The Impact of Customer Service Accounts on Social Media Consumer Engagement: A Natural Experiment

Ahreum Kim
University of Illinois at Chicago
akim239@uic.edu

Ramah Al Balawi
Baruch College- City University of New York
ramah.albalawi@baruch.cuny.edu

Yuheng Hu
University of Illinois at Chicago
yuhenghu@uic.edu

Liangfei Qiu
University of Florida
liangfei.qiu@warrington.ufl.edu

Abstract

This study explores the effect of creating dedicated customer service (CS) accounts on consumer engagement with the Main accounts for brands on social media. Given the importance of customer-brand interactions, creating dedicated CS accounts can allow brands to deliver faster and more efficient responses to consumer needs. However, dedicated CS accounts could diminish consumer engagement with brands' Main accounts on social media. This research aims to address this gap by examining whether segregating customer service interactions into dedicated accounts affects consumer engagement with Main accounts on social media. Using a large Twitter dataset, we observe an overall increase in consumer engagement on Main accounts following the creation of CS accounts. We extend this study to examine the mediating role of consumer tweet traffic to uncover the underlying mechanism. The findings of this study provide important insights for brands to facilitate consumer engagement on social media.

Keywords: dedicated customer service accounts, consumer engagement, customer relationship management, service-dominant logic

1. Introduction

Since the rise of social media platforms like Facebook and Twitter (currently known as X), almost all brands, whether large or small, are using these platforms to build and manage customer relationships and consumer engagement (Chung et al., 2020; Kumar et al., 2022). Social media has become an integral part of a brand's marketing strategy to motivate consumer engagement, which in turn, has been shown to significantly improve consumer satisfaction, increase firms' sales, and enhance firm profitability (Kumar et al., 2018; Lee et al., 2018). Additionally, social media platforms have become increasingly popular among consumers who use such platforms to connect and engage with brands. According to the Sprout Social Index, 78% of consumers find that social media platforms provide fast and direct channels to connect with brands.[1]

In addition to enhancing and motivating consumer engagement, brands are leveraging social media platforms by offering customer service to manage their customer relationships more efficiently. Given the unique nature of social media platforms, consumers can voice their complaints directly to brands, and brands can address those complaints publicly, revolutionizing customer relationship management (Al Balawi et al., 2023; Roy et al., 2023). Therefore, many brands, nowadays, create separate customer service accounts (*henceforth referred to as CS accounts*) that serve as official channels to handle customer service requests, helping brands in providing better customer service through faster and more efficient responses to consumers.[2] Those CS accounts are distinct from the main accounts (*henceforth referred to as Main accounts*) on the same social media platforms that are generally dedicated to branding efforts.

Many brands have already adopted this approach of creating separate accounts on the same social media platform. For example, Best Buy, a well-known consumer electronic retailer, created its official Twitter

[1] See https://media.sproutsocial.com/uploads/Sprout-Social-Index-Edition-XVII-Accelerate.pdf (Last accessed: April 30, 2024)

[2] See https://sproutsocial.com/insights/multiple-twitter-accounts/ (Accessed April 30, 2024)

URI: https://hdl.handle.net/10125/109556
978-0-9981331-8-8

Main account "*@BestBuy*" in November 2008.[3] In December 2012, Best Buy created a separate CS account on the same social media platform, Twitter, "*@BestBuySupport*",[4] to address consumer questions and requests. Another example is Amazon, one of the largest online retailers, which has its primary Twitter Main account, "*@Amazon*", created in February 2009.[5] In October 2009, Amazon created its dedicated CS account, "*@AmazonHelp*".[6] Other brands went even a step further by creating multiple accounts on the same platform, such as Walmart, a major player in the retail industry, that has multiple accounts including "*@walmarthelp*",[7] "*@WalmartCanada*",[8] and "*@WalmartAction*"[9] on top of their Main account "*@Walmart*".[10]

On one hand, creating dedicated CS accounts can help in segmenting audiences and consumers to better target brands' customer service efforts and activities to the right segments, thus, responding faster to consumers and improving overall social media strategies. This approach can contribute to fostering stronger connections with consumers, enhancing brand perception and equity (Brodie et al., 2013; Cooil et al., 2008; Kumar et al., 2008; Tran et al., 2023), and eventually improving firm profitability (Xue et al., 2007). However, on the other hand, creating dedicated CS accounts might have a detrimental impact on consumer engagement. Creating separate accounts might lead to consumer confusion, elevating cognitive load (Paas et al., 2003), possibly decreasing consumer satisfaction (Hu et al., 2017), and ultimately reducing consumer engagement (Kirschner et al., 2011). Therefore, empirically, there is no uniform behavior in creating CS accounts.

