Lisette de Vries, Sonja Gensler, & Peter S.H. Leeflang

Effects of Traditional Advertising and Social Messages on Brand-Building Metrics and Customer Acquisition

This study examines the relative effectiveness of traditional advertising, impressions generated through firm-to-consumer (F2C) messages on Facebook, and the volume and valence of consumer-to-consumer (C2C) messages on Twitter and web forums for brand-building and customer acquisition efforts. The authors apply vector autoregressive modeling to a unique data set from a European telecom firm. This modeling approach allows them to consider the interrelations among traditional advertising, F2C impressions, and volume and valence of C2C social messages. The results show that traditional advertising is most effective for both brand building and customer acquisition. Impressions generated through F2C social messages complement traditional advertising efforts. Thus, thoroughly orchestrating traditional advertising and a firm's social media activities may improve a firm's performance with respect to building the brand and encouraging customer acquisition. Moreover, firms can stimulate the volume and valence of C2C messages through traditional advertising that in turn influences brand building and acquisition. These findings can help managers leverage the different types of messages more adequately.

Keywords: traditional advertising, social media, brand building, customer acquisition, vector autoregressive modeling

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Every year, U.S. firms invest approximately $130 billion in traditional advertising (e.g., television, radio, print, and outdoor) to build their brands and increase sales (eMarketer 2014). Yet empirical evidence has suggested that firms are gradually shifting their traditional advertising investments to, for example, social media to pursue similar objectives (eMarketer 2016; Hudson et al. 2016; Statista 2016). Many firms have established a social media presence by operating pages on social networking sites such as Facebook. Firms post messages on these pages to interact with consumers by exploiting the network structure and to ultimately build the brand and stimulate sales (De Vries, Gensler, and Leeflang 2012). We call these posts firm-to-consumer (F2C) social messages.

To leverage these messages, managers need to know how effective F2C social messages are for building the brand and influencing consumer behavior. Previous research has shown that F2C social messages have a positive effect on existing customers' expenditures (e.g., Goh, Heng, and Lin 2013; Kumar et al. 2016). However, we lack knowledge about the effectiveness of firms' social media activities in comparison to their traditional advertising investments. Moreover, we know little about potential complementary effects of F2C social messages and traditional advertising (Kumar et al. 2016). Such knowledge is, however, critical for managers to leverage and orchestrate traditional advertising and F2C social messages effectively (Chen and Xie 2008; Edelman 2010). Furthermore, previous studies have focused on the impact of F2C social messages on existing customers' behavior but have not investigated the potential impact on new customer acquisition.

In addition to a firm's own efforts to build the brand and affect consumer behavior, it is well known that messages initiated by consumers influence other consumers (e.g., Babić Rosario et al. 2016; Hennig-Thurau, Wiertz, and Feldhaus 2015; You, Vadakkepatt, and Joshi 2015; Zhu and Zhang 2010). Such messages can be product reviews as well as messages posted on forums, microblogs (e.g., Twitter), brand communities, and other social media sites. We call messages that are initiated by consumers and targeted to other consumers consumer-to-consumer (C2C) social messages. Managers need a clear understanding of the effects of C2C social messages on the brand and consumer behavior relative to the impact of their own efforts. Moreover, managers need to know whether their own communication activities affect C2C social messages because this would allow them to exert some influence on what consumers say about the brand. Previous studies that compare traditional advertising and C2C social messages have indicated that C2C social messages can be more effective for increasing sales and customer acquisition (e.g., Trusov, Bucklin, and Pauwels 2009). Moreover, these studies have suggested that traditional advertising and

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consumer messages are complements (Fossen and Schweidel 2017; Gopinath, Thomas, and Krishnamurthi 2014). Yet few studies have considered C2C and F2C social messages jointly, and the findings of these studies with respect to the effectiveness of these messages are mixed (Goh, Heng, and Lin 2013; Kumar et al. 2013). To date, no empirical research has considered traditional advertising, F2C social messages, and C2C social messages simultaneously to compare the effectiveness of the different types of messages. Thus, we also have little knowledge about the interrelations among the different messages, though there is no doubt that such interrelations are likely to exist (Hewett et al. 2016).

The aim of this study is to close this gap in the literature by examining the relative effectiveness of traditional advertising, F2C social messages, and C2C social messages for *both* brand building and customer acquisition over time, and to study the interrelations among the different messages. We focus on customer acquisition because it is a critical performance measure that has just recently received more attention (Katsikeas et al. 2016). By considering customer acquisition (i.e., number of new customers), we are able to study the behavioral outcomes of traditional advertising, F2C social messages, and C2C social messages. By accounting for brand-building metrics (i.e., consumers' brand awareness, consideration, and preference), we can examine both indirect and direct effects of the different messages on customer acquisition (Bruce, Peters, and Naik 2012).

We collected a unique data set from a European telecom firm (which maintains contractual relationships with consumers) and Nielsen that contained weekly data on traditional advertising, F2C social messages, and C2C social messages over 119 weeks. We also have weekly information about brand-building metrics and customer acquisition. The traditional advertising measure comprises the firm's joint expenditures on television, radio, print, and outdoor advertising. The number of impressions of firm-initiated messages on Facebook based on likes, comments, and shares of the firm's original messages represent F2C social messages. We therefore use the term F2C impressions when describing and discussing the results of the empirical study. The impressions provide information about the spreading of a firm's message. We consider Facebook because it is the firm's main social media platform to communicate with consumers. Consumer-to-consumer social messages include the number (C2C volume) and valence (C2C valence) of messages initiated by consumers about the firm on Twitter and the most popular forums in the country where the focal firm operates. We do not consider online reviews because the content of the reviews is mostly about phones and less about the specific services offered by the focal firm. By taking C2C social messages on Twitter and forums into account, we cover the majority of C2C social messages about the focal firm.

To elicit the effectiveness of traditional advertising, F2C impressions, and C2C social messages (C2C volume and C2C valence), we use vector autoregressive (VAR) modeling. This methodology allows us to determine the relative effectiveness of traditional advertising, F2C impressions, and C2C social messages by computing their elasticities for the brand-building metrics and customer acquisition on the basis of impulse response function (IRF) analyses (e.g., Dinner, Van Heerde, and Neslin 2014). In addition, the VAR model approach enables us to examine the interrelations among traditional advertising, F2C impressions, and C2C social messages (Hewett et al. 2016).

With our work, we contribute to the extant literature in several ways. First, we consider traditional advertising, impressions generated through F2C social messages, and C2C social messages simultaneously and compare their effectiveness. Second, we elaborate on the complementary effects of and interrelations among traditional advertising, F2C impressions, and C2C social messages. Third, we take both brand-building and behavioral metrics into account to assess the effectiveness of the different messages over time. Using brand-building *and* behavioral metrics allows us to address current calls to consider multiple performance metrics at different levels to derive more insightful managerial implications (Katsikeas et al. 2016). Accordingly, our study is more comprehensive than previous studies and allows for richer insights that help managers to orchestrate the different messages effectively.

