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Battle of the Brand Fans: Impact of Brand Attack and Defense on Social Media☆

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Abstract

Fans of a brand attack fans of rival brands on social media. Given the nature of such rival brand fan attacks, managers are unsure about how much control they should exercise on brand-negative comments on their owned social media touchpoints, and what brand actions drive these Attack, Defense and Across (ADA) posts. Multimethod analysis identifies ADA's impact across industries of technology, fast food, toothpaste, beverages, and sports apparel. Sentiment analysis identifies that fans posting in both communities stimulate both brand-negative and brand-positive comments. Despite their relatively low prevalence (1–6% of all posts), ADA posts induce broader social-media brand engagement as they substantially increase and prolong the effects of managerial control variables such as communication campaigns and new-product introductions. Brand managers, thus, have specific levers to stimulate the positive consequences of rival brand fan posting on their owned media.

Keywords: Social media; eWOM; Rival brands; Brand engagement; Attack; Defense; Across pages; Sentiment analysis; Time series analysis

Introduction

> [On Pepsi Facebook page after Pepsi Super Bowl half time show in 2016]
> *Pepsi...watered down Coke! And Katy Perry? Yuck!? What's with the horrible halftime shows anymore? Need real musicians out there for a change!Was an awesome show Pepsi!! Put Coke to shame! Their commercial even sucked, WELL DONE! CONGRATS!!*
> *"Nike is a big liar big loser..dislike..Adidas forever"* post 2015 on Nike Facebook page.
> *"Nike is dead.."* same fan posting 2015 on the Adidas Facebook page.

As the above quotes show, brand fans not only show their feelings on the social media pages of the brands they love, but also post on the social media pages of rival brands. They attack a rival brand on its own Facebook page (e.g., attacking Pepsi for its halftime show), defend their brand against such attacks (e.g., the next Pepsi quote), and post across rival brand pages (e.g., Adidas fan posting on both Nike and on Adidas pages)[1]. Managers are understandably concerned with rival brand fans posting on the brand's owned media, badmouthing the brand

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[1] As detailed in the content analysis, *Across* concerns fans who actively post across brand pages. *Attack* is negative about the brand (or positive about the rival brand) in its own ecosystem. Finally, *Defense* is negative about the rival brand or positive about the focal brand, defending it from both *Across* and *Attack*.

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and its actions such as new product introductions, advertising campaigns, and public relation sponsorships (Chiechi 2016; Loten 2012). The implicit assumption is that such posts hurt the brand, at least on the social media platform they appear (Fournier and Lee 2009). A key question for managers is, thus, how to deal with such posts. Many hesitate to censor negative comments for fear of public backlash as experienced by high profile firms such as United Airlines and Walmart (Sullivan 2012). But what if the implicit assumption is incorrect? An alternative strategy is to stand back and let the brand's page followers defend against attacks, which may stimulate engagement. Thus, our research questions are: "What are the consequences of ADA in terms of the social media page volume and valence, two common social media performance metrics?" and "Which events, including the brand's and the competing brand's marketing, play a role in ADA and its consequences?"

Relevant previous literature is rich on the motivations behind consumers posting or commenting on brand's social media pages. First, key motivations behind eWOM are deemed to be consumers' self-enhancement and the desire to support or damage a company (e.g. Hennig-Thurau et al. 2004; Kähr et al. 2016). While positive eWOM intuitively benefits the brand, negative eWOM does not necessarily hurt it (Berger, Sorensen, and Rasmussen 2010; Ein-Gar, Goldenberg, and Sagiv 2012; Ho-Dac, Carson, and Moore 2013). However, this stream of research has not yet quantified how such negative eWOM plays out on the brand's *owned social media pages*, where brand fans can react to it. Moreover, the focus has been on negative online reviews and complaints, which typically involve specific feedback on brands that the poster has possibly used, as compared to the general dislike (often without evidence of actual product experience) expressed in our opening quotes (and as verified in our empirical analysis). Second, (online) consumer engagement has been studied within a group of specific brand fans. Although previous studies have identified competitors and competitive actions as a possible "strong contextual force affecting customer engagement" (van Doorn et al. 2010, p. 258), these cross-competitive effects, their potential dynamics, and outcomes on customer engagement behavior have not yet been explored (Verhoef et al. 2009). The challenges of collecting and analyzing data from multiple brands appear to be the key reason for the focus on a solo brand's social-media platform (see "cross-sectional studies" in Brodie et al. 2013, p. 161). Our study overcomes these limitations by demonstrating cross-brand fan interaction over time and quantifying its drivers and consequences for rival-brand sets — thus giving specific empirical insights to manage this phenomenon.

We collect several years of Facebook page data from the main rival brands in mobile phone technology (Apple–Samsung), carbonated beverages (Coke–Pepsi), fast food (McDonald's–Burger King), toothpaste (Colgate–Crest) and sports apparel (Nike–Adidas). Our analysis proceeds in four steps. First, we identify which page comments represent Attack (negative about the brand and/or positive about the rival brand) and Defense (positive about the brand and/or negative about the rival brand in response).

Next, we classify page comments as Across by identifying users who posted on the pages of both rival brands (as Milad did in the opening quotes). Third, we combine the thus-constructed daily dataset of Across, Attack and Defense with brand-related events (as potential driving variables) and page-level total comments and sentiment (as outcomes). For each rival brand pair, Vector Autoregressive Models quantify how Attack, Defense and Across (ADA) behavior is dynamically driven by brand-related events and in turn how much ADA behavior affects brand-relevant outcomes. We find broad support for our hypotheses that marketing actions drive ADA and that ADA's impact is positive, rather than negative for typical social media performance metrics. As a result, brand managers obtain specific levers that drive different realizations of ADA.

Research Background

Electronic Word of Mouth and Its Consequences

Electronic word of mouth (eWOM) is commonly defined as any form of positive or negative statement about a product, service or company, produced by consumers and made publicly available through web-based services such as e.g., social media, websites, review platforms or internet forums (Hennig-Thurau et al. 2004). Positive eWOM substantially increases sales (Chevalier and Mayzlin 2006; Pauwels, Aksehirli, and Lackmann 2016). In contrast, negative eWOM should lead to lower product image (Ho-Dac, Carson, and Moore 2013), company value (Goldenberg et al. 2007) and sales (see e.g. Dellarocas and Wood 2008; Moe 2009). Later research, however, reveals that negative eWOM does not necessarily have negative consequences for the brand. On the one hand, lesser-known brands may benefit from negative eWOM through an increase of general awareness (Berger, Sorensen, and Rasmussen 2010). On the other hand, consumers who have a strong identification with a brand, show little or no reaction to negative eWOM (Ho-Dac, Carson, and Moore 2013; Wilson, Giebelhausen, and Brady 2017).

Motivations and Drivers of eWOM

Beyond the sentiment expressed in eWOM and its consequences for eWOM receivers, researchers have also analyzed consumer motivations, such as self-enhancement (Hennig-Thurau et al. 2004) as drivers of giving eWOM. Consumers wish to share their experiences with the brands, products, and also other consumers to either (1) support their favorite brand or (2) to take vengeance for a disappointing consumer experience (Kähr et al. 2016). In both cases, consumers perceive their eWOM articulation as an *instrument of power* to support or damage a company — what Kähr et al. (2016) refer to as 'brand sabotaging'.

Specific brand events may induce eWOM, such as new product introductions (e.g. Marchand, Hennig-Thurau, and Wiertz 2017), events (e.g. Trusov, Bucklin and Pauwels 2009) and advertising campaigns (e.g. Pauwels, Aksehirli, and Lackmann 2016). Moreover, social media users also talk about company performance, management and ethical/legal issues. One initial marketing activity might lead consumers to share, promote, censor, or manipulate information, sending it

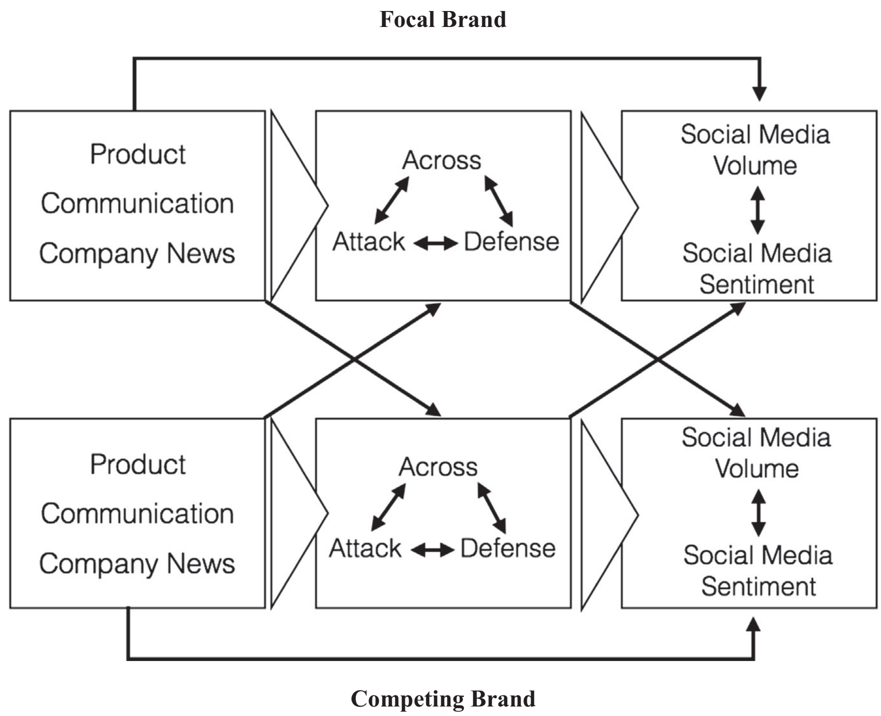


Fig. 1. Conceptual framework.

further into the network, triggering other reactions, which may then lead to even more reactions from other involved consumers in the network (Hewett et al. 2016).

Previous research on eWOM has been largely influenced by customer review sites and online forums, where interaction across users was limited through the website based structure. In contrast, social media sites allow the direct and dynamic exchanges across users as illustrated in our opening quotes. Positive or negative eWOM may not only motivate or demotivate consumers from buying, but may also trigger further eWOM and social media activities from other consumers who wish to support one of the two sides involved: the user or the company. Instead of a binary interaction between dissatisfied (or satisfied) consumers and their companies, eWOM extends to a triangular structure that involves the posting user, the affected companies and other users, who may (or may not) react to the initial eWOM post (Kozinets et al. 2010).

Conceptual Development

Fig. 1 visualizes our conceptual framework, starting from the brand-related events (e.g. Product, Communication and Company News) that may drive the Attack, Defense and Across comments and their consequences[2] in volume and valence of overall Facebook posts for both the focal brand (top) and competing brand (bottom part of the Figure).

The structure of the social internet leads to significant changes in information search behavior, information exchange and interaction between users, consumers, and companies (e.g., Hennig-Thurau, Hofacker, and Bloching 2013). Consumers have heterogeneous preferences and varying levels of brand loyalties. What happens when they are exposed to information that is favoring an opposing brand and therefore challenging their own brand perception? Before the advent of social media, such consumers could more easily ignore this incoming information to reduce perceived dissonance with their current brand perception (Cohen and Goldberg 1970). In contrast, social media both allows rival brand fans to *Attack*, i.e. insert negative remarks in the brand's own ecosystem (e.g. its Facebook page) and allows fans to actively object to these remarks and coming to the *Defense* their brand. In such cases, we even observe the brand fans to post *Across* on the rival brand's social media page, actively trying to negate the information they disagree with. While online reviews and complaints originate from own, but dissatisfied customers having specific problems (Chen, Wu, and Yoon 2004; Ho-Dac, Carson, and Moore 2013), such Attack and Across posts tend to assert in more general terms the superiority of one brand over another. As a result Attack posts will be less detailed, more general, focus on broader aspects of brand consumption and brand lifestyle, and will thus also be shorter than common negative online reviews.

As shown in Fig. 1, we envision multiple plausible scenarios as to the causality among these posting types over time. For one, an Across post may induce both Attack and Defense in a

[2] Given the absence of other performance data in our empirical analysis, we focus on the volume and valence of all comments on the brands' Facebook pages. These metrics have been quantitatively linked to brand attitudes, sales and even company stock market performance in several recent papers (see You, Vadakkepatt, and Joshi 2015 for review and meta-analysis).

Table 1
Sentiment analysis results for brand rivalry contexts.

Brands and Industry	Apple	Samsung	Coke	Pepsi	McDonalds	Burger King	Nike	Adidas	Colgate	Crest
Classification data from McAuley et al. (2015)	Electronics		Grocery and Gourmet Food		Food		Sports and Outdoors		Health and Personal Care	
Positive	3,000		3,000		10,000		3,000		3,000	
Negative	3,000		3,000		10,000		3,000		3,000	
Prediction Hit Rate	90%		93%		90%		90%		89%	
Start of Observation	September 11, 2013		November 21, 2014		March 30 2010		February 17, 2011		February 20, 2012	
End of Observation	January 13, 2015		March 17, 2015		March 12 2015		March 15, 2015		March 10, 2016	
Total number of comments	165,773	92,191	37,027	94,011	6,715	100,843	52,417	68,142	41,087	33,957
Positive	107,273	43,883	19,277	61,554	2,029	20,107	7,870	7,357	7,141	13,326
Negative	6,404	11,045	2,651	10,323	1,226	10,541	2,949	3,389	2,728	3,655
Neutral	52,096	37,263	15,099	22,134	3,460	70,195	41,598	57,396	31,218	16,976

conversation that stays within the brand's Facebook page. For another, an Attack post may lead the defending fans to post Across on the rival brand's Facebook page, which in turn sparks Attack and Defense on that page.

ADA Drivers (H1)

As shown in Fig. 1, we posit that ADA may be driven by marketing activities and company news of the rival brands. Agenda-setting theory argues that consumers regard an issue as important according to its salience (i.e., the rate and prominence of coverage) in media (McCombs and Shaw 1972, as quoted in Borah and Tellis 2016, p. 5). For example, a Samsung new product announcement is widely publicized, which may mobilize Apple fans to denounce it on Samsung's Facebook page, leading Samsung fans to defend it. Our approach aligns with several recent studies that use endogenous variables like brand stimuli (Kähr et al. 2016) or newsworthy events like product recalls (Borah and Tellis 2016) in analyzing social-media chatter.

H1. ADA is driven by (a) marketing activities and (b) other events regarding one or both brands in the brand rivalry and the companies that own them.

Consequences (H2)

In marketing literature, competition focuses on the prosperity of one brand at the expense of the rival brands. So, according to common wisdom, rival-brand fans hurt the focal brand by, for example, posting negative reviews, ridiculing the focal brand's new products and communication, and in general aiming to convert the focal brand's prospective customers to the rival brand instead. Thus, brand managers are advised to guard against such rival-brand fans encroachments (e.g., Fournier and Lee 2009, p. 108). The exception appears to be new markets, where the interplay between Attack-brand (adopters of that brand) and cross-brand (adopters of competing brands) communication influences technology adoption behavior and has a substantial effect on the growth of markets under competition (Libai, Muller, and Peres 2009). Even in mature product categories, many new customers learn of and about brands through observing social media (Court et al. 2009). For instance, having never bought a snowboard, consumers can quickly learn which two brands engage the most fan rivalry, and hence start to follow these brands. Likewise, being attacked by rival brand fans may (re) activate an existing fan's probrand feelings and behavior (Schouten and McAlexander 1995). Thus, we posit that rival fans' engagement on a focal brand's platform stimulates the focal brand's consumers to respond, typically in favor of the focal brand. This should increase the overall volume of comments on the brand's Facebook page and may have a net positive result on overall sentiment (two metrics easily available to and often used by brand managers to evaluate social media performance). Thus, social media performance for the focal brand may increase through activation and mobilization of the fans of both focal and rival brands.

H2. The net result of ADA is not negative for the focal brand's social media performance (as common wisdom suggests), but positive for the involved brands.

Data and Method

Data Sets and Data Collection

Given the costs of the elaborate data collection and analyses, we focus on the Facebook pages of a handful of known rival brands. The industries are vastly different, ranging from mobile phone technology (Apple–Samsung[3]), carbonated beverages (Coke–Pepsi), fast food (McDonald's–Burger King), toothpaste (Colgate–Crest) and sports apparel (Nike–Adidas). As established in previous research, these categories differ in many ways, such as average consumer involvement — which shows up in the many more Facebook comments for mobile phones compared to toothpaste (see Table 1). We collected digital data via a customized social-media web crawler using R in Version 3.2.1 that extracts all publicly available information from any Facebook brand page. This information includes posts, number of likes and shares for each post, comments for each post, the number of likes for each comment, and all publicly available

[3] Due to the lack of an official Apple Facebook page, we used Facebook's API to identify the largest Facebook Apple fan group to collect comments and posts.

Table 2
Marketing activities and other events as drivers of ADA.

Types of brand-related events	Events	Examples in our data
New product news	Announcements and previews	Apple Introduces iPhone 5 McDonald's is testing mac and cheese
	Launches and product updates	Coca-Cola Life Arrives On Shelves Nationwide Crest Toothpaste Update Eliminates Microbeads
Marketing communications	Advertising campaigns	Colgate Super Bowl Ad Will Urge People to Turn Off Faucet
	PR/advertorial/sponsorship	A whopper of a wedding! Fast food chain pay for Mr. Burger's marriage to Miss King
Brand news	Co-branding	Adidas and Porsche Design join forces to reveal co-created Porsche Design Sport 16 FG boot
	Retail	Apple Store Grand Central Opens Friday, December 9
	Strategic partnership/collaboration	Samsung and Oculus collaborate to create an immersive new dimension of mobile life with the first widely available mobile VR headset optimized for Galaxy
Company news	Performance	PepsiCo Declares 43rd Consecutive Annual Dividend Increase
	Acquisitions	Samsung to Acquire LoopPay, Transformative Digital Wallet Platform
	Leadership	Sue Wagner Joins Apple's Board of Directors
Ethics news	Ethical issues	FIFA sponsor Adidas in a tough spot amid scandal
	Legal issues	Retired soldier who sued Burger King after finding two needles in his Triple Stacker – one of which he swallowed – reaches out-of-court settlement

information about the poster and the commenting person. This information allows us to observe how fans of both brands in the duo talk to one another (MacKinnon 1995). We made sure the start date for our data sets was after the creation of both brands' Facebook pages (Table 1).

Additionally, we collected potential driving events and dates for each brand by gathering available public information on key developments and events relating to the brand and its company owner. We used companies' official press release websites, several online business databases (NASDAQ, Yahoo Finance, and similar), Google search trends, and significant news websites to capture all relevant company-related news for the time periods for which we have the social-media data. To enhance conceptual insights and managerial actionability, we classify these events as related to new products (new product announcements/previews versus actual launches/updates), to marketing communications (advertising versus public relations), to the brand (e.g. cobranding, strategic partnerships, retail openings), to the company's management (e.g. performance, acquisitions, leadership) and to the company's ethical/legal issues. While the last category carries negative connotations for the company, the other categories represent decisions (and their outcomes) made either by brand managers or by senior managers. Table 2 shows examples of each event type, with information available to the public and thus to managers and researchers.

Sentiment and Content Analysis: Coding ADA Types

We first conduct a sentiment and automated content analysis to assess the valence of Facebook comments and code the ADA types. The sentiment analysis categorizes user posts and comments as positive, negative, or neutral. Sentiments are then together with brand mentions used to derive an automated content analysis to determine whether a comment can be classified as an Attack, Defense or an Across post. Automated content analysis has commonly been used to attain a condensed description or to categorize the phenomenon of interest (Kassarjian 1977; Kolbe and Burnett 1991); also in marketing studies (e.g., Humphreys 2010; Kübler and Albers 2010). The automated content analysis codes our focal and rival-brand sets for brand mentions[4] and determines whether a comment is an attack, a defense, an across posts or neither of them.

For *Attack posts*, we have identified two possible scenarios: user posts and comments on a focal brand's own Facebook page with *negative sentiment about the brand* or posts and comments with *positive sentiment about the rival brand*.

On similar grounds, we have identified two possible scenarios to classify the *Defense* posts on a particular Facebook brand page: posts and comments with *positive sentiment about the brand* or posts *with negative sentiments about the rival brand*. *Across posts* have been discerned finding the posts and comments from individuals who posted on both brand pages via the common Facebook user IDs on both brand pages. A research assistant, trained in structured content analysis, classified the data into the different types of ADA interactions (Burnard 1996). Details of possible scenarios – joint use of mentions and sentiments – to obtain the categorization matrix are shown in Appendix 1.

Disagreements, which existed for only a handful of posts, were solved by consensus after discussion with the first author. Using sentiment and automated content analysis together, we labeled these three types of ADA in the Facebook data for each brand dyad. Appendices 2–6 show the descriptive statistics among the variables used in the time series analysis. Given the low occurrence of subtypes of brand news, company news and ethics news, we include 7 brand-related events in our analysis: new product announcements & previews, product launches & updates, advertising, public relations, brand news, company news and ethics news.

To obtain the sentiment of each user comment and post, we conducted an intensive machine-learning based sentiment analysis. Mullen and Collier (2004) as well as Kübler, Colicev, and Pauwels (2017) show that linear kernel based Support Vector

[4] A detailed list with all related brand-, product-, and service related search terms of the automated content analysis may be obtained from the authors upon request.

Machines (SVMs) are most suitable for sentiment analysis in a marketing and social media context. SVMs rely on training data to infer probabilities that specific words or word combinations indicate a positive or negative sentiment. Suitable, category specific training is thus crucial for precise sentiment measurement.

To train the SVM, we follow Hoon et al. (2013) and use category-specific product reviews as training data. The data originates from Amazon's publicly available review data set (McAuley et al. 2015, see Table 1 for more details). To ensure that our training data only consists of unambiguously positive and negative reviews, we follow Hoon et al. (2013), by only using reviews that come with a very low (1-star) or very high (5-stars) rating. For each rating category we randomly sample 3,000 positive (5-star) and 3,000 negative (1-star) reviews out of the approx. 50 million available product category specific Amazon reviews. We use the obtained data to train the linear SVM algorithm integrated in the "RTextTools" R-package (Version 1.4.2). After training, the RTextTools package offers a simple predictive function to classify the user comments and posts from our different Facebook brand pages as positive or negative. The RTextTools package further delivers a classification likelihood ranging from 0 to 100% for each classified document. Comments with a low classification likelihood may thus not belong to one of the two sentiment categories and may thus be treated as neutral comments. Following Jurka et al. (2013) we thus only assign a text to a category if the classification likelihood is above 75%.

To test the sentiment classification power of our algorithm, we used a sample of 1,500 positive and negative reviews, which we again randomly drew from the McAuley et al. (2015) data. Table 1 reports the corresponding hit rates indicating a sufficient predictive power. Additionally, we have asked two research assistants who were not familiar with our research questions to screen the sentiment scores for 200 randomly sampled posts. They independently confirmed each case for which our threshold in the sentiment analysis concluded the sentiment was either positive or negative.

Time Series Analysis: Impact of ADA

We deploy persistence modeling (e.g., Dekimpe and Hanssens 1999; Kireyev, Pauwels, and Gupta 2016) to both analyze whether marketing activities drive ADA (H1) and whether how much and when ADA drives the social media performance of both brands in each rival duo (H2). First, we used Granger causality tests with lags from 1 to 14 (days) to investigate temporal causality in ADA and online sentiment. Next, we quantified the relations among these variables with Vector Autoregressive (VAR) models. Specifically, we included as endogenous variables the daily time series of (1) ADA types, (2) Facebook volume and valence, and (3) brand-related events for both involved brands in the category. Exogenous variables include an intercept and day-of-week dummies. Eq. (1) shows the matrix notation of the VAR model for each analyzed industry:

$$\mathrm{Y_t} = \mathrm{A} + \sum_{i=1}^{p} \Phi_i \mathrm{Y}_{t-i} + \psi \mathrm{X_t} + \Sigma_t, \quad t = 1, 2, \ldots, T \tag{1}$$

where Y_t is the m × 1 vector of endogenous variables (where m is the number of endogenous variables), A is a m × 1 vector of intercepts, X_t is the vector of exogenous control variables, Σ_t is the m × 1 matrix of residuals and Φ_i is the m × m matrix of parameters for lag i. The 24 endogenous variables are the daily number of both brands' (1) *Attack, Defense, and Across* posts, (2) total Facebook posts (*volume*) and their *valence* score, (3) the events (as described in Table 2) of *product announcements, product launches, advertising campaigns, public relation campaigns, brand related news, company related news, and ethics news*. The exogenous variables are the *weekday dummies* with Friday as the reference day not included in the model.

The maximum number of time lags p is determined as 1 by the Bayesian Information Criterion, and the residuals have a full variance–covariance matrix Ω allowing same-day effects of each endogenous variable on another (see e.g. Colicev et al. 2017 for a recent social media application).

From this model, we derived the Forecast Error Variance Decomposition (FEVD) and the Generalized Impulse Response Functions (GIRF) — similar to Srinivasan, Vanhuele, and Pauwels (2010). The FEVD quantifies the extent to which a variable is dynamically explained by the other variables in the model, thus addressing H1. The GIRF quantifies the net effects of ADA on volume and valence metrics (H2), which provides us with concrete managerial implications from stimulating ADA activity. Finally, we apply the restricted IRF approach from Pauwels (2004) to analyze how ADA changes the performance effect of brand-related events Specifically, we compare the unrestricted cumulative effect and its duration to the restricted effect that restricts all ADA variables to remain in steady state.

Findings

Prevalence of ADA Types From the Sentiment and Content Analysis

Table 3 shows for each ADA variable the daily average amount of posts and their relative occurrence compared to the overall number of posts (volume) of the brand's Facebook Page. The last row shows the average occurrence across studied brands. First, Across involves 1.45% of all posts, clearly demonstrating that some posters do not limit themselves to one brand's page. Next in line is Attack (1.42%). However, the brand's fans also defend it: Defense represents 0.50% of all posts. Moreover, we note that the % of ADA is the smallest among high-tech brands (Apple and Samsung, given the higher amount of technical questions and answers), medium for fast moving consumer goods and highest for products associated with competition, such as Nike. For each studied brand, as can be expected, ADA posts represent a small minority of the overall posts.

Text Analysis Comparing Attack Posts to Negative Online Reviews

To empirically contrast Attack Post with the negative online reviews studied in previous literature, we collected for each brand 3,000 negative online reviews from third-party sites such

Table 3
Details on ADA manifestations: Across, Attack, and Defense.

Facebook pages	ADA Across	%ADA	%Total	ADA Attack	%ADA	%Total	ADA Defense	%ADA	%Total
Apple	473	26%	0.3%	1,058	58%	0.6%	293	16%	0.2%
Samsung	274	28%	0.4%	501	51%	0.7%	211	21%	0.3%
Coke	636	37%	1.7%	866	51%	2.3%	199	12%	0.5%
Pepsi	468	36%	1.7%	648	50%	2.3%	186	14%	0.7%
McDonalds	84	71%	1.2%	28	24%	0.4%	6	5%	0.1%
Burger King	164	10%	0.1%	979	58%	1.0%	534	32%	0.5%
Nike	1,501	47%	2.9%	1,315	41%	2.6%	356	12%	0.7%
Adidas	1,159	54%	1.70%	768	36%	1.10%	235	10%	0.40%
Colgate	846	50%	2.1%	639	37%	1.6%	223	13%	0.5%
Crest	825	49%	2.40%	540	31%	1.60%	367	20%	1.10%
Average			1.45%			1.42%			0.50%

as Amazon.com, Twitter and Yelp. A basic word count reveals that negative online reviews are on average 2 to 3 times longer than Attack, Defense and Across posts. We then compared content and word frequencies between the ADA posts and the negative reviews. Fig. 2a and b shows the resulting word clouds with the 200 most common words for the three ADA post types and the negative reviews for Coke and Pepsi. The overlap in topics is minimal: negative reviews use more specific words that address particular problems of a product (e.g. "I don't like the new taste of Pepsi"; "The new design of Coke cans is bad") while Attack posts commonly remain more general and do not address specific product issues (e.g. "Coke sucks," "Apple users are stupid").

For a more detailed inspection, we plotted the hierarchical dendrograms of the word occurrence and word co-occurrence frequencies. Fig. 3a (Attack posts) and b (negative reviews) show the exemplary results for Coke. In line with our rationale, we find that topics in negative reviews are more heterogeneous than in the case of the ADA posts, where we see sentiment specific words like "love," or "don't like" appearing higher in the frequency structure. This shows up as a flatter general structure for online reviews (words pictured at the top occur more frequently) than in the case of the Attack posts. The dendrograms further reveal which words commonly occur together (visualized by the tree structure). For the negative reviews, we see that specific product-related topics such as taste and flavor are commonly addressed together with the brand name. In the case of Attack posts we find that Coke gets directly compared with Pepsi. Also we see on the right hand side of the graph that sentiment and affection related words occur directly together, indicating that fans express their general preference or affiliation with one or the other brand. Attack posts are thus contentwise substantially different from negative online reviews. Each of the above differences is robust across all brands in our sample.[5]

[5] Due to space limitation, we were not able to include all wordclouds and dendrograms into the paper. All other wordclouds and dendrograms are available from the authors upon request.

How ADA Drives Outcomes and Is Driven by Brand-related Events

Now we have (1) identified specific comments as ADA behavior and (2) calculated the positive and negative sentiment of each brand's overall comments, we assess the hypotheses on the extent ADA is driven by brand-related events and drives the Volume and Valence online metrics that brand managers often use for engagement.

The full results of the Granger causality tests are shown in Appendix 7. The tests reveal that, at the 5% significance level and for each brand, Defense (positive comments by own brand fans) is driven by both Across and Attack. We infer that rival brand fan comments on the brand's own Facebook page result in a 'rallying of the troops' to defend the brand. Moreover, ADA on one page is Granger causing the overall volume and/or valence of comments on both the own page and the rival brand's page. Thus, while ADA represents a small minority of the overall posts, this activity drives the typical social media performance metrics reported to brand managers.

Next, we estimate a Vector Autoregressive (VAR) model for each rival brand dyad. One lag was selected by the BIC for each industry, and Table 4 shows the explanatory power for social media metrics volume (posts) and valence (sentiment). In each rival brand dyad, the model explains substantially more variance of ADA and Volume (Posts) for the leading brand than for the challenger brand. In contrast, Valence for the challenger brands is explained substantially better than their ADA metric.

Drivers of ADA and of Performance Metrics (H1)

Based on the estimated VAR models, the Forecast Error Variance Decomposition shows the relative importance of each endogenous variable's past for the outcome variable. Fig. 4 shows this FEVD for Apple's Posts (total Volume on that Facebook page).

Looking back 1 day, past Posts explain about half (50%) of current Posts, but this relative importance steadily declines as we look back further in the past. Attack behavior explains 21% of Apple Posts, while the driver of Apple New Product Announcements only explains 9%. Most important in explaining Apple Posts (looking back 5 days or more) is Apple Across,

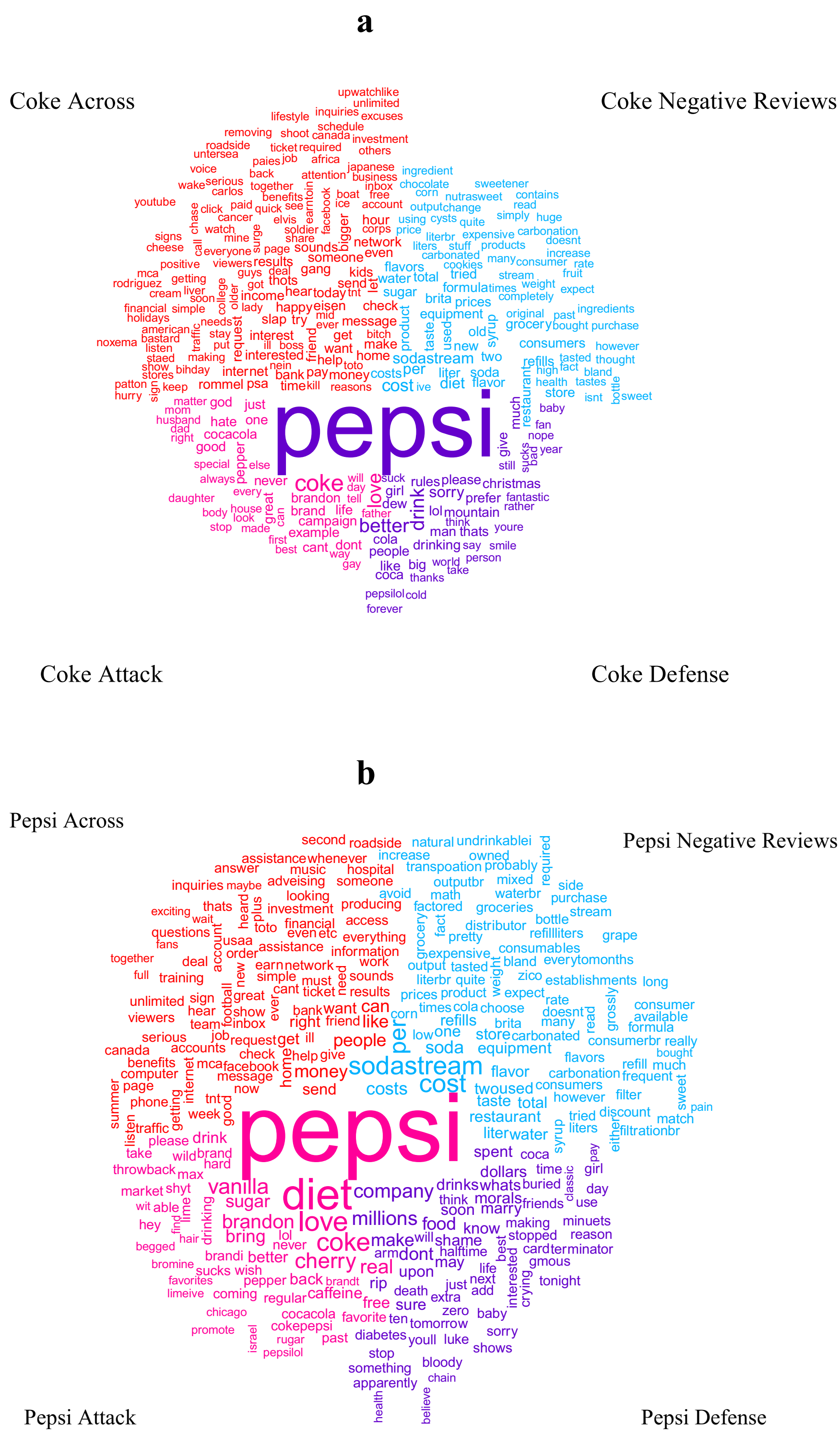


Fig. 2. a: Wordcloud for Coke. b: Wordcloud for Pepsi.

i.e. posts from people who also post on the Samsung page. Thus, despite Apple Across representing only 0.3% of all posts (Table 3), it is responsible for 36% of this total volume. Tables 5a–5j shows the top 5 drivers for the ADA types and the outcome variables for each brand.

In all cases, a marketing activity variable is a top five driver of ADA, in support of H1. The type of marketing though differs across brands. For Apple (Table 5a), new product announcements are the key driver, while for Samsung (Table 5b), launches and company news for both brands matter most. Coke

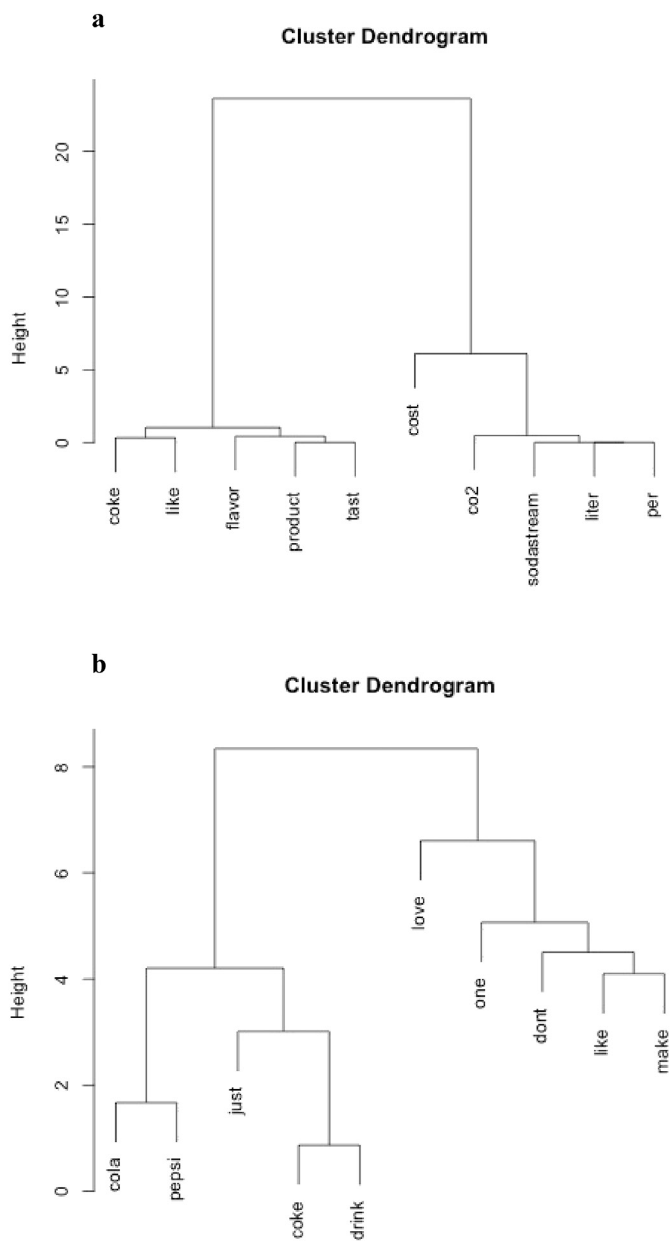


Fig. 3. a: Dendrogram for Coke negative reviews. b: Dendrogram for Coke Attack posts.

Table 4
Explanatory power (R^2) for ADA, volume and valence.

	Across	Attack	Defense	Volume (posts)	Valence (sentiment)
Apple	0.50	0.58	0.65	0.63	0.39
Samsung	0.11	0.28	0.28	0.20	0.24
Coke	0.51	0.60	0.61	0.61	0.32
Pepsi	0.21	0.31	0.36	0.42	0.41
McDonald's	0.09	0.04	0.08	0.32	0.43
Burger King	0.31	0.29	0.33	0.49	0.21
Nike	0.07	0.09	0.10	0.14	0.06
Adidas	0.08	0.24	0.05	0.49	0.03
Colgate	0.09	0.06	0.07	0.30	0.11
Crest	0.09	0.33	0.28	0.65	0.25

(Table 5c) is affected by brand news, while Pepsi is mostly driven by both Coke and Pepsi communication. Brand news is key for McDonalds, while company news is key for Burger King. Finally, ethics news is key for Nike, but company news for Adidas.

As to consequences, ADA activity is a top three driver of both Volume and Valence. Thus, consistent with our conceptual framework, brand-related events (mostly marketing actions) do drive ADA activity, offering managers concrete levers to pull if it is desirable to increase ADA. But is it?

Sign and Magnitude of ADA Elasticities on Volume and Valence Metrics (H2)

Based on the same VAR model, the Generalized Impulse Response Functions (GIRF) show the sign, magnitude and timing of 1 unit increase in ADA activity on Volume and Valence Metrics. For instance, Fig. 5 shows the response of Coke Volume Posts to respectively Coke ADA Across and Pepsi ADA Across, with the typical 1-standard error bands (e.g. Srinivasan, Vanhuele, and Pauwels 2010).

While Coke ADA Across has its peak impact on the same day, Pepsi ADA Across works with a 1-day wear in and obtains a higher cumulative effect (the area under the curve) until both effects become insignificantly different from 0 at day 7.

Accumulating all significant effects (the area under the curve in Fig. 3), we obtain the cumulative effect of 1 ADA post on performance. We transform these to elasticities to allow comparison across settings in Tables 6–10.

In all but 1 case, the elasticity of each own ADA variable on own Volume and Valence is positive or not statistically significantly different from zero at the 5% level. The same holds true for the effect of ADA on the rival brand page on the focal brand's Volume and Valence. Thus, we find broad support for H2 that ADA is not reducing, but often increasing social media performance metrics, and that for both brands. The exceptions occur for McDonald's, which gets the lowest daily number of comments in our analysis, and sees this Volume further decline with McDonald's ADA Across and Burger King Attack (negative comments on Burger King on its site). A substitution effect could be responsible here; i.e. fans choosing to trash the competition on its site instead of commenting on McDonald's own site.

As to the *magnitude* of the elasticities, we observe interesting differences in each pair between the brand leading (in US sales at the time of the data collection) and the brand challenging this leadership (Samsung, Pepsi, Burger King, Adidas, Crest). Elasticities are consistently highest elasticities for the Leading Brand's cross on the Leading Brand's Volume. The elasticity tends to be bigger for higher involvement products Apple (1.87) and Nike (0.84) than for lower-involvement products Crest (0.53) and McDonald's (0.40). The highest elasticity is observed for Coke (2.28). Right after the effect of ADA Across, ADA Defense (i.e. own fans defending the brand on its Facebook page) has a consistently high elasticity of around 0.50 for both the Leading and Challenger brands. Cross-elasticities are typically more modest, and often not significantly different from zero.

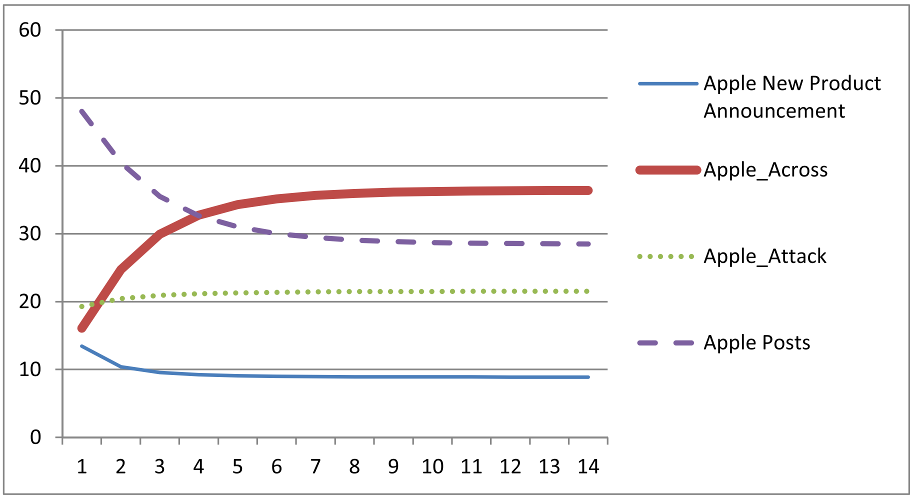


Fig. 4. Apple posts (volume) Forecast Error Variance Decomposition.

Table 5a
Forecast Error Variance Decomposition for Apple.

	Across	Attack	Defense	Volume (posts)	Valence (sentiment)
1st driver	Own Past (76%)	Own Past (43%)	Own Past (41%)	Apple Across (36%)	Own Past (52%)
2nd driver	Apple Posts (9%)	Apple Across (29%)	Apple Attack (23%)	Own Past (28%)	Apple Posts (21%)
3rd driver	Apple New Product Announcement (8%)	Apple New Product Announcement (17%)	Apple Across (19%)	Apple Attack (21%)	Apple Across (11%)
4th driver	Apple Launch (2%)	Apple Launch (3%)	Apple New Product Announcement (4%)	Apple New Product Announcement (9%)	Apple Attack (6%)
5th driver	Samsung Launch (1%)	Samsung Brand News (2%)	Apple Launch (2%)	Apple Defense (5%)	Apple Defense (4%)

Table 5b
Forecast Error Variance Decomposition for Samsung.

	Across	Attack	Defense	Volume (posts)	Valence (sentiment)
1st driver	Own Past (94%)	Own Past (79%)	Own Past (70%)	Own Past (46%)	Own Past (47%)
2nd driver	Apple Brand News (1%)	Samsung Brand Events (7%)	Samsung Attack (8%)	Samsung Defense (18%)	Samsung Posts (22%)
3rd driver	Apple Launch (1%)	Samsung Across (6%)	Samsung Across (7%)	Apple Attack (14%)	Apple Posts (13%)
4th driver	Samsung Launch (1%)	Samsung Launch (3%)	Samsung Brand News (3%)	Samsung Across (12%)	Apple Valence (8%)
5th driver	Apple New Product Announcement (1%)	Apple New Product Announcement (1%)	Samsung Launch (1%)	Samsung Defense (5%)	Samsung Defense (5%)

Table 5c
Forecast Error Variance Decomposition of Coke.

	Across	Attack	Defense	Volume (posts)	Valence (sentiment)
1st driver	Own Past (69%)	Coke Across (53%)	Coke Across (51%)	Own Past (39%)	Coke Posts (32%)
2nd driver	Coke Brand News (9%)	Own Past (17%)	Coke Attack (22%)	Coke Across (32%)	Own Past (24%)
3rd driver	Pepsi Posts (4%)	Coke Brand News (10%)	Own Past (14%)	Coke Defense (16%)	Coke Across (19%)
4th driver	Pepsi Ads (4%)	Pepsi Ads (4%)	Pepsi Ads (3%)	Coke Defense (6%)	Coke Brand News (11%)
5th driver	Coke Posts (3%)	Pepsi Brand News (4%)	Coke Posts (2%)	Coke Brand News (5%)	Coke Attack (8%)

Table 5d
Forecast Error Variance Decomposition of Pepsi.

	Across	Attack	Defense	Volume (posts)	Valence (sentiment)
1st driver	Own Past (78%)	Own Past (71%)	Own Past (58%)	Own Past (39%)	Coke Posts (32%)
2nd driver	Coke Across (7%)	Pepsi Across (18%)	Pepsi Attack (12%)	Coke Across (32%)	Own Past (24%)
3rd driver	Coke Brand News (4%)	Pepsi Posts (4%)	Pepsi Across (9%)	Coke Defense (16%)	Coke Across (19%)
4th driver	Pepsi Ads (2%)	Coke Across (2%)	Pepsi posts (3%)	Coke Defense (6%)	Coke Brand News (11%)
5th driver	Coke Posts (2%)	Coke PR (2%)	Coke Across (2%)	Coke Brand News (5%)	Coke Attack (8%)

Table 5e
Forecast Error Variance Decomposition of McDonalds.

	Across	Attack	Defense	Volume (posts)	Valence (sentiment)
1st driver	Own Past (85%)	Own Past (70%)	Own Past (63%)	Own Past (76%)	Own Past (86%)
2nd driver	McD Brand News (4%)	McD Across (15%)	McD Attack (18%)	McD Across (11%)	McD Posts (3%)
3rd driver	BK Marketing News (4%)	McD Brand News (4%)	McD Across (14%)	BK Ethics News (3%)	McD Across (3%)
4th driver	BK Ethics News (1%)	BK Across (3%)	McD Brand News (2%)	BK Defense (2%)	BK Marketing News (2%)
5th driver	McD Posts (1%)	BK Brand News (2%)	BK Ethics news (1%)	McD Valence (1%)	McD Brand News (2%)

Table 5f
Forecast Error Variance Decomposition of Burger King.

	Across	Attack	Defense	Volume (posts)	Valence (sentiment)
1st driver	Own Past (69%)	Own Past (65%)	Own Past (59%)	Own Past (41%)	Own Past (91%)
2nd driver	McD Across (12%)	BK Across (23%)	BK Attack (19%)	BK Attack (39%)	BK Attack (3%)
3rd driver	BK Company News (8%)	McD Across (4%)	BK Across (11%)	BK Defense (6%)	BK Posts (2%)
4th driver	BK Launch (4%)	BK Launch (3%)	McD Across (5%)	BK Product Launch (5%)	BK Company News (1%)
5th driver	McD Valence (3%)	BK Company news (1%)	BK Launch (1%)	McD Ethics News (3%)	BK Brand News (1%)

Table 5g
Forecast Error Variance Decomposition of Nike.

	Across	Attack	Defense	Volume (posts)	Valence (sentiment)
1st driver	Own Past (84%)	Own Past (81%)	Own Past (67%)	Own Past (62%)	Own Past (93%)
2nd driver	Nike Ethics News (5%)	Nike Across (12%)	Nike Attack (22%)	Nike Defense (26%)	Nike Defense (1%)
3rd driver	Adidas Brand News (3%)	Nike Ethics News (5%)	Nike Valence (4%)	Nike Across (9%)	Adidas Brand News (0.9%)
4th driver	Nike Valence (2%)	Adidas Brand News (1%)	Nike Across (3%)	Adidas Across (1%)	Nike Ethics News (0.8%)
5th driver	Nike Posts (1%)	Nike Valence (1%)	Nike Ethics news (2%)	Nike Attack (1%)	Nike Across (0.6%)

Table 5h
Forecast Error Variance Decomposition of Adidas.

	Across	Attack	Defense	Volume (posts)	Valence (sentiment)
1st driver	Own Past (71%)	Own Past (74%)	Own Past (64%)	Own Past (68%)	Own Past (91%)
2nd driver	Adidas Attack (14%)	Adidas Across (12%)	Adidas Attack (25%)	Adidas Attack (24%)	Adidas Posts (5%)
3rd driver	Adidas Company News (4%)	Adidas Valence (7%)	Adidas Across (4%)	Adidas Valence (3%)	Adidas Defense (2%)
4th driver	Nike Valence (4%)	Adidas Company News (3%)	Adidas Company News (2%)	Adidas Defense (3%)	Adidas Company news (0.5%)
5th driver	Adidas Marketing News (2%)	Nike Product Launch (1%)	Adidas Brand News (1%)	Adidas Across (2%)	Nike Product Launch (0.3%)

Table 5i
Forecast Error Variance Decomposition of Colgate.

	Across	Attack	Defense	Volume (posts)	Valence (sentiment)
1st driver	Own Past (93%)	Own Past (97%)	Own Past (93%)	Own Past (83%)	Own Past (94%)
2nd driver	Crest Across (3%)	Colgate Ads (1%)	Colgate Across (2%)	Colgate Across (7%)	Colgate Posts (3%)
3rd driver	Colgate Ads (1%)	Colgate Across (0.6%)	Colgate Posts (2%)	Colgate Defense (5%)	Colgate Defense (19%)
4th driver	Colgate Posts (0.7%)	Colgate Posts (0.4%)	Crest Across (1%)	Colgate Attack (2%)	Crest Posts (0.5%)
5th driver	Crest Company News (0.6%)	Crest Brand News (0.3%)	Colgate Attack (1%)	Crest Across (1%)	Colgate Brand News (0.3%)

Table 5j
Forecast Error Variance Decomposition of Crest.

	Across	Attack	Defense	Volume (posts)	Valence (sentiment)
1st driver	Own Past (95%)	Own Past (87%)	Own Past (74%)	Own Past (82%)	Own Past (87%)
2nd driver	Crest Posts (3%)	Crest Posts (7%)	Crest Posts (16%)	Crest Defense (6%)	Crest Posts (10%)
3rd driver	Crest company news (0.4%)	Crest Defense (4%)	Crest Attack (7%)	Crest Attack (5%)	Crest Defense (1%)
4th driver	Crest Valence (0.3%)	Colgate Company News (0.4%)	Crest Across (1%)	Crest Across (4%)	Crest Brand news (0.4%)
5th driver	Colgate Across (0.2%)	Crest Across (0.3%)	Colgate Defense (0.5%)	Colgate Defense (1%)	Crest Across (0.4%)

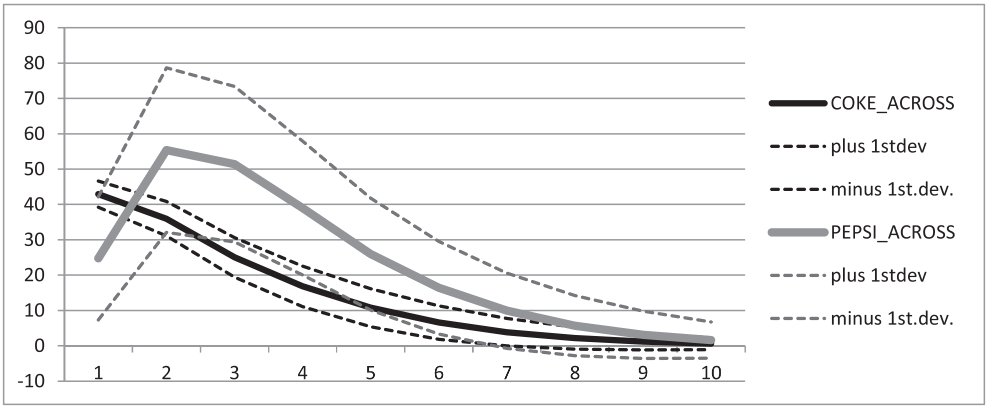


Fig. 5. Coke's posts (volume) increase from 1 Across post on Coke vs Pepsi Facebook page.

Table 6
Cumulative[a] elasticities of ADA on volume & valence for Apple & Samsung.

	Apple volume	Apple valence	Samsung volume	Samsung valence
Apple Across	**1.87**	−0.02	−0.02	−0.04
(standard error)	(0.55)	(0.02)	(0.02)	(0.03)
Samsung Across	**0.04**	0.00	**0.21**	**0.09**
(standard error)	(0.02)	(0.01)	(0.08)	(0.04)
Apple Attack	**1.76**	0.00	**0.03**	0.00
(standard error)	(0.43)	(0.01)	(0.01)	(0.02)
Samsung Attack	0.00	0.00	**0.36**	**0.05**
(standard error)	(0.03)	(0.13)	(0.14)	(0.02)
Apple Defense	**1.87**	−0.01	0.00	−0.03
(standard error)	(0.34)	(0.01)	(0.02)	(0.02)
Samsung Defense	0.00	0.00	0.20	0.02
(standard error)	(0.02)	(0.02)	(0.07)	(0.02)

[a] Accumulated estimates and standard errors over all periods where estimate exceeds the standard error in absolute value. If no period reaches this threshold, the displayed standard error is the one of the same-day elasticity. In bold the cumulative elasticities that are significantly different from zero at the 95% level.

Table 7
Cumulative[a] elasticities of ADA on volume & valence for Coke & Pepsi.

	Coke volume	Coke valence	Pepsi volume	Pepsi valence
Coke Across	**2.28**	0.00	**0.56**	−0.10
(standard error)	(0.71)	(0.02)	(0.22)	(0.08)
Pepsi Across	**0.22**	−0.10	**0.57**	−0.07
(standard error)	(0.07)	(0.06)	(0.19)	(0.04)
Coke Attack	**0.46**	0.00	**0.10**	−0.03
(standard error)	(0.11)	(0.02)	(.05)	(0.02)
Pepsi Attack	**0.19**	0.00	**0.55**	−0.06
(standard error)	(0.09)	(0.03)	(0.11)	(0.04)
Coke Defense	**0.41**	0.00	0.04	−0.02
(standard error)	(0.13)	(0.01)	(0.03)	(0.02)
Pepsi Defense	0.00	−0.09	**0.54**	−0.09
(standard error)	(0.03)	(0.06)	(0.16)	(0.06)

[a] Accumulated estimates and standard errors over all periods where estimate exceeds the standard error in absolute value. If no period reaches this threshold, the displayed standard error is the one of the same-day elasticity. In bold the cumulative elasticities that are significantly different from zero at the 95% level.

Table 8
Cumulative[a] elasticities of ADA on volume & valence for McDonald's & Burger King.

	McDonald's volume	McDonald's valence	Burger King volume	Burger King valence
McDonald's Across	**0.40**	**−0.14**	**0.03**	0.00
(standard error)	(0.11)	(0.06)	(0.01)	(0.02)
Burger King Across	0.00	0.00	0.03	0.00
(standard error)	(0.01)	(0.01)	(0.01)	(0.01)
McDonald's Attack	**0.02**	0.00	−0.01	0.00
(standard error)	(0.01)	(0.01)	(0.01)	(0.01)
Burger King Attack	−0.05	0.00	**0.39**	−0.01
(standard error)	(0.02)	(0.02)	(0.14)	(0.01)
McDonald's Defense	**0.03**	0.00	−0.01	0.00
(standard error)	(0.01)	(0.01)	(0.01)	(0.01)
Burger King Defense	−0.24	0.00	**0.90**	−0.03
(standard error)	(0.16)	(0.01)	(0.27)	(0.02)

[a] Accumulated estimates and standard errors over all periods where estimate exceeds the standard error in absolute value. If no period reaches this threshold, the displayed standard error is the one of the same-day elasticity. In bold the cumulative elasticities that are significantly different from zero at the 95% level.

Table 9
Cumulative[a] elasticities of ADA on volume & valence for Nike & Adidas.

	Nike volume	Nike valence	Adidas volume	Adidas valence
Nike Across	**0.84**	−0.05	0.00	−0.02
(standard error)	(0.21)	(0.03)	(0.01)	(0.02)
Adidas Across	0.00	0.00	**0.12**	0.00
(standard error)	(0.04)	(0.01)	(0.04)	(0.01)
Nike Attack	**0.08**	0.00	0.00	0.00
(standard error)	(0.03)	(0.02)	(0.01)	(0.02)
Adidas Attack	0.00	0.00	**0.25**	0.00
(standard error)	(0.02)	(0.01)	(0.07)	(0.01)
Nike Defense	**0.74**	**0.04**	0.00	−0.02
(standard error)	(0.15)	(0.01)	(0.02)	(0.02)
Adidas Defense	0.00	0.01	**0.23**	**0.03**
(standard error)	(0.03)	(0.01)	(0.08)	(0.01)

[a] Accumulated estimates and standard errors over all periods where estimate exceeds the standard error in absolute value. If no period reaches this threshold, the displayed standard error is the one of the same-day elasticity. In bold the cumulative elasticities that are significantly different from zero at the 95% level.

Table 10
Cumulative[a] elasticities of ADA on volume & valence for Colgate & Crest.

	Colgate volume	Colgate valence	Crest volume	Crest valence
Colgate Across	**0.22**	−0.01	0.00	0.00
(standard error)	(0.07)	(0.01)	(0.02)	(0.01)
Crest Across	**0.21**	0.00	**0.53**	−0.01
(standard error)	(0.10)	(0.02)	(0.21)	(0.01)
Colgate Attack	**0.06**	0.00	0.00	0.00
(standard error)	(0.02)	(0.01)	(0.03)	(0.02)
Crest Attack	0.00	−0.01	**0.09**	−0.01
(standard error)	(0.01)	(0.01)	(0.03)	(0.01)
Colgate Defense	**0.34**	**0.05**	−0.20	−0.04
(standard error)	(0.12)	(0.02)	(0.12)	(0.03)
Crest Defense	0.00	0.00	**0.11**	0.01
(standard error)	(0.03)	(0.02)	(0.04)	(0.01)

[a] Accumulated estimates and standard errors over all periods where estimate exceeds the standard error in absolute value. If no period reaches this threshold, the displayed standard error is the one of the same-day elasticity. In bold the cumulative elasticities that are significantly different from zero at the 95% level.

In sum, the GIRF analysis across the four studied brands reveals *the important managerial implications* of ADA Activity: 1 more ADA Across can increase overall volume with tens, even hundreds of posts. The GIRFs of brand drivers on ADA and Volume (available upon request) show that own brand-related events are most powerful in driving the Facebook page's ADA. In the cola category, Pepsi *Advertising,* Coke and Pepsi *Public Relations/Sponsorships* are the main drivers of ADA activity. In contrast, *product innovation* is key in the Apple–Samsung rivalry: *Announcements* for Apple and the actual *Launch* for Samsung. Thus, ADA activity can be influenced by variables (largely) under managerial control.

How ADA Increases and Prolongs the Engagement Impact of Brand-related Events

Table 11 shows the cumulative effect size and duration (in days) of events on engagement metrics, both allowing for ADA changes (the unrestricted impulse response function) and restricting ADA to its status quo (the restricted impulse response function).

For each analyzed brand, at least one marketing control variable significantly affects engagement on its own Facebook page and on the rival brand Facebook page. However, without ADA activity, these effects are relatively small and short-lived. ADA activity amplifies the impact of marketing on Facebook engagement, and often adds many days of significant effects. For instance, without ADA, an Apple new product obtains 796 more comments on its own page, and 11 on Samsung's page — all within two days. Accounting for the product-caused ADA activity adds many more days to the effect, for a total of 3,003 comments on the Apple page and 102 on Samsung's page. Moreover, Samsung's valence decreases due to this ADA activity, with no such effect significant when we restrict ADA to remain at status quo.

Discussion

Our findings make contributions to the marketing field and have important implications for managers. We also discuss limitations and further research suggestions.

Table 11
Unrestricted (with) and restricted (without ADA) cumulative engagement effects (duration) of marketing control variables.[a]

		Leader volume	Challenger volume	Leader valence	Challenger valence
Apple New Product Announcement	With ADA	3,003.357 (30 days)	101.556 (14 days)		−0.056 (15 days)
	Without ADA	795.519 (2 days)	10.740 (1 day)		0.000 (0 days)
Samsung New Product Launch	With ADA	75.940 (2 days)			0.021 (3 days)
	Without ADA	0.000 (0 days)			0.000 (0 days)
Coke Public Relations	With ADA	1,320.609 (5 days)	103.213 (4 days)	0.284 (3 days)	−0.157 (2 days)
	Without ADA	774.418 (2 days)	24.627 (1 day)	0.098 (1 day)	−0.078 (1 day)
Pepsi Advertising	With ADA	745.507 (4 days)		−0.064 (2 days)	0.075 (4 days)
	Without ADA	236.017 (2 days)		0.000 (0 days)	0.000 (0 days)
Pepsi Public Relations	With ADA				0.034 (2 days)
	Without ADA				0.000 (0 days)
McD Advertising	With ADA	3.465 (4 days)		0.249 (6 days)	
	Without ADA	1.162 (2 days)		0.088 (2 days)	
BK Advertising	With ADA			−0.151 (2 days)	0.015 (5 days)
	Without ADA			−0.060 (1 days)	0.004 (3 days)
BK New Product Launch	With ADA		1,205.255 (10 days)		
	Without ADA		378.069 (2 days)		
Nike Advertising	With ADA	1.918 (2 days)	1.051 (2 days)	−0.021 (2 days)	
	Without ADA	1.134 (2 days)	0.000 (0 days)	0.000 (0 days)	
Adidas Advertising	With ADA		3.638 (5 days)	−0.069 (3 days)	
	Without ADA		1.424 (2 days)	0.000 (0 days)	
Colgate New Product Launch	With ADA	3.793 (2 days)		0.081 (2 days)	
	Without ADA	2.121 (1 day)		0.058(2 days)	
Colgate Brand News	With ADA	2.949 (7 days)	2.949 (7 days)	0.064 (11 days)	−0.119 (19 days)
	Without ADA	1.402 (3 days)	1.402 (3 days)	0.035 (1 day)	−0.052 (1 day)

[a] Unit effects (of drivers coded as 0/1 variables), only significant effects are displayed. The duration is the number of days for which the effect is significant.

Research Contributions

As the first empirical analysis of cross-brand platform brand posting, our study contributes to the dynamic understanding of ADA's drivers and consequences. Firstly, ADA could be driven by marketing actions — consistent with findings on more general forms of eWOM (e.g. Pauwels, Aksehirli, and Lackman 2016). Thus, marketing activity could induce some brand fans to attack rival brands, even on the rival brand's own social media platform. Second, ADA has a positive impact on the social-media performance (especially on the volume of comments) for both brands in a rivalry. Our findings are consistent with positive effects of rivalry (e.g., Berendt and Uhrich 2015) and the productive aspect of competition in brand wars (e.g., Libai, Muller, and Peres 2009). While we don't have empirical data to analyze exactly where this increased volume comes from, we speculate that strong brand rivalries take attention away from third brands and other categories in our 'attention economy' (Davenport and Beck 2001).

We thus challenge the assumption that negative eWOM leads to bad results for brands (Berger and Milkman 2012; Kähr et al. 2016). Hewett et al. (2016) also emphasize that 'online word of mouth has fallen into a negativity spiral, with negative messages leading to greater volume, and firms are adjusting their communications strategies in response' (p.1). If rival-brand interdynamics are initiated by brand-related events, ADA can act as a buffer, not only softening any potential negative blows for the focal brand but also changing the valence and increasing the volume of social media engagement. ADA aligns with van Doorn et al.'s (2010) five-dimension model of customer engagement where van Doorn et al. (2010) assume negative valence hurts the focal brand, we show that ADA's negative valence may benefit the brand, and our magnitude findings suggest that this purpose has greater potential than van Doorn et al. (2010) suggest.

More generally, our time series analysis shows that, similar to the pre-purchase mind-set metrics in Srinivasan, Vanhuele, and Pauwels (2010), ADA represents an important missing link in the relationship between the brand marketing events and online engagement metrics because ADA dynamics amplify and/or prolong the impact of marketing activities such advertising, public relations and new product introductions. The ADA amplification also enriches our understanding of the dynamics of WOM (Kozinets et al. 2010) and virality (Berger and Schwartz 2011).

Managerial Implications

In light of the positive social media performance effects of ADA, managers can (1) monitor ADA both at their own and their rivals' pages, (2) leverage ADA to respond to the competition, and (3) influence the rival brand's customers/fans to amplify brand fortunes and attenuate negative company news.

First, as to monitoring, several studies show how the brand's own social media performance impacts its sales (Hennig-Thurau, Wiertz, and Feldhaus 2014; Pauwels, Aksehirli, and Lackmann 2016; Srinivasan, Rutz, and Pauwels 2015; Stephen and Galak 2012). Yet, currently, there is no social-media performance metric or way to measure engagement based on rivalry dynamics. Although managers sometimes perform brand audits to understand the social-media performance of their competitors, they generally use those to benchmark individual brand performance rather than to envision integrative and layered brand management and communication strategies. Managers can and should monitor ADA types at both their own and their rival brands' social media pages to keep their finger on the pulse of how fans and detractors interact. The kind of arguments fans and rival brands get into is often far beyond what managers can communicate themselves (legally or ethically) but provides hints as to how fans and detractors perceive the brand identity and its offerings.

Second, beyond monitoring, ADA is driven by the company's marketing activities, such as new product announcements (Apple), introductions (Samsung) and marketing communication (Coke, Pepsi, Nike) and is a prominent mechanism to impact social media performance metrics. Thus, by providing the appropriate content, managers can initiate and manage ADA and unlock engagement with rival brands that will boost their brand's social media performance. In contrast to Kähr et al.'s (2016) assertion that polarized positioning induces consumer sabotage, we stress that ADA can ameliorate negative consumer behavior and even transform it into a positive social media outcome for the brand. Failing to engage in the rivalry may allow third brands to take the company's place, with e.g., rather passive Adidas and Puma possibly ceding their place of Nike challenger to aggressive newcomer UnderArmour, who attacks Nike head on. The leveraging of inter-brand dynamics might be an important and effective tool to reinforce positioning and ranking in the category.

Third, given their desire to influence communication around their brand, managers struggle with deciding and implementing the best level of control (e.g.; whether or not to have an open-wall policy or ways to respond to the hatred and negative comments on their brand's social media pages). Our study strongly implies that allowing brand-negative comments does not necessarily hurt the brand but might instead increase the engagement. Where would these synergistic effects come from? They can come from either expanding the buzz in the category and/or sucking the air out of the buzz for third brands. In today's information-rich and thus attention-scarce world (Simon 1971, p. 40–41), such ADA for the two leading brands could thus act like the alternating price promotions for Coke and Pepsi to limit the market share of third brands (Lal 1990). Future research is needed to investigate this potential.

Limitations and Directions for Future Research

Limitations of our study include the choice of rival brand duos, the data collection at the brand's Facebook pages (and not e.g. third-party blog sites), and the accuracy of the sentiment analysis. Sentiment analysis methods and machine learning (also used in sentiment analysis) are relatively young methods that keep improving. ADA analysis will improve in tandem with sentiment analysis. Future research should compare our choice of sentiment analysis and valence (as the ratio of positive comments to all comments) with alternative approaches. For one, a key reason that we hardly find a significant effect of ADA on page valence, may be that ADA also greatly increases neutral comments, which are the denominator of our valence measure.

Directions for future research also directly follow from our reported differences across brands and categories — for which space considerations prohibit a thorough discussion in this empirical paper. Why do our variables explain substantially more of ADA and Volume for the leading brand, but more Valence for the challenger brand? Likewise, what factors determine which drivers are more likely to induce ADA across brands and categories? Importantly, how prevalent is ADA beyond the studied brands? In our study, the *number* of ADA comments is lower for brand rivalries in lower (e.g. toothpaste) versus higher (e.g. electronics) involvement categories. Interestingly though, the % of all comments that are ADA varies within the 1%–6% range in all categories, because the lower involvement categories also see less comments in general. Does the same ratio apply to all product (and service) categories? On the one hand, we would expect a lower prevalence of ADA in categories and for brands that engender less customer passion (e.g. business-to-business categories and "me-too" brands that are neither leading the category nor challenging the leader). In such situations, there is less need for marketing managers to monitor ADA at their own and the competing brands' social media pages. On the other hand, based on our highest reported prevalence for athletic apparel brands, we would expect an even higher % of ADA for sport rivalries and politics, where the winner-takes-all nature provides more motivation for ADA behavior. In such situations, managers could gain most from tracking ADA and analyzing how it reinforces – or attenuates – the performance impact of their own and their rival brands' marketing actions. Finally, how does ADA behavior fit into our theories regarding fan typologies, brand engagement, the motivations of consumers to post eWOM and the consequences of this eWOM for the sender and the receiver? In the tradition of Empirics-Theory-Empirics-Theory (ETET) research (Ehrenberg 1995), the current paper analyzed multiple datasets to describe an empirical phenomenon with its prevalence, drivers and consequences. We urge future research to theorize, building on our observations.

Conclusions

Despite the negative sentiment expressed by rival brand fans, brand managers should not fear such comments on the brand's social media page, as they induce fans to defend their brand and lead to a net increase in social media performance. Our analysis quantified the consequences of rival brand fan comments across industries of technology, fast food, toothpaste, beverages, and sports apparel. While ADA represents only 1–6% of all posts, these exert a substantial, dynamic and beneficial effect on the overall number of comments. Moreover, ADA substantially increases and prolongs the effects of managerial control variables such as communication campaigns and new-product introductions. Brand managers thus have specific levers to stimulate such beneficial consumer exchanges.

Appendix A

Appendix 1
Categorization matrix for automated ADA content analysis.

Categorization matrix	How can we find them?	Ways to identify DwE	Sentiment	Type of ADA
ACROSS [Cross posters]	People who actually post on both pages	Find the common poster ids on both brand pages		Across
WITHIN Brand Specific PAGE: **Defense** or **Attack**	Mention brands	Focal Brand	Neutral	
			Positive	Defense
			Negative	Attack
		Enemy Brand	Neutral	
			Positive	Defense
			Negative	Attack
		Enemy **and** Focal Brand [& related]	Neutral	
			Positive for Enemy (Negative for Focal)	Attack
			Negative for Enemy (Positive for Focal)	Defense

Appendix 2
Descriptive statistics of variables used in the model for Apple and Samsung.

	Apple								Samsung							
	NP announce	NP launch	Brand news	Across	Defense	Attack	Volume	Valence	NP announce	NP launch	Brand news	Across	Defense	Attack	Volume	Valence
Mean	0.02	0.07	0.13	0.97	3.503	6.19	331.1	0.68	0.05	0.10	0.23	0.22	0.37	0.33	37.69	0.35
Median	0	0	0	0	1	1	100	0.67	0	0	0	0	0	0	25	0.33
Maximum	4	5	11	23	78	187	4,438	1	1	7	11	7	10	16	312	0.82
Minimum	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0
Std. Dev.	0.26	0.43	0.74	2.35	7.80	16.45	595.4	0.22	0.22	0.53	0.71	0.68	0.98	1.03	38.29	0.17

Appendix 3
Descriptive statistics of variables used in the model for Coke and Pepsi.

	Coke								Pepsi								
	Public relations	Company news	Brand news	Across	Defense	Attack	Volume	Valence	Public relations	Advertising	Company news	Brand news	Across	Defense	Attack	Volume	Valence
Mean	0.06	0.04	0.05	2.17	7.49	5.84	313.8	0.15	0.19	0.08	0.06	0.18	1.83	4.09	1.14	91.52	0.19
Median	0	0	0	1	1	0	43	0.11	0	0	0	0	1	2	1	43	0.16
Maximum	1	1	1	22	139	94	4,169	0.61	2	1	1	2	13	27	17	629	0.62
Minimum	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0
Std. Dev.	0.24	0.20	0.22	3.34	19.79	14.49	669.7	0.15	0.49	0.28	0.24	0.46	2.43	4.91	2.09	111.2	0.13

Appendix 4
Descriptive statistics of variables used in the model for McDonalds and Burger King.

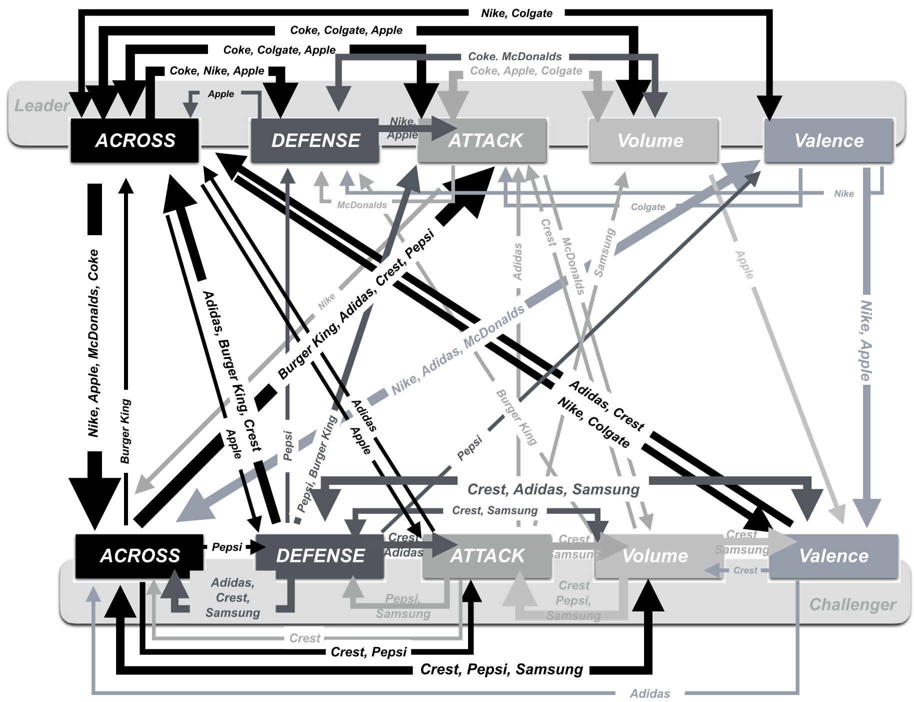
	McDonald's										Burger King									
	NP launch	Advertising	Brand N.	Company	Ethics N.	Across	Defense	Attack	Volume	Valence	NP launch	Advertising	Brand N.	Company N.	Ethics N.	Across	Defense	Attack	Volume	Valence
Mean	0.05	0.23	0.10	0.20	0.11	0.23	0.09	0.02	8.12	0.30	0.04	0.11	0.02	0.14	0.12	0.50	2.98	1.63	307.4	0.21
Median	0	0	0	0	0	0	0	0	4	0.18	0	0	0	0	0	0	2	1	185	0.21
Maximum	2	5	3	4	2	5	14	2	119	1	2	2	1	2	1	19	48	36	3,383	0.5
Minimum	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
Std. Dev.	0.27	0.59	0.38	0.58	0.36	0.62	0.81	0.16	13.1	0.35	0.20	0.33	0.15	0.37	0.32	1.35	5.37	3.10	430.4	0.07

Appendix 5
Descriptive statistics of variables used in the model for Nike and Adidas.

	Nike										Adidas								
	NP launch	Advertising	Brand News	Company N.	Ethics N.	Across	Defense	Attack	Volume	Valence	Advertising	Brand N.	Company N.	Ethics N.	Across	Defense	Attack	Volume	Valence
Mean	0.02	0.05	0.02	0.09	0.01	0.90	0.19	0.57	3.87	0.14	0.02	0.05	0.12	0.01	1.23	0.59	0.16	4.66	0.12
Median	0	0	0	0	0	0	0	0	2	0.12	0	0	0	0	0	0	0	3	0.10
Maximum	8	3	1	11	1	15	9	16	260	1	1	4	9	2	17	13	11	90	0.7
Minimum	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Std. Dev.	0.33	0.25	0.15	0.76	0.09	1.61	0.64	1.30	11.99	0.13	0.14	0.28	0.61	0.11	1.89	1.40	0.70	8.99	0.10

Appendix 6
Descriptive statistics of variables used in the model for Colgate and Crest.

	Colgate									Crest								
	NP launch	Advertising	Brand news	Company N.	Across	Defense	Attack	Volume	Valence	NP launch	Brand news	Company N.	Ethics	Across	Defense	Attack	Volume	Valence
Mean	0.01	0.10	0.01	0.21	0.57	0.43	0.15	4.83	0.22	0.01	0.11	0.19	0.03	0.56	0.37	0.25	9.01	0.34
Median	0	0	0	0	0	0	0	2	0.19	0	0	0	0	0	0	0	2	0.29
Maximum	3	2	2	5	11	60	6	172	1	3	4	5	3	15	21	8	189	1
Minimum	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Std. Dev.	0.12	0.33	0.12	0.53	1.13	1.88	0.47	9.59	0.22	0.12	0.36	0.50	0.20	1.11	1.07	0.73	18.72	0.28



Appendix 7. Results of Granger causality tests.

References

Berendt, Jan and Sebastian Uhrich (2015), "Exploring the Love–Hate Relationship Between Archrivals: The Rivalry Ambivalence Model," *Proceedings of the 23rd Conference of the European Association for Sport Management*.

Berger, Jonah, Alan T. Sorensen, and Scott J. Rasmussen (2010), "Positive Effects of Negative Publicity: When Negative Reviews Increase Sales," *Marketing Science*, 29, 5, 815–27.

——— and Eric Schwartz (2011), "What Drives Immediate and Ongoing Word-of-Mouth?" *Journal of Marketing Research*, 48, October, 869–80.

——— and Katy Milkman (2012), "What Makes Online Content Viral?" *Journal of Marketing Research*, 49, 2, 192–205.

Borah, Abishek and Gerard J. Tellis (2012), "Halo (Spillover) Effects in Social Media: Do Product Recalls of One Brand Hurt or Help Rival Brands?" *Journal of Marketing Research*, 53, 2, 143–60.

Brodie, Roderick J., Ana Ilic, Biljana Juric, and Linda D. Hollebeek (2013), "Consumer Engagement in a Virtual Brand Community: An Exploratory Analysis," *Journal of Business Research*, 66, 1, 105–14.

Burnard, Philip (1996), "Teaching the Analysis of Textual Data: An Experiential Approach," *Nurse Education Today*, 16, 4, 278–81.

Chen, Pei-Yu., Shin-yi Wu, and Jungsun Yoon (2004), "The Impact of Online Recommendations and Consumer Feedback on Sales," *ICIS 2004 Proceedings*," Vol, 58, 1, 711–24.

Chiechi, Prelini U. (2016), "Fake reviews: why and how businesses can steer clear of fraudulent content and gain consumers' trust", *betaNews*, accessed June 12, 2017 at https://betanews.com/2015/12/17/fake-reviews-why-and-how-businesses-can-steer-clear-of-fraudulent-content-and-gain-consumers-trust/.

Chevalier, Judith A. and Dina Mayzlin (2006), "The Effect of Word of Mouth on Sales: Online Book Reviews," *Journal of Marketing Research*, 43, 3, 345–54.

Colicev, Anatoli, Ashwin Malshe, Koen Pauwels, and Peter O'Connor (2017), "Improving Consumer Mind-set Metrics and Shareholder Value through Social Media: The Different Roles of Owned and Earned," *Journal of Marketing*, 4.

Cohen, Joel B. and Marvin E. Goldberg (1970), "The dissonance model in post-decision product evaluation," *Journal of Marketing Research*, 315–21.

Court, David, Dave Elzinga, Susan Mulder, and Ole J. Vetvik (2009), "The Consumer Decision Journey," *McKinsey Quarterly*, 3, 1–11.

Davenport, Thomas H. and John C. Beck (2001), *The Attention Economy: Understanding the New Currency of Business*. Harvard Business School Press.

Dekimpe, Marnik G. and Dominique M. Hanssens (1999), "Sustained Spending and Persistent Response: A New Look at Long-term Marketing Profitability," *Journal of Marketing Research*, 36, 4, 397–412.

Dellarocas, Chrysanthos and Charles A. Wood (2008), "The sound of silence in online feedback: Estimating trading risks in the presence of reporting bias," *Management Science*, 54, 3, 460–76.

Ehrenberg, Andrew SC. (1995), "Empirical generalisations, theory, and method," *Marketing Science*, 14.3_supplement, G20–8.

Ein-Gar, Danit, Jacob Goldenberg, and Lilach Sagiv (2012), "The role of consumer self-control in the consumption of virtue products," *International Journal of Research in Marketing*, 29, 2, 123–33.

Fournier, Susan and Lara Lee (2009), "Getting Brand Communities Right," *Harvard Business Review*, 87, 4, 105–11.

Goldenberg, J., B. Libai, S. Moldovan, and E. Muller (2007), "The NPV of bad news," *International Journal of Research in Marketing*, 24, 3, 186–200.

Hennig-Thurau, Thorsten, Kevin P. Gwinner, Gianfranco Walsh, and Dwayne D. Grensler (2004), "Electronic Word-of-Mouth via Consumer-Opinion Platforms: What Motivates Consumers to Articulate Themselves on the Internet?" *Journal of Interactive Marketing*, 18, 1, 38–52.

———, Charles F. Hofacker, and Björn Bloching (2013), "Marketing the Pinball Way: Understanding How Social Media Change the Generation of Value for Consumers and Companies," *Journal of Interactive Marketing*, 27, 4, 237–41.

———, Caroline Wiertz, and Fabian Feldhaus (2014), "Does Twitter Matter? The Impact of Microblogging Word of Mouth on Consumers' Adoption of New Movies," *Journal of the Academy of Marketing Science*, 43, 3, 375–94.

Hewett, Kelly, William Rand, Roland T. Rust, and Harald J. van Heerde (2016), "Brand Buzz in the Echoverse," *Journal of Marketing*, 80, 3, 1–24.

Ho-Dac, Nga, Stephen Carson, and William Moore (2013), "The Effects of Positive and Negative Online Customer Reviews: Do Brand Strength and Category Maturity Matter?" *Journal of Marketing*, 77, 6, 37–53.

Hoon, Leonard, Rajesh Vasa, G.Y. Martino, Jean-Guy Schneider, and Kon Mouzakis (2013), "Awesome! Conveying Satisfaction on the App Store," *Proceedings of the 25th Australian Computer–Human Interaction Conference: Augmentation, Application, Innovation, Collaboration*, 229–32.

Humphreys, Ashlee (2010), "Megamarketing: The Creation of Markets as a Social Process," *Journal of Marketing*, 74, 2, 1–19.

Jurka, Timothy P., Loren Collingwood, Amber E. Boydstun, Emiliano Grossman, and Wouter van Atteveldt (2013), "RTextTools: A Supervised Learning Package for Text Classification," *The R-Journal*, 5, 1, 6–12.

Kähr, Andrea, Bettina Nyffenegger, Harley Krohmer, and Wayne D. Hoyer (2016), "When Hostile Consumers Wreak Havoc on Your Brand: The Phenomenon of Consumer Brand Sabotage," *Journal of Marketing*, 80, 3, 25–41.

Kassarjian, Harold H. (1977), "Content Analysis in Consumer Research," *Journal of Consumer Research*, 4, 1, 8–18.

Kireyev, Pavel, Koen Pauwels, and Sunil Gupta (2016), "Do Display Ads Influence Search? Attribution and Dynamics in Online Advertising," *International Journal of Research in Marketing*, 2015 (in press).

Kolbe, Richard H. and Melissa S. Burnett (1991), "Content-Analysis Research: An Examination of Applications with Directives for Improving Research Reliability and Objectivity," *Journal of Consumer Research*, 18, 2, 243–50.

Kozinets, Robert V., Kristine de Valck, Andrea C. Wojnicki, and Sarah J.S. Wilner (2010), "Networked Narratives: Understanding Word-of-Mouth Marketing in Online Communities," *Journal of Marketing*, 74, 2, 71–89.

Kübler, Raoul and Sönke Albers (2010), "Communication Behavior of Companies in Product Recalls Without Customer Identification Information," *Marketing-Journal of Research and Management*, 6, 1, 19–30.

———, Anatoli Colicev, and Koen Pauwels (2017), "Social Media's Impact on Consumer Mindset: When to Use Which Sentiment Extraction Tool?" *MSI Working Paper Series*, 17–122.

Lal, Rajiv (1990), "Price Promotions: Limiting Competitive Encroachment," *Marketing Science*, 9, 3, 247–62.

Libai, Barak, Eitan Muller, and Renana Peres (2009), "The Role of Attack-Brand and Cross-Brand Communications in Competitive Growth," *Journal of Marketing*, 73, 3, 19–34.

Loten, Angus (2012), "Small Firms, Start-ups Drive Crowdsourcing Growth," *Wall Street Journal*, accessed June 12, 2017 at https://www.wsj.com/articles/SB10001424052970204653604577251293100111420&gt.

MacKinnon, Richard (1995), "Searching for Leviathan in Usenet," in *Cybersociety: Computer-Mediated Communication and Community,* Steven G. Jones, editor. Sage, 112–38.

Marchand, André, Thorsten Hennig-Thurau, and Caroline Wiertz (2017), "Not All Digital Word of Mouth is Created Equal: Understanding the Respective Impact of Consumer Reviews and Microblogs on New Product Success," *International Journal of Research in Marketing*, 34, 2, 336–54.

McAuley, Julian, Christopher Targett, Qinfeng Shi, and Anton van den Hengel (2015), "Image-based Recommendations on Styles and Substitutes," *Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval*, 43–52.

McCombs, Maxