Business practice of social media - Platform and customer service adoption

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Completed Research Paper

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Abstract

This paper examines the key drivers in business adoptions of the platform and customer service within the context of social media. We carry out the empirical analyses using the decision trajectories of the international airline industry on Twitter. We find that a firm's decision-making is subject to both peer influence and consumer pressure. Regarding peer influence, we find that the odds of both adoptions increase when the extent of peers' adoption increases. We also identify the distinctive role of consumers. Specifically, before the platform adoption, firms learn about potential consequences from consumer reactions to peers' adoptions. Upon the platform adoption, consumer voices directed at a firm itself is more crucial to customer service adoption. Furthermore, while both positive and neutral voices facilitate platform adoption, only positive voices significantly contribute to customer service adoption. The findings confirm the distinct trade-offs faced by firms at different adoption stages: while firms are motivated to adopt the platform to reach potential customers, firms care more about the online reputation when deciding customer service adoption.

Keywords: Social Media, Customer Service, Technology Adoption, Peer Influence, Consumer Pressure

Introduction

As communications become increasingly integrated with the digital space, social media becomes one of the most prominent channels for firms to reach and engage with customers. According to the CMO survey in February 2020,[1] social media spending has been growing steadily, reaching 13.3% of the marketing budget and is expected to rise by 62% over five years. Although it is well-recognized that social media is appealing, companies still seem to be skimming the surface of social media's potential for marketing purposes only. In fact, firms can do more than marketing engagement, as more and more customers refer to social media for redress seeking. From 2013 to 2015, the volume of tweets targeted at brands and their Twitter service handles has grown 2.5 times.[2] In light of the trend, some industries start to unlock this new functionality of social media and begin to transform social media into contact centers (Gunarathne et al. 2018).

Compared to conventional media (e.g., newspapers, television, radio, etc.), social media presents several strengths. First, social media platforms are typically freely available and can help firms reach a maximum

[1]https://cmosurvey.org/wp-content/uploads/2020/02/The_CMO_Survey-Highlights-and_Insights_Report-Feb-2020.pdf
[2]https://hbr.org/2015/07/your-company-should-be-helping-customers-on-social

number of audience. As such, marketing activities and customer service provisions on social media are far less expensive than those on conventional media. For instance, the Cost-Per-Thousand Impressions (CPM) of social media is less than $3, while radio comes in at around $10 and the CPM for TV is a whopping $28.[3] Second, social media equips firms with better control over the audience group than conventional media, from the demographics to the time of the day the post will go live.[4]

In the meantime, the public two-way communications on social media posit various uncertainties. As customers are free to voice their opinions to a large audience, it renders firms to have little control over how the public will react once the message is out there. If firms respond to customers' feedback efficiently and effectively, it can foster customer-brand relationships and create a positive brand image to bystanders. For example, a report by Twitter shows that 44% are more likely to share their experiences with friends after receiving a brand response.[5] If firms fail to properly address customer concerns in a timely manner, the negative publicity can easily become unwieldy and ultimately hurt product sales, customer-brand relationship, and brand equity (Ahluwalia et al. 2000; Chevalier and Mayzlin 2006).

Due to the uncertainties associated with the vast publicity, firms hesitate to utilize social media for customer service provision, despite that the marketing practice is relatively common. According to our data, as a top customer-centric industry that provides customer care on social media, 55% of the international airlines incorporated customer service practice on Twitter by December 2017. Given the large variations of business practices on social media, we aim to answer the following question: *What drives organizational decisions to adopt social media for marketing and customer service?* A few pioneering works have either conceptually developed high-level propositions (Culnan et al. 2010) or qualitatively analyzed the determinants of social media adoption through surveys and interviews (Bogea and Brito 2018; Michaelidou et al. 2011; Sinclaire and Vogus 2011; Tiago and Verissimo 2014; Wamba and Carter 2016). To our best knowledge, few works distinguish firms' decisions for marketing and customer service on social media, and there is no work analyzing organizational social media adoption as a dynamic process.

To fill the gap in the literature, our paper tries to do the following. First, we distinguish the *platform adoption* (i.e., social media profile creation for marketing or engagement purposes) from the *customer service adoption* (i.e., the application of social media for customer service), as social media was applied in different ways across organizations and over time. According to our data, it takes firms non-trivial periods to make both decisions (see Table 1). Specifically, the average time from Twitter launch to a firm's Twitter profile creation is 58 months, and the average time from the Twitter account creation to the customer service application is 24 months. In other words, firms gradually learn and dynamically explore new functionalities of social media platforms that can best align with their business operations. Therefore, firms are likely to have different considerations at different stages. Second, drawing on the enterprise technology adoption literature (Rogers 2010; Tornatzky and Fleischer 1990) and the institutional theory (Powell and DiMaggio 2012), we extend the environmental construct and identify two groups of factors that significantly affect firms' decision-making. Specifically, we consider peer influence and demand-side factors. *Peer influence* refers to the external environment faced by firms, which is measured as peers' level of adoption and consequences following the adoption. *Demand-side* factors correspond to the pressures imposed by consumers, which are measured by consumers' voices and sentiment toward firms on social media.

We carry out the empirical analyses using the decision trajectories of 274 international airlines on social media. In particular, for each of the international airlines with an official Twitter account, we collect its full trajectory from the public launch date of Twitter (i.e., July 15, 2006) to December 2017, with all the historical tweets posted by firms *and* associated consumer voices about (or sent to) the firms. We focus on the airline industry because it is a top industry that has extensively leveraged Twitter for real-time customer service. We identify when firms created official accounts *and* when they started the provision of customer service on Twitter. We start with duration analyses for each adoption decision and then propose a two-stage model to jointly estimate the effects of key drivers in firms' decision-making.

The findings suggest that a firm's decision-making is subject to both *peer influence* and *consumer pressure*

[3] https://uhurunetwork.com/social-media-vs-traditional-media/

[4] https://muckrack.com/blog/2018/08/01/differences-between-traditional-media-and-social-media

[5] https://blog.twitter.com/marketing/en_us/topics/research/2016/study-twitter-customer-care-increases-willingness-to-pay-across-industries.html

and these two factors affect the social media platform and customer service adoptions differently. First, we find that the odds of both adoptions increase when the extent of peers' adoption increases. In particular, while both types of adoptions from peers significantly facilitate a focal firm's platform adoption, only peers at the more advanced stage (i.e., peers that started customer service provisions) matter in the customer service adoption. Second, we find evidence of firms' learning about potential consequences from consumer reactions to peers' adoptions, where firms are attracted by positive consumer voices but discouraged by negative voices following peers' platform adoption. However, such knowledge spillover no longer exists in the customer service adoption. Upon the platform adoption, consumer voices directed at the firm itself is more crucial to the customer service adoption, because customer service adoption is more of a within-firm transformation that highly relies on its independent ability to handle customer voices publicly. Third, We find that higher volume and sentiment directed at the firm itself positively contribute to both the platform adoption and customer service adoption. Furthermore, while firms equally value positive and neutral voices in the platform adoption, only positive voices can significantly contribute to customer service adoption. The findings confirm the different trade-offs faced by firms at different adoption stages: while platform adoption is mainly driven by the motivation to reach potential customers, firms with a better online reputation are more likely to opt in the customer service application.

