.

We believe the current paper significantly contributes to the literature by deepening our understanding of social media customer service. First, by explicitly differentiating public channels from private channels based on the different degrees of visibility of customer complaints, we offered a useful conceptual framework to understand an important but largely overlooked aspect of customer service in the social media era. The coexistence of public and private channels is a fundamental feature of social media customer service, which is absent in all traditional forms of customer service where firm-customer interactions, whether delivered in person, by phone, through email, or via live chat, are designed to be private. Indeed, as discussed in the literature review, the definitions of public and private channels have been ambiguous and inconsistent in previous literature.

Second, we provided the first empirical evidence on the divergence of firms' and customers' preferences regarding public versus private voicing channels. Because existing literature offers little insight into customers' preferences regarding the public and private channels of customer service, our study provides a starting point for future research. More importantly, customers' and firms' diverging preferences toward open voice and private message suggest a hidden tug-of-war between the traditional mode of customer service featuring *firm control* and the new mode of customer service featuring *shared control*. We believe this insight is new to the literature and is valuable to customers, firms, and society, especially given the recent trend of shifting social media customer service to private channels, including Twitter's direct message, Facebook messenger, and text messages.

The current paper has several limitations that future studies can address. First, we do not observe customers' direct messages in the natural experiment because of the private nature of the data. If researchers could collaborate with firms to obtain such private messages, they could essentially see the other side of the coin and conduct a DID analysis using private messages, which will complement the current study. Moreover, because the adoption of OpenDM may cause some customers who would otherwise refrain from complaining to do so privately, they can further study the interesting question of whether OpenDM causes customers to switch from no voice to private voice. Second, although the airline industry is a pioneer in conducting customer service on social media, exploring the generalizability of our results by studying OpenDM shocks that affect other industries will be worthwhile. Future researchers who have access to data from other industries could investigate whether product or service characteristics may moderate the effect. Third, research with field data is required to study the voice decision and channel choice jointly at the individual level, which can help us better understand the underlying behavioral mechanism. Fourth, we only analyzed Twitter in the current study. Future studies could investigate the extent to which our results can be generalized to other social media platforms.

Managerial Implications

Our research provides practical recommendations for companies hoping to manage their social media customer service operations. We argue that practitioners need to undergo a fundamental mindset shift regarding their use of social media for customer service. Specifically, managers can improve their customer service operations by (1) reallocating staffing resources, (2) improving social media listening and intelligence operations, and (3) streamlining the complaint process. Overall, our recommendations highlight the importance for operations managers to transition from treating social media as a passive communication channel to embracing it as a source of competitive advantages.

First, because service recovery is a key operational issue (Miller et al. 2000), an effective and speedy recovery is essential in preventing double-deviation (Grégoire et al. 2009). Our research shows that customers continue to engage with firms publicly to voice complaints and may only prefer the private channel for non-complaints. Such a customer self-selection means that firms should staff customer service representatives well-trained in complaint resolution and de-escalation for the public channel, while staffing service representatives knowledgeable in traditional customer support for the private channel. This division of labor is beneficial both to the firm and to its customers because the skills required to calm an emotionally charged customer voicing their discontent publicly on social media are more complex than merely finding a plug-and-play solution, which is probably sufficient for most inquiries that are communicated privately. In fact, we encourage B2C firms, especially those in the hospitality industry, to establish a dedicated public relations (PR) team within their customer service departments to only manage customer complaints on public channels. Such a staffing strategy can increase the efficiency of customer service operations and prevent a potential social media crisis from happening in the first place. This is much more cost-effective than engaging in PR management after negative posts on social media spiral out of control.

Second, our findings suggest that firms can conduct an effective intelligence operation by monitoring the public channels of firms in the same industry because customers tend to complain through public channels. For example, firms may mine public tweets posted by customers of their competitors to identify operational areas where their competitors are falling short. By doing so, firms can anticipate potential issues within their own operations and take necessary steps to prevent them. Similarly, by mining public tweets posted by customers of downstream or upstream firms in the supply chain, firms can more proactively manage potential disruptions to their supply chain operations. In summary, since customers tend to share their complaints publicly, which can provide important diagnostics to the underlying business operations, and as business operations become increasingly interconnected, firms can take advantage of such valuable information to better manage their own operations.

