What Drives Advertising Success on Facebook? An Advertising-Effectiveness Model

Measuring the Effects on Sales Of "Likes"and Other Social-Network Stimuli

MALTE BRETTEL
RWTH Aachen University
brettel@time.rwth-aachen.de

JENS-CHRISTIAN REICH
RWTH Aachen University
The Boston Consulting Group
reich.jens-christian@bcg.com

JOSE M. GAVILANES
RWTH Aachen University
The Boston Consulting Group
gavilanes.jose@bcg.com

TESSA C. FLATTEN
TU Dortmund
tessa.flatten@tu-dortmund.de

Online social networks have challenged the current knowledge of advertising effectiveness. Using 12 months of aggregate-level, daily data from a major German e-commerce retailer, the authors of the current study analyzed four types of advertising stimuli on Facebook—"stream" (news feed) impressions, page views, "Likes," and user contributions—to determine their short-term and long-term impact on sales. Access to the data provided an opportunity to integrate a direct-aggregation approach that accounted for time lags between user activity and sales effects. This research builds on an earlier framework for studying how advertising works (Vakratsas and Ambler, 1999), reflecting changes brought on by emerging online channels.

INTRODUCTION

Online social networks provide an exciting environment for researchers and a promising interactive advertising channel for marketers (Trusov, Bucklin, and Pauwels, 2009). Some scholars have proclaimed a paradigm shift in communication (Kietzmann, Hermkens, McCarthy, and Silvestre, 2011). In particular, Facebook, with its interactive character and media richness, has, with other online social networks, driven the rapid development of social media (Hensel and Deis, 2010).

Facebook's applicability to advertising—and its consequent impact for marketers—have yet to be proven (Kelly, Kerr, and Drennan, 2010). Such proof is important in the light of the call for improved marketing accountability (Luo and Donthu, 2006).

Advanced models, including those that measure the effects of long-term advertising, have offered some insight into how digital advertising works (Breuer and Brettel, 2012). Little is known, however, about what drives advertising success in online social networks.

Management Slant

- On Facebook, a user's click on "Like" is a strong long-term sales driver due to high carryover effects.
- Visits to a company's Facebook page are strong short-term sales drivers.
- "Likes" and contributions to a Facebook page create substantial, positive synergy effects.
- "Stream" (news feed) impressions have a significantly negative sales impact.
- Further research is needed to improve the understanding of targeted advertising for different customer groups, for various products sold, and to include other online and offline channels as part of an integrated marketing campaign.

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To that end, the authors of the current study sought to address two research questions that have been raised in previous studies (Godfrey, Seiders, and Voss, 2011; Osinga, Leeflang, and Wieringa, 2010; Winer, 2009):

- RQ1: Which stimuli in a social network drive short-term sales?
- RQ2: What is the long-term impact of Facebook stimuli on sales?

The current scholars believe they are the first to have analyzed the sales impact of diverse stimuli in a social network while modeling time lags between user activity and sales effects. The goal: to deepen the understanding of how successful advertising works and is best implemented in a social network like Facebook.

LITERATURE REVIEW

Social Networks and Advertising

Advertisers increasingly are engaging in social media and use online social networks to target customers (Deal, 2014). There is evidence that exposure to an advertisement in a social network can prolong ad recall, awareness, and purchase intent (Nielsen, 2010).

Scholars have noted the importance of using social networks to improve advertising effectiveness to engage the customer in the social network and create comments (Pooja *et al.*, 2012) and take advantage of the network's potential to spread messages that are

- vivid (de Vries, Gensler, and Leeflang, 2012);
- entertaining (Taylor, Lewin, and Strutton, 2011); and
- targeted (Tucker, 2012).

Such social interactions can build customer loyalty and lead to purchases (Algesheimer, Dholakia, and Herrmann, 2005; Zhou, Zhang, Su, and Zhou, 2012).

These findings on the importance of customer engagement are consistent with studies that involved offline and online media (Kilger and Romer, 2007). On a social-network site, a potential, current, or former customer can engage in electronic word-of-mouth (e-WOM) to broadcast his or her views on a specific product (or, more broadly, a company) to a multitude of people and institutions.

This social-network user functions as a brand advocate and communication multiplier for the company's effort to acquire new customers (Trusov *et al.*, 2009; Wallace, Buil, De Chernatony, and Hogan, 2014). Users' friends often have similar preferences, needs, and interests, all of which can result in similar buying behavior (Yang and Lin, 2006) and facilitate customer acquisition.

Knowledge shared via e-WOM often is characterized by a diversity and quantity of information that traditional media seldom offer (Hung and Li, 2007). One survey revealed that 89 percent of the respondents trusted the recommendations of friends, compared to 48 percent for television spots and only 18 percent for short message service (SMS) advertisements (Nielsen, 2009). This result is in line with studies that have emphasized the importance of WOM for the buying decision (Riegner, 2007) and in the marketing mix (Jamhouri and Winiarz, 2009).

In the context of social networks, communities of like-minded customers can proliferate WOM recommendations (Algesheimer *et al.*, 2005) that can influence purchasing decisions with a substantial carryover effect (Trusov *et al.*, 2009). Combining engagement on a social network with exposure to other interactive advertising channels (*i.e.*, e-mails and banners; (Baron, Brouwer, and Garbayo, 2014) or television (Nagy and Midha, 2014; Spotts, Purvis, and Patanaik, 2014) can further increase advertising effectiveness (Phillips, McFadden, and Sullins, 2010).

Social networks, however, also can suffer from credibility and acceptance issues (Levy and Gvili, 2015; Kelly *et al.*, 2010) that may discourage users from spreading WOM and thereby diminish advertising effectiveness (Chu, 2011). This finding is in line with divergent analyses comparing the advertising effectiveness of social networks with other channels. Some studies have found a comparatively lower advertising effect for social networks (Stacey *et al.*, 2011), particularly for "Likes" and comments (Stacey, Pauwels, and Lackman, 2011), whereas other studies have found that social networks have stronger direct and viral effects than other channels (Phillips *et al.*, 2010).

Scholars have explored the effectiveness of selected stimuli related to social media and social networks, and their comparison of social-network advertisements with other advertising formats has led to divergent results. Their research, however, primarily has depended on surveys, experiments, and case studies in small-brand communities focused on select customers (Phillips *et al.*, 2010; Zhou *et al.*, 2012), rather than on field data from Facebook, the largest social network worldwide.

In fact, analyses of the advertising effectiveness of all social networks still are under-represented in current research (Khang, Ki, and Ye, 2012). Measuring these advertising effects, especially their sales impact, is of particular interest (Winer, 2009).

Moreover, research in this field rarely has applied advanced models that include time lags to reveal a realistic picture of how advertising stimuli take effect (Osinga *et al.*, 2010). To the best of the current authors' knowledge, no study has performed a comparative analysis of various types of stimuli on Facebook and their sales impacts while taking into account time lags. The authors intend to bridge this gap.

Extending the Advertising-Processing Framework

A meta-analysis of more than 250 articles offered a framework for studying how advertising works (Vakratsas and Ambler, 1999). According to the framework, advertising input with components like message content and repetition could trigger three mental intermediate responses before it became manifest in consumer behavior, such as making a purchase:

- cognition ("thinking");
- affect ("feeling"); and
- experience (based on prior consumer behavior).

The intermediate responses were filtered by factors, including

- opportunity (hindered by, for instance, the level of an advertisement's distraction potential and intrusiveness [Goodrich, Schiller, and Galletta, 2015]);
- ability (based on the consumer's brand knowledge);
- motivation to process information (stimulated by information relevance); and
- attitude toward the advertisement.

These filters determined whether the consumer was in a state of high or low elaboration—cognitive processing as a consumer response to advertising (Vakratsas and Ambler, 1999). In a state of high elaboration, if a consumer was motivated and able and had the opportunity to deal mentally with an advertisement, he or she more likely would process the advertisement *cognitively* than affectively, leading to a strong immediate and persistent advertising effect.

The advertising ecosystem, however, changes almost daily, and the consumer-engagement challenges for marketers are significantly different than they were 16 years ago. The continuing emergence of new online channels calls for an extension of this framework. Criteria such as source credibility—for example, through a message forwarded by a friend on Facebook (Taylor *et al.*, 2011), and advertising repetition through repeat exposure to various types of stimuli on Facebook (MacInnis, Rao, and Weiss, 2002)—have become important in the era of social networks.

Online channels also have been characterized by new criteria, such as interactivity (Rappaport, 2007), as users have more control over advertising exposure and can participate, and engage, in multi-way communication processes (Stewart and Pavlou, 2002). Stimuli on social networks also have varying levels of media richness that address multiple senses, from text-only comments to animated video postings (Klein, 2003).

The current study applied the earlier framework (Vakratsas and Ambler, 1999) to derive hypotheses on the effectiveness of the different stimuli on Facebook. The authors also took into account interactivity criteria and media richness to enhance their understanding of how social networks function in an advertising context.

HYPOTHESES DEVELOPMENT

Advertising-Effectiveness Measures Of Facebook

The current researchers considered four antecedents to their model (Fisher, 2009; See Figure 1):

- "Stream" (news feed) impressions are advertising input within social media channels like Facebook. "Stream" impressions are generated by a company or its followers within the network. A subscriber to the group automatically can see them on the main profile page after logging in (passive consumption). These impressions usually show plain text and sometimes a small picture.

- Page views: Visits to a group's main page, which often consists of content-rich, static text, and brand-related visuals or product pictures (active consumption).

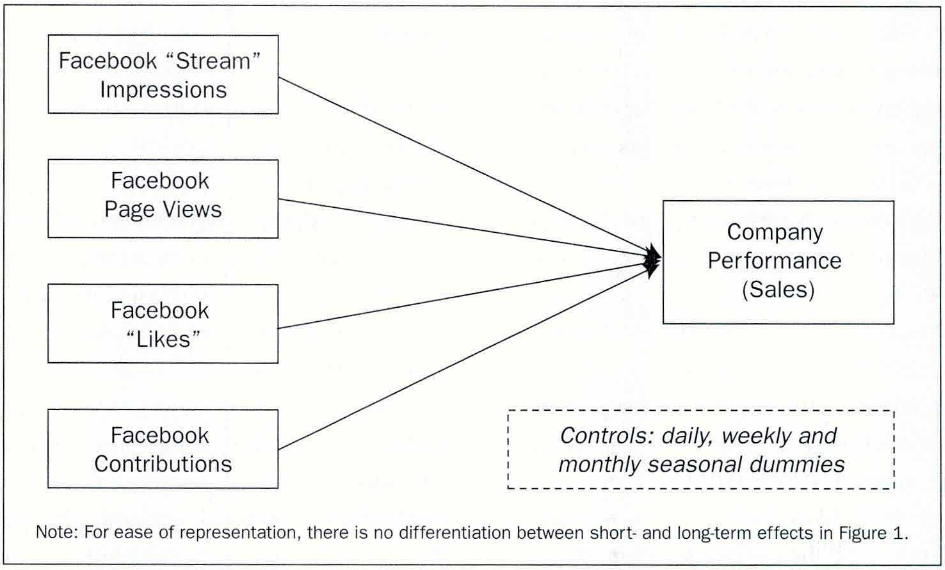

Figure 1 Impact of Facebook Stimuli on Company Performance (Sales)

- "Likes": A Facebook user can support content on the group's page or can support the group itself by clicking on "Like" (active support).

- User contributions to the group's content, such as verbal comments, uploaded photos, and videos (active contribution with the highest level of interactivity).

This model incorporates measures that represent attention (page views), interaction (contributions), and qualitative aspects ("Likes").

The researchers applied the earlier advertising-processing framework (Vakratsas and Ambler, 1999) to the Facebook-specific stimuli of "stream" impressions, page views, "Likes," and contributions—a selection that spans a broad spectrum of interactivity levels. The four stimuli, along with their time-lagged effects, were analyzed for their short- and long-term impact on sales.

"Stream" Impressions

The first page a user sees after signing in on Facebook is the place where the main browsing activity within the Facebook platform takes place and where the highest share (27 percent) of engagement occurs (Lipsman, Mudd, Rich, and Bruich, 2012). This page is separated into two parts: On the right side of the page a small column-only sponsored advertisement for which companies have to pay for is presented. Within the bigger middle column of this page, stories are presented in the form of small news feeds that usually consist of plain text and a small picture. "Stream" impressions are generated when the company's news feeds are shown to the users on this page. Those impressions are based on two sources: company or Facebook user.

- Company-generated impressions show advertising input to Facebook users based on, for example, a post in the company's profile, which is displayed to Facebook users who are following the corresponding company page.

- Non-paid user-generated impressions are presented to Facebook users not as a result of company postings but on the basis of actions of another Facebook user, who, for example, "Likes" a company posting.

How much attention do users pay to these company feeds? A "stream" impression of a feed generated by the company or its group members competes with other content on the page, such as banner advertisements on the sidebar (Baron *et al.*, 2014). Still, one can assume that users browse through their home-feed page vertically, as this feed lists news from their friends. Company feeds might irritate the user by distracting him or her from an intended task, such as conecting with friends. The lack of user control and risk of an unfavorable attitude toward the advertisement possibly impede the advertising effectiveness.

In the current study, the researchers analyzed the "stream" impressions of one of Germany's top-10 online retailers. This company spread only one post every second day, which reduced such unfavorable effects. Moreover, the "stream" impressions in the current analysis also were created by group members who forwarded a post to their friends (higher message credibility), so the researchers expected a positive sales effect.

H1: Facebook "stream" impressions have a significant positive short-term impact on sales.

Page Views

Facebook users can access a company's official Facebook page by

- clicking on its Facebook feed or Web page;
- using a search function; or
- directly through external sources, such as links on other pages or search engines.

Compared to "stream" impressions, a page view shows that the user has the opportunity and motivation to visit the page, as he or she was not led there automatically while focusing on another task. The current authors assumed that the user considers a company's offer in his or her mind and already shows a certain interest in it. Hence, there is a comparatively higher degree of user control, relevance, and motivation, leading to a more favorable attitude toward the advertising stimulus.

H2: Facebook page views have a significant positive short-term impact on sales.

"Likes"

One of the most popular key performance indicators among Facebook specialists is the number of "Likes." The number of "Likes" that a page has—or the number of "Likes" a specific post or campaign has managed to generate—frequently is discussed in market reports that suggest consumers more likely will purchase after "Liking" a brand (Cruz and Mendelsohn, 2010).

By "Liking" a posting or content on a page, the user actively supports that content, indicating a positive attitude. This activity implies a higher degree of user control, relevance, and motivation compared to "stream-impression" viewing or page views. Generally, if users actively support content, by providing their input they indicate high involvement. This is a strong argument for the likelihood of a high level of elaboration and, therefore, a potentially strong impact on short-term sales.

H3: Facebook "Likes" have a significant positive short-term impact on sales.

Contributions

Another very popular measure among practitioners and researchers is the number of user comments and contributions (de Vries *et al.*, 2012).

The elaboration effect is even stronger when a user contributes to content. Contributing takes more time than passive consumption of advertisements, reflecting high motivation and opportunity likelihood, as the user controls when to engage. Contributing also reflects the user's ability to process the company's promotional communication and play an active part in it.

When a user creates content, his or her opinion automatically is shared among friends. The user thus sends the advertising message for the company, which benefits from the user's perceived source credibility. Moreover, the sender and recipient often have similar interests. That, in turn, supports processing of the advertisements. The user becomes a multiplier of the message, which can lead to an increase in the advertisement's overall effectiveness and result in a significant impact on short-term sales. This supports earlier the framework of seminal research that advertising content is triggered by the ability and motivation to process this content and then triggers mental responses (*e.g.*, cognitive and emotional) before it becomes manifest in consumer behavior, such as making a purchase (Vakratsas and Ambler, 1999).

H4: Facebook contributions have a significant positive short-term impact on sales.

Time Lags and Long-Term Effects

The authors believe they have performed the first study that analyzes the time-lagged effects and long-term impact Facebook advertising stimuli have on sales.

An advertising stimulus can carry over its impact to the next period (a varied number of days, for the purposes of this study) and beyond. This is referred to as the carryover effect (Herrington and Dempsey, 2005). The percentage of advertising effect that takes place in future periods is represented by the carryover coefficient (λ), that is, a positive value of the coefficient ($\lambda > 0$) confirms the existence of a long-term effect.

Scholars have demonstrated that including time lags improves model fit compared to traditional advertising-effectiveness models (Palda, 1965). The first meta-analysis in this area revealed that 90 percent of the cumulative advertising effect on sales occurred three to nine months after exposure (Clarke, 1976). Later, it was found that 93 percent of television advertising and 37 percent of print advertising carry over into future periods (Naik and Raman, 2003). And, research analyzing time lags on price-comparison and online banner advertisements demonstrated that there could be a misleading interpretation of the effectiveness of a channel if long-term effects were not considered. In one scenario, including carryover effects increased the effectiveness of price-comparison by 5 percent and for banner advertising by 54 percent (Breuer, Brettel, and Engelen, 2011).

In the current study's applied framework, a higher elaboration level leads to longer-lasting advertising effects reinforced by repetition of advertisements. The framework also holds that involvement of multiple senses and animation—media richness—helps to embed the message in the recipient's mind (Vakratsas and Ambler, 1999). Hence, the current authors expected Facebook advertising stimuli to have not only a short-term but also a long-term cumulative impact on sales.

H5a: Facebook stimuli, such as "stream" impressions, page views, "Likes," and contributions, exert a time-lagged long-term impact on sales, with a positive carryover coefficient λ for all stimuli.

According to the current framework, a high level of elaboration and repeated exposure to an advertisement result in long-lasting advertising effects. The framework holds that consumers assimilate advertising messages better when multiple senses are involved and not only a single sense is addressed. "Stream" impressions of company feeds usually consist of plain text and sometimes a small picture, but the company's main page confronts the viewer with a number of short, but also more content-rich, texts and photo posts.

With a "Like" or a contribution, the viewer responds to a broad variety of media, including videos, which represent the highest level of media richness. The current evaluation of media richness, therefore, is in line with the authors' previous assessment of how likely a stimulus elaboration is. Thus, the authors expected positive carryover-effects for all stimuli and did not expect a change of direction of advertising effects. This thinking led to the conclusion that the long-term sales effects would exceed the respective short-term effects.

H5b: The cumulative long-term impact on sales of Facebook stimuli (*i.e.*, "stream" impressions, page views, "Likes," and contributions) is stronger than the short-term effect found for each stimulus and does not change its direction.

DATA AND METHODOLOGY

Data Description

The authors of the current study independently used field data from one of Germany's top-10 e-commerce retailers, which requested anonymity. The data and the conditions under which they were gathered were detailed as follows:

- Consumers could access the retailer's Facebook profile
  - ✧ by clicking a link on the company's website;
  - ✧ by looking up the company's name using the Facebook search option; or
  - ✧ through other external Web pages, like Google.

- These were the main access points, and there was no further advertising campaign during the studied period that might have included special invitations to participate or similar promotional activities relating to Facebook. Using and participating in the social network was free for users and the company; the only costs for the company resulted from managing the group and creating content for it.

- The content on the company's Facebook profile mainly consisted of posts created by the company and Facebook users. The posts were of different types:
  - ✧ brand building;
  - ✧ product display;
  - ✧ videos with advertising; and
  - ✧ occasional announcements of special deals and promotions.

- The majority of retailer's posts were rich in media and included pictures, videos, links, and text. The Facebook page was managed actively by a small team in the company whose task it was to coordinate actions with the marketing department and to create content for the posts; the team posted with an average frequency of 15 posts per month (*i.e.*, one post every second day, on average).

- The researchers captured all purchases made during this period, thereby collecting a unique sample consisting of daily data on transactions from the entire customer base of more than 2 million customers. The period under review spanned a full year from October, 2010 to September, 2011, thus allowing the researchers to address the potential for seasonal bias.

- The data provided, on a day-by-day basis, sales figures and aggregate-level figures on total "stream" impressions, page views, "Likes", and contributions on Facebook, a major advertising channel used during that period. This meant that Facebook users were able to view the company's posts on their user's mainstream site, and they could visit the company's Facebook profile and browse through the posts.

- Visitors also could
  - ✧ "Like" the profile itself;
  - ✧ "Like" each post issued by the company; or
  - ✧ "Like" contributions of other users.

- Users also could contribute their own content by commenting on the posts of the company. Visitor comments could include plain text, emoticons, and external links to other sites, small pictures, or videos. These are the general options Facebook offers its users; the company, itself, did not impose any restrictions.

- Both the posting designs and the product price levels largely remained unchanged, and no new advertising or social media channels were introduced during the analyzed period. At this time, the retailer that collected the current sample was the key player in this market and had the highest share of voice, which reduced the impact of potential competitor reactions.

ANALYSIS

The current authors used a direct-aggregation approach (Srinivasan and Weir, 1988) to calculate a compound advertising effect, or ad stock, for each stimulus (Herrington and Dempsey, 2005; Koyck, 1954; Srinivasan and Weir, 1988). This approach did not require a maximum number of lags to be specified *a priori*, increasing the flexibility of the estimation procedure. A "truncation bias," therefore, could be avoided (Hanssens, Parsons, and Schultz, 2001: p. 292).

Estimating time lags up-front can be based on "subjective decisions which are arbitrary or, at best, *ex post facto*" (Clarke, 1976: p. 346) as marketing theory does not provide generalizable guidance on the lag structure of advertising channels.

The authors of the current study believed, therefore, that a direct-aggregation approach could be advantageous for analyzing a rapidly evolving medium. Moreover, a direct-aggregation approach calculates only one nonlagged and one lagged exogenous variable. Hence, compared to other methods, this approach would be less exposed to autocorrelation, multicollinearity and to the measurement errors and reliability issues of parameter estimates. The well-established direct-aggregation approach yields stable results even for daily data spanning a full year and remains parsimonious for lags that exceed a full month (Clarke, 1976; Greene, 2008).

In the current model, sales were a function of the compound ad stocks. To avoid biased coefficient estimates, the researchers also incorporated weekly and monthly seasonal dummies, including the Christmas season (Pauwels and Weiss, 2008). The ad stock was calculated as the sum of current and past advertising effects at a diminishing rate for "stream" impressions (SI; See Equation 1). To calculate these effects, the current researchers assumed a distinct carryover (λ) for each stimulus.

Equation 1:

$$SI^*_t = [(1 - \lambda)SI_t + \lambda SI^*_{t-1}]$$

$$SI^*_{t-1} = [(1 - \lambda)SI_{t-1} + \lambda SI^*_{t-2}]$$

The advertising stocks for the remaining three stimuli were calculated accordingly.

Hence, the short-term advertising effect was represented by the sales impact on the same day the effect was evoked, and the long-term effect represented the total, cumulated sales impact over all periods.

The researchers performed a restricted grid search for values of $0 \le \lambda \le 1$ (Zellner and Geisel, 1970) and estimated λ for each stimulus to minimize the residual sum of squares (RSS). As this calculation algorithm is time-intensive, the researchers started with increments of $\lambda = 0.02$, which leads to $51^4 = 6{,}765{,}201$ regressions for direct effects only; they then refined their interim results using increments of $\lambda = 0.01$. Once the carryover parameters, which minimized the RSS of the regression, had been identified, the researchers calculated the respective ad stocks and arrived at the current and total sales effects using regression.

RESULTS

The researchers compared the overall fit of

- a first model (Model 1), which included time lags and synergies;
- a second model (Model 2) without synergies; and
- a third basic linear regression model (Model 3) without time lags and synergies.

The variables in the analysis were free of multicollinearity (See Table 1). All models, however, suffered from serial autocorrelation with a Durbin-Watson (DW) test value of 0.58 to 0.75 (Durbin and Watson, 1950), so the current researchers applied generalized least squares (GLS) regression to account for serial autocorrelation and heteroscedasticity (Herrington and Dempsey, 2005). Still, Model 3 showed an unsatisfactory DW test value of 2.36, which indicated negative autocorrelation, compared to satisfactory values of 2.12 for Model 2 and 2.08 for Model 1, indicating no autocorrelation.

This result emphasized the importance of integrating time lags in the current analysis. Moreover, Model 1 outperformed the other models, with a lower Akaike information criterion (Akaike, 1973) of 435.65, compared to 438.98 and 472.26 for Models 2 and 3, respectively.

The values for the Bayesian information criterion were: 486.35 for Model 1, compared to 485.77 for Model 2 and 519.05 for Model 3. According to the *F*-test (Akaike, 1973), the adjusted R^2 of Model 1 was significantly higher (50.21 percent) than the adjusted R^2 of Model 2 (47.89 percent) and the adjusted R^2 of Model 3 (41.43 percent).

Analysis of Model 1 with Time Lags And Synergies

The 90-percent duration interval (days until 90 percent of the total cumulative advertising effect has decayed) was calculated as log (1 – 0.9)/log λ (Clarke, 1976; See Table 2). As the current researchers used ad stocks, which distributed an input between the present and following periods, the regression coefficients represented the long-term total effect of that input. Equation 2 describes how to determine the short-term, same-day effects (Clarke, 1976; Sethuraman, Tellis, and Briesch, 2011, p. 458–459). The statistical program Stata 12 was used for this analysis.

Model 1, Equation 2:

long-term elasticity = short-term elasticity / (1 – carryover coefficient)

—or equivalently—

short-term elasticity = long-term elasticity * (1 – carryover coefficient)

All stimuli in the current analysis positively affected short-term sales, with the exception of "stream" impressions (See Table 2). Accordingly, the researchers rejected their first hypothesis but could confirm H2, H3, and H4. H5a postulated

TABLE 1
Correlations and Summary Statistics

Variables	"Stream" Impressions	Page Views	Likes	Contributions	Sales
"Stream" Impressions	1				
Page Views	0.71	1			
"Likes"	0.62	0.65	1		
Contributions	0.44	0.39	0.49	1	
Sales	0.27	0.52	0.35	0.18	1
Minimum	–1.32	–2.28	–1.96	–0.43	–2.66
Maximum	3.36	4.51	5.13	14.88	5.22

Note: All variables were standardized before the analysis.

TABLE 2

GLS Standardized Parameter Estimates of Direct Effects

Parameter (channel)	Short-Term Effect	Standard Error	Carry-Over (λ)	90% Duration Interval	Long-Term Effect	Standard Error
"Stream" Impressions (SI)	−0.14***	0.031	0.12	1.09	−0.16***	0.036
Page Views (PV)	0.16***	0.038	0.32	2.02	0.24***	0.056
"Likes" (L)	0.02***	0.004	0.96	56.41	0.53***	0.089
Contributions (C)	0.01**	0.004	0.95	44.89	0.18**	0.080

*p < 0.10, **p < 0.05, ***p < 0.01

Note: All variables were standardized before the analysis (dummy variables excluded from table for reasons of clarity).

a time-lagged long-term impact of Facebook stimuli on sales. On the basis of positive carryover coefficients (λ; See Table 2), this hypothesis could be confirmed as well.

Finally, Hypotheses 5b postulated that the long-term effects of all Facebook stimuli are stronger than the short-term effects and do not change direction. The absolute values of all long-term coefficients were higher than the corresponding short-term coefficients and did not change direction (See Table 2). A consideration of the 95-percent confidence intervals revealed that contributions and "Likes" had no intersection and, therefore, were significantly different. This meant that H5b could be confirmed for contributions and "Likes" but could not be confirmed for page views and "stream" impressions.

The researchers performed additional model checks to verify their results.

- According to the *F*-test, the overall significance of the regression exceeded 99.99 percent. Approximately 50 percent of total sales variance was explained by the four stimuli and their synergies on Facebook. A maximum variance inflation factor of 4.31 and a condition number of 7.54 showed that the model was free of multicollinearity (Greene, 2008).
- The augmented Dickey-Fuller test (Dickey and Fuller, 1979) proved that the variables in their regression were stationary at the 1 percent significance level. Since the current study analyzed a leading brand—one of the top-10 e-commerce retailers in Germany—this result was not surprising (Osinga *et al.*, 2010; Srinivasan, Pauwels, Hanssens, and Dekimpe, 2004; Trusov *et al.*, 2009). As some scholars have done (Naik and Raman, 2003), the current researchers included lagged sales as one of their explanatory variables and found no improvements in the model.
- A Granger causality test (tested for up to 16 lags; Dickey and Fuller, 1979; Granger, 1969) proved that, in the current model, sales were caused by advertising and not vice versa (endogeneity test).

POST HOC ANALYSIS

In analyzing various stimuli, the current researchers considered the relative importance of each stimulus and thus conducted an additional two-step analysis to achieve more fine-grained results.

- Step 1 focused on the synergistic effects that two or more stimuli could have when deployed simultaneously.
- Step 2 compared the relative size of the main and interaction effects. This enabled making recommendations about which stimulus was more effective in fostering sales.

Step 1: Synergistic Effects

Synergies in advertising have been defined as "the added value of one medium as a result of another medium, causing the combined effect of media to exceed the sum of their individual effects" (Naik and Raman, 2003, p. 385). Synergies also have been identified

- within offline and online media;
- across offline and online media; and
- from online media that have an offline effect on within-media synergies (Naik and Peters, 2009).

Because of these findings, marketers have attached considerable importance to aligning the execution of advertisements, and they have taken synergistic effects into account when planning integrated marketing campaigns.

Research in the field of relational marketing, however, also has demonstrated the potential for negative effects (resulting in an inverted U-shaped function) on the response of existing customers if a customer is exposed to advertisements beyond an ideal level of communication (Godfrey *et al.*, 2011). Studies incorporating synergies typically take into consideration these additional effects when calculating the interaction terms of the channels involved.

In the current model, sales are a function of the compound ad stocks. To account for synergies (Model 1, Equation 3), the current researchers multiplied the respective advertising inputs and calculated the interaction terms (Green, 1973), a method that particularly is applicable when real advertising and sales data are used (Godfrey *et al.*, 2011; Naik and Peters, 2009), as is the case in the current study.

Model 1, Equation 3:

$$S_t = \alpha + \beta_{SI}\, SI^*_t + \beta_{PV}\, PV^*_t + \beta_L\, L^*_t + \beta_C\, C^*_t + \beta_{SIPV}\, SI^*_t\, PV^*_t + \beta_{SIL}\, SI^*_t\, L^*_t + \beta_{SIC}\, SI^*_t\, C^*_t + \beta_{PVL}\, PV^*_t\, L^*_t + \beta_{PVC}\, PV^*_t\, C^*_t + \beta_{LC}\, L^*_t\, C^*_t + u_t$$

S_t: Sales volume of day t

α: Intercept

u_t: Error term

SI^*_t, PV^*_t, L^*_t, C^*_t: Ad stock of "stream" impressions, page views, "Likes", and contributions (stimuli), respectively, on day t

β_{SI}, β_{PV}, β_L, β_C: Regression coefficients of stimuli

$SI^*_t\, PV^*_t$, $SI^*_t\, L^*_t$, $SI^*_t\, C^*_t$, $PV^*_t\, L^*_t$, $PV^*_t\, C^*_t$, $L^*_t\, C^*_t$: Ad stock of stimuli interaction terms

β_{SIPV}, β_{SIL}, β_{SIC}, β_{PVL}, β_{PVC}, β_{LC}: Regression coefficients of stimuli interaction terms

Those synergistic effects can be calculated to analyze short-term effects, but as in the current main research model, time-lag effects of advertising had to be considered as well. Correspondingly, the researchers conducted this procedure for both short- and long-term effects.

The current results showed

- the significances were on the same level;
- the coefficients' directions were the same; and
- the size of the coefficients' impacts varied only slightly between short- and long-term effects (See Table 3).

The researchers identified three significant effects in this analysis:

- The interactions between "stream" impressions and page views, and the interactions between "stream" impressions and contributions, had a significant negative impact on sales, whereas…

TABLE 3

GLS Standardized Parameter Estimates of Interaction Effects

Parameter (Channel)	Short-Term Effect	Standard Error	Carry-Over (λ)	90% Duration Interval	Long-Term Effect	Standard Error
SI * PV	−0.05*	0.025	0.04	0.71	−0.05*	0.026
SI * L	−0.03	0.023	0.12	1.07	−0.04	0.027
SI * C	−0.08***	0.024	0.11	1.06	−0.09***	0.027
PV * L	0.02	0.027	0.31	1.95	0.03	0.039
PV * C	−0.01	0.032	0.30	1.93	−0.02	0.045
L * C	0.02**	0.007	0.91	25.00	0.21**	0.082

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Note: All variables were standardized before the analysis (dummy variables excluded from table for reasons of clarity).

- … the interactions between "Likes" and contributions had a significant positive impact on sales.
- Other pairs show no significant coefficients.

Step 2: Main and Interaction Effects

In their second step, the authors of the current study compared the relative sizes of the main and interaction effects, which enabled making recommendations about which stimulus was superior compared to the others. To do this, they calculated the 95-percent high and low confidence intervals of the relevant stimuli and examined whether there were an intersection.

The authors used standardized values in their comparison of the relative effect sizes of the different stimuli to ensure comparability among the different regression coefficients. This allowed them to compare how one standard deviation of an advertising input affected the sales output. For a parsimonious comparison of the Facebook stimuli main effects, the authors took the coefficient interval of page views as a reference point (this being the strongest short-term coefficient) and compared this with the other coefficients.

Starting with the direct short-term effects, the results showed relatively small regression coefficients, especially for "Likes" and contributions; the latter's confidence intervals indicated that their effects were significantly weaker than those of page views. "Stream" impressions had a strong impact but in a negative direction.

Regarding the direct long-term effects, the impact of "Likes," in particular, became stronger in the long run and was significantly stronger than that of page views. Even though contributions displayed an increased effect size in the long term, their impact did not significantly differ from that of page views. "Stream" impressions again created a relatively weak but significantly negative long-term effect compared to the positive impact of page views.

In summary, page views represented the strongest short-term stimulus, whereas "Likes" were the strongest long-term stimulus.

DISCUSSION

As expected, the current analyses revealed that advertising on Facebook significantly can affect sales, primarily in the long run and particularly by creating "Likes." Contributions and especially "Likes" develop their strong impact on sales only in the long run because of their high carryover effects.

Despite their low relevance for short-term sales, "Likes" and contributions over the long term are the strongest cumulative-sales drivers. With a beta of 0.53 for "Likes" and 0.18 for contributions, their long-term effects exceed their short-term impact by more than a factor of 20. This result underscores how important it is to account for time lags when analyzing Facebook stimuli.

One reason for this might be the engaging nature of social networks, which can offer companies a platform to retain their customers and stimulate repurchases that may happen long after advertising exposure, depending on the individual buying cycle of the consumer (long-term effect). This involvement is expected to be high for "Likes" and contributions, as these measures require an active engagement of the user.

The lagged effect of "Likes" and contributions might also occur because engaging a user on this platform is a more difficult and time-consuming task than is creating a "stream" impression or a page view. Another reason why "stream" impressions and page views do not show a significantly stronger long-term effect can be the high information density of those stimuli to the users (crowded stimuli). This suggests that solely media richness cannot compensate for crowded stimuli.

Social networks also provide users with the possibility to spread e-WOM (*e.g.*, by contributing a comment or clicking "Like"). In this respect, "Likes" and contributions can function as an indicator of content quality: The more "Likes" or contributions a posting generates, the more attention it receives, leading to additional exposures to the original posting—a self-energizing process. It may take some time to collect "Likes" and contributions, however—another possible reason for the significant, but lagged, sales impact.

Moreover, positive substantial synergies exist between "Likes" and contributions, as they form the third-strongest long-term effect ($\beta = 0.21$). Including synergies in the current model, therefore, not only improves overall model fit but ensures that the potential of a social network as advertising medium is fully appreciated and understood.

Unexpected Results

The current analyses also showed unexpected results, creating new insights on how advertising in a social network, such as Facebook, takes effect. Among these,

- "Likes" have the strongest long-term effect of all stimuli, even compared to contributions. On Facebook, where many comments compete for the user's attention, a "Like" may be more easily perceived and mentally processed than a more complex time-consuming comment.

  Another explanation for the strong effect of "Likes" might be the users' positive attitude to content. Users seem to identify themselves and their preferences with the content displayed. This leads to a stronger cognitive and emotional involvement. A single contribution, however, can be positive, neutral, or even negative. It might involve a higher level of interaction and engagement on the part of the user, but a single contribution also can be a means of venting negative feelings about the content. This effect can decrease the positive advertising effect of contributions.

- "Stream" impressions have a significantly negative impact on sales. A "stream" impression is pushed to the user, so it was the only intrusive and distracting stimulus in the current analysis (Winer, 2009). As such, it has a high potential to annoy users, becoming an unfavorable opportunity to process the advertisement, which can drive them away from, rather than toward, buying the product it advertises (Goodrich *et al.*, 2015; Taylor *et al.*, 2011).

  "Stream" impressions can be generated by a friend who clicked "Like" for a posting, which is then automatically forwarded to friends. The recipient might, then, be annoyed by this message, resulting in a negative direct effect, and may even write a negative comment on the posting, resulting in negative synergy of "stream" impressions and contributions.

  To generate a positive effect, it seems important that a user is allowed to interact with the brand voluntarily and to opt for engagement with Facebook. This contact, which seems to be highly sensitive with respect to intrusiveness and distraction, can have additional negative effects when combined with other stimuli, such as page views and contributions.

  This finding might be explained by the motives of those who use social-network sites, most of whom do so to keep in touch with relatives and friends or to be entertained, rather than to obtain recommendations or find product information (Simmons Experian Information Solutions, Inc., 2009).

  Although a "stream" impression still may lead to a positive reaction and may help acquire new customers, its negative, intrusive effect seems to dominate. Further differentiation among various types of "stream" impressions might shed more light on this unexpected result. It could be hypothesized, for example, that company-induced impressions might be perceived as more intrusive than user-induced ones.

- Synergies within Facebook in general play a less-important role than expected. The current study's results indicated that only for users really engaging with the brand can a positive synergistic effect be generated, for example, that of "Likes" and contributions. By contrast, some users might feel annoyed by advertising "stream" impressions and consequently comment on it, resulting in negative synergy between "stream" impressions and contributions.

These first indications deserve a more detailed analysis going forward. A page view, which seems to be too weak to form the basis for a strong, synergistic effect, differs substantially from the other stimuli. Page views are a stronger short-term sales trigger than the other stimuli are, but page views fail to establish a comparably long-term impact (low carryover effect of λ = 32 percent). Page views seem to promote short-term, impulsive purchases rather than long-term, brand-loyal purchases.

The positive effects of "Likes" and contributions, in the long term, reflected their positive synergy regarding sales. The current authors observed a similar effect between contributions and "stream" impressions, albeit in an unexpected negative direction. This could support the argument that contributions also can take the form of negative comments on the advertising content. If users become irritated by "stream" impressions, they are able to comment on them immediately. This has a synergistic effect, as other users can read those negative comments and might feel inclined to issue a negative comment as well or to delay or even cancel an upcoming purchase.

Although this result was unexpected, it is very important for practitioners and researchers to acknowledge that online channels, such as Facebook, not only offer companies the possibility to address and engage customers in more interactive ways but offer customers the possibility to react to advertising activities they dislike. This can have a negative impact on sales and, in turn, on company performance.

IMPLICATIONS

For Practitioners

The current study demonstrated a comprehensive approach to analyzing advertising effectiveness on the basis of data that are readily available through Facebook free of cost and that can be downloaded online with just one click (through Facebook Insights). The authors encourage marketers to pursue this approach to analyze, control, and optimize their interactions with customers on Facebook.

Generalizing their empirical results *ceteris paribus*, the authors recommend using Facebook for advertising only if a company is willing to invest the time and manpower required to engage the user. The predominant strength of Facebook as an advertising channel is that it affects sales in the long term. It is critical for a company to generate contributions and "Likes," which mutually increase their effect size in the long run.

To realize immediate sales, however, practitioners should focus on page views featuring content that induces impulsive purchases (*e.g.*, through special temporary offers). In general, marketers should be cautious in their use of "stream" impressions, as these can evoke a negative sales effect when used too extensively; instead, marketers should allow users to determine when, and how intensely, they want to engage with the company.

For Researchers

Results revealed three considerations:

- The risk of focusing on a single stimulus on social networking sites in an advertising context: The stimuli available vary significantly in terms of their direct and synergistic sales impacts, so they should be differentiated in advertising-effectiveness analyses.

- The importance of incorporating long-term effects when modeling the different Facebook stimuli and their sales impact.

- Synergies should be included in such analyses to improve overall model fit. Attempts to foster synergies (*e.g.*, with "stream" impressions), however, might have a negative sales impact. Hence, synergistic effects can vary significantly not only in their strength but in their effect direction.

- "Stream" impressions create a negative sales impact, so they represent a significant risk of losing sales.

Moreover, this research underscores the importance of including criteria such as source credibility, advertisement repetition, media richness, interactivity and, especially, intrusiveness and distraction when developing a framework on advertising processing in a social network.

FUTURE RESEARCH RECOMMENDATIONS

As an online advertising channel, Facebook targets a specific customer group of Internet users willing to engage on a social network platform, which limits its reach. This channel, therefore, should be part only of a broader, integrated marketing campaign. Research that broadens the information about the customer segments targeted by this advertising channel—and that analyzes the interplay of this study's stimuli with other online and offline advertising channels—would be worthwhile.

Studies in this field could further expand the current understanding of how, for whom, and under which circumstances social networks like Facebook work for advertising. Moreover, although the authors found first indications of negative e-WOM effects through "stream" impressions, additional analyses are required regarding the pitfalls involved—and the opportunities available—to acquire or retain customers by employing this stimulus.

Despite the overall negative sales impact of "stream" impressions, it seems reasonable to assume that not all messages that are spread via "stream" impressions evoke the same effect. Similar to previous studies on banner or in-store advertisements (Baron *et al.*, 2014; Chandon, 2001), research examining the qualitative differences of advertising messages and their sales relevance, such as advertising content and design, would help to clarify the value of this stimulus.

It could be relevant for future studies on the effectiveness of Facebook as an advertising channel to analyze different types of customers. The current study contained aggregated data on all purchases without any differentiation of customer groups. Heterogeneous reactions, however, could be expected, especially regarding new customers, who still need to be convinced and acquired, and existing customers, who already know the brand from past interaction. All studies should include time lags to arrive at a fair assessment of advertising effectiveness.

LIMITATIONS

The current empirical results faced a certain limitation because the researchers used data from one of Germany's top-10 e-commerce retailers, which they collected over the course of a single year. This focus on a single website of a well-known firm limits the generalizability of the study's findings. Thus, the question could be raised whether future studies can confirm the current findings (*e.g.*, for e-commerce companies that are smaller and less well known).

As social networks constitute a rapidly evolving medium in its infancy, additional studies looking at different time horizons are called for. Due to the novelty of this topic the current authors have focused on an exploratory analysis based on a data set of a single year.

Future studies should rely on longer time series that allow longitudinal studies. JAR

Malte Brettel is a professor of business administration at RWTH Aachen University, Germany, and professor of entrepreneurship at WHU Otto Beisheim School of Management. He has co-founded several companies, including AbeBooks.com. Brettel's areas of research interest include entrepreneurial management and development. His work has been published in various books and journals, including *Strategic Management Journal, Journal of Product Innovation Management,* and *Journal of Business Venturing.*

Jens-Christian Reich is an associate researcher at RWTH Aachen University, where he focuses on return on marketing investment, advertising effectiveness, and social-media advertising. Reich also is a project leader specializing in digital disruption at The Boston Consulting Group in Düsseldorf, Germany.

Jose M. Gavilanes is a research assistant at the RWTH Aachen University chair for business administration and sciences for engineers and scientists/Centre for Entrepreneurship. His research specialty is return on marketing investment, advertising effectiveness, marketing research methods, social-media advertising, and qualitative content analysis. Gavilanes also is a consultant specializing in the retail industry and consumer goods at The Boston Consulting Group in Düsseldorf, Germany.

Tessa C. Flatten is a professor of technology management at TU Dortmund, Germany. She received her doctoral degree from RWTH Aachen University. Her research focuses on innovation and technology management, as well as entrepreneurship. Her work has been published in *Entrepreneurship Theory* and *Practice or Research Policy.*

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