The results show that the different messages are effective in building a brand and enhancing customer acquisition. With respect to building a brand, traditional advertising is most effective in creating awareness and consideration. However, C2C valence is most effective in spurring preference. Traditional advertising is again most effective in enhancing customer acquisition, followed by F2C impressions and C2C volume. The results suggest that the firm's social media activities complement its traditional advertising efforts. In addition, traditional advertising enhances the volume and valence of C2C social messages, which in turn spur consumers' preference and acquisition. Given the effectiveness of traditional advertising, managers should carefully trade off its effectiveness and costs (i.e., efficiency) when making marketing investment decisions.

In the next section, we elaborate on previous research related to our study and highlight the need for an empirical study that addresses the gap in research. Then, we describe our data and introduce the modeling approach. Subsequently, we present and elaborate on the empirical findings. Finally, we conclude with a discussion of the study's implications, limitations, and research opportunities.

Previous Research on the Effectiveness of Traditional Advertising, F2C Social Messages, and C2C Social Messages

The effectiveness of traditional advertising, F2C, and C2C social messages can be assessed by examining their impact on brand-building and behavioral outcomes. Brand awareness, consideration, and preference are three commonly used metrics to evaluate the effects on brand building (e.g., Draganska, Hartmann, and Stanglein 2014; Srinivasan, Vanhuele, and Pauwels 2010). Recent studies have demonstrated the brand-building and sales capabilities of a single type of message—traditional advertising (e.g., Sethuraman, Tellis, and Briesch 2011; Srinivasan, Vanhuele, and Pauwels

TABLE 1
Overview on Studies Considering More Than One Type of Message

Authors	Traditional Advertising	C2C	F2C	Brand-Building Metrics	Sales	Acquisition
Bruce, Foutz, and Kolsarici 2012	+	Online reviews			+	
Fossen and Schweidel 2017	+	Twitter				
Gopinath, Thomas, and Krishnamurthi 2014	+	Forum			+	
Onishi and Manchanda 2012	+	Blog			+	
Stephen and Galak 2012	+	Blog, community			+	
Trusov, Bucklin, and Pauwels 2009	+	WOM referrals				+
Villanueva, Yoo, and Hanssens 2008	+	WOM referrals				+
Goh, Heng, and Lin 2013		Facebook community	+		+	
Kumar et al. 2013		WOM	+		+	+
Kumar et al. 2016	+		+		+	
This study	+	Microblog, forums	+	+		+

Notes: The plus signs indicate that the study considered the specific variable.

2010), C2C social messages (e.g., Hennig-Thurau, Wiertz, and Feldhaus 2015), and F2C social messages (e.g., Goh, Heng, and Lin 2013; Hutter et al. 2013; Kumar et al. 2016; Rishika et al. 2013). Yet research considering more than just one type of message is scarce, as we illustrate in Table 1.

Some studies compare the effectiveness of traditional advertising and C2C social messages (Table 1). Note that these studies also contain other forms of C2C social messages than the ones we consider. The results of these studies indicate that C2C messages are more effective than traditional advertising at generating sales for microlending loans (Stephen and Galak 2012) and acquiring customers for a web hosting service (Villanueva, Yoo, and Hanssens 2008) or a social network (Trusov, Bucklin, and Pauwels 2009). Moreover, C2C social messages and traditional advertising work as complements for enhancing sales of cell phone introductions (Gopinath, Thomas, and Krishnamurthi 2014) and movies (Bruce, Foutz, and Kolsarici 2012; Onishi and Manchanda 2012). Overall, these studies suggest that C2C social messages may be more effective than traditional advertising in stimulating sales and acquisitions. However, we lack knowledge on the relative effectiveness of traditional advertising and C2C social messages to build a brand.

Very few studies that consider F2C social messages take other messages into account (Table 1). Comparing F2C and C2C social messages, Goh, Heng, and Lin (2013) find that C2C social messages are more effective than F2C social messages for evoking apparel purchases.[1] Kumar et al. (2013) show that F2C social messages lead to substantially more C2C social messages, which, in turn, affect sales of an ice cream store. The study shows the viral capacities of F2C social messages and that different types of social messages can enhance one another. Kumar et al. (2016) find that F2C social messages have positive effects on retail sales, even when controlling for traditional advertising. Overall, the studies on F2C social messages provide scattered insights into the relative effectiveness of these messages on behavioral outcomes and do not provide any insights into the relative effects on brand building.

The discussion of previous studies shows that there are two major gaps in the literature: (1) no simultaneous assessment of the relative effectiveness of traditional advertising, F2C social messages, and C2C social messages and (2) a lack of knowledge of the effects of these messages on brand-building metrics. Yet it is important to consider traditional advertising, F2C social messages, and C2C social messages jointly because the different messages are omnipresent today and are likely to affect consumers simultaneously. Moreover, the different messages are part of the "echoverse," that is, the communications environment of a firm (Hewett et al. 2016). Thus, we need to acknowledge that the different message types might influence one another. For example, a recent study by Fossen and Schweidel (2017) suggests that traditional advertising positively affects the volume of C2C social messages about the advertised brand. Firms generally do not have much influence on *what* consumers talk about online (C2C social messages), but if traditional advertising affects C2C social messages, firms actually do have a tool to influence these messages indirectly. Firms might plan their F2C social messages in accord with their traditional advertising activities or vice versa. Moreover, F2C social messages might stimulate consumers to talk about the brand on other social media sites (e.g., Kumar et al. 2013). Because previous studies have considered only a limited set of messages, we lack insights into the interrelations among the different messages. Knowledge about these interrelations, however, enables managers to exert greater influence on the echoverse and, finally, on critical performance metrics.

Table 1 also shows that current studies have considered only behavioral performance measures, thereby simply treating intervening processes as a "black box" (Srinivasan, Vanhuele, and Pauwels 2010). Accounting for brand-building metrics, however, allows for examining both indirect and direct effects of messages on customer acquisition (Bruce, Peters, and Naik 2012). Considering brand-building metrics alongside behavioral metrics helps managers better understand the full effects of the different messages.

[1]Rishika et al. (2013) consider both firm and consumer messages in a firm-initiated social media community, but they aggregate the messages and, thus, do not distinguish between the two types of messages.

Because previous studies have provided only scattered insights into the relative effectiveness of the different messages, it is difficult to form expectations beforehand. Thus, we refrain from formulating propositions. We rather provide empirical insights into the relative effectiveness of the different message types (i.e., traditional advertising, F2C social messages, and C2C social messages) on brand-building and behavioral outcomes and the interrelations among these messages.

Empirical Application

Data

We use contractual data on customer acquisition from a European telecom firm related to its activities in one European country. Moreover, we obtained data from the firm's social listening tool on C2C social messages and data from its Facebook page to measure F2C impressions. We combine these data with Nielsen data on traditional advertising and complement all data with survey panel data from an external company on brand-building metrics. The data period ranges from week 30 in 2011 to week 44 in 2013, with all data reported on a weekly basis. Table 2 contains a detailed overview of all variables, their descriptions, measures, and sources.