Such a dilemma can create challenges for brands on whether to create dedicated CS accounts on a social media platform as the effect on consumer engagement with the Main accounts is unknown due to the transfer of activities to the CS accounts. To the best of our knowledge, no prior research has examined this phenomenon, and the effect of creating CS accounts on consumer engagement with the Main accounts remains ambiguous. Therefore, this work aims to fill this research gap and answer this important question: *"What is the effect of creating a dedicated CS account on consumers' engagement with the Main account on social media platforms?"* Additionally, we extend this work to uncover the underlying mechanism by examining the mediating effect of consumers' tweet traffic to the Main account on consumer engagement.

To address the research question and examine the underlying mechanism, we collect a large Twitter dataset using Twitter's public API. We collect tweets (posts) from 98 brands in 11 different industries. In addition to brands' tweets, we collect the number of likes per brand tweet, the number of retweets per brand tweet, and the number of replies received per brand tweet. Additionally, we collect consumers' tweets mentioning or directed to brands using their official Twitter handler (preceded with the '@' symbol). We construct an unbalanced panel dataset at the brand-week level to conduct our empirical analyses. To examine the effect of creating dedicated CS accounts on consumer engagement, we use a fixed effects approach combined with propensity score matching (PSM) to create a proper control group for treated brands. We investigate the underlying mechanism by conducting a separate mediation analysis on consumers' tweet traffic on the Main account.

Our findings reveal several key points. Overall, we observe an increase in consumer engagement with brand posts on the Main accounts after creating CS accounts. Specifically, we observe an average increase in the number of likes by approximately 39% after creating a CS account. Similarly, we observe an average increase in the number of retweets by about 40% and an average increase in the number of replies to brand posts by around 19% after creating a CS account. Additionally, we find that the mediating effect of consumers' tweet traffic on the Main accounts is positive and significant.

The findings of this study offer valuable insights. First, we contribute to the literature on consumer engagement on social media and customer relationship management, by exploring and quantifying the impact of creating CS accounts on consumer engagement with the Main accounts. Second, we draw on the Service-Dominant Logic (SDL) framework and examine the effect of creating dedicated CS accounts on consumer engagement. Furthermore, this study has practical implications. It provides empirical evidence that using separate CS accounts is beneficial to brands by enhancing and fostering more engaging value co-creation between brands and consumers.

[3] See https://twitter.com/BestBuy (Last accessed: April 9, 2024)
[4] See https://twitter.com/BestBuySupport (Last accessed: April 9, 2024)
[5] See https://twitter.com/amazon (Last accessed: April 9, 2024)
[6] See https://twitter.com/amazonhelp (Last accessed: April 9, 2024)
[7] See https://twitter.com/walmarthelp (Last accessed: April 29, 2024)
[8] See https://twitter.com/WalmartCanada (Last accessed: April 29, 2024)
[9] See https://twitter.com/WalmartAction (Last accessed: April 29, 2024)
[10] See https://twitter.com/Walmart (Last accessed: April 29, 2024)

2. Related studies

This study is related to two streams of literature: (i) consumer engagement in social media, and (ii) social media customer relationship management. In this section, we review related literature in those streams and highlight the contribution of our work to past studies.

2.1. Consumer engagement in social media

Social media platforms facilitate direct and open two-way communication between brands and consumers (Chung et al., 2020; Gunarathne et al., 2018). Consumer engagement in social media encompasses participation and interaction with a brand's content that can be translated into various actions such as "liking" posts to express approval, "retweeting" brand posts to share them with their network, or directly replying to the brand's posts with comments or questions (Kumar et al., 2022; Lee et al., 2018; Yang et al., 2019). Consumer engagement behavior can signal a consumer's interest in the brand and can contribute to fostering positive brand attitudes (Kumar et al., 2022). Active engagement with brands on social media often leads to stronger brand loyalty and advocacy (Brodie et al., 2011; Habibi et al., 2014; Laroche et al., 2012), underlining the importance of understanding and fostering consumer engagement in social media for building positive brand relationships (Kumar & Pansari, 2016; So et al., 2016).

To maintain competitiveness, brands employ various strategies to increase consumer engagement such as trademarking hashtags (Kumar et al., 2022). One essential approach involves responding promptly and professionally to consumer comments and requests. Prompt responses demonstrate a brand's commitment to consumer satisfaction, thus, increasing consumer interactions with the brand (Davidow, 2000; Mattila & Mount, 2003). Therefore, brands use social media platforms and provide customer service to turn satisfied consumers into enthusiastic promoters (Hollebeek et al. 2014). This study contributes to this stream of literature by providing empirical evidence for the positive effect of creating dedicated CS accounts on consumer engagement.

2.2. Social media customer relationship management

Customer relationship management has long been recognized by researchers and practitioners to be crucial for brands. Hirschman's (1972) Exit, Voice, and Loyalty theory suggests that when consumers experience a decreased quality of service, they can either exit or leave the organization or business providing the service or voice their complaints to receive a response or compensation from brands. Based on this theory, prior research has provided different frameworks to properly and effectively manage consumers' complaints to increase consumer satisfaction and avoid risks that could result from these complaints (Gu and Ye 2014; Maecker et al. 2016), such as the spread of negative word of mouth (Fornell & Wernerfelt, 1987; Smith et al., 1999).

With the advances in information and mobile technologies, social media platforms have empowered consumers by publicly voicing their complaints to a wider audience (Gunarathne et al., 2018). This has created new challenges for brands to effectively manage their customer relationships. Prior research has examined online responses to consumers and their impact on consumer satisfaction (Gu & Ye, 2014) and consumer churn (Maecker et al., 2016). This work contributes to this stream of literature by examining how creating CS accounts to manage consumer complaints can impact consumer engagement beyond the direct impact on customer service.

3. Theoretical foundation and hypothesis development

Traditionally, the concept of value in marketing was primarily associated with the inherent qualities of products or services, relegating consumers to passive recipients of this value. However, the emergence of the theoretical framework, Service-Dominant Logic (SDL), has changed this perspective, emphasizing that value is co-created through dynamic collaboration and interactions between consumers and organizations (Vargo & Lusch, 2004). SDL underscores the active role of consumers in the value co-creation process, where value is not merely transferred from brands to consumers but is jointly generated and co-created through interactions and exchange of services (Prahalad & Ramaswamy, 2004; Vargo & Lusch, 2008). In this framework, consumers are not only recognized as recipients but also as active contributors in the value co-creation process, driven by antecedents such as interactions with brands (Ribeiro et al., 2023). This framework provides a lens that extends beyond the traditional brand-consumer interactions to encompass a network of actors contributing resources (Vargo & Lusch, 2014; Wu & Gao, 2019).

In the digital landscape, SDL underscores the interactions on social media platforms, where a dynamic web of value co-creation emerges. Social media platforms, such as Twitter, facilitate two-way communication, enabling consumers to engage with brands actively and participate in value co-creation processes (Finne & Grönroos, 2017; Grönroos &

Voima, 2013). Leveraging their social media skills, consumers can interact with brands by contributing their insights, feedback, and other resources to enrich the overall brand experience (Hollebeek, 2011). In addition, consumers personalize their brand experiences through social media engagement, aligning them with their individual interests and integrating the brand seamlessly into their online activities (Hollebeek et al., 2014; Kumar et al., 2019).

Based on this theorizing, when brands create dedicated CS accounts on social media platforms, they may not only streamline complaint management but also foster consumer co-creation of value on the brand's Main accounts. First, by directing consumer complaints and inquiries to CS accounts, brands cultivate a more positive environment on their Main accounts. This emphasis on positive interactions encourages greater consumer engagement and empowers them to actively shape their interactions, thereby contributing to value creation through their engagement (Hennig-Thurau et al., 2004). Moreover, satisfied consumers assisted by a CS account are more likely to engage in the value co-creation process with the brand, which eventually enhances the overall value of the brand and interactions in the Main account (Chen & Vargo, 2014). Therefore, creating dedicated CS accounts on Twitter can influence consumer engagement on Main accounts, which can be translated into tangible increases in engagement metrics such as likes and replies to brands' social media posts. Therefore, based on this discussion, the following hypothesis is advanced:

Hypothesis: Creating a dedicated CS account increases consumer engagement on a brand's Main account.

4. Data and context

To empirically test our hypothesis, we collect data from Twitter, a leading microblogging social media platform. First, we search Twitter with keywords such as "customer care" and "customer service" (CS accounts) and identify an initial list of 512 brands. Then, from the identified CS Twitter accounts, we identify the official Main Twitter accounts and the date the CS accounts were created (see Figure 1). Next, we use Twitter API to collect posts (tweets) issued by the Main accounts as well as tweets mentioning those accounts using the '@' symbol followed by the official Twitter handle. We use data from the 12 months before and after a brand created a CS account.

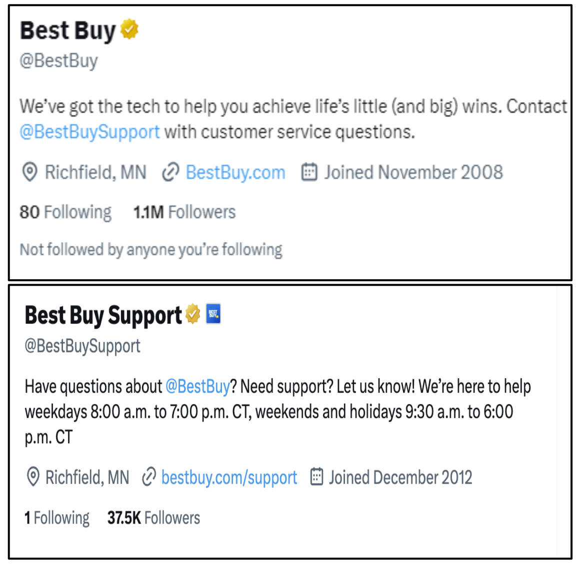


Figure 1 Main (Top) and CS (Bottom) Twitter accounts

Since some brands have their CS accounts created before their Main accounts, we exclude them from our data construction. Additionally, some accounts were inactive during the period of data collection, exhibiting insufficient activity of less than 100,000 tweets over the 24 months. The final number of treated brands (that created CS accounts) is 71 brands. Simultaneously, we randomly identified 266 brands on Twitter that have Main accounts only (did not create any CS accounts) as potential candidates for the control group.

4.*1. Propensity score matching*

Following Goh et al. (2013), Kumar et al. (2018), and Pan and Qiu (2022), we create a control group for the treated brands using PSM to ensure comparability between treated and control groups based on observable characteristics. As mentioned earlier, we have 71 treated brands and 266 control brands. We create the control group by matching each treated brand with the most similar control brand based on the following characteristics: (i) total brand tweet, (ii) dummy verified status, (iii) the number of days since a brand joined Twitter, (iv) following count, (v) followers count, (vi) industry that the brand belongs to, and (vii) year account is created.

The matching procedure utilized a logit model based on the covariates mentioned above to obtain the predicted propensity score. Then, we use a 1:1 nearest neighbor-matching approach based on propensity scores to match each treated brand with a control brand. To evaluate the quality of matching, we perform t-tests of equality of means before and after the matching to check that the characteristics between the treated and control group units are balanced. Following the matching process, an initial 71 brands were successfully paired. The t-test comparing the mean values of covariates between the treatment and control groups generally revealed no significant differences in the characteristics of the two groups, indicating successful mitigation of potential bias prior to further analysis. Detailed results are presented in Tables 1 and 2.

Table 1 Differences in mean before matching

	Before matching			
Variables	Mean Treated (N=71)	Mean Control (N=266)	t-Statistics	p-value
tweet_count	10.093	10.824	-3.809***	0.000
verified	0.650	0.972	-9.095***	0.000
days	8.422	8.480	-3.469***	0.001
following_count	6.996	6.703	0.975	0.332
followers_count	10.269	12.978	-11.836***	0.000

*Note: Industry dummy and time dummy are not reported in this table. ***: p<0.01, **: p<0.05, *: p<0.1*

Table 2 Differences in mean after matching

	After matching			
Variables	Mean Treated (N=71)	Mean Control (N=71)	t-Statistics	p-value
tweet_count	10.871	10.824	0.186	0.853
verified	0.916	0.972	-1.456	0.148
days	8.481	8.480	0.018	0.986
following_count	7.413	6.703	1.861*	0.065
followers_count	12.081	12.978	-3.403***	0.001

*Note: Industry dummy and time dummy are not reported in this table. ***: p<0.01, **: p<0.05, *: p<0.1*

Following the PSM matching, we exclude matched pairs for treated brands with minimal time gaps (equal to or less 60 days) between the CS account and the Main account creation date, matched pairs for treated brands with the CS account created date preceding their Main account created date, and matched pairs with control brands having insufficient tweeting (posting) activities. The final dataset consists of 49 treated brands and 49 control brands. We construct a panel dataset by aggregating the data at the week-brand level. The total number of observations in the panel dataset is 8,358.[11]

[11] The total number of observations is 8,358, which is less than the expected value of 9,996 observations (Number of brands × Number of Groups × Number of weeks (time periods) = 49×2×102). This is due to the inactivity of some brands during specific weeks within the study period.

Table 3 provides the definitions of the key variables in this study and Table 4 reports the descriptive statistics of those variables.

Table 3 Definitions of key variables

Variables	Variable Definition
log(Likes)$_{i,t}$	The logarithm of the average number of likes received by tweets from brand *i* in week *t*.
log(Retweets)$_{i,t}$	The logarithm of the average number of retweets received by tweets from brand *i* in week *t*.
log(Replies)$_{i,t}$	The logarithm of the average number of replies received by tweets from brand *i* in week *t*.
WC$_{i,t}$	The average number of words in tweets from brand *i* in week *t*.
WPS$_{i,t}$	The average number of words per sentence in tweets from brand *i* in week *t*.

Table 4 Descriptive statistics with variables

Variables	Obs.	Mean	Std	Min	Max
log(Likes)$_{i,t}$	8,358	0.705	1.013	0.000	7.650
log(Retweets)$_{i,t}$	8,358	1.151	1.098	0.000	9.391
log(Replies)$_{i,t}$	8,358	0.546	0.659	0.000	5.360
WC$_{i,t}$	8,358	15.043	3.657	1.000	39.667
WPS$_{i,t}$	8,358	6.639	1.923	0.500	21.000

5. Empirical model and main results

To examine the effect of creating a dedicated CS account on consumer engagement, we follow Kumar et al. (2022) and introduce the following fixed effects regression model:

$$\log(DV)_{i,t} = \beta_{11}CS_{i,t} + \beta_{12}WPS_{i,t} + \beta_{13}WC_{i,t} + \eta_i + \theta_t + \varepsilon_{i,t}, \quad (1)$$

where $DV_{i,t}$ is the log average number of likes, the log average number of retweets, or the log average number of replies for brand i at time (week) t.[12] $CS_{i,t}$ is a dummy variable indicating whether brand i has created a dedicated CS account at time t (takes the value 1 in the post-treatment period and 0 in the pre-treatment period; $CS_{i,t}$ is always zero for firms that did not create a CS account). $WPS_{i,t}$ and $WC_{i,t}$ are control variables that represent the average words per sentence and the average word count by brand i at time t, respectively. η_i represents brand fixed effect, and θ_t refers to time fixed effect. $\varepsilon_{i,t}$ denotes the error term.

[12] We apply a logarithmic transformation to the variables to address skewness concerns and interpret the results as percentage change.

Table 5 shows the estimation results of our main model in Equation (1). In general, the results show a significant impact of creating dedicated CS accounts on consumer engagement on Main accounts. From columns 1, 2, and 3, the coefficients of CS are significant and positive. Creating a CS account can increase the number of likes, retweets, and replies to a brand post by about 39%, 40%, and 19%, respectively.

Table 5 Fixed effects regression result

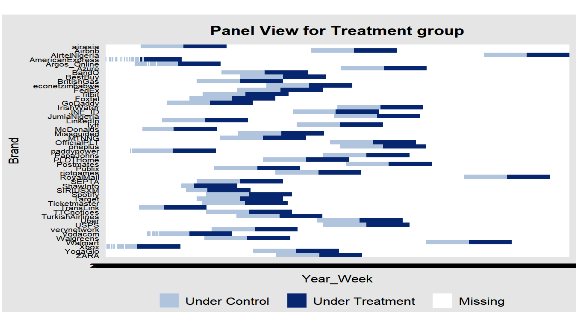
DV	(1) log(Likes)	(2) log(Retweet)	(3) log(Replies)
CS	0.390*** (0.113)	0.403*** (0.107)	0.189** (0.072)
WPS	-0.022* (0.013)	-0.008 (0.014)	-0.013 (0.009)
WC	0.017 (0.013)	0.019** (0.009)	0.017* (0.008)
Brand FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Obs.	8,358	8,358	8,358
Adj. R^2	0.720	0.603	0.572

*Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

6. Robustness checks

6.1. Stacked difference-in-differences

A potential concern with our main model arises regarding the staggered adoption among brands. Staggered adoption refers to the nuanced timeline at which different brands create dedicated CS accounts on Twitter at different times. This phenomenon is depicted in Figure 2. The figure on the right illustrates the various brands in the treated group are under control (light color) and under treatment (dark color) periods, whereas the left figure represents the corresponding brands in the control group that are under control (light color) periods. To address this issue, we employ a Stacked Difference-in-Differences (DID) approach to account for variations in the timing of creating CS accounts across brands.



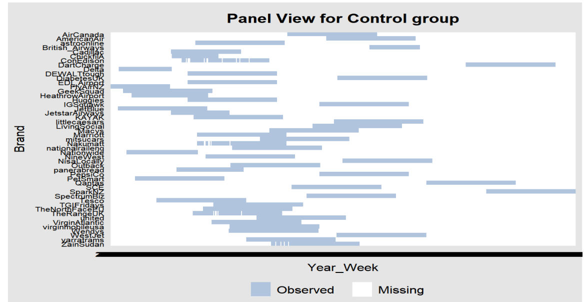


Figure 2 Staggered adoption of CS accounts by brands

The Stacked DID approach is a robust method for handling staggered adoption of interventions (Cengiz et al., 2019). Stacked DID enables us to evaluate the treatment effect by comparing changes in consumer engagement and brand CRM activities before and after CS account creation for each brand within the treatment group, along with their counterparts in the control group. By creating cohort-specific datasets for each ever-treated cohort, comprising the treated cohort and all never-treated units, Stacked DID allows for the calculation of average effects across all cohorts. This method employs fixed effects regression while controlling for stack-unit interaction fixed effects and stack-year interaction fixed effects. Specifically, our Stacked DID model is formulated as follows, following the approach outlined by Gardner (2022):

$$\log(DV)_{c,g,p} = \beta_{\alpha 11} CS_{c,g,p} + \beta_{\alpha 12} WPS_{c,g,p} + \beta_{\alpha 13} WC_{c,g,p} + \eta_{c,g} + \theta_{c,p} + \varepsilon_{c,g,p}, \quad (2)$$

where $DV_{c,g,p}$ is the outcome of interest, which is the log average number of likes, the log average number of retweets, or the log average number of replies for group c (the treated cohort), and brand unit g during each week time p. $CS_{c,g,p}$ is a dummy variable indicating whether the stack-unit brand cg has created a dedicated CS account at stack-time cp. $WPS_{c,g,p}$ and $WC_{c,g,p}$ are control variables that represent the average words per sentence and the average word count by stack-unit brand cg at stack-time cp, respectively. $\eta_{c,g}$ represents the stack-unit interaction fixed effects cg and $\theta_{c,p}$ indicates the stack-week interaction fixed effects cp, and $\varepsilon_{c,g,p}$ represent the error term.

Table 6 shows the stacked DID analysis results in Equation (2). The results are consistent with our main analysis. Overall, creating CS accounts significantly impacts consumer engagement.

Table 6 Stacked DID regression result

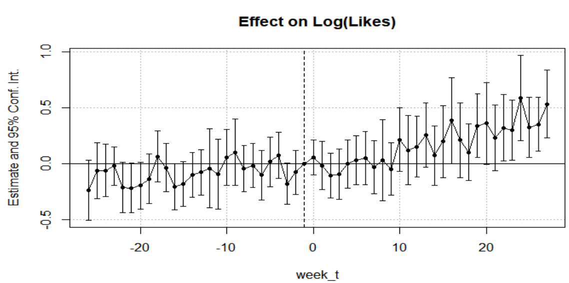
DV	(1) log(Likes)	(2) log(Retweet)	(3) log(Replies)
CS	0.365***	0.399***	0.173***

