Measuring Marketing Success: Estimating the Effect of Social Media and TV Advertising on Brand Attention

By Daniel Guhl, Hannah Winkler von Mohrenfels, Jannina Abshagen and Daniel Klapper

1. Introduction

New media forms have emerged in the last couple of years and digital media has supplemented traditional media. This has introduced opportunities as well as risks for firms and researchers alike. Especially the presence of online social networks has “vastly influenced human interaction on an individual, community, and larger societal level, and underscores the convergence of the online and offline worlds” [1]. In October 2011, social network activity accounted for one in every five minutes of the total time users spent online (comScore 2011).

The combined on- and offline media usage by consumers and firms generates rich databases to measure the performance and efficiency of diverse marketing tools. The increased data availability has spurred research. While several studies have addressed the power of word-of-mouth (WOM) regarding customer acquisition, sales, referral programs, or contagion in social networks, yet few studies have made use of the databases social networks provide to measure marketing impact. Onishi/Manchanda (2012) find that new and traditional media act synergistically and that there is a need for understanding the specific relationship between traditional and new media, because managers then can more adequately allocate resources. Hence,
there is a “call for creativity in new metrics for liquid media” (Russell 2009) to enable researchers and practitioners to tap the full potential these data provide.

To this end, our paper focuses on empirically demonstrating how TV advertising data combined with online data from social networks and web search queries can be used to measure marketing efforts. Furthermore, based on the assumption that searchers are undoubtedly paying attention to keywords they search for (e.g., Da/Engelberg/Gao 2011), we interpret brand-related online search data as brand attention metric. This metric is openly accessible and gives researchers and companies the possibility to gain insights into marketing effects without the need for costly panel or survey data.

Additionally, effects of traditional media, such as TV advertisements, should not be neglected in analyzing marketing effects. Particularly TV advertising is still a common way to promote firms, brands, and their products. Worldwide advertising expenditures increased by over 7% in 2011, whereof 65% were due to advertising spending on TV (Nielsen 2012).

We demonstrate our approach by estimating the effects of TV advertising and social network activity on brand attention, next to the impact of TV advertising on social networks. Nowadays, social networks are a platform to discuss TV spots. In this respect, TV broadcasts could influence the chatter about a brand or its products and thus might affect brand attention.

In order to examine the dynamic relationships between different marketing means, this study is based on the modeling approach proposed by Dekimpe/Hanssens (1999) (and applied by Trusov/Bucklin/Pauwels 2009 in an online marketing context), who use established econometric methods in time series analysis. Vector autoregressive (VAR) models are applied to capture complex dynamic relationships among brand attention, traditional marketing, and social network variables. To our best knowledge, the current study is the first that links diverse on- and offline marketing efforts to a metric of online brand attention. A quantification of immediate (same period) as well as short-run (1 day to 3 weeks) effects allows a comparison of different types of media.

This paper is structured as follows: The next section briefly summarizes previous literature, on which we have built our research propositions on. Section 3 presents the data. We discuss the operationalization of the variables as well as descriptive statistics. Section 4 explains the modeling approach, which is then applied to our dataset. Section 5 concludes with a summary of main findings and an outlook identifying further research topics.

2. Previous research and research propositions

Clark/Doraszelski/Draganska (2009) measure the influence of traditional advertising tools on brand awareness. Expenditures for a wide range of traditional media (such as TV advertising, newspapers, or radio) are used to estimate brand awareness effects. Brand awareness is quantified as the percentage of respondents, who were able to rate the brand in a brand quality survey. A positive impact of advertising spending on brand awareness is identified.

A measure, which is related to brand awareness, is brand attention and past research has used several different brand awareness and attention measures. Whereas brand awareness is usually measured via brand memory or recall (e.g., Finn 1988), the most frequently found proxy for brand attention is the time spent looking at an advertisement (e.g., Pechmann/Stewart 1990). A more recent approach, as used by Chandon et al. (2009) or Pieters/Warlop/Wedel (2002), monitors eye movements with eye-tracking methodology to measure brand attention.

Another very recent approach uses search engine users’ search data to measure attention, and actually, this kind of data has aroused interest in several scientific fields. For instance, Da/Engelberg/Gao (2011) propose Google search queries as a measure for investor attention. The fact that search is a revealed measure of attention, as users are undoubtedly paying attention to the things they look for, legitimates the metric as appropriate. Favorable features of the metric are, that attention is measured in real time and data access is not restricted. In the field of epidemiology, Ginsberg et al. (2009) use search data to predict flu outbreaks. Vosen/Schmidt (2011) introduce search query data to marketing research, in order to create a new indicator for consumption. They emphasize the benefits of search data as compared to common survey-based indicators and show that the Google indicator outperforms the survey-based indicators.