The focal brand was one of the top five telecom providers in the market of mobile subscription plans in the specific country at the time of the study. There were four main competitors, which, together with the focal brand, had a combined market share of approximately 80%. However, the focal brand was not the largest of these five brands because of its specific target group, which comprises young adults between 16 and 30 years old—a target group that is connected through social media and uses online media actively (Statista 2014). We have information from the survey panel that approximately 80% of the target group had a Facebook account and that about 60% logged in to their account daily. At the time of the study, the firm had the largest Facebook page in the country with respect to the number of "brand fans" (on average, 100,000 consumers). The firm actively used traditional advertising, and the average number of weekly impressions was approximately 436,881.[2]

Traditional advertising. We use joint gross media expenditures on TV, print, radio, and out-of-home to measure traditional advertising investments (Table 2). Nielsen does not directly observe how much firms actually spend on traditional advertising through TV, print, radio, and out-of-home because firms are reluctant to provide this information. Therefore, Nielsen measures advertising expenditures indirectly, using public and national television channels, and provides data about commercials according to their gross rating point tariffs (i.e., excluding discounts and price negotiations).

F2C impressions. We use the weekly number of viral impressions of the firm's posts on Facebook (Table 2). This number considers impressions of the focal firm's posts on Facebook when consumers like, comment on, or share the messages with each other. We consider viral impressions because they reflect the spreading activity through the network: those impressions might be particularly effective for building a brand and generating acquisitions.

The focal brand's original F2C messages contain promotional messages about phones, subscriptions, or service offers of the focal firm but also information unrelated to the category such as recommendations for going out and sweepstakes. In general, F2C social messages are positive, but shared F2C social messages may have different content and may differ in valence from the original message if consumers comment negatively. We do not have information about the valence of shared F2C social messages, but previous research has shown that the share of negative comments to firms' posts is rather small (De Vries, Gensler, and Leeflang 2012). We do not consider any consumer-initiated conversations about the firm on Facebook. Such messages would be C2C social messages according to our definitions, and the focal firm has no information about C2C social messages posted on Facebook.

C2C social messages. We measure the volume (i.e., number) and valence of messages initiated by consumers on forums and Twitter, whereby Twitter accounts for the largest part. Thus, we consider specific types of C2C social messages. Yet Twitter and the most popular forums capture the majority of C2C social messages about the focal firm according to conversations with the management. The number of C2C social messages reflects the chance of consumers seeing these messages (i.e., the more C2C social messages are posted, the greater the likelihood that consumers will see them). The valence of C2C social messages echoes the sentiment in the marketplace and is the difference in shares of positive and negative messages (Table 2). The values for the valence measure range between –1 and +1, where –1 (+1) indicates that no positive (negative) but only negative (positive) messages are posted in a certain week. If valence is equal to zero, there are as many positive as negative messages posted.

Brand-building metrics and customer acquisition. A third-party organization gathered data on different brand-building metrics related to the brand: unaided brand awareness, consideration, and preference (Table 2). The share of consumers who mention the focal brand spontaneously as a brand operating in the specific industry measures unaided brand awareness. Brand consideration is the share of consumers who would consider the focal brand for a given purchase occasion. Brand preference is the share of consumers who prefer the focal brand to competing brands. Each week, this organization interviews 130 target consumers (i.e., young adults), producing an accumulated 15,470 interviews (some consumers might be interviewed more than once) over 119 weeks. The sample is not random but targeted and weighted. Over the weeks, the demographic characteristics of the panel members remain the same. Previous studies considering brand-building metrics used similar samples (Bruce, Peters, and Naik 2012; Srinivasan, Vanhuele, and Pauwels 2010). Customer acquisition is the number of newly acquired customers per week (Table 2).

[2]We derived the number of impressions from the ad spending and the cost per thousand impressions.

TABLE 2
Description of Variables

Variable Name	Description	Measurement Unit	Source
Endogenous Variables			
Traditional advertising	Telecom firm's traditional gross media expenditures on TV, radio, print, and out-of-home advertising	Gross media expenditures (€)	Nielsen
F2C impressions	Number of impressions of the focal firm's messages on Facebook based on likes, comments, and shares of those messages	Impressions	Facebook Insights
C2C volume	Total number of C2C social messages (positive, neutral, and negative) on forums and Twitter	Volume	Online tool of the telecom firm
C2C valence	Sentiment in the marketplace [(positive C2C messages – negative C2C messages)/(all C2C messages)]	Share	Online tool of the telecom firm
Unaided awareness	Respondents list all telecom providers they know	Percentage of respondents	External party via telecom firm (survey)
Consideration	Respondents list the telecom providers they would consider if they had to choose one	Percentage of respondents	External party via telecom firm (survey)
Preference	Respondents name the telecom provider they would prefer if they had to choose a new telecom provider	Percentage of respondents	External party via telecom firm (survey)
Acquisition	Number of newly acquired customers	Volume	Telecom firm's database
Control Variables			
Holidays	Public and school holidays	Dummy	Own research
Media events	Important news items related to the telecom sector, specific telecom providers, or new technology	Dummy	News archives online
Buzz events	Important interventions that created online buzz	Dummy	Social media
Promotions	Number of promotions by focal firm divided by the number of promotions by focal firm + four most important competing firms	Percentage	Nielsen
Traditional advertising competition	Traditional media expenditures on television, radio, print, and outdoor by the four most important competitors	Gross media expenditures (€)	Nielsen
C2C social messages competition	Number of C2C messages on forums and Twitter about the four most important competitors	Volume	Online tool of the telecom firm

Control variables. Several other factors could also affect the brand-building metrics and customer acquisition. Namely, we consider promotions, media and buzz events, holidays, and competition. First, promotions are important stimuli to attract new customers and might also affect brand-building metrics (Pauwels, Hanssens, and Siddarth 2002). We gathered all the individual descriptions of price promotions for the focal firm and its four main competitors. The price promotions apply to annual or two-year subscription plans (e.g., 50% discount for 24 months). All telecom providers in the market use similar promotions. To control for the effect of price promotions, we consider a variable that reflects the promotion intensity of the focal firm—that is, the number of price promotions of the focal firm in a specific week divided by the total number (focal firm + competitors) of price promotions in that week (Table 2). The value of this variable ranges between 0 and 1 and equals 1 if the focal firm is the only firm in a given week that offers a price promotion.

Second, we control for media and buzz events to consider extraordinary short-term interventions. To control for media events, we searched national news archives for important news related to the telecom sector, specific telecom providers, or new telecom-related technology. These news items might describe service failures (e.g., a fire caused service disruptions), new subscription terms being introduced by telecom providers, introduction of new mobile phone models, or major quality improvements of the network. News could probably also cover major price shifts of one or more telecom provider. However, during our observation period no such interventions occurred. Moreover, we identified social media buzz events by inspecting F2C impressions and C2C volume. Buzz events are described by a large deviation from the mean value (i.e., mean +3 SD) and could be either positive or negative. We identified three buzz events, which were related to announcements of new mobile service offers of the focal brand that created large amounts of short-term online buzz.