Third, because our study shows that customers tend to use the public channel for complaints when both channels are equally convenient, firms wishing for an improved public sentiment as a result of customers switching to the private channel[21] will be disappointed. Although firms seem to be nudging complaining customers toward private channels by responding more promptly in private channels, dissatisfied customers do not seem to be easily persuaded. On the contrary, because of self-selection when customers choose between open voice and private message, negative voices are more likely to remain in public view, which, ironically, defeats the myopic motivation of promoting private social media customer service for a more positive brand image online. Moreover, Twitter already warned in a blog post[22] that "*it's important to treat both types of messages with equal priority*." Instead, firms struggling to maintain a positive brand image on social media should consider investing in a dedicated and customer-friendly online portal that specializes in accepting and handling private complaints. To make this online portal attractive, firms need to ensure a streamlined and intelligent process by, for example, incorporating pre-filled forms and drop-down lists to minimize the cost for customers. At the very least, customers should find it much easier to complain through such a portal than to complain by composing their own sequence of messages on social media.

Concluding Remarks

For consumers, forsaking the public channel to rely entirely on the private channel of social media customer service will be a step backward institutionally, even though it might be a step forward technologically. From the firm's perspective, the good old days of the traditional mode of customer service are likely gone for good. As United Airlines' former CEO Oscar Munoz lamented after his widely criticized response[23] to a PR crisis, "*It's a new era with regard to social media and it's just something we have to adapt to and accept*." Likewise, firms should recognize and accept the coexistence of the public and private channels of social media customer service.

Whatever the strategic motivation is, and no matter how it is delivered, customer service, at its core, is about fairness: customers want to be treated fairly. In this new era of disruptive technologies, we believe the only way for firms to truly harness the power of social media customer service is to embrace the new

[21] For example, Conversocial (now part of Verint), a social media customer service software provider, quoted the customer management center at Argos the following arguments for its product: *Messenger Customer Chat supplements existing live chat and gives our customers a familiar and convenient way to contact us, while allowing Argos to further promote private messaging as a channel, reducing instances of public complaints while increasing customer satisfaction and convenience.*
[22] Source: https://blog.twitter.com/marketing/en_us/a/2016/best-practices-using-direct-messages-for-customer-service-0.html (Last access: Sept. 4, 2022)
[23] Source: https://www.nytimes.com/2017/04/14/business/united-airlines-passenger-doctor.html (Last access: Sept. 4, 2022)

level of openness and transparency enabled by technologies and not to look back. As the old parable goes, "And no man puts new wine into old bottles; else the new wine will burst the bottles, and be spilled, and the bottles shall perish."

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Open Voice or Private Message?

The Hidden Tug-of-War on Social Media Customer Service

E-Companion A

Table A1: Performance of the SVM Classifier on 3,700 Tweets Using 10-Fold Cross Validation

	Accuracy	Precision (+)	Recall (+)	F1 (+)	Precision (-)	Recall (-)	F1 (-)	AUC
Fold 1	0.80	0.68	0.70	0.69	0.85	0.84	0.84	0.77
Fold 2	0.78	0.77	0.66	0.71	0.78	0.86	0.82	0.77
Fold 3	0.76	0.78	0.63	0.70	0.75	0.87	0.81	0.77
Fold 4	0.77	0.80	0.62	0.70	0.76	0.89	0.82	0.78
Fold 5	0.81	0.81	0.69	0.75	0.81	0.89	0.85	0.81
Fold 6	0.76	0.83	0.61	0.70	0.73	0.90	0.81	0.78
Fold 7	0.81	0.78	0.65	0.71	0.82	0.90	0.86	0.80
Fold 8	0.71	0.74	0.50	0.60	0.69	0.87	0.77	0.72
Fold 9	0.79	0.75	0.62	0.68	0.81	0.89	0.85	0.78
Fold 10	0.82	0.77	0.67	0.72	0.84	0.90	0.87	0.81
Average	**0.78**	**0.77**	**0.64**	**0.70**	**0.78**	**0.88**	**0.83**	**0.78**

Note: This table reports the SVM classifier's performance in the case of binary classification. The (+) symbol represents the positive case (complaints), and the (-) symbol represents the negative case (non-complaints).

Table A2: Classification Performance of Different Models

Case	Classifier	Precision	Recall	F-Score
-	SVM	0.787	0.88	0.831
-	FORESTS	0.781	0.855	0.815
-	LOGITBOOST	0.709	0.927	0.803
-	BAGGING	0.698	0.927	0.794
-	TREE	0.637	0.987	0.773
+	SVM	0.773	0.63	0.693
+	FORESTS	0.733	0.627	0.674
+	LOGITBOOST	0.778	0.407	0.533
+	BAGGING	0.761	0.375	0.501
+	TREE	0.829	0.118	0.204

Table A3 DID Analysis with Additional Control Variables

	DV: Number of Tweets			DV: Social Media Influence		
	Non-complaint	Complaint	All	Non-complaint	Complaint	All
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*Before	0.218**	0.00753	0.0168	-0.417***	-0.0322	-0.0310
	(0.0589)	(0.0568)	(0.0669)	(0.0501)	(0.0309)	(0.0395)
Treatment*Before* Non-complaint			0.192**			-0.387***
			(0.0866)			(0.0511)
Lag_follower	0.0131	-0.0402	-0.0135	0.00724	-0.0328	-0.0128
	(0.0433)	(0.0417)	(0.0611)	(0.0368)	(0.0227)	(0.0222)
Lag_delay	-0.0611	0.122	0.0307	0.104	-0.0147	0.0444
	(0.116)	(0.112)	(0.101)	(0.0987)	(0.0610)	(0.0594)
Lag_complaint	0.123	0.384***	0.254***	-0.137**	-0.153***	-0.145**
	(0.0818)	(0.0789)	(0.0709)	(0.0695)	(0.0430)	(0.0419)
Airline fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
# observations	972	972	1,944	972	972	1,944
R-squared	0.305	0.501	0.316	0.245	0.162	0.484

Note: This table reports the results of a DID analysis with additional control variables to account for potential changes in service quality. These control variables include the lagged number of followers, number of mishandled baggage, and number of complaints each airline received. The data comes from the U.S. Department of Transportation. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Sample Complaining and Non-Complaining Tweets Delta Air Lines Received

Complaints	**Non-Complaints**
	


Fern C
@fer_cucci

@Delta you guys have the WORST first class service for internal flights within the US -- not happy with this terrible service at the moment.

3:03 PM · Jun 29, 2016 · Twitter for iPhone


Lord Rupert Everton
@nicklynamup

@Delta what are the hours of the ticket counter at Omaha?

7:35 PM · Jun 29, 2016 · Twitter for iPhone

Table A5: Sample Complaining and Non-Complaining Tweets in Each Content Category

Content Category	**Complaints**	**Non-Complaints**
Customer Service	- You are the worst. Been on the phone / hold with you for 5 hours. Now waiting another 2 hours for our next call back. - how do you calculate lifetime value of a customer? You definitely lost one today...Hey would you pull a stunt like this - I did so 2 weeks ago which is why I'm frustrated with the lack of response. It's clear that nobody cares there.	- Hello. If I give you a booking locator can you tell me how much it would be to upgrade to Delta Comfort? - Need to change an itinerary, can you help? - can you tell me when delta releases the newest deals?
Delay and Cancellation	- still not on plane bc you can't find a replacement fire extinguisher. Now going to land in Toronto at least 4hrs late wtf - this is too much.. Got flight canceled, bad service, rerouted to New Orleans and now have had two delays. Not good - worst experience today. Have been delayed and change of flights THREE times	- my flight was cancelled when I got to the airport. BWI or nearby airport 2 LAX possible 2nite? I would take multiple flights - Hey - with delays & cancellations due to the outage, what's the most up to date way to check status of 730 flight out of SFO? - Weather related delays at KBOS. This flight has diverted to Bangor.
Flight Experience	- Passenger on flight asked attendant for tissues; he directed her to bathroom. She asked if he could get some 4 her, he said no. - we've been sitting on the plane for over 1.5 hour, still grounded for another 60 min. Older gent next to me is asking for air	- got some new planes and I feel like I'm on a spaceship amazing socool futuristic - I'm on the plane, and I have wifi! \o/

	- I'm not a fan of any longer. Old old plane for a long long flight. Why do we pay so much for so little?	- just landed in Atlanta on my first flight with y'all..I'll be back. Safety video made me lol
Baggage	- you guys misplaced my bags 2 weeks ago, not even a single call from ur airlines till date. need I say more? - bag drop process is the slowest I've ever seen anywhere, 1hr and counting just to drop a bag... - You guys lost my luggage, arrived in the Bahamas from Atlanta an hour ago with nothing to wear.	- can I stick dcorative threaded patches on my suitcases for identifying purposes? I.e. NASA logo patches, air force logo patches - Thanks for all!! Your community manager is a very professional assistant. My uncle received his luggage! - what about the car seat and I have a lot of bath & body works lotion and spray can I pack it in my luggage (NO CARRY ON)

Table A6: Scenarios Used in Randomized Survey Experiment

Complaint-Related	**Inquiry-Related**
Your flight landed in the destination airport, and you realized your luggage is missing. Compose a message to voice your complaint.	You are going on a ski trip and would like to find out how to check in your ski equipment. Compose a message to ask the airline representative.
You are waiting at the gate and the announcement says your flight has been delayed. You are going to miss your connection now that the flight is delayed. Compose a message to voice your complaint.	You are trying to use your airline miles to buy a plane ticket. However, your miles have expired. Compose a message to ask the airline representative how to reinstate the expired miles.
During your flight you realized that one of the flight attendants was rude and impatient with passengers. Compose a message to voice your complaint.	You have a specific dietary restriction, and you would like your meal to be prepared accordingly. Compose a message to request your special meal.
You are flying to Chicago to attend an important business meeting. When you arrive at the airport you find out that the flight has been cancelled unexpectedly. Compose a message to voice your complaint.	You bought a plane ticket to New York City for a business meeting, but the meeting has just been cancelled. Compose a message to see if you can cancel your flight.
On your international flight you were provided with low quality meals. Compose a message to voice your complaint.	You are flying to Miami this weekend, but the weather report says a hurricane is likely to hit Miami on Saturday. Compose a message to find out if your flight will be affected.

E-Companion B: Content Analysis

Based on our main results, only the number of public non-complaints significantly decreased after Delta adopted OpenDM. In this section, we further investigated which types of non-complaints were more likely to shift to the private channel. To this end, we adopted a deep learning approach to analyze which topic(s) of tweets decreased in number after the OpenDM adoption. Specifically, we used a Bidirectional and Auto-Regressive Transformers (BART, Lewis et al., 2020) model, which has features related to both BERT due to the use of the bidirectional encoder and GPT due to the use of a left-to-right decoder. We used the BART model trained on the Multi-Genre Natural Language Inference (MultiNLI) Corpus (Williams et al., 2018), which contains around 443,000 premise-hypothesis pairs labeled as entailment, neutral, or contradiction. Therefore, the trained BART model can compute the probability that a given tweet entails any given air travel-related labels. Note that this text classification approach does not require a separate labeled data set containing air travel-related tweets because the classification has been treated as a textual entailment problem. This approach is called the zero-shot text classification (Yin et al., 2019).

For our study, we specified four commonly occurring themes in the context of air travel: (1) customer service, (2) delay and cancellation, (3) flight experience, and (4) baggage.[1] The objective of the text classification task was to determine, for a given tweet, which of the four themes was the most likely label. Operationally, we treated the tweet classification as a textual entailment problem, where we considered the tweets as premises and the labels as hypotheses. The objective was to determine whether a given hypothesis followed from the premise. For example, a hypothetical tweet, "My flight has been delayed for more than 4 hours," would be treated as a premise. The classification model would return the probabilities that the tweet was consistent with the hypotheses (1) "this text is about customer service," (2) "this text is about delay and cancellation," (3) "this text is about flight experience," and (4) "this text is about baggage issues," respectively. After the classification for each tweet, we obtained the probability that the tweet was related to customer service, delay and cancellation, flight experience, or baggage issues, where the four probabilities were normalized to sum to 1. We considered a tweet to belong to a specific category if the corresponding probability was at least 0.8.[2] We investigated how the numbers of non-complaint and complaint tweets in each category changed before and after the OpenDM shock. We reported the results in the following tables (Tables B1 and B2). Based on the results, we found that the adoption of OpenDM mainly shifted customers' non-complaint tweets on flight delays, cancellations, and flight

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[1] These categories were chosen from the list of complaint categories used by the US Department of Transportation and were the more common categories in 2016, the year of the OpenDM shock we used in our empirical analysis. https://www.transportation.gov/sites/dot.gov/files/docs/resources/individuals/aviation-consumer-protection/261581/2016-december-atcr.pdf

[2] We provide sample complaint and non-complaint tweets for each content category in Table A5 of E-Companion A. Note that the classification of content categories is independent of the classification of complaint/non-complaints.

experiences. One possible explanation for such findings is that these questions are more personal and flight-specific. To allow the airline representative to answer these questions, the customer might need to provide individual and potentially sensitive information, such as flight number or customer name, which led them to choose the private channel with a higher probability. For baggage-related non-complaint tweets, we found that there were not many baggage-related public tweets in the first place. In addition, many of these tweets were related to the general baggage policy, such as the policies on checked or carry-on bags.

On the other hand, for complaint tweets, we did not observe significant changes in any of the four categories, which further suggests the lack of compositional change in complaint tweets. This finding helps alleviate the concern of unobserved time-varying confounding factors.

Table B1: Content Analysis for Non-Complaint Tweets

	Number of non-complaint tweets			
	(1)	(2)	(3)	(4)
	Customer service	Delay & cancellation	Flight experience	Baggage
Treatment * Before	-0.0417	0.266***	0.110**	0.0431
	(0.0523)	(0.0815)	(0.0450)	(0.0834)
Airline FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R-squared	0.186	0.138	0.173	0.073
# observations	972	972	972	972

Note: This table reports the treatment effects on the content of non-complaint tweets. We interact the Treatment dummy with the Before dummy for each group. All regressions include day of week fixed effects, week fixed effects, and airline fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Table B2: Content Analysis for Complaint Tweets

	Number of complaint tweets			
	(1)	(2)	(3)	(4)
	Customer service	Delay & cancellation	Flight experience	Baggage
Treatment * Before	-0.0987	0.0479	0.0339	-0.0897
	(0.0621)	(0.0878)	(0.0445)	(0.0817)
Airline FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R-squared	0.200	0.209	0.273	0.193
# observations	972	972	972	972

Note: This table reports the treatment effects on the content of complaint tweets. We interact the Treatment dummy with the Before dummy for each group. All regressions include day of week fixed effects, week fixed effects, and airline fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

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E-Companion C: DID with Always Adopters as Control

Our empirical design is different from the traditional difference-in-differences (DID) model because airlines in the control group have adopted the OpenDM throughout the entire sample period. To understand our identification strategy, consider a simplified scenario with two groups and two periods.

- The control group ($D = 1$) adopted the technology at $t = 0$ which remained in place at $t = 1$.
- The treated group ($D = 0$) adopted the technology at $t = 1$ which was not in place at $t = 0$.

Because the control group had the technology in place at $t = 1$, without imposing some strong assumption, there is no way to estimate the counterfactual potential outcome at $t = 1$ for the treated group had the group not adopted the technology at $t = 1$, which means we cannot estimate the post-treatment ATT as in a traditional DID model. However, we may estimate the counterfactual potential outcome at $t = 0$ for the treated group had the group adopted the technology earlier, at $t = 0$, using the observed outcome from the control group. In this way, we can estimate the pre-treatment ATT.

To facilitate discussion, define the treatment d as the adoption of the technology at $t = 0$. More specifically,

- $d = 0$: the technology is not in place at $t = 0$ but is in place at $t = 1$.
- $d = 1$: the technology is in place at $t = 0$ and at $t = 1$.

Let Y_d^t be the potential outcome at period t given the treatment status d. More specifically,

- $Y_0^{t=0}$: a unit's potential outcome at $t = 0$ if the technology is not in place at $t = 0$ but is in place at $t = 1$.
- $Y_0^{t=1}$: a unit's potential outcome at $t = 1$ if the technology is not in place at $t = 0$ but is in place at $t = 1$.
- $Y_1^{t=0}$: a unit's potential outcome at $t = 0$ if the technology is in place both at $t = 0$ and $t = 1$.
- $Y_1^{t=1}$: a unit's potential outcome at $t = 1$ if the technology is in place both at $t = 0$ and $t = 1$.

Let Y^t be the observed outcome at period t and we obtain the usual observation rule:

$$Y^t = Y_1^t \cdot D + Y_0^t \cdot (1 - D).$$

To reduce notation, let's omit X with the understanding that all results naturally extend to the conditional case.

$$\begin{aligned}
\text{ATT}_0 \equiv\ & \mathbb{E}[Y_1^{t=0}|D=0] - \mathbb{E}[Y_0^{t=0}|D=0] \\
=\ & \mathbb{E}[Y_1^{t=0} - Y_1^{t=1}|D=\color{blue}{0}] + \mathbb{E}[Y_1^{t=1}|D=0] - \overbrace{\mathbb{E}[Y^{t=0}|D=0]}^{\text{observation rule}} \\
\overset{\text{PT}}{=}\ & \mathbb{E}[Y_1^{t=0} - Y_1^{t=1}|D=\color{blue}{1}] + \mathbb{E}[Y_1^{t=1}|D=0] - \mathbb{E}[Y^{t=0}|D=0] \\
\overset{\color{red}{\text{NC}}}{=}\ & \mathbb{E}[Y^{t=0} - Y^{t=1}|D=1] + \mathbb{E}[Y_{\color{red}{0}}^{t=1}|D=0] - \mathbb{E}[Y^{t=0}|D=0] \\
=\ & \underbrace{\mathbb{E}[Y^{t=0} - Y^{t=1}|D=1]}_{\text{time-reversed difference for control group}} - \underbrace{\mathbb{E}[Y^{t=0} - Y^{t=1}|D=0]}_{\text{time-reversed difference for treated group}}
\end{aligned}$$

where we used a new version of the parallel trend assumption (PT) and the new assumption of no carryover (NC).

- PT: the potential outcomes if the technology is in place in both periods would have evolved in parallel for the two groups, i.e.,

$$Y_1^{t=1} - Y_1^{t=0} \perp\!\!\!\perp D.$$

- NC: the potential outcome at $t = 1$ would be the same whether the technology is in place at $t = 0$ or not, given the technology is in place at $t = 1$. In other words, there is no **carryover** effect of technology adoption. Mathematically,

$$Y_0^{t=1} = Y_1^{t=1} \Longrightarrow \mathbb{E}[Y_0^{t=1}|D=0] = \mathbb{E}[Y_1^{t=1}|D=0].$$

  The NC assumption is likely satisfied in our setting because our key outcome variable is aggregated from individual customer decisions which are not vulnerable to carryover effect. Indeed, most customers do not engage in multiple conversations with an airline during our sample period, which makes sense because air travel is infrequent for most people.

So, to estimate $\text{ATT}_0 = \mathbb{E}[Y_1^{t=0}|D=0] - \mathbb{E}[Y_0^{t=0}|D=0]$ is to estimate

$$\underbrace{\mathbb{E}[Y^{t=0} - Y^{t=1}|D=1]}_{\text{time-reversed difference for } \color{blue}{\text{control group}}} - \underbrace{\mathbb{E}[Y^{t=0} - Y^{t=1}|D=0]}_{\text{time-reversed difference for } \color{red}{\text{treated group}}}.$$

Compare this with the usual DID estimator:

$$\underbrace{\mathbb{E}[Y^{t=1} - Y^{t=0}|D=1]}_{\text{time-reversed difference for } \color{red}{\text{treated group}}} - \underbrace{\mathbb{E}[Y^{t=1} - Y^{t=0}|D=0]}_{\text{time-reversed difference for } \color{blue}{\text{control group}}}.$$

We can simply run the usual regression but

- switch the treatment status (i.e., $\tilde{D} \equiv 1 - D$), and
- relabel the time backward before running the regression.

Alternatively, run the DID backward and flip the sign of the estimate.