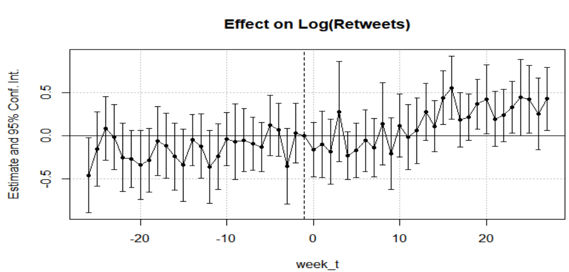
	(0.090)	(0.086)	(0.056)
WPS	0.001 (0.001)	-0.003* (0.002)	-0.006*** (0.001)
WC	0.001 (0.001)	0.022*** (0.001)	0.008*** (0.001)
Brand FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Obs.	191,574	191,574	191,574
Adj. R^2	0.694	0.529	0.481

*Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

6.2. Relative time model

Another concern with the main model is the violation of the pre-treatment "parallel" assumption, i.e., the treated and control groups do not exhibit similar trends in consumer engagement in the absence of the treatment (Angrist & Pischke, 2009). To alleviate this concern, we adopt a relative time model that incorporates 26 lead (pre-treatment effects) and 26 lag indicators (post-treatment effects). In Figure 3, we plot the coefficients of the leads and lags with their confidence intervals, which provide evidence that the parallel trend assumption holds.





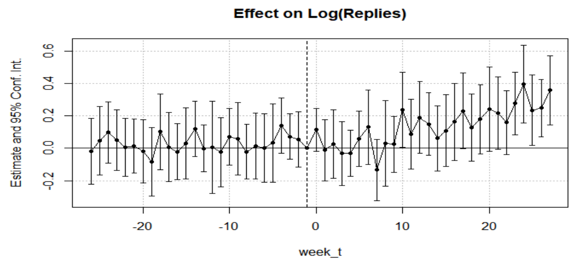


Figure 3 Relative time model for log(Likes), log(Retweets) and log(Replies)

7. Mediation analysis

An important question that arises is what drives the observed effects of creating CS accounts on consumer engagement with the Main accounts. To answer this question, we uncover the underlying mechanism by examining the mediating effect of consumers' tweet traffic on the Main account. Based on our theorization, we expect that creating dedicated CS accounts can influence consumers to generate more posts, which in return co-create value for brands by influencing consumer engagement. Figure 4 presents the conceptual model of the underlying mediation effect. The treatment variable, creating dedicated CS accounts, impacts consumer engagement through the mediating variable, consumer tweet traffic (Baron & Kenny, 1986).

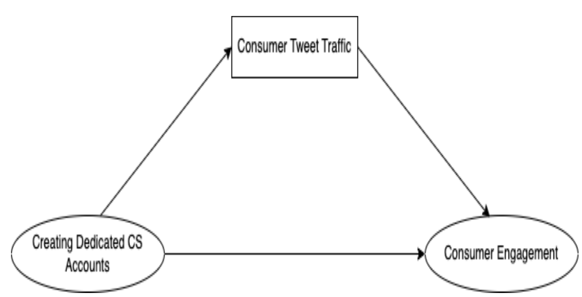


Figure 4 Conceptual model for mediation analysis

To estimate the mediating effect, we follow the following two-step procedure:

Step 1:

$$\log(TotalTweets)_{i,t} = \beta_{20} + \beta_{21}CS_{i,t} + \beta_{22}WPS_{i,t} + \beta_{23}WC_{i,t} + \eta_i + \theta_t + \varepsilon_{i,t}, \quad (3)$$

Step 2:

$$\log(DV)_{i,t} = \beta_{30} + \beta_{31}CS_{i,t} + \beta_{32}TotalTweets_{i,t} + \beta_{33}WPS_{i,t} + \beta_{34}WC_{i,t} + \eta_i + \theta_t + \varepsilon_{i,t}, \quad (4)$$

where $\log(TotalTweets)_{i,t}$ is the mediating variable indicating the log average number of consumer tweet traffic to brand i at week t. Following the specification in Equations (3) and (4), the mediation effect of consumer tweet traffic is estimated by $\widehat{\beta_{21}} \times \widehat{\beta_{32}}$. A bootstrap analysis was conducted to obtain the standard error and confidence intervals (Hayes, 2017). The results of the mediation analysis are in Table 5.

From Table 7 in Column (2-1), the estimated coefficient of $CS_{i,t}$, i.e., $\widehat{\beta_{21}}$ in Equation (3) is significant, indicating a positive effect of creating dedicated CS accounts on consumer tweet traffic on the Main account. In Columns (3-1), (3-2), and (3-3), the estimated coefficient of $\log(TotalTweets)_{i,t}$, i.e., $\widehat{\beta_{32}}$ in Equation (3), is statistically significant, which indicates a positive effect of consumer tweet traffic on our dependent variables, $\log(Likes)_{i,t}$, $\log(Retweets)_{i,t}$ and $\log(Replies)_{i,t}$. The mediation effect of consumer tweet traffic on $\log(Likes)_{i,t}$, $\log(Retweets)_{i,t}$ and $\log(Replies)_{i,t}$ is 0.158, 0.139, and 0.104, respectively. These results show that consumer tweet traffic mediates the effect of creating dedicated CS accounts on consumer engagement with the Main accounts.

Table 7 Estimation results for mediation effect

	Mediating effect Step 1	Mediating effect Step 2		
DV	(2-1) log(Total Tweets)	(3-1) log(Likes)	(3-2) log(Retweet)	(3-3) log(Replies)
CS	0.877*** (0.044)	0.404*** (0.023)	0.493*** (0.026)	0.209*** (0.015)
log(Total Tweets)	-	0.180*** (0.006)	0.159*** (0.007)	0.119*** (0.004)
WPS	-0.173*** (0.012)	- 0.018** (0.006)	0. 046*** (0.007)	-0.021*** (0.004)
WC	-0.027*** (0.006)	-0.026*** (0.003)	-0.053*** (0.004)	-0.004*** (0.002)
Constant	7.485*** (0.091)	-0.007 (0.063)	0.528*** (0.004)	-0.049 (0.042)
Time FE	Yes	Yes	Yes	Yes
Brand FE	Yes	Yes	Yes	Yes
Obs.	7,945	7,945	7,945	7,945
Adj. R2	0.092	0.198	0.163	0.170

*Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Note: The number of observations in the mediation analysis (7,945) is lower than that of the main analysis (8,358) due to some brands did not receive any tweets from customers on some time periods

8. Discussion

By conducting this empirical study on the impact of creating dedicated CS accounts on consumer engagement, this work contributes to the literature on consumer engagement on social media, SDL theory, and customer relationship management. To the best of our knowledge, no prior study has examined this effect, and this study fills an important gap in the literature and provides important practical implications. Drawing on SDL theory, we examine the effect of creating dedicated CS accounts on three consumer engagement measures, which are the number of likes, the number of retweets, and the number of replies received by a brand to its posts on its Main account. Additionally, we uncover the underlying mechanism by examining the mediation effect of consumer tweet traffic to the Main account.

This research holds several implications for practitioners and social media managers on how to leverage social media platforms to increase consumer engagement. First, we explore the impact of creating dedicated CS accounts within the realm of brand targeting and segmenting consumer strategies. This offers insights into how brands can strategically leverage CS accounts to optimize their social media presence. Second, we expand the discussion surrounding the SDL theory in the context of social media. We introduce SDL theory to highlight the collaborative nature of value creation between brands and consumers on social media platforms, and by doing so, we underscore the significance of SDL principles in guiding brands towards effective engagement strategies. Furthermore, we investigate the mediating role of consumer tweet traffic on consumer engagement. This multifaceted exploration offers a more delicate understanding of the dynamics at play, emphasizing the interconnectedness of brand and consumer in social media.

While this research offers valuable insights, there are several limitations that offer possible future directions to our research. First, although our analysis includes Twitter data from brands in multiple sectors, future research can examine the moderating effect of different brand sizes. Second, our focus was primarily on Twitter, a leading microblogging social media platform. Future studies could study different social media platforms. Third, and due to data limitations, we do not examine the effect of creating CS accounts on brands' social media CRM strategies and the effect on consumer satisfaction. Despite the limitations above, our study contributes to a deeper understanding of the complexities inherent in brand-customer interactions on social media platforms. By examining the implications of CS account utilization, expanding upon SDL theory, and considering both brand and customer perspectives, we offer valuable insights that can inform strategic decision-making and enhance brand-customer relationships in social media.

9. References

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