Third, we consider national holidays. Public (e.g., Easter, Christmas) and school holidays could affect the number of acquisitions. The school holiday during the summer actually covers almost the complete months of July and August. In these months, many consumers are traveling. National holidays might also be related to investments in traditional advertising and consumers' social media activities.

Finally, we consider competitors' advertising activities and the volume of C2C social messages related to competitors, both of which lead to more clutter and might decrease the likelihood that consumers notice traditional advertising or C2C social messages by or about the focal firm. We cannot control for competitive F2C social messages/impressions, because this information was not available. Because the main competitors have a much smaller Facebook presence, we believe this is not problematic (Pauwels 2004; Srinivasan, Vanhuele, and Pauwels 2010).

Descriptive Statistics

Table 3 illustrates the substantial variation in traditional advertising, F2C impressions, and C2C volume and valence for the focal brand over time. The gross media expenditures for traditional advertising are, on average, 407,347 EUR. The average number of weekly F2C impressions is 121,153. According to a manager of the focal firm, the firm posted, on average, one F2C social message per day during our observation period. Thus, the weekly number of impressions is generated by about seven firm posts. However, the F2C messages differ with respect to their virality. The F2C social messages reach approximately 46,055 unique consumers every week who are not "fans" of the firm's social media page (not reported in Table 3). The average number of active users of the page is 17,340 per week, with a maximum of active users of 126,566 in a specific week (not reported in Table 3). The average number of C2C social messages is 1,778. The average valence of C2C social messages equals −.50, which indicates that the sentiment in the market is generally negative. This observation is not surprising given that we study a commodity.

To keep the absolute acquisition numbers anonymous, we constructed an index. Table 3 shows that customer acquisition also varies over time. Moreover, we observe large variations in the brand-building metrics. For example, brand awareness equals 53% on average but ranges between 37% and 68%. This rather large range might seem surprising; however, the considered brand is relatively smaller than its four main competitors. The variation actually suggests that brand-building metrics might be affected by traditional advertising, F2C impressions, and C2C social messages.

In the Web Appendix, we provide time series graphs and highlight some interesting potential relations between the different messages and the brand-building metrics. For example, these graphs suggest a positive relation between traditional advertising, awareness, and consideration. Moreover, the time series graphs suggest a positive relation between F2C impressions and consideration. In addition, peaks in preference seem to follow peaks in C2C volume, which might indicate that C2C social messages positively affect preference. This model-free evidence suggests that the different messages might be related to variations in the brand-building metrics. Yet part of the variation in brand-building metrics might also be due to measurement error (e.g., Naik and Tsai 2000). Because we are interested in the relative effectiveness of traditional advertising, F2C impressions, and C2C social messages, a bias induced by measurement error might not be that critical. However, to test for potential biases due to measurement error, we conduct a robustness check.

Table 4 reports the bivariate correlations among the variables whereby we eliminated any trend in the variables before computing the correlations. In general, many correlations are significant, which seems promising for further analyses. Insignificant correlations might be a result of the multivariate nature of the relations. Thus, we might find significant relations when we consider the multivariate nature of the relations appropriately.

Methodology

We are interested in the effects of traditional advertising, F2C impressions, and C2C social messages on both brand building

TABLE 3
Descriptive Statistics of Relevant Variables

	M	SD	Min	Max
Endogenous Variables				
Traditional advertising (EUR)	407,346.90	329,632.80	21,430.00	1,246,570.00
F2C impressions	121,152.80	305,556.50	1,570.00	2,262,655.00
C2C volume	1,778.28	718.67	568.00	3,430.00
C2C valence	−.50	.22	−.99	.21
Unaided awareness[a] (share)	.53	.07	.37	.68
Consideration (share)	.30	.05	.18	.42
Preference (share)	.15	.03	.08	.22
Acquisition[b] (index)	100.00	38.42	40.74	218.89
Control Variables (Exogenous)				
Promotions (share)	.30	.23	.00	1.00
Traditional advertising competition (EUR)	4,884,590.00	1,336,693.00	1,632,151.00	7,956,551.00
C2C volume competition	29,872.75	14,657.07	15,015.00	153,314.00

[a]We deleted one outlier whose value was three times the standard deviation below the mean.
[b]For confidentiality reasons, we provide an index for customer acquisition.
Notes: This table reports weekly averages.

TABLE 4
Correlations Among Variables (Detrended)

	$\ln(TA)_t$	$\ln(C2C\_vol)_t$	$\ln(C2C\_val)_t$	$\ln(F2C)_t$	$\ln(A)_t$	$\ln(Con)_t$	$\ln(Pref)_t$	$\ln(Acq)_t$
$\ln(TA)_{t-1}$	.568***	.149	.309***	–.199**	.206**	.216**	.040	.299***
$\ln(C2C\_vol)_{t-1}$	.166*	.868***	.180*	–.031	.069	–.106	–.149	–.267***
$\ln(C2C\_val)_{t-1}$	.278***	.238***	.319***	–.169*	.046	–.017	.124	.316***
$\ln(F2C)_{t-1}$	.062	–.074	–.075	.282***	–.126	.022	–.061	.001
$\ln(A)_t$	.066	.017	.029	.045	1.000	.212**	.115	.025
$\ln(Con)_t$	.143	–.153*	.012	–.118	.212**	1.000	.422***	.225**
$\ln(Pref)_t$	.004	–.174*	.136	–.050	.115	.422***	1.000	.281***
$\ln(Acq)_t$	.202**	–.288***	.265***	–.009	.025	.225**	.281***	1.000
$Promotions_t$	.062	–.188**	.025	–.103	.149	.261***	.197**	.402***
$\ln(TA_{comp})_t$	.129	.041	.149	.078	.086	–.018	.053	.132
$\ln(C2C_{comp})_t$	.110	.665***	.297***	.003	.007	–.128	–.033	–.124

*$p < .10$.
**$p < .05$.
***$p < .01$.

and customer acquisition over time, as well as the interrelations among them. Thus, we need to employ a method that allows for considering these complex (inter)relations. We use a VAR model with exogenous variables (VARX). We focus on the cumulative effects (i.e., short- and long-term effects) of the different messages over time and compute elasticities with impulse response functions. This way, we can compare the relative effectiveness of traditional advertising, F2C impressions, and C2C social messages.

We first test whether traditional advertising, F2C impressions, C2C social messages (volume and valence), brand-building metrics, and acquisition are actually endogenous. To this end, we conduct Granger causality tests. We use one to four lags when conducting the Granger causality test and report the lowest *p*-values of this test in Table 5 (Trusov, Bucklin, and Pauwels 2009). The results in Table 5 show that 41 out of 56 effects are significant at the 10% level. Thus, most variables Granger-cause each other. We model a full dynamic system to adequately capture endogeneity and account for interrelations and feedback effects. Feedback effects include effects among brand-building metrics; effects of brand-building metrics and customer acquisition; and effects of brand-building metrics and customer acquisition on traditional advertising, F2C impressions, and C2C social messages. Moreover, there are no theoretical reasons to impose restrictions on the parameters, which might cause biases in the later impulse response analyses (Enders 2004, p. 292).

Next, we test for stationarity of the time series. Because we consider a constant term and a deterministic time trend to capture the impact of omitted, evolving variables, we use the Phillips–Perron (PP) test to assess stationarity (Pauwels 2004). The widely used augmented Dickey–Fuller test has low power in this case (e.g., Enders 2004). All metric variables are stationary because the PP test is significant for all variables (Table 6).

We specify the full dynamic system of the VARX model in Equation 1. The vector of endogenous variables—traditional advertising (TA), F2C impressions (F2C), volume of C2C social messages (C2C_vol), valence of C2C social messages (C2C_val), awareness (A), consideration (Con), preference (Pref), and customer acquisition (Acq)—is explained by its own past values, and it accounts for the dynamic relations among those variables. We include constant terms (α) and a deterministic time trend (δ_t) for all endogenous variables (e.g., Pauwels 2004). We control for media and buzz events ($X_{1(2)}$ equals 1 if an event occurs and 0 otherwise), holidays

TABLE 5
Results of the Granger Causality Tests

	Dependent Variables							
Dependent Variable Granger-Caused By …	**Traditional Advertising**	**C2C Volume**	**C2C Valence**	**F2C Impressions**	**Awareness**	**Consideration**	**Preference**	**Acquisition**
Traditional advertising	—	.056	.081	.002	.001	.016	.060	.008
F2C impressions	.001	.083	n.s.	—	.078	.071	.057	n.s.
C2C volume	.027	—	.025	.000	.086	.094	.041	n.s.
C2C valence	n.s.	.100	—	n.s.	n.s.	n.s.	.063	n.s.
Awareness	n.s.	.078	.077	.031	—	.037	.055	n.s.
Consideration	.016	n.s.	.074	n.s.	.087	—	n.s.	.080
Preference	.041	.002	n.s.	.046	.005	.094	—	.085
Acquisition	.003	.052	.030	n.s.	.018	.026	.000	—

Notes: n.s. = not significant ($p > .10$). Minimum *p*-values across four lags.

(X_3 equals 1 if a holiday occurs and 0 otherwise), competitive traditional advertising (TA_{comp}), volume of competitive C2C social messages ($C2C_{comp}$), and promotion intensity (P). We use an ln-ln specification. Because the C2C valence measure ranges between [−1, +1], we add the value +1 to the original values before applying the ln-transformation.

(1)

$$\begin{bmatrix} \ln(TA_t) \\ \ln(F2C_t) \\ \ln(C2C\_vol_t) \\ \ln(C2C\_val_t) \\ \ln(A_t) \\ \ln(Con_t) \\ \ln(Pref_t) \\ \ln(Acq_t) \end{bmatrix} = \begin{bmatrix} \alpha_{TA} \\ \alpha_{F2C} \\ \alpha_{C2C\_vol} \\ \alpha_{C2C\_val} \\ \alpha_{A} \\ \alpha_{Con} \\ \alpha_{Pref} \\ \alpha_{Acq} \end{bmatrix} + \begin{bmatrix} \delta_{t,TA} \\ \delta_{t,F2C} \\ \delta_{t,C2C\_vol} \\ \delta_{t,C2C\_val} \\ \delta_{t,A} \\ \delta_{t,Con} \\ \delta_{t,Pref} \\ \delta_{t,Acq} \end{bmatrix} + \begin{bmatrix} \theta_{1,1} & \theta_{1,2} & \theta_{1,3} \\ . & . & . \\ . & . & . \\ \theta_{8,1} & \theta_{8,2} & \theta_{8,3} \end{bmatrix} \times \begin{bmatrix} X_{1,t} \\ X_{2,t} \\ X_{3,t} \end{bmatrix} + \begin{bmatrix} \beta_{1,1} & \cdots & \beta_{1,3} \\ \vdots & \ddots & \vdots \\ \beta_{8,1} & \cdots & \beta_{8,3} \end{bmatrix} \times \begin{bmatrix} \ln(TA_{comp,t}) \\ \ln(C2C_{comp,t}) \\ P_t \end{bmatrix} + \sum_{j=1}^{J} \begin{bmatrix} \Phi^j_{1,1} & \cdots & \Phi^j_{1,8} \\ \vdots & \ddots & \vdots \\ \Phi^j_{8,1} & \cdots & \Phi^j_{8,8} \end{bmatrix} \begin{bmatrix} \ln(TA_{t-j}) \\ \ln(F2C_{t-j}) \\ \ln(C2C\_vol_{t-j}) \\ \ln(C2C\_val_{t-j}) \\ \ln(A_{t-j}) \\ \ln(Con_{t-j}) \\ \ln(Pref_{t-j}) \\ \ln(Acq_{t-j}) \end{bmatrix} + \begin{bmatrix} \varepsilon_{t,TA} \\ \varepsilon_{t,F2C} \\ \varepsilon_{t,C2C\_vol} \\ \varepsilon_{t,C2C\_val} \\ \varepsilon_{t,A} \\ \varepsilon_{t,Con} \\ \varepsilon_{t,Pref} \\ \varepsilon_{t,Acq} \end{bmatrix},$$

where t indicates the week, j indicates the number of lags included in the model, and J is the maximum number of lags. The matrix Θ contains the parameters for the exogenous dummy variables X_i. The matrix B contains the parameters for the exogenous metric control variables TA_{comp}, $C2C_{comp}$, and P. The parameters $\Phi^j_{i,i}$ for the lagged endogenous variables reflect the direct (diagonal) and indirect (off-diagonal) effects among the endogenous variables. Finally, ε_t are the error terms for each endogenous variable.

The final prediction error, Akaike information criterion (AIC), Schwarz information criterion (SC), and Hannan–Quinn information criterion all suggest that the number of endogenous lags in the VARX model is one (here: J = 1). The

TABLE 6
Unit Root Test Results (PP Test)

	PP Test Statistic	Stationary?
Traditional advertising	−5.743***	✓
F2C impressions	−8.146***	✓
C2C volume	−4.693***	✓
C2C valence	−9.849***	✓
Unaided awareness	−10.542***	✓
Consideration	−11.123***	✓
Preference	−12.504***	✓
Acquisition	−3.431*	✓
Traditional advertising competition	−5.621***	✓
C2C social competition	−8.342***	✓

*$p < .10$.
***$p < .01$.
Notes: H_0: The series contains a unit root (i.e., nonstationary). All variables are ln-transformed. The critical values for the PP test are –4.03 (1% level), –3.45 (5% level), and –3.15 (10% level).

estimated model is a stationary VARX model because the absolute value of the autoregressive parameters is less than one (|Φs| < 1; see the Web Appendix; Dekimpe and Hanssens 1995). Both the Lagrange multiplier and Portmanteau autocorrelation test indicate no autocorrelation in the residuals (Web Appendix), which is an important assumption of a VARX model (e.g., Hamilton 1994).

Because the endogenous parameters of a VARX model are not interpretable (e.g., Dekimpe and Hanssens 1995), we use orthogonalized IRFs to examine the impact of traditional advertising, F2C impressions, and C2C social messages on brand-building metrics and customer acquisition. We use a Cholesky decomposition that transforms the VARX model into a system with uncorrelated error terms, such that the impulses can be interpreted orthogonally (e.g., Dekimpe and Hanssens 1995; Hamilton 1994). A possible difficulty with the Cholesky decomposition is that researchers must determine a priori a causal ordering of the variables in the system. The first variable in the system will affect all other variables, but the others cannot *directly* influence this first variable. For example, acquisition might have feedback effects on advertising (e.g., decline in acquisition results in more traditional advertising) but firms usually cannot change their advertising investments instantaneously (e.g., Dekimpe, Hanssens, and Silva-Risso 1999; Leeflang and Wittink 1992; Pauwels 2004). Thus, in a model with only traditional advertising and performance measures, it makes sense to put performance last (e.g., Dekimpe, Hanssens, and Silva-Risso 1999). However, in our model, acquisition could have same-period feedback effects on F2C impressions and C2C social messages. Therefore, we continuously change the ordering of the endogenous variables and compute averages over the different responses that result from one-standard-deviation shocks (e.g., Dekimpe and Hanssens 1995). To derive the standard errors of the estimates, we use Monte Carlo bootstrapping with 1,000 runs (e.g., Wiesel, Pauwels, and Arts 2011). Drawing on the IRFs, we compute the cumulative elasticities (accumulation of significant effects with t-statistics greater than 1 in absolute value, following previous studies such as Dekimpe, Hanssens, and Silva-Risso [1999], Pauwels [2004], and Trusov, Bucklin, and Pauwels [2009]). This way, we can compare the effects across traditional advertising, F2C impressions, and C2C social messages (Ataman, Van Heerde, and Mela 2010; Dinner, Van Heerde, and Neslin 2014). All effects are nonpersistent because they abate after a few weeks.

Results

Relative Effectiveness of Traditional Advertising, F2C Impressions, and C2C Social Messages

As Table 7 shows, traditional advertising messages are effective in building the brand because they create awareness (.024) and consideration (.022), meaning that a 1% increase in traditional advertising leads to a .024% increase in awareness and a .022% increase in consideration, respectively. These elasticities resemble elasticities found in previous research (Srinivasan, Vanhuele, and Pauwels 2010). Traditional advertising also positively affects acquisition; a 1% increase in traditional advertising leads to a .202% increase in newly acquired customers, which also corresponds to elasticities found in meta-analyses (Sethuraman, Tellis, and Briesch 2011). We also observe that the effect of traditional advertising lasts longer for customer acquisition than for awareness and consideration (weeks 2–9 vs. weeks 2–4 and week 2, respectively).

Firm-to-consumer impressions affect consideration and acquisition significantly. A 1% increase in F2C impressions leads to a .007% (week 3) increase in consideration and a .103% (weeks 1–6) increase in customer acquisitions. Valence of C2C messages affects brand preference; a 1% increase in the valence of C2C social messages results in a .042% increase in preference (week 2). Volume of C2C social messages, instead, affects acquisition; a 1% increase in the number of C2C social messages leads to a .056% increase in customer acquisitions (weeks 3–5).

When comparing traditional advertising, F2C impressions, and C2C social messages, we find that traditional advertising is most effective in creating awareness and consideration. A potential reason for traditional advertising's effectiveness with respect to awareness might be that traditional advertising is broadcasted over many different channels, which contributes to its large reach (Tellis 2004). In addition to its large reach, traditional advertising seems to inform consumers about the brand and its offerings (Vakratsas and Ambler 1999). Consumers can evaluate whether the brand or product fits their needs, and in this way traditional advertising influences consumers' consideration sets (Terui, Ban, and Allenby 2011). Furthermore, we find that F2C impressions are effective in creating consideration, but the effect is much smaller than that of traditional advertising. Consumers seem to consider the brand simply because people they know talk about it, which is in line with previous research (Schulze, Schöler, and Skiera 2014). Moreover, only C2C valence affects preference significantly. The reason might be that C2C social messages target consumers who are interested in a product category and search for product information (Lu et al. 2014; Stephen and Galak 2012). Consumer-to-consumer social messages usually emphasize consumers' product experiences, which support evaluations of different alternatives (Lu et al. 2014; Muthukrishnan and Kardes 2001; Schlosser 2011). The higher credibility and the unique type of information that is provided (compared with traditional advertising and F2C impressions) might make C2C social messages more helpful for consumers to evaluate the brand and its offerings and to influence preference (Gilly et al. 1998; Gruen, Osmonbekov, and Czaplewski 2006; Smith, Fischer, and Chen 2012).[3] A potential reason for the insignificant relation between traditional advertising, F2C impressions, and preference might also be that consumers are less receptive to these messages because they primarily follow different activities, such as consuming a movie while watching TV or connecting with friends on social media. Consumers might be less likely to deeply elaborate on the messages, which might limit their impact on preferences (Adomavicius et al. 2013; Gupta and Harris 2010; Tellis 2004).

Traditional advertising is, however, most effective in generating acquisition (.202 vs. .103 and .056, respectively). Traditional advertising's reach and the provided information seem to help consumers to make their final purchase decision (Sethuraman, Tellis, and Briesch 2011). Nevertheless, F2C impressions and C2C volume also affect customer acquisition as suggested by previous studies (Babić Rosario et al. 2016; Goh, Heng, and Lin 2013; Trusov, Bucklin, and Pauwels 2009; Villanueva, Yoo, and Hanssens 2008).

Interrelationships Among the Messages

We examine how traditional advertising, F2C impressions, and C2C social messages affect one another (Table 7). We find that a 1% increase in F2C impressions increases traditional advertising by .223% in the subsequent weeks, whereas a 1% increase in traditional advertising decreases F2C impressions by .345% in the subsequent weeks. These results suggest that the time series of traditional advertising and F2C impressions move asynchronously; peaks in traditional advertising follow peaks in F2C impressions.

Peaks in F2C impressions and traditional advertising can be expressed by positive changes in F2C impressions ($\Delta F2C_t = (F2C_t/F2C_{t-1}) - 1$) and traditional advertising ($\Delta TRAD_t = (TRAD_t/TRAD_{t-1}) - 1$). We compute the correlation between $\Delta F2C_t$ and $\Delta TRAD_{t+1}$ to align the two time series. This correlation is positive and equals .182, which offers some model-free evidence for the finding that traditional advertising follows social media activities. Moreover, personal conversations with marketing managers of the focal firm confirmed this firm behavior. As one marketing manager mentioned in a personal conversation, the focal firm coordinates its marketing activities

[3]It could be the case that C2C social messages actually do contain messages that are sponsored by firms. This occurs, for example, when firms provide free products (e.g., mobile phone) to consumers and ask them to write a review about this product. We cannot infer from our data whether this happened for our brand. We mention this issue as a limitation of our study, and we thank an anonymous reviewer for this suggestion.

TABLE 7
Cumulative Effects (Elasticities) of Traditional Advertising, F2C Impressions, and Volume and Valence of C2C Social Messages on Brand Building and Customer Acquisition and Interrelations

	Impulses in …											
	Traditional Advertising			F2C Impressions			C2C Volume			C2C Valence		
Responses of …	Elasticity	Wear-In	Wear-Out	Elasticity	Wear-In	Wear-Out	Elasticity	Wear-In	Wear-Out	Elasticity	Wear-In	Wear-Out
Awareness	.024	2	4	—	—	—	—	—	—	—	—	—
Consideration	.022	2	2	.007	3	3	—	—	—	—	—	—
Preference	—	—	—	—	—	—	—	—	—	.042	2	2
Acquisition	.202	2	9	.103	1	6	.056	3	5	—	—	—
Traditional advertising				.223	2	4	—	—	—	—	—	—
F2C impressions	−.345	2	4				—	—	—	−.265	2	3
C2C volume	.037	1	1	—	—	—				—	—	—
C2C valence	.096	3	5	—	—	—	—	—	—			

Notes: Dashes indicate insignificant effects; empty cells indicate own effects, which were not examined. Wear-in indicates the week in which the effect first occurs; wear-out indicates the week in which the effect dies out.

across the different channels (i.e., social media and traditional advertising) on the basis of its understanding of the market. Another marketing manager exemplified in another personal conversation that she believes that social media is very effective for the target group and might influence effectiveness of traditional advertising positively. Therefore, she initiates marketing campaigns on social media followed by investments in traditional advertising. The parameters in the VARX model also reflect this firm behavior. We find a positive parameter for F2C impressions in week $t - 1$ on traditional advertising investment in week t ($\Phi = .100$, $t = 2.310$), whereas we find a negative parameter for traditional advertising in week $t - 1$ on F2C impressions in week t ($\Phi = -.314$, $t = -1.874$). Consequently, we find a positive elasticity for F2C impressions on traditional advertising and a negative elasticity for traditional advertising on F2C impressions when conducting the IRF analyses (Table 7).

Moreover, we find that a 1% increase in traditional advertising positively affects C2C volume with .037%, confirming previous research showing that a firm's advertising messages spur online messages among consumers (e.g., Fossen and Schweidel 2017; Hewett et al. 2016; Onishi and Manchanda 2012). Thus, the firm's advertising stimulates consumers to talk about the firm to others. In addition, consumers who do talk tend to react favorably to traditional advertising; a 1% increase in traditional advertising increases the valence of C2C social messages by .096%. In addition, we find a negative elasticity from valence of C2C social messages to F2C impressions (−.265). There might be multiple explanations for this effect (e.g., no spillover effect between platforms, the firm does not react to favorable C2C social messages in their F2C social messages). Unfortunately, we cannot use our data to explore the specific reason.

Feedback Effects and Control Variables

We find evidence for some feedback effects and discuss the most noteworthy ones. Improvements in acquisition lead to more F2C impressions (a 1% increase in acquisition leads to .239% more impressions), which could be caused by increases in the number of consumers who like the brand and become active users of the page—at least temporarily. Moreover, awareness positively affects volume and valence of C2C social messages; a 1% increase in awareness leads to a .028% increase in C2C volume and a .129% increase in C2C valence. This result suggests that traditional advertising also indirectly affects the volume and valence of C2C social messages through awareness.

We next discuss some of the notable findings from the exogenous parameters (Web Appendix). The deterministic trend is significant and negative for traditional advertising ($\alpha = -.014$), indicating that traditional advertising investments slightly diminish over time. The deterministic trend for C2C volume is instead significant and positive ($\alpha = .006$), indicating a slight positive trend over time. The media events dummy affects volume of C2C social messages as well as acquisition significantly and positively ($\theta = .072$ and $\theta = .096$, respectively). The effects could be caused by the fact that this variable captures, for example, new phone introductions, which might lead consumers to talk about these introductions and to an increase in newly acquired customers. The buzz events stimulate awareness ($\theta = .075$). However, buzz events are negatively related to C2C valence and preference ($\theta = -.592$ and $\theta = -.324$, respectively). These results indicate that consumers discussed the focal firm's new mobile service offerings that created the buzz critically.

Comparison with Alternative Models

To test whether our proposed model is appropriate and robust, we also estimated a restricted model, which is based on the idea that there exists a certain ordering among the brand-building metrics such that there is a path from awareness to consideration to preference (e.g., Vakratsas and Ambler 1999; see Web Appendix).[4] We estimated this model by using a seemingly unrelated regression model because this is most appropriate when the right-hand side variables of the equations are not identical (Enders 2004). The results and the explanatory power of the seemingly unrelated regression model are comparable to the VARX model (Web Appendix). However, the unrestricted VARX model fits conceptually better to the suggested relationships, is generalizable, and thus seems more appropriate. It allows for adequately capturing the complex (inter)relations between the different messages, the brand-building metrics, and customer acquisition over time.

To show the robustness of our results and to examine whether the brand-building metrics might be prone to measurement error, we also estimate a VARX model without the brand-building metrics, all else being equal. Measurement error could possibly lead to inconsistency or upward biases in the parameter estimates (Bruce, Peters, and Naik 2012; Naik and Tsai 2000). Model fit of this model is slightly lower than that of the original model ($\Delta AIC = 2.26$; $\Delta SC = .78$). We computed the elasticities for the effects of traditional advertising, F2C impressions, and C2C social messages on acquisition. A 1% increase in traditional advertising leads to a .219% increase in acquisition (full model: .202%), a 1% increase in F2C impressions leads to a .126% increase in acquisition (full model: .103%), and a 1% increase in C2C volume leads to a .102% increase in acquisition (full model: .056%). Again, the valence of C2C messages does not affect acquisition. We observe that the effect of volume of C2C social messages on acquisition is higher in this reduced model, but the substantive findings do not change. Thus, the substantive results are robust against different model specification and do not seem to be affected by potential measurement errors in the brand-building metrics.

As a final robustness check, we estimated a VARX model with F2C reach instead of F2C impressions. This model fits the data equally well ($AIC = 4.22$, $SC = 7.35$). We again find that traditional advertising is most effective in stimulating acquisitions, followed by F2C reach and C2C volume (.205,

[4]We thank one of our anonymous reviewers for this suggestion. We also tested another VARX model where we exogenously control for months by adding 11 monthly dummies to the VARX model instead of the HOLIDAY dummy. However, because many additional parameters need to be estimated, model fit does not improve.

.088, and .072, respectively). To conclude, the alternative model specifications show robustness of our results.

Discussion

Summary of Findings and Theoretical Contributions

Our study contributes to the literature on the effectiveness of traditional advertising, F2C impressions, and C2C social messages by demonstrating their impact on brand building and customer acquisition. By considering attitudinal *and* behavioral outcome measures, we respond to a recent call to consider multiple outcome measures in empirical studies (Katsikeas et al. 2016). Whereas previous empirical studies have questioned the relative effectiveness of traditional advertising (e.g., Trusov, Bucklin, and Pauwels 2009; Villanueva, Yoo, and Hanssens 2008), we find support that traditional advertising is still effective today.

More specifically, the results indicate that traditional advertising is the most effective way to influence consumers' awareness, consideration, and customer acquisition. Firm-to-consumer social messages and the impressions generated through these messages are also effective in stimulating consideration and acquisitions beyond traditional advertising. This finding is in line with previous studies (Kumar et al. 2016). Consumer-to-consumer social messages, instead, are effective in creating preference and acquisitions. That is, valence of C2C social messages stimulates preference while volume of C2C social messages stimulates acquisitions. However, C2C social messages are least effective in stimulating customer acquisitions. Our results differ in that regard from previous findings suggesting that C2C social messages are more effective in generating sales and acquisition than traditional advertising (Stephen and Galak 2012; Trusov, Bucklin, and Pauwels 2009; Villanueva, Yoo, and Hanssens 2008). Yet it is important to note that the previous studies considered communities and word-of-mouth (WOM) referrals, which are different from the types of C2C social messages we consider in this study. As such, the specific type of C2C social messages might influence the effectiveness of these messages.

Moreover, we find that interrelations among traditional advertising, F2C impressions, and C2C social messages exist. Our results thus support previously discussed complementary relations (e.g., Bruce, Foutz, and Kolsarici 2012; Fossen and Schweidel 2017). Our study provides additional evidence that traditional advertising spurs volume of C2C social messages (Fossen and Schweidel 2017). Furthermore, traditional advertising generates more favorable C2C social messages. We do not find a relation from F2C impressions on C2C social messages, as some previous studies did (Kumar et al. 2013). A potential reason for the insignificant relation might be that Kumar et al. (2013) specifically design a social media campaign to maximize C2C social messages through F2C social messages. Finally, we find evidence for feedback effects. These findings illustrate the complexity of the relations among the firm's "echoverse" and outcome variables and highlight the need for methodological approaches that can capture those relations to effectively orchestrate a firm's efforts to build a brand and improve customer acquisition (Hewett et al. 2016). We illustrate that VARX models can capture the complex (inter)relations and allow for assessing the relative effectiveness of traditional advertising, F2C impressions, and C2C social messages.

Managerial Implications

This study offers four important managerial implications. First, traditional advertising is still an effective medium to build a brand and to enhance customer acquisition. If managers consider shifting marketing investments from traditional advertising to other types of messages, they should take not only costs but also effectiveness into account. Our results further suggest that F2C social messages can complement traditional advertising efforts if they spread through the social network (Fulgoni 2015). Overall, traditional advertising and the firm's social media page are powerful means for brand building and customer acquisition. Thoroughly orchestrating traditional advertising and F2C social messages might improve a firm's performance. Second, investments in traditional advertising prompt more and more favorable C2C social messages. The positive impact of traditional advertising on the volume and valence of C2C social messages allows managers to exert greater influence on the echoverse and, finally, on critical performance metrics (Hewett et al. 2016). Third, the positive feedback effect of customer acquisition on F2C impressions suggests that newly acquired customers engage with the brand through social media and leverage the firm's marketing efforts. Fourth, for managers it is useful to track the effects of traditional advertising, F2C impressions, and C2C social messages on both brand-building and behavioral metrics. Monitoring brand-building and behavioral metrics leads to insights that help managers to orchestrate and leverage different types of messages more adequately.

Limitations and Further Research

The study also has some limitations that offer fruitful areas for further research. Because we did not observe the costs of current levels of monetary investments in the different messages, we cannot offer specific advice about how to allocate marketing budgets efficiently. Further research should try to derive specific implications on budget allocation in a complex world where traditional advertising, F2C social messages, and C2C social messages are interrelated.

The data set did not comprise information about, for example, paid social media; online reviews; or display, search engine, and mobile advertising, because these types of messages are rarely used by the focal firm or not relevant. Therefore, not considering these different types of messages did not affect our substantial results. However, future studies might extend the set of messages under investigation to enhance our knowledge about the relative effectiveness of the messages and their interrelations in specific settings. Moreover, we did not observe traditional WOM, which might have resulted in an omitted variable bias. Thus, future studies should collect information on traditional WOM.

Further research might also consider competitive actions more extensively.[5] In our study, the main competitors of the

[5]We thank one of our anonymous reviewers for this suggestion.

focal firm hardly used social media. Therefore, we think that neglecting competitive F2C did not affect our results. Further research may also want to include other social media sites than Facebook (e.g., Instagram).

In our study, the attitudinal and behavioral metrics originated from two different data sources (survey vs. sales measures). We are aware that survey data are estimates themselves and are prone to measurement error (Bruce, Peters, and Naik 2012; Srinivasan, Vanhuele, and Pauwels 2010), which could lead to inconsistency in the parameter estimates (Bruce, Peters, and Naik 2012). Bruce, Peters, and Naik (2012) suggest a factor solution to eliminate measurement error in case of multiple (>10) brand-building metrics. Alternatively, Naik and Tsai (2000) develop new estimators that use Kalman filtering and wavelet theory to eliminate biases from measurement error in dynamic advertising models. Such corrections are highly relevant if one wants to derive optimal budget allocation decisions. In our study, we are interested in the relative effectiveness of the different messages. If biases occur as a result of measurement error in the brand-building metrics, all parameters for the different messages are equally affected. The results of the VARX model without brand-building metrics further indicate that the effectiveness with respect to acquisition is not affected by potential measurement errors in the brand-building metrics.

Furthermore, we would applaud studies proposing new methods for obtaining brand-building data that can be directly linked to behavioral metrics, especially because these measures are frequently collected with the help of small panel samples, which might impede a comprehensive analysis. This was also the case in our study and might have caused some insignificant results.

The F2C measure in our study is not a "clean" measure because it considers impressions and not the original posts of the focal firm. Yet it captures the spreading capability of F2C social messages. Further research might consider the actual number of posts and the content of these messages. It is likely that some F2C social messages are more engaging than others. However, it is not possible to disentangle which messages obtained more impressions than others. Moreover, it could be that some other external sources drive F2C impressions. We encourage other researchers to reexamine the found effects and to gain knowledge on the underlying processes that explain the effectiveness F2C social messages.[6] Moreover, it would be worthwhile to consider the content of the comments on firms' posts. This would allow for more insights into what consumers talk about and how engaging the firm's posts are. Furthermore, it would be useful to shed more light on the drivers of the lagged effect of F2C impressions because this effect contributes to the impressions' effectiveness. In addition, consumers might propagate a firm's messages through other platforms (e.g., YouTube) and might amplify the effectiveness of traditional advertising and F2C social messages in this way. Further research could explore this topic. Finally, it might be that firms actually do sponsor C2C social messages. Unfortunately, we are not able to observe this in our data. An interesting question is how consumers would react if they learned that C2C social messages are incentivized by the firm (Verlegh et al. 2013).[6]

Despite its limitations, this study is the first to compare the relative effectiveness of traditional advertising, F2C impressions, and C2C social messages and provides initial insights into the complex (inter)relations. This article thus makes a significant contribution to the existing literature and offers fruitful avenues to enhance further research.

[6] We thank one of our anonymous reviewers for this suggestion.

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