Literature Review

Our paper closely relates to the literature on organizational technology adoption and business social media adoption. We review these two streams of literature separately.

Organizational Technology Adoption

Technology, organization, and environment (TOE) and diffusion of innovation (DOI) are the two dominating theories in the literature on the organizational adoption of information technology (Oliveira and Martins 2011). Under the TOE framework, Tornatzky and Fleischer (1990) identified three aspects that influence an enterprise's IT adoption: *technological context* in terms of the existing practices and the external technologies that are available to the firm; *organizational context*, such as a firm's scope, size, and managerial structure; *environmental context* that consists of a firm's industry, competitors, and dealings with the government. Within the DOI framework, Rogers (2010) proposed three key constructs that affect the diffusion of innovation at the firm level: *leader characteristics* and attitude toward changes; *internal characteristics* of organizational structure regarding the centralization, complexity, formalization, interconnectedness, and organizational slack; *external characteristics* such as system openness.

Drawing on the TOE and DOI theory, researchers further incorporated institutional theory to understand how organizational decisions are shaped by their peers. The institutional theory (DiMaggio and Powell 1983; Powell and DiMaggio 2012) posits that firms become more similar due to three types of isomorphic pressures: *coercive pressure* results from both formal and informal pressures exerted on organizations by other organizations upon which they depend, and by cultural expectations in the society within which organizations function; *mimetic pressure* results from standard responses to uncertainty when an organization faces a problem with little causes or unclear solutions; *normative pressure* comes from the sharing of information, rules, and norms through relational channels amongst members of a network, which facilitates consensus and strengthens the influence of these norms on organizational behavior. Under the lens of institutional theory, various studies have shown that these isomorphic pressures could influence organizational predisposition toward various conventional technology applications, ranging from financial electronic data interchange (Teo et al. 2003), B2B e-marketplaces (Son and Benbasat 2007), to grid computing (Messerschmidt and Hinz 2013).

Although the dominant paradigm of innovation adoption and diffusion demonstrates its power in various settings, it may not apply to the social media adoption, given several fundamental differences between social media platforms and the traditional IT adoption. First, the concern of social media adoption does not lie in the monetary or installation cost, which is a main obstacle for traditional IT adoption. Rather, it is the uncertainties from the publicity and the shared-control by customers and brands that deter firms from the adoption of social media. Second, most of the previous survey- and interviewed-based studies were conducted after participants' acceptance or rejection decisions rather than during the active decision-making process (Venkatesh et al. 2003). However, a distinguishing feature of social media is the rapidly changing external factors shaped by both competitors and consumers. Therefore, we employ firms' social media trajectories to explore the time-varying external factors in firms' decision-making. By proposing the new constructs that are critical for open-access technologies, the current paper introduces an important and novel angel to the technology adoption literature.

Business Social Media Adoption

Despite increasing academic attention on new opportunities brought by social media applications, limited research has focused on organizational adoption of the social media. For example, Sinclaire and Vogus (2011) assessed the strategic adoption of social media through analyses of 72 global companies and survey of eight high-level managers. The paper suggested that firms' use of social media sites because their customers, competitors and suppliers are using them. Through the survey data of 92 small and medium B2B brands in the UK, Michaelidou et al. (2011) identified two top barriers in firms' adoption of social network for marketing: the lack of relevance within the industry a company operates, and uncertainty of benefits following the adoption. Follow-up research further suggested that firms are faced with internal and external challenges in social media adoption Kuikka and Äkkinen (2011), where internal challenges relate to the management challenges within the firm and external challenges typically associate with company image, brand or external relations. However, depending on the surveyed sample, papers have identified different effects of these factors. For marketing managers of large corporations in Portugal, 56% recognize the prominent role of external competitive pressure and 49% rate internal efficiency as the second-most influential factor (Tiago and Verissimo 2014). In contrast, for small- and medium-sized enterprises, (Wamba and Carter 2016) suggested that organizational and manager characteristics have a significant impact on social media adoption while environmental characteristic do not have much impact on the social media adoption decision.

Although these studies provide helpful insights into firms' considerations in the adoption of social media, to the best of our knowledge, no prior study has investigated why firms opt into the customer service practice. Therefore, our paper aims to fill this gap by investigating the trade-off between the costs and benefits for different business practices on social media (i.e., adoption for marketing and customer service). Moreover, the cross-sectional survey- or interview-based data in previous studies cannot capture time-varying circumstances faced by firms. In contrast, we analyze the dynamic decision-making process using the real-world trajectories of the airline industry, which covers 274 firms with enough variations in both the adoption type and timing.

Hypothesis Development

In the current paper, we consider two types of adoptions: *platform adoption* refers to social media account creation for basic access or marketing purposes; and *customer service adoption* refers to customer service provisions via social media channels (henceforth referred to as SMCS adoption). Building on the framework of TOE and DOI (Rogers 2010; Tornatzky and Fleischer 1990), we develop hypotheses corresponding to two sets of external factors relating to the costs and benefits of adoption.

Peer Influence

Prior research has shown that organizational decision-making closely relates to peer groups in various settings, ranging from determining corporate capital structures and financial policies (Leary and Roberts 2014), to the adoption of financial electronic data interchange (Teo et al. 2003). In the context of social media platform and SMCS adoption, we hypothesize that peers' behaviors can affect a firm's adoption decision from two aspects.

First, peers' adoption imposes competitive pressure, which facilitates a firm to adopt the new innovation as a way to maintain its competitive advantages in the market. As suggested in the previous literature, following peers' initiated differentiation strategy, a firm will take similar actions to catch up (Porter and Advantage

1985) or take counteractions to defend their relative competitive positions (Smith et al. 1991). Moreover, due to the vast publicity of social media platforms, peer pressure can be even more salient. Since customers can observe and compare the online presence across firms, they may shift to a competitor if a firm fails to provide proper care as their competitors do, which may hurt the brand reputation and even the market share. To defend the potential online market, firms shall be more likely to adopt the social media platform and SMCS following their peers' initiatives.

Hypothesis 1: *An increase in peers' platform (or SMCS) adoption will increase a firm's likelihood of adopting the platform (or SMCS).*

Second, knowledge spillover from peers' adoption can reduce uncertainties about an innovation, thereby facilitating a firm's adoption. As suggested by DiMaggio and Powell (1983), uncertainty is a powerful force that encourages firms to imitate their competitors. When goals are ambiguous or when the environment creates symbolic uncertainty, organizations may model themselves on other organizations. Compared with the one-way communication in traditional news media, the two-way communication of social media posits many uncertainties, as the platform is jointly controlled by firms and customers. Given a firm and its peers are structurally equivalent because they provide a similar product, serve similar customers, and are committed to similar constraints, consequences following peers' adoptions can inform the focal firm regarding the potential risks and rewards of each adoption decision.

Compared with the conventional technology applications, information from peers' social media accounts is publicly available, thereby making customers' feedback readily accessible to non-adopters. Due to the vast publicity and connectivity, each customer service intervention may incur be amplified. While active management of customers' complaints gives firms an opportunity to turn a service failure into a positive brand experience, it can be risky to firms when the amplification effect goes the opposite way. Moreover, compared to service successes, service failures tend to grab more attention because negative information is often considered by consumers as more informative than positive information when they form their overall evaluations of a brand (Ahluwalia et al. 2000). To sum up, if social learning does exist, we shall expect that positive consumer voices (i.e., compliment) directed at peer firms will encourage adoption. In contrast, the effect of negative consumer voices (i.e., complaint) can go either way.

Hypothesis 2A: *Positive consumer voices following peers' platform (or SMCS) adoption will increase a firm's likelihood of adopting the platform (or SMCS).*

Hypothesis 2B: *Negative consumer voices following peers' platform (or SMCS) adoption will decrease a firm's likelihood of adopting the platform (or SMCS).*

Consumer Pressure

Besides a firm's adaptive learning from peers, downstream customers' behaviors associated with the firm itself can directly affect its decision through the following channels.

First, the intensity of consumer voice signifies the potential online market. When the volume is high enough, firms can be motivated to adopt social media as a way to attract customers, collect real-time feedback, and rectify service failures. Empowered by the popularization of social media and smartphones, customers can easily express their opinions about firms in real-time. Hence, social media serves as an ideal channel for firms to listen to conversations, identify emerging trends, and learn about customers' interests. For example, before launching its foray into all-day breakfast offerings in 2015, McDonald's combed through eight years of social media posts to track demand for the new service, which would require significant investment in operational training and management as well as supply-chain operations.[6] Starbucks also listens to the voices of its customers on Twitter during new product launches and perform real-time sentiment analyses, which helps the firm to determine the success of a new product and react to potential issues on the spot (e.g., by reducing prices or changing the coffee blend) (Gallaugher and Ransbotham 2010; Mandviwalla and Watson 2014; Müller et al. 2016).

Hypothesis 3A: *The likelihood of adopting the platform (or SMCS) is higher as the volume of consumer-*

[6]https://deloitte.wsj.com/cmo/2018/05/18/getting-the-most-out-of-social-media-investments/

initiated voices directed at a firm increases.

Second, while the volume of consumer voices may increase the likelihood of adoption, the valence of consumer voices can affect a firm's decisions in competing directions. Hirschman (1970) suggested that a consumer expresses his/her dissatisfaction to a representative of the organization in the hopes of arriving at a satisfactory solution that prevents exit from the organization. If firms leave consumer complaints unattended, firms will be at the risk of not only losing existing customers but also signaling their disregard to potential customers. Through the social media adoption and customer service practice, firms can offer dissatisfied consumers a channel to seek redress before communicating their dissatisfaction with others or discontinuing the business with the firm. If handled properly, it can even foster consumers' emotional commitment to the brand. For example, McKinsey reports that 82% of customers who have a good customer experience on Twitter are more likely to recommend the brand.[7] A study conducted by Twitter shows that, 69% of people who tweeted negatively say they feel more favorable when a business replies to their concern, and they are willing to spend 3-20% more on the products sold by the brand if they receive a response.[8] Following this scenario, negative voices can facilitate a firm to start customer support as a way to rectify misbehavior.

On the other hand, firms may worry about the negative publicity, especially when they lack the ability to properly handle negative consumer voices in the public space. As suggested by Melancon and Dalakas (2018), in the age of social media, consumer voices become a hybrid of *service complaints* (intended for an internal/organization audience with the motivation of rectifying the service failure) and *negative publicity* (intended for an external audience with the motivation of spreading a negative viewpoint or doing harm to the organization) . In fact, He et al. (2019) find that complaining customers prefer to communicate with firms publicly, even with the availability of a private communication channel. When a firm fails to handle customer complaints in a timely manner, voices from a subgroup of consumers can quickly go viral and the negative word-of-mouth will hurt brand awareness, sales, and revenue (Kim et al. 2016). A cautious firm caring about brand reputation shall value consumer voices by sentiment, therefore, negative consumer voices may prevent firms from adopting social media platform and opening the customer service channel.

Hypothesis 3B: *The likelihood of adopting the platform (or SMCS) is higher as the sentiment of consumer-initiated voices about (or directed at) a firm increases. Specifically, positive (negative) consumer voices will facilitate (impede) both adoption decisions.*

Data

Sample

We focus on firms' adoption decisions on Twitter because it is a most frequently used social media platform by the Fortune 500's public firms (Culnan et al. 2010). The live and conversational features make Twitter an ideal place for businesses to advertise, engage with, and provide customer service.[9] The open access also allows us to track firms' full trajectories and all associated consumer voices. We choose the airline industry as the sample because it has extensively leveraged Twitter for marketing and real-time customer service, which provides us with enough variations in adoption types and decision timing.[10]

Our sample covers 274 public Twitter accounts maintained by major international airlines worldwide.[11] For each firm, we collected its full archive tweets and all consumers' voices directed at the firm (i.e., consumer's tweet containing a brand name or the Twitter handle), from Twitter's public launch date, July 15, 2006 to December 31, 2017. We distinguish two types of adoptions: *platform adoption* (i.e., creation of a Twitter

[7] https://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/social-care-in-the-world-of-now

[8] https://blog.twitter.com/marketing/en_us/topics/research/2016/study-twitter-customer-care-increases-willingness-to-pay-across-industries.html

[9] Twitter is extensively used for social media customer service, where 80% of social customer service requests come from Twitter. https://blog.twitter.com/marketing/en_us/a/2016/making-customer-service-even-better-on-twitter.html

[10] https://www.socialbakers.com/blog/1866-airlines-finance-telecom-are-still-the-top-industries-in-social-customer-care

[11] For firms with multiple Twitter accounts, we include only the main account for two reasons: First, main accounts typically started customer service earlier than subsidiary accounts; Second, customers tend to seek help from the main account, which is much more influential and easier to find.

account) and *SMCS application* (i.e., provision of customer service on Twitter). From a firm's Twitter profile, we can identify the exact date of platform adoption. To identify the SMCS adoption time, we proceed in the following steps. First, for each firm, we calculate the volume of consumer-initiated voices directed at the firm ($ConsumerVoice$), the volume of brand replies to consumer-initiated voices ($BrandReply$), and the ratio of consumer-initiated voices that get replied by the brand ($ReplyRatio$). Next, we identify the earliest time when a firm started to reply to consumers and the brand response level gradually increased afterwards or reached a steady level. Figure 2 shows an example of the Twitter account @AirCanada. Based on consumer voices, brand replies, and the brand reply ratio, we determine its Twitter Adoption time as July 2009 and SMCS Adoption as August 2010. We identify the adoption decision at the monthly rather than a more granular level because a monthly-level measure is less sensitive to the noisy activities by brand or customers during the initial dates of the adoption. To identify the competitors' network within the airline industry, we collect each airline's active routes from Aviation Edge[12] and manually extract the changes in routes from anna.aero.[13] We establish a competitive relationship if two firms share overlapped routes, and we identify an airline's list of competitors accordingly.

Variable Construction

Table 1 provides a summary of key variables and definitions. We aggregate the data to firm-month level and the sample period ends for a firm upon its adoption of SMCS or in December of 2017, whichever comes first. Following the TOE framework, we incorporate ***organizational characteristics*** that could affect the probability of adoption, which include the alliance (i.e., No alliance, Oneworld, Star Alliance, and SkyTeam) and the airline type (i.e., low-cost carrier, regional carrier, and full-service carrier).

To capture the effect of ***peer influence***, we construct two sets of variables: level of peers' adoption and consequences following peers' adoption. For a firm i, we first identify its competitors as those airlines having at least one common route with the firm. Next, we measure the extent of peer adoption through two variables: $compPlatform_{i,t}$ is the number of competitors that have adopted the Twitter platform but not SMCS up to time t; $compSMCS_{i,t}$ is the number of competitors that have adopted both Twitter and SMCS up to time t. We measure the potential consequences following peers' adoption with three variables, $compVoicePos^{d}_{i,t}$, $compVoiceNeg^{d}_{i,t}$, and $compVoiceNeu^{d}_{i,t}$, corresponding to the volume of positive, negative, and neutral customer voices received by i's competitors following decision d, where d can be the Twitter platform adoption or SMCS adoption.[14] These consumer voices following peers' adoptions can inform a firm regarding consumers' reactions to each decision.

We measure the demand-side ***consumer pressure*** from two dimensions: volume and valence. Those two dimensions have been widely used to model consumer voices in the previous literature (Chen et al. 2011; Dewan and Ramaprasad 2014). Specifically, we construct $volume_{i,t}$ as the number of consumer initiated voices sent to firm i at time t, and construct $sentiment_{i,t}$ as the average voice sentiment directed to firm i at time t. To directly test the effects of consumer voices by valence, we decompose consumer-initiated voices into positive ($voicePos_{i,t}$), neutral ($voiceNeu_{i,t}$), and negative voices ($voiceNeg_{i,t}$).

Initial Analysis on the Adoption Decision

Herd Behavior vs. Peer Influence

Oftentimes, it is difficult to differentiate peer influence from herd behavior. The former refers to a firm imitates others because it perceives peers' behaviors as a "safe" way to proceed in case of unclear situations or goals. The latter refers to a firm subject to peer influence but makes strategic decisions to defend its relative competitive position within a market. When it comes to the business adoption of technologies, managers may also depend on a pioneer "penguin" to shove into the water and imitate the behavior once they find

[12] https://aviation-edge.com/airline-routes-database-and-api/

[13] https://www.anna.aero/all-new-airline-routes/

[14] We include consumers' reactions following competitors' corresponding decisions in the analysis but we omit the superscript d for ease of illustration.

evidence that the "water" is safe and welcoming.[15] To distinguish whether firms strategically take similar actions subject to *peer influence*, or they simply imitate others, we start with an analysis of the adoption timing across firms.

Figure 3 plots the percentage of adoptions up to a calendar time on the x-axis. We can observe a large variation of adoption timing across firms, suggesting that firms' adoptions are unlikely driven by herding behavior. Otherwise, we shall observe clustered adoptions on the timeline as latter adopters can just imitate early adopters without caring too much about the timing of adoption. Nonetheless, the technology could diffuse in such a way even if it is driven by the herding behavior, as different herds of firms may learn at a different rate. To check if this is the case, we further analyze the time it takes for a firm to make the same adoption following the first move in its cohort. If the adoption pattern is mainly driven by herding, we shall expect to see adoption lags close to zero. As shown in Figure 4, there is a wide range of adoption lags following peers' move. This further validates that firms' adoption decisions are unlikely driven by mimetic pressure, but likely to be customized and strategic behavior succumbs to peer pressure.

Duration Models

The data used in this study is best described as a time-to-event data set, where we consider adoption as an event. Accordingly, we start with a duration analysis to examine the key drivers leading to the Twitter platform and SMCS adoption. Given that the data is organized at the monthly level, we choose the discrete-time model (Jenkins 1995). Specifically, we define a "failure" if a firm made an adoption, and the sample period stopped for this firm when the adoption became effective. We specify the baseline hazard function as the logarithm of time, $ln(t)$.[16] We apply the maximum likelihood estimation of the discrete logistic (i.e., proportional odds) model. To alleviate the concern of reverse causality, we include the lagged explanatory variables throughout the analyses (Peng and Dey 2013). We also incorporate non-peers' adoptions to account for unobserved common factors that affect the channel popularity and adoptions among all firms.

Table 2 report the results corresponding to the platform adoption and SMCS adoption. We find significantly positive coefficient estimates for *peerPlatform* and *peerSMCS* in the corresponding decision stage, suggesting the positive impact of *peer influence* in focal firms' adoption decisions. Take column 1 as an example, with one more competitor adopting Twitter, the odds of platform adoption increases by about 10.8% (i.e., $exp(0.103) - 1$). Similarly, with one more competitor adopting SMCS (column 5), the odds of platform adoption increases by about 19.8% (i.e., $exp(0.181) - 1$).

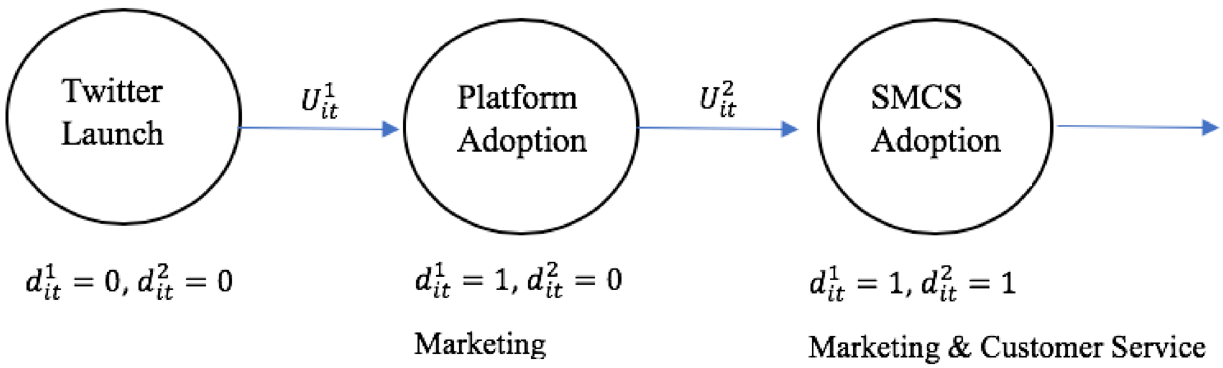
Firms also display different learning patterns at different stages. For *platform adoption* (columns 1 - 2), we observe a significant positive effect of $peerVoicePos$, implying that firms are encouraged by the potential positive word-of-mouth when making the entry decision to the social media platform. For *SMCS adoption* (columns 5 - 6), we do not observe persistent evidence of learning from peers. The finding seems to be surprising at first glance, but it actually reflects a key difference between the Twitter platform and the SMCS adoption decision. While the former is mainly driven by firms' efforts to reach online customers for marketing purposes, the latter is more of a within-firm decision that highly relies on its independent ability in public customer care provision.

Regarding *consumer pressure*, we find a significantly positive impact of voice volume but an insignificant effect of consumer sentiment(column 1). For SMCS adoption (column 5), both volume and sentiment are significantly positive. This is consistent with firms' differential learning patterns across stages: While firms compete for the customer base with peers in the platform adoption, they care more about brand reputation and consumers' perceptions in the SMCS adoption. When decomposing consumer voices by sentiment, we notice that neutral voices (*voiceNeu*) can significantly facilitate the platform adoption (column 2), and positive voices (*voicePos*) can significantly increase the odds of SMCS adoption (column 6). One thing to notice is that, before the platform adoption, consumer voices directed to a firm are measured as all customer tweets mentioning its brand name. In other words, the cost of collecting consumer voices about the firm itself

[15]The phenomenon is called the "penguin effect", which was coined by Farrell and Saloner (1986) as "Penguins who must enter the water to find food often delay doing so because they fear the presence of predators. Each would prefer some other penguin to test the waters first."

[16]The estimation results are not sensitive to alternative specifications of the baseline hazard function, such as polynomial in time.

Figure 1. Conceptual Framework



Note. We define $d_{it}^1 = 1$ if firm i opened a Twitter account at t, and $d_{it}^2 = 1$ if firm i started to use Twitter for customer service at t. U_{it}^1 and U_{it}^2 correspond to firms' latent utility function for the first stage (i.e., from Twitter launch to platform adoption) and second stage (i.e., from platform adoption to SMCS adoption).

is higher than directly learning about possible consequences from peers with a Twitter handle (i.e., platform adoption). This may explain the larger effect of competitors' consumer voices in a firm's platform adoption.

While we have controlled for airline type and alliance, there could still be systematic differences across firms. To further alleviate the concern due to time-invariant individual heterogeneity, we implement a fixed-effects model following the literature designed for non-repeated events (Allison 2009; Allison and Christakis 2006). Compared with the baseline survival analysis, we make two changes: (1) Firms with no variation on the adoption status are dropped from the sample, as they contribute nothing to the likelihood. This leads to a significant reduction in the number of observations for SMCS adoption analysis, as firms that had not started SMCS by December 2017 are dropped from the analysis. (2) The baseline hazard function $ln(t)$ is excluded from the fixed effects model as any monotonically increasing function of time will incur the complete separation problem, thus preventing the maximum likelihood estimation of other covariates in the model. Table 2 (columns 3-4, 7-8) report the results of the fixed-effects model, where all the estimates remain qualitatively the same, suggesting the robustness of the findings.

Two-Stage Model

In the previous section, we estimate the social media platform and customer service adoption separately. However, the two decisions are likely correlated with unobserved firm heterogeneities. For instance, early adopters of the platform may be inherently more capable and thus are more likely to adopt SMCS. Comparatively, those laggards may be less experienced and naturally less willing to start SMCS. Moreover, the SMCS adoption is conditional on the platform adoption, which makes the separate duration analysis less efficient. As can be seen from the timeline in Figure 1, a firm first decides whether to adopt Twitter platform (Stage I). Upon Twitter account creation, it becomes aware of the SMCS channel, evaluates the costs and benefits of SMCS and makes the adoption decision correspondingly (Stage II). To check the robustness of the results, we propose a two-stage model that accounts for the inherent correlation of the two stages and jointly estimates the key determinants in firms' decision-making.

Model Specification

The formal model is specified as the following. We use d_{it}^1 and d_{it}^2 to denote whether firm i adopted the platform and SMCS at time t, respectively. Specifically, we define $d_{it}^1 = 1$ if firm i opened a Twitter account at t, and $d_{it}^2 = 1$ if firm i started the customer service provision at t. Following the notation, a firm i can be in one of the three possible states at time t: no adoption($d_{it}^1 = 0$); adopted the platform but not SMCS($d_{it}^1 = 1, d_{it}^2 = 0$); adopted the SMCS($d_{it}^1 = 1, d_{it}^2 = 1$).

For a firm i at time t, we model its latent utility function for the first stage and second stage as follows:

$$\begin{cases} U_{it}^1 = \beta_1 X_{it}^1 + v_{it}^1 + \epsilon_i^1 \\ U_{it}^2 = \beta_2 X_{it}^2 + v_{it}^2 + \epsilon_i^2 \end{cases}$$

where X_{it}^1 and X_{it}^2 are the key factors in firms' adoption decisions, which include organizational constructs such as the firm alliance and type; external constructs include *peer influence* and *consumer pressure*. We include v_{it} to capture the exogenous firm- and time-specific shocks, where we assume the shocks follow the standard normal distribution $N(0,1)$ and are independent across time t. We also allow for the persistent individual heterogeneity, ϵ_i^1 and ϵ_i^2, which are freely correlated and follow a mean-zero bivariate normal distribution with the following variance-covariance matrix.[17]

$$\begin{pmatrix} \epsilon_i^1 \\ \epsilon_i^2 \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \quad \begin{pmatrix} \sigma_1 & \rho \\ \rho & \sigma_2 \end{pmatrix} \right]$$

Following the notation, we can write the probability of firm i being in each state at time t as follows:

$$\begin{cases} p_{it}^1 = Pr(d_{it}^1 = 0, d_{it}^2 = 0) = Pr(U_{it}^1 < 0) \\ p_{it}^2 = Pr(d_{it}^1 = 1, d_{it}^2 = 0) = Pr(U_{it}^1 > 0, U_{it}^2 < 0) \\ p_{it}^3 = Pr(d_{it}^1 = 1, d_{it}^2 = 1) = Pr(U_{it}^1 > 0, U_{it}^2 > 0) \end{cases}$$

Accordingly, the log-likelihood of observing firm i's stream of adoption outcomes is given by

$$lnL = \sum_{i=1}^{N} \sum_{t=1}^{T_i} [(d_{it}^1 d_{it}^2) lnp_{it}^3 + d_{it}^1 (1 - d_{it}^2) lnp_{it}^2 + (1 - d_{it}^1) lnp_{it}^1]$$

where N is the total number of unique firms in the sample, T_i stands for the last sampling period of firm i. If a firm adopts SMCS during our sample period, the sample for this firm stops at its SMCS adoption time T_i. Otherwise, T_i corresponds to the last period of the data collection (i.e. December 2017). We then find parameters that maximize the aggregated log-likelihood across firms. We re-parameterize $\sigma_2 = \beta_{\sigma_2}^2$ and $\rho = \frac{exp(\beta_\rho)-1}{exp(\beta_\rho)+1}$ to restrict the parameter space to $\sigma_2 \geq 0$, $-1 \leq \rho \leq 1$. The estimates and variance for ρ and σ_2 are then calculated based on the delta method.

MLE Results

Table 3 reports the MLE estimation of the two-stage model. Similar to the previous sections, we include lagged measures for independent variables in the analysis to alleviate the concern of reserve causality. While the majority of the estimates are qualitatively the same as the duration analysis, the two-stage estimation is more efficient. More importantly, the significantly positive estimates for ρ imply the underlying correlations over the two decisions, which supports the validity and necessity of the proposed two-stage model.

Regarding *peer influence*, the duration model suggests a positive but insignificant effect of competitors' SMCS adoption (*compSMCS*). The two-stage model suggests that both peers' platform (*compPlatform*) and SMCS adoption (*compSMCS*) significantly contribute to the Twitter platform adoption (see Stage I). Conditional on platform adoption, only the coefficient estimate for *compSMCS* is significantly positive in stage II. The results support **Hypothesis 1**, highlighting that firms closely monitor their peers and act strategically to retain and serve customers.

Consistent with the duration analysis, we find evidence of knowledge spillover through learning from peers' adoptions. The positive effect of $compVoicePos$ suggests that positive consumer feedback following peers' Twitter creation can facilitate a focal firm to adopt the platform as well. Meanwhile, potential negative publicity induces stronger inertia in firms' Twitter presence, as the the coefficient estimate for $compVoiceNeg$ is significantly negative (see Stage I). Interestingly, such effect disappears in Stage II estimations. As we

[17] For identification purposes, we normalize σ_1 to 1 in the maximum likelihood estimation following the previous literature (Lambrecht et al. 2011).

mentioned earlier, Twitter profile creation corresponds to the simple access to the platform, while SMCS adoption is much more complex and requires within-firm adaptations of business processes. Therefore, while information from pioneers' adoptions is valuable for firms to learn about the costs and benefits in the platform adoption, consumer voices directed at the firm itself is more crucial to SMCS adoption. Collectively, **Hypotheses 2A-2B** are supported for the platform adoption but not for SMCS adoption.

Regarding *consumer pressure*, the estimates are significantly positive for *volume* and *sentiment* in both stages (see column 1). The findings support **Hypotheses 3A-3B**, where higher volume and sentiment positively contribute to both the platform adoption and SMCS adoption. When we further decompose consumer voices directed at a firm by sentiment, the findings suggest that firms react to consumer voices differently at the two stages. In Stage I, the coefficient estimates are significantly positive for both *voicePos* and *voiceNeu* (see Stage I of column 2), while the estimate for *voiceNeg* is significantly negative. Therefore, firms care about the potential audience size and any non-negative voices will significantly contribute to firm's adoption of the Twitter platform. In Stage II, consistent with the duration analysis, only positive consumer voices significantly facilitate SMCS adoption (see Stage II of column 2). We believe that such results can explain the dilemma faced by firms at different decision stages. For Twitter platform adoption, a higher volume of consumer voices signifies a promising online customer base, thus forces firms to pay attention, discounting the effect of the sentiment. On the contrary, when planning for SMCS transformation, firms with an established brand image (i.e., a higher volume of positive voices) are more capable of public communications with customers, thus more likely to adopt SMCS.

Discussion and Conclusion

Drawing upon the literature in technology adoption, this paper systematically examines the key drivers that affect business adoption of social media platforms and customer service. This work contributes to the literature and the practice in the following aspects.

First, to the best of our knowledge, this paper is the first work on business adoption of customer service in the new setting of social media. Compared with conventional technology innovations that typically require extensive investment and re-structuring of the firm, social media distinguishes itself by low cost, real-time interactions, and shared control by brands and customers. An understanding of the factors affecting this choice is therefore essential both for organizational decision-makers and producers of such technologies.

Second, little attention has been paid to the influence of demand-side customers on enterprise technology adoption in previous literature. We propose and identify the critical role of consumer voice in firms' decision-making. Traditionally, firms learn about customers' needs through surveys. Our findings show that consumers' voices and tone on social media provide firms with a new source to identify such needs. The proposed constructs not only add to the environmental context of the TOE framework but also is critical considering the vast publicity of social media and open access technologies alike.

Third, while previous literature recognizes that the adoption involves several distinctive stages, there is often a lack of data to estimate the process with sufficient accuracy (Lambrecht et al. 2011; Van den Bulte and Lilien 2007). Moreover, the survey- and interview-based retrospective study may not capture the active decision-making process (Venkatesh et al. 2003). Using a real-world record-based panel data set, we distinguish different adoption stages and examine the dynamic evolving process in firms' decision-making. We also propose a two-stage model that jointly estimate firms' adoption decisions. Our way of modeling explicitly accounts for within-firm unobserved heterogeneity over time, which allows for higher estimation accuracy and efficiency.

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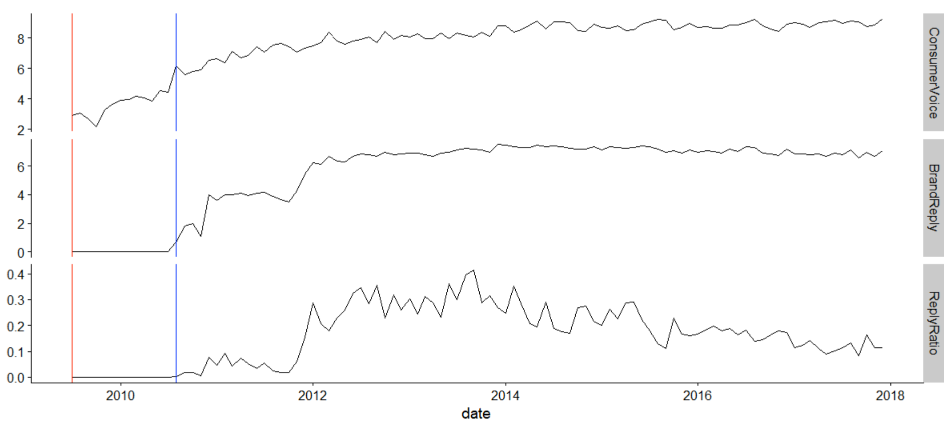
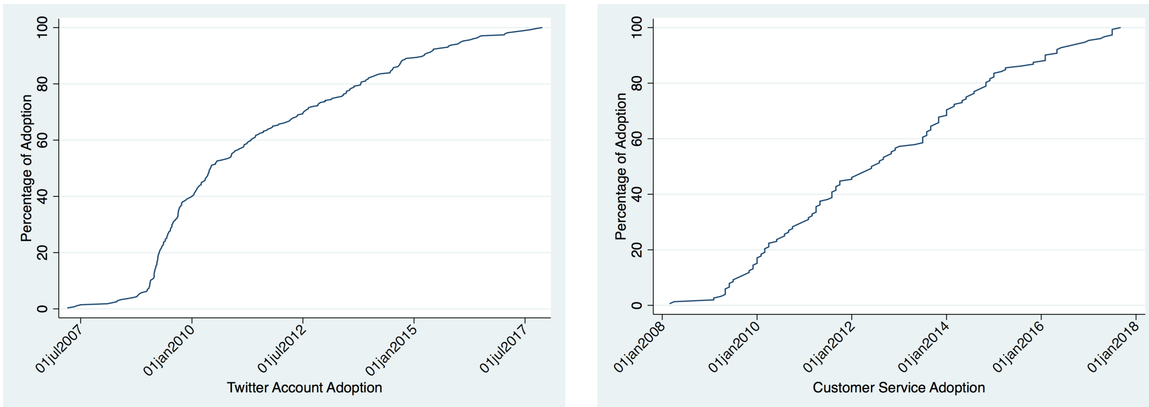


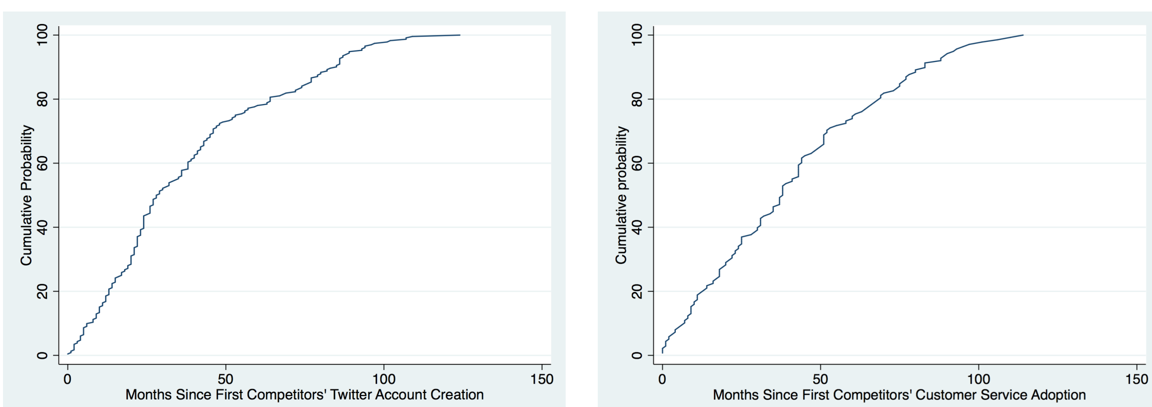
Figure 2. Determination of Adoption Time

Note. This figure shows an example of Twitter trajectories from Air Canada (@AirCanada), where the vertical axes correspond to the log-transformed volume of consumer voice, brand reply, and the brand reply ratio. We identify its Twitter platform Adoption time as July 2009 (red line) and SMCS Adoption as August 2010 (blue line).



Note. This figure shows the distribution of the adoption time across firms. The y-axis stands for the percentage of adopters up to a time on the x-axis. The left panel corresponds to Twitter platform adoption, and the right panel corresponds to SMCS adoption.

Figure 3. Distribution of Firm's Adoption Time



Note. This figure shows the distribution of time lags (in month) from the first peer's adoption of the platform (or SMCS) to a firm's adoption of the platform (or SMCS).

Figure 4. Distribution of Time Lags since First Peer's Adoption

Table 1. Summary Statistics

Variable	No. of obs.	Mean	Std. Dev.	Definition
		Organizational Construct		
$TwitterAdoptionLag_i$	274	58.21	29.32	Months between Twitter platform launch and firm's Twitter account creation
$SMCSAdoptionLag_i$	152	24.39	23.70	Months between firm's Twitter account creation and SMCS adoption
Alliance$_i$				Airline alliance
No Alliance	200			
Oneworld	17			
SkyTeam	20			
Star Alliance	37			
Type$_i$				Airline type
Low-cost	77			
Regional	64			
Full-service	133			
		External Construct		
Peer Influence				
$peerPlatform_{i,t}$	21,101	2.913	3.951	Number of firm i's competitors that adopted Twitter but not SMCS
$peerSMCS_{i,t}$	21,101	0.125	0.422	Number of firm i's competitors that adopted both Twitter and SMCS
$peerVoicePos_{i,t}^{platform}$	21,101	1.209	13.229	Volume of positive consumer voices directed at competitors that adopted Twitter but not SMCS
$peerVoiceNeu_{i,t}^{platform}$	21,101	4.064	46.277	Volume of neutral consumer voices directed at competitors that adopted Twitter but not SMCS
$peerVoiceNeg_{i,t}^{platform}$	21,101	1.091	17.726	Volume of negative consumer voices directed at competitors that adopted Twitter but not SMCS
$peerVoicePos_{i,t}^{smcs}$	21,101	11.5	191.101	Volume of positive consumer voices directed at competitors that adopted Twitter and SMCS
$peerVoiceNeu_{i,t}^{smcs}$	21,101	69.06	427.149	Volume of neutral consumer voices directed at competitors that adopted Twitter and SMCS
$peerVoiceNeg_{i,t}^{smcs}$	21,101	6.479	20.921	Volume of negative consumer voices directed at competitors that adopted Twitter and SMCS
Consumer Pressure				
$volume_{i,t}$	21,101	69.49	807.19	Volume of consumer voices
$sentiment_{i,t}$	21,101	0.025	0.158	Average consumer voice sentiment
$voicePos_{i,t}$	21,101	6.510	247.738	Volume of positive consumer voices directed at firm i
$voiceNeu_{i,t}$	21,101	56.501	747.737	Volume of neutral consumer voices directed at firm i
$voiceNeg_{i,t}$	21,101	4.201	27.249	Volume of negative consumer voices directed at firm i

Note. This table reports summary statistics and definitions of key variables at the firm(i)-month(t) level. *Organizational Construct* corresponds to cross-sectional descriptive data for 274 airlines with an official Twitter account. *External Construct* corresponds to the monthly panel data for 274 firms from Twitter launch (or first available observation) to their SMCS adoption.

Table 2. Separate Stage Duration Model

	Platform Adoption				SMCS Adoption			
	Baseline		Fixed Effects		Baseline		Fixed Effects	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Influence								
peerPlatform	0.103***	0.106***	0.079*	0.085*	-0.111	-0.114	-0.124	0.162
	(0.036)	0.036	(0.045)	(0.051)	(0.073)	(0.073)	(0.123)	(0.153)
peerSMCS	-0.059	-0.056	-0.048	-0.052	0.181**	0.176**	0.264**	0.284*
	(0.076)	(0.076)	(0.091)	(0.092)	(0.082)	(0.082)	(0.124)	(0.160)
peerVoicePos	0.226*	0.216*	0.348*	0.348*	0.031	-0.011	0.284	0.278
	(0.119)	(0.120)	(0.181)	(0.182)	(0.214)	(0.216)	(0.483)	(0.611)
peerVoiceNeg	-0.197*	-0.192*	0.046	0.054	-0.085	-0.090	1.106***	1.242***
	(0.114)	(0.114)	(0.176)	(0.177)	(0.186)	(0.186)	(0.375)	(0.446)
peerVoiceNeu	0.039	0.038	0.837***	0.845***	0.031	0.080	1.047*	0.722
	(0.073)	(0.073)	(0.123)	(0.122)	(0.133)	(0.132)	(0.598)	(0.720)
Consumer Pressure								
volume	0.077*		0.871***		0.223***		0.024***	
	(0.043)		(0.092)		(0.053)		(0.006)	
sentiment	0.207		0.236		1.093***		2.117**	
	(0.369)		(0.468)		(0.383)		(1.023)	
voicePos		-0.040		0.243		0.389***		1.095**
		(0.126)		(0.158)		(0.136)		(0.500)
voiceNeg		-0.161		0.034		-0.131		1.097*
		(0.126)		(0.160)		(0.122)		(0.610)
voiceNeu		0.171**		0.782***		0.050		2.734***
		(0.073)		(0.114)		(0.099)		(0.491)
Chanel Popularity								
platformPopularity	0.0403***	0.0402***	0.020**	0.021**	0.025	0.026	0.054*	0.039
	(0.007)	(0.007)	(0.009)	(0.009)	(0.016)	(0.017)	(0.028)	(0.035)
SMCSPopularity	-0.030*	-0.031*	0.023	0.026	-0.025	-0.020	-0.065	-0.082
	(0.017)	(0.017)	(0.019)	(0.019)	(0.028)	(0.028)	(0.042)	(0.053)
Airline Type & Alliance	Y	Y	Y	Y	N	N	N	N
Baseline Hazard	Y	Y	N	N	Y	Y	N	N
Fixed Effects	N	N	Y	Y	N	N	Y	Y
loglikelihood	-1127.8	-1126.8	-701.8	-703.6	-703.8	-705.7	-216.7	-218.20
Observations	13188	13188	13188	13188	7913	7913	2504	2504

Note. $^{***}p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses. This table reports the results of the duration model. Columns 1-4, 5-8 correspond to the Twitter platform and SMCS adoption, respectively. In the fixed effects model (columns 3-4, 7-8), time-invariant airlines' attributes (i.e., airline type and alliance) are absorbed by the fixed effects.

Table 3. Two-Stage Model Estimation

	MLE Result			
	(1)		(2)	
	Stage I	Stage II	Stage I	Stage II
Peer Influence				
peerPlatform	0.205***	0.006	0.208***	0.003
	(0.007)	(0.012)	(0.008)	(0.011)
peerSMCS	0.312***	0.206***	0.317***	0.190***
	(0.042)	(0.074)	(0.042)	(0.070)
peerVoicePos	0.749***	-0.360	0.738***	-0.337
	(0.078)	(0.225)	(0.044)	(0.210)
peerVoiceNeg	-1.469***	0.110	-1.468***	0.111
	(0.047)	(0.108)	(0.053)	(0.099)
peerVoiceNeu	0.064	0.093	0.070	0.083
	(0.056)	(0.221)	(0.062)	(0.201)
Consumer Pressure				
volume	0.135***	0.066**		
	(0.012)	(0.026)		
sentiment	0.687***	0.684***		
	(0.111)	(0.207)		
voicePos			0.198***	0.199***
			(0.035)	(0.063)
voiceNeg			-0.186***	-0.087
			(0.036)	(0.059)
voiceNeu			0.106***	-0.017
			(0.020)	(0.037)
ρ	0.418***		0.357***	
	(0.071)		(0.044)	
σ_2	0.794***		0.592***	
	(0.120)		(0.281)	
2-stage Correlation	Y		Y	
Control Variables	Y		Y	
Observations	21101		21101	
loglikelihood	-6428.565		-6451.074	

Note. $^{***}p < 0.01$, $^{**}\ p < 0.05$, $^{*}\ p < 0.1$. Standard errors in parentheses. This table reports the MLE estimation for the two-stage model, which impose cross-stage correlations within each firm. Stage I refers to the period from the Twitter platform launch to a firm's Twitter account creation (i.e., platform adoption). Stage II corresponds to the period from a firm's Twitter account creation to the SMCS adoption.