Based on previous research results, we expect TV advertising to increase brand attention and, thus, to have a positive impact on the number of brand-related search queries:

**P1: TV advertising has a positive impact on the level of brand attention.**

Online social networking offers a variety of innovative possibilities for companies to monitor their image, and to strengthen customer relationships, too. Researchers, as well as practitioners, are becoming increasingly interested in the interaction between on- and offline marketing tools. In the last couple of years, several studies were conducted.

Trusov/Bucklin/Pauwels (2009) compare the effect of traditional offline marketing and online WOM referrals on acquiring social network members. They find that the WOM effect is considerably larger than the effect of traditional marketing. For WOM, a long-term elasticity of .53 on member acquisition is estimated.

With over 1 billion active users (as of October 2012), Facebook is the largest online social network (Facebook
Facebook enables firms and individuals to create profiles, make friends with other users (i.e., connect with other users), and to publish or share contents, which are not restricted in length. With their Facebook presence, companies intend to strengthen the relationship to their customers, who might “like” their brands or connect by “becoming a friend.” By directly communicating with connected users, firms are able to increase their reach within the network, because each interaction might be shown in the news feeds of their friends’ friends. Since brand communities are commonly used to create and express opinions (McAlexander/Schouten/Koenig 2002), it is likely that users state opinions and give feedback about brand-related issues on company profiles in social networks. The same should be the case for firms’ advertising campaigns. Therefore, we expect more users to interact with the company when the company is advertising on television:

P2: TV advertising has a positive impact on posting activity in Facebook.

Social networks are designed to enable users to share parts of their lives and opinions. Therefore, when a user talks about a company or becomes a fan of a social networking site, other users become aware of this. Vieweg et al. (2010) argue that the spread of information in a social network can enhance situational awareness in case of emergencies. We thus predict the activity within the Facebook network to heighten the attention towards a brand:

P3: Facebook activity has a positive impact on the level of brand attention.

Yamamoto/Matsumura (2011) present a study, which is closely related to Trusov/Bucklin/Pauwels (2009), but include the effects of TV advertising on creating buzz in the social network Twitter. The authors use a structural equation approach to model the relationships among TV advertising, offline WOM, and customer acquisition. A positive influence of TV advertising on buzz in Twitter is observed next to a strong impact on customer acquisition. Twitter offers a microblogging service, which allows twitterers (i.e., users) to publish short posts to a network of other users. Twitter reports statistics of 340 million so-called tweets (i.e., posts) per day (Twitter 2012). By “following” a person or firm, users can acquire their tweets. A person or firm that is being followed is a so called “follower.” Besides being able to tweet, Twitter has a function to copy original posts by other twitterers and retweet (i.e., tweet the original content of other posts) them. @-messages are another function for directly addressing other users. Referring to a user by typing “@” in front of its name makes the @-message appear on that user’s timeline of posts.

Keeping in mind that Twitter is basically designed to express opinions and to comment on events in daily life, events such as a TV spots seem like a potential topic to be addressed within this network. Building on a major finding of Yamamoto/Matsumura (2011) that TV advertising increases buzz in Twitter, we expect a positive effect of TV advertisements on Twitter activity, as well:

P4: TV advertising has a positive impact on posting activity in Twitter.

In line with the above argumentation about the impact of activity in social networks, we presume that an increase in Twitter messages about a company will increase brand attention:

P5: Twitter activity has a positive impact on the level of brand attention.

As companies usually provide a vast amount of information on their Facebook profiles, consumers who frequently visit a company’s profile should feel less of an urge to search for additional online information. On the other hand, as tweets are restricted to a length of only up to 140 characters, Twitter activity might not satisfy consumers’ information interests completely, and therefore, seems likely to prompt additional search. With Facebook being an information-providing tool, we conclude that Facebook activity leads to lower brand attention, in terms of search queries, than Twitter activity does:

P6: Twitter activity has a higher impact on brand attention than Facebook activity.

3. Data

To account for a typical setting of events within and outside social networks, we apply our model to data from a medium-sized FMCG company, which advertised its brand on TV and interacts with consumers in social networks. The online data we refer to can be easily collected by researchers or firms themselves as demonstrated in the next sections. The data from the company cover 48 weeks, from January 1st to December 12th, 2011. However, we subset the data to the time window from April 18th to October 4th, 2011, to focus on the period when the spots of the TV campaign were aired. Our analysis is based on four main variables, which we will explain in greater detail in the following sections: brand attention (Search Volume Index, SVI hereafter), TV advertising (TV), Facebook posts (FB), and Twitter posts (TW). All variables are available on the daily level. Hence, we have 170 observations for each variable in total. Fig. 1 shows time series plots and Tab. 1 summarizes descriptive statistics, as well as contemporaneous correlations [2].

Brand attention: We use Google search volume data to measure brand attention. As explained above, the frequency of search queries should be an appropriate and direct indicator for the attention toward a brand or its products. In particular, the data can be accessed on the Internet, and can be downloaded easily and free of charge. Google, which accounts for 95 % of all search queries (Netmarketshare 2012), provides with Google Trends (2015) a tool that tracks the volume of keyword
search queries, which are entered by users into the search engine. We chose the brand name as the keyword to extract search data, in order to further examine brand attention. The SVI summarizes normalized search frequencies. The maximum search volume over the total chosen period (monthly or yearly) is normalized to be 100 and the rest of the sample is scaled accordingly. The granularity of the SVI depends on the chosen period. For a monthly period, SVI data is provided on the daily level; whereas for a yearly period, SVI data is provided on the weekly level. To receive SVI data on the daily level, which is in spite of the normalization comparable across several months, we collected both, daily data monthly, as well as weekly data yearly. We then rescaled the daily data for each month by multiplying each day with the SVI for the respective week from the weekly data. Fig. 1 (top-left panel) shows the SVI time-series, which strongly varies over time and covers the possible range of values (from 0 to 100) almost completely.

**Television advertising:** The company supplied audience data for their total TV advertising campaign in the year 2011. The sample covers the size of the TV audience for each spot broadcasted on most major public TV channels. These channels comprised a very high overall penetration and 43.6 % of the total daily average market share in 2011 (AGF/GfK 2012). In addition, broadcast times of the spots covered the whole day and were not constrained to specific time spans. Concerning the goal of the campaign, the firm was primarily interested in increasing the overall attention toward the brand by introducing its first TV advertisements.

TV spots were broadcasted from May to early September. We added a reasonable number of days before and after this time period (2–3 weeks, which is the approx. length of dynamic effects in the data, see below) to account for wear-in and -out effects in our analysis. Fig. 1 (top-right panel) depicts the gross reach of the TV audience in 100,000 per day. TV broadcasts appeared almost every day during the campaign. There were four short breaks between advertising flights. The correlation between SVI and TV is quite strong (> .6, see Tab. 1).

**Facebook:** To raise brand attention, the brand was active in two popular online social networks, namely Facebook and Twitter. In Facebook, the company counted wall posts, likes, and any type of comment on the page on a daily basis. We focused on the posts by the brand itself and posts by Facebook users to build our FB variable, which sums counts of both types on the daily level.

Fig. 1 (bottom-left panel) visualizes Facebook activity on the company profile. The graph displays the aggregate number of Facebook posts over 25 calendar weeks. The total number of posts under examination is more than 13,000 with a daily average of almost 80 posts.

Tab. 1: Correlations and descriptive statistics (daily data)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Descriptive Statistics</th>
<th>Contemporaneous Correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>SVI</td>
<td>36.39</td>
<td>18.64</td>
</tr>
<tr>
<td>TV</td>
<td>24.23</td>
<td>26.29</td>
</tr>
<tr>
<td>FB</td>
<td>78.79</td>
<td>82.37</td>
</tr>
<tr>
<td>TW</td>
<td>52.24</td>
<td>33.44</td>
</tr>
</tbody>
</table>

Note: (*) correlation is non-significant at the .05 level (two-tailed)

Fig. 1: Time series plots of main variables (daily data)
There seems to be noticeable increase in the level of posting activity during the weeks of the brand’s advertising campaign. This could be an indicator for people reacting in Facebook to the TV spots. The relation between \( FB \) and \( SVI \) is less obvious and the positive correlation between both variables is not statistically significant.

**Twitter:** The company provided a list that contained the posts about the brand from the Twitter network. The real-time posts include the name of the brand as a keyword and cover each of the posting functions (i.e., tweets, @-messages, and retweets). More specifically, the Twitter dataset includes the username and the content of an individual post, the actual time of the post, and the number of followers and followees of each tweeter. To obtain information about the chatter regarding a brand or its products, Twitter provides a tool to search for posts that contain any keyword of interest [3]. The advanced search option allows users to gather posts including specific content in different languages, by account or even regional restrictions, for instance. To obtain comparable data to Facebook, we sum the different posts in Twitter by the brand itself and external users on the daily basis.

A sample of approx. 9,000 posts was collected and the number of daily posts varies between 0 and 184 with an average value of 52. A detailed descriptive tweet analysis (not presented here for the sake of brevity) revealed that the brand actively uses Twitter to address other people in the network, whereas external tweerers are mainly using Twitter to publish tweets about the brand instead of interacting. Fig. 1 (bottom-right panel) depicts the Twitter activity. A correlation between \( TV \) and \( TW \), as well as \( TW \) and \( SVI \) is clearly visible.

4. Modeling direct and indirect effects of TV advertising, social networks, and brand attention

4.1. Modeling approach

This section further elaborates on the model chosen to measure direct and indirect effects among the variables of interest concerning traditional marketing, social networks, and the proposed measure of brand attention in our analysis. We are particularly interested in answering the following two research questions:

1. Which instruments are how effective in creating brand attention?
2. When do the effects occur (taking into account potential wear-in and wear-out effects, as well as dynamic relationships between all variables)?

According to Hill/Griffiths/Lim (2012, p. 336), a dynamic relationship is defined as a condition where a present change in one variable affects itself or other variables in future time periods. For instance, a rise in the size of TV audience may imply a higher number of posts in periods besides the one at which the change is observed. Thus, it is possible that effects do not occur instantaneously but are distributed over future time periods. These dynamics have to be taken care of in adequate model specifications. Endogeneity and dynamic links between brand attention, TV audience, and social networks can be tested by Granger causality statistics (Granger 1969). The idea behind Granger causality analysis is to determine whether past values of one variable contain information that improve the predictions of another variable in the set. Granger causality tests are performed on each pair of variables considered in this analysis. If two or more variable are endogenous, we model their relationship in a dynamic system of equations (Lütkepohl 2005). If variables do not Granger-cause any other variable, we could still use them as exogenous variables in the model.

One way to capture endogeneity and the described dynamics in an appropriate modeling framework, is persistence modeling, which is in general a multi-step approach (see Dekimpe/Hanssens 2004 for more details):

1. The first step is a test for unit-roots of the variables. A variable with a unit-root is non-stationary (= evolving). A standard test for stationarity of time series is the augmented Dickey-Fuller (ADF) test (Dickey/Fuller 1979). The null hypothesis that the variable contains a unit root is tested against the alternative that the time series is generated by a stationary process.

2. If variables are evolving over time, we have to check for cointegration. Cointegration between variables means that a linear combination between them exists that results in stable residuals, which can be analyzed using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al. 1992).

3. Based on the outcome of step 1 and 2, we can specify a dynamic model. If all variables are stable in step 1 (Ho is rejected), we can specify a vector autoregressive (VAR) model in levels (e.g., Trusov/Bucklin/Pauwels 2009). If cointegration exists, one has to use a Vector Error Correction (VEC) model (e.g., Dekimpe/Hanssens 1999), if not, one can build a VAR in differences (e.g., Nijs et al. 2001). Mixed models are also possible (Dekimpe/Hanssens, 2004) and OLS, GLS, or MLE can be used for estimation.

4. Because the before mentioned models may consist of many parameters, the interpretation is not straightforward. Therefore, it is common to use so called Impulse Response Functions (IRF), which trace the impact of a shock in an endogenous variable on current and future values of itself, or on other endogenous variables in the system. We apply the generalized IRF (GIRF) approach proposed by Pesaran/Shin (1998) because it is unaffected by the ordering of variables (e.g., Dekimpe/Hanssens 1999). Furthermore, the (G)IRFs enable researchers to disentangle the length of the effects. Immediate effects are the same-period effects of the shocks. Summing up all statistically significant (G)IR estimates \( |h_{(k)}| > 1 \), see Nijs et al.
2001 or Trusov/Bucklin/Pauwels (2009) of a shock over time, result in the short-run effect. This time window is called “dust-settling” period. The long-run (or permanent, or persistent) effect is the effect the (G)IRF converges to. If the time series has a unit-root, the long-run effect is > 0.

In the next section, we apply the steps of the approach described above to our data set. All variables (SVI, TV, FB, and TW) were transformed using the natural logarithm to make the positively skewed distributions comparable to the normal distribution. This also facilitates the interpretation of estimation results because coefficients can then be interpreted as elasticities later on (Nijs et al. 2001). However, we add a 1 to the variables TV, FB, and TW before taking logs because these variables contain zero values on some days (Albers 2012). Please note that using variables in logs (given their elasticity values are < 1) has the additional advantage to capture diminishing returns of the variables, which makes sense in the context of this paper (i.e., effects of traditional advertising and social media of brand attention).

4.2. Empirical results

Granger causality tests: Several causality tests were applied for lags up to 20 days in order to examine whether Granger causality can be rejected in general, or not. Tab. 2 contains the minimum p-values across 20 lags for each pair of the considered variables (i.e., ln(SVI), ln(TV), ln(FB), and ln(TW)). The first column indicates the respective dependent variable, and the following columns contain the independent variables.

As expected in our propositions in Section 2, TV advertising Granger-causes each of the other variables. It helps to predict the level of brand attention, as well as the posting activity in Facebook and Twitter (at least on the 5% significance level). Additionally, the number of Twitter posts helps to predict brand attention. Posts on Facebook do not Granger-cause brand attention (on a reasonable significance level). However, Facebook posts do Granger-cause Twitter posts, et vice versa. Brand attention Granger-causes TV audience, as well as Twitter posts. Because each variable Granger-causes, or is Granger-caused by, at least one other variable, a full dynamic system is necessary (Trusov/Bucklin/Pauwels 2009). This allows estimating each endogenous variable based on the joint interactions of the other endogenous variables.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>... is Granger-caused by</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SVI</td>
</tr>
<tr>
<td>SVI</td>
<td>.05</td>
</tr>
<tr>
<td>TV</td>
<td>.00</td>
</tr>
<tr>
<td>FB</td>
<td>.10</td>
</tr>
<tr>
<td>TW</td>
<td>.00</td>
</tr>
</tbody>
</table>

Note: Minimum p-values across 20 lags

Tab. 2: Granger causality tests

Unit-root tests: In order to construct the econometric model appropriately, we analyzed the time series properties of the underlying data. In order to perform the ADF test, the lag length needs to be known. The optimal lag length can be determined by minimizing information criteria such as the Akaike information criterion (AIC) or the Schwarz information criterion (SC) (Hill/Griﬃths/Lim 2012, p. 366), of which we have used the AIC. The t-values of the lagged variables (in logs) are -4.75 for SVI, -3.92 for TV, -5.29 for FB, and -4.8 for FB. For the given sample size and in case of controlling for a deterministic trend and drift, the critical value for α = .05 is -3.43. Hence, in all cases the null hypothesis of a unit root can be rejected at least on the 5% significance level. All variables seem stationary, and this implies, a suitable model can be chosen (VAR model in levels), we don’t have to test for cointegration, and long-run effects cannot exist.

Model specification and estimation: Vector autoregressive (VAR) models represent a general framework to model complex dynamic interrelationships among stationary variables. VARs explain endogenous variables by their own past, in addition to past values of the remaining variables (Lütkepohl 2005). The framework captures direct and indirect effects, and appropriately accounts for endogenous relationships among variables within the model. To this end, we specify a dynamic regression model of TV advertising, posting activity in Facebook and Twitter, as well as brand attention as follows:

\[ \begin{align*}
\text{ln}(\text{SVI}_t) &= \alpha_1 + \delta_1 \cdot t + \sum_{s=1}^{4} \gamma_{1,s} \cdot s + \epsilon_{1,t} \\
\text{ln}(\text{TV}_t) &= \alpha_2 + \delta_2 \cdot t + \sum_{s=1}^{4} \gamma_{2,s} \cdot s + \epsilon_{2,t} \\
\text{ln}(\text{FB}_t) &= \alpha_3 + \delta_3 \cdot t + \sum_{s=1}^{4} \gamma_{3,s} \cdot s + \epsilon_{3,t} \\
\text{ln}(\text{TW}_t) &= \alpha_4 + \delta_4 \cdot t + \sum_{s=1}^{4} \gamma_{4,s} \cdot s + \epsilon_{4,t}
\end{align*} \] (1)

In equation system (1), the (K = 4) main variables ln(SVI), ln(TV), ln(FB), and ln(TW) are defined as described previously; \( \alpha \) is an intercept for each equation (\( k \) indexes the equation) to account for fixed components in the model; \( \delta \) captures the effect of deterministic (linear) trends of omitted variables that gradually change over time; \( s \) are day-of-week dummies (s indexes weekdays and Sunday is the reference), and \( \gamma_{j,s} \) are the corresponding parameters; \( \beta_{j} \) are the autoregressive effects and endogenous cross-variable lagged effects, where \( j \) indexes the number of lags, \( J \) is the maximum number of lags, and \( t \) indexes days; and \( \epsilon \) are residuals that capture instantaneous (same period) effects and are distributed multivariate normal.

This system can be estimated efficiently (equation-by-equation) using OLS because all right-hand side variables...
les are identical across equations. The optimal lag-length is 2 and was determined by the AIC (Trusov/Bucklin/Pauwels 2009). Hence, we have estimated a model with 64 parameters (4 intercepts, 4 trend effects, 4·6 day-of-week effects, and 2·4·4 autoregressive and endogenous effects). Because we use 2 lags, we have 168 observations per equation and therefore 152 degrees of freedom for the estimation. The corresponding observation-to-parameter ratio is 9.5, which is acceptable. Detailed estimation results can be found in Tab. A1 in the appendix.

Many of the β parameters have absolute t-values larger than 1 and we refrain from setting insignificant parameters to zero and re-estimating a smaller model because we don’t have an issue with too few degrees of freedom (Dekimpe/Hanssens 2004). Diagnostic tests for residual autocorrelation and heteroscedasticity are passed. Day-of-week seasonality seems to be especially important for the SVI variable and all variables have a slight linear trend. The results look reasonable in terms of fit with R²-values between 28% (FB) and 77% (TV). To illustrate the appropriateness of the model to predict the data, Fig. 2 shows the actual ln(SVI)-values (data) vs. the predicted values (model) on the daily level. Both time series are very close (R² of 74%), and the model is clearly capable of explaining the variation of brand attention over time.

Before we continue with the analysis of the GIRFs in the next section, we briefly discuss the covariance matrix of the residuals. It is important to keep in mind that the model captures same-period effects of the endogenous variables via the error-term. Therefore, the covariance (and correlation) matrix in Tab. 3 helps to understand the contemporaneous relationships between the endogenous variables after controlling for endogeneity, dynamic effects, trends, and seasonality.

The covariance between most variables is positive, which makes sense. Comparing the magnitude of the residual correlations with the ones of the raw data in Tab. 1 indicates that the model captures with its dynamic parts a considerable proportion of the correlations. The negative contemporaneous relationship of SVI and FB is quite interesting. We will investigate this finding in greater detail in the next section.

### Generalized Impulse Response Functions

As mentioned before, (G)IRFs help to understand the complex dynamic and cross-equation relationships of a VAR model. GIRFs use the residual covariance matrix and all estimated β parameters to derive the expected effects, which a (one-unit) shock in one variable (e.g., TV) has simultaneously on all the other variables (e.g., SVI, FB, and TW). To get a first impression of the interrelationships among the different variables, Fig. 3 and 4 graphically depict a subset of the computed GIRFs from the estimated VAR model in Eq. 1. For each GIRF (solid line) a confidence interval (+/- 1 standard error) is plotted (shaded area). The standard errors are computed via bootstrapping using 1,000 replications (Lütkepohl 2005). Each GIRF is drawn over a period of 21 days (= 3 weeks) as this covers all fluctuations in the considered impulse response relationships before the values converge. The respective periods of dust-settling are marked in the following graphs by dashed vertical lines. Due to logarithmic transformations of all variables prior to estimation, the estimated GIRFs can be directly interpreted as elasticities.

<table>
<thead>
<tr>
<th></th>
<th>ln(SVI)</th>
<th>ln(TV)</th>
<th>ln(FB)</th>
<th>ln(TW)</th>
</tr>
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<tbody>
<tr>
<td>ln(SVI)</td>
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<td>.424</td>
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<tr>
<td>ln(FB)</td>
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<td>.044</td>
<td>.704</td>
<td>.087</td>
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<td>ln(TW)</td>
<td>.038</td>
<td>.144</td>
<td>.036</td>
<td>.249</td>
</tr>
</tbody>
</table>

Tab. 3: Covariance matrix (lower triangle incl. diagonal) and correlation matrix (upper triangle) of the residuals

Fig. 2: Model fit
To analyze the performance of TV advertising in greater depth, GIRFs of the activity in social networks are plotted in Fig. 3. The effects of a shock in $\ln(TV)$ evolve similarly for both Facebook and Twitter, but there are also slight differences. The $FB$ elasticity with respect to $TV$ starts with a low value of .04, reaches almost .1 after day 1, and starts to drop again after day 4. The immediate elasticity of $TW$ with respect to $TV$ is higher (.12) and keeps this value for the first 3 days. The GIRF of $TW$ has also slightly narrower confidence intervals. Elasticities of both variables taper off slowly during the next periods and the dust-settling periods end at day 18 ($FB$) and 19 ($TW$). Hence, the short-run effect of TV advertising on social media lasts roughly 2.5 weeks. The results indicate that users indeed react to TV spots, and that a firm’s presence in social networks can help to monitor and interpret the performance of this instrument. Moreover, as similar effects over time were observed for both networks, the robustness of the results is supported.

Fig. 4 depicts the effects of TV advertising, as well as posting activity in Facebook and Twitter on the level of brand attention. Two different effect patterns emerge. The results for shocks in $\ln(TV)$ and $\ln(TW)$ (left and right panel) are discussed first. Responses to shocks in these variables fade out during dust-settling periods of 17 and 15 days. During the dust-settling periods, only positive and significant responses of $\ln(SVI)$ are observed. The immediate $SVI$ elasticity has a slightly lower value with respect to $TW$ (.07) than with respect to $TV$ (.11). However, the $SVI$ elasticity with respect to $TW$ wears-in quickly and reaches a maximum value of .12 after 1 day.

The $SVI$ elasticity with respect to $FB$ follows a second, differently looking pattern (Fig. 4, center panel). The immediate elasticity has a slightly negative value of -.05. However, after 3 days the elasticity turns positive, and after 5 days it reaches its maximum of .03. Then the elasticity fades out and the dust-settling period ends after 17 days. A possible explanation for this finding might be that due to an increase of Facebook posts, people search less on Google for the brand because brand-related information is acquired on Facebook itself. After several days the elasticity becomes positive because of the positive relationships between $FB$ and $TW$, as well as $FB$ and $TV$.

To further compare the different effects and to derive appropriate conclusions, the overall impact during dust-settling periods is quantified next. The GIRFs fluctuate during each dust-settling phase. Therefore, effects should be accumulated during dust-settling periods in order to assess their total size ($Dekimpe/Hanssens$ 1999). This is done by adding up all estimated levels of GIRFs during dust-settling periods. Immediate and Short-run elasticities for the dust-settling phases of the relations of interest are reported in Tab. 4.

Adding up elasticities for the first 3 days, 7 days, and 14 days, respectively, differentiates the effects during each dust-settling period. This gives a detailed overview how the elasticities evolve over time. The first 3 rows show the elasticities of $SVI$ with respect to $TV$, $FB$, and $TW$. Facebook and Twitter elasticities with respect to TV advertising are displayed in rows 4 and 5. The numbers in
Elasticity of... w.r.t. ... immediate 3 days 7 days 14 days dust-settling

<table>
<thead>
<tr>
<th></th>
<th></th>
<th>immediate</th>
<th>3 days</th>
<th>7 days</th>
<th>14 days</th>
<th>dust-settling</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVI</td>
<td>TV</td>
<td>.11</td>
<td>.41</td>
<td>.60</td>
<td>.75</td>
<td>.77 (17 days)</td>
</tr>
<tr>
<td>SVI</td>
<td>FB</td>
<td>-.05</td>
<td>-.08</td>
<td>.02</td>
<td>.12</td>
<td>.14 (17 days)</td>
</tr>
<tr>
<td>SVI</td>
<td>TW</td>
<td>.07</td>
<td>.38</td>
<td>.55</td>
<td>.65</td>
<td>.65 (15 days)</td>
</tr>
<tr>
<td>FB</td>
<td>TV</td>
<td>.04</td>
<td>.32</td>
<td>.61</td>
<td>.82</td>
<td>.86 (18 days)</td>
</tr>
<tr>
<td>TW</td>
<td>TV</td>
<td>.12</td>
<td>.48</td>
<td>.77</td>
<td>.97</td>
<td>1.02 (19 days)</td>
</tr>
</tbody>
</table>

Tab. 4: Immediate and cumulative elasticities during the dust-settling period

parentheses in the last column refer to each dust-settling period’s length.

The accumulated, short-run SVI elasticities are rather high, especially with respect to TV (.77) and TW (.65). Hence after 17 days, a 10% increase in TV audience results in a 7.7% increase in the level of brand attention. In contrast after 15 days, a 10% increase in Twitter posts results in a 6.5% increase in the level of brand attention. As mentioned before, at first the elasticity of SVI with respect to FB is negative and after several days it becomes positive. To be more specific, a 10% increase in Facebook posts has a (statistically significant) effect of reducing the level of brand attention by .5% at the same day. After 3 days, the reduction accumulates to .8%. Over the whole dust-settling period of 17 days however, the 10% increase in Facebook posts results in a solid 1.4% increase in the level of brand attention. Therefore, even though the immediate SVI elasticity with respect to FB is negative and the short-run SVI elasticity with respect to TV and TW is about 5 times higher, Facebook posts are a reasonable means to increase brand attention and should not be neglected in media budget allocation decisions. In sum, the traditional tool (TV advertising) is still most effective in driving brand attention. But the effects of posting activity on brand attention must be taken into account, too. The derived elasticity values enable researchers and practitioners alike to apply easy-to-use elasticity-based allocation rules (e.g., Fischer et al. 2011; Albers 2012).

The elasticities of FB and TW with respect to TV are very similar. However, TV has a 20% to 30% higher effect on TW than on FB, which exceeds a value of 1 over the whole dust-settling period. The effect on Facebook posts takes a few days until it “wears-in”.

The instantaneous advertising elasticities appear to be plausible compared to prior literature. Sethuraman/Tellis/Briesch (2011) report in their recent meta-study an average short-term (“long-term”) advertising elasticity of .12 (.24). However, our elasticities are not related to sales (or share) and measured on a daily level. Therefore, these numbers must be compared with caution. Actually, we expect high (short-run) elasticity values because brand attention (operationalized as internet search behavior) is an early step in the customer’s buying process, whereas the buying-decision itself (= sales) is the final one.

Our analysis tested the research propositions stated in Section 2 of this study. We focused on finding empirical evidence either confirming or disconfirming assumptions about the relations among TV audience size, social network activity, and brand attention operationalized with Google search data. Another methodical goal was to suggest, how to measure the consequences of marketing activities with the aid of social media and search engine data. In summary, P1, P2, P4, P5, and P6 are supported. TV advertising has a positive impact on the level of brand attention and on posting activity in Facebook and Twitter. Furthermore, Twitter activity has a positive impact on the level of brand attention, which is higher than the impact of Facebook activity. The impact of Facebook activity on the level of brand attention (P3) is more difficult to interpret. The immediate effect is negative, but after several days, the effect turns positive and the full short-run effect over the whole dust-settling period is actually positive.

5. Conclusion

In sum, the goal of this research has been to propose a method that allows companies and researchers to quantify the dynamic relationships of marketing actions within and outside of social networks. We furthermore derive elasticities of different marketing tools with regard to brand attention. Thereby, we establish a new way of tracking the performance of marketing means which enables companies to understand the effect of their marketing actions and presence in social networks and allocate their resources accordingly.

The empirical analysis uses data from a medium-sized company. We find that TV advertising increases the posting activity in social networks. These effects last for almost 3 weeks and the immediate elasticities are between .04 and .12. TV advertising and posting activity in Twitter have similar immediate and short-run effects on brand attention. The effects last about two and a half weeks and the elasticities are between about .1 (immediate) and .7 (short-run). The posting activity in Facebook at first has a negative effect on brand attention. From the third day on however, the effect is positive. Also, the short-run elasticity is .14.

Our research also has some limitations. The data we use for our approach comes from a single medium-sized company, which implies that we cannot analyze the effects that might arise within different kinds of industries, companies, brands, or products. Furthermore, the data
comprises one big advertising campaign covering only half a year. For time series analyses this is a rather restricted data set, nevertheless it is sufficiently rich because of its high granularity. Lastly, while we propose to use the SVI variable as a measure for brand attention more research is needed to analyze the validity of this measure.

Appendix

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Variable</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ln(SVI)</td>
<td>ln(TV)</td>
</tr>
<tr>
<td></td>
<td>ln(TV)</td>
<td>ln(FB)</td>
</tr>
<tr>
<td></td>
<td>ln(FB)</td>
<td>ln(TW)</td>
</tr>
</tbody>
</table>

\[
b_{1.24} = 0.892 \ln(SVI) + 1.438 \ln(TV) - 0.232 \ln(FB) + 0.468 \ln(TW)
\]

\[
b_{1.24} = 0.013 \ln(SVI) + 0.642 \ln(TV) + 0.118 \ln(FB) + 0.060 \ln(TW)
\]

\[
b_{1.24} = 0.023 \ln(SVI) + 0.909 \ln(TV) - 0.069 \ln(FB) + 0.163 \ln(TW)
\]

\[
b_{1.24} = 0.027 \ln(SVI) + 0.141 \ln(TV) + 0.147 \ln(FB) + 0.125 \ln(TW)
\]

\[
b_{1.24} = 0.048 \ln(SVI) + 0.188 \ln(TV) - 0.082 \ln(FB) + 0.049 \ln(TW)
\]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Variable</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ln(SVI)</td>
<td>ln(TV)</td>
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<tr>
<td></td>
<td>ln(TV)</td>
<td>ln(FB)</td>
</tr>
<tr>
<td></td>
<td>ln(FB)</td>
<td>ln(TW)</td>
</tr>
</tbody>
</table>

\[
R^2 = 0.736
\]

Tab. A1: Regression results (Standard errors in parentheses)

Notes


[2] The numbers for the variables TV, FB, and TW reported in the descriptive analysis are transformed linearly to maintain the anonymity of the collaborating company. However, in all econometric analyses, the actual data was used.


References


Facebook (2012): http://newsroom.fb.com/


Keywords
Brand attention, social media, TV advertising, marketing measurement, time series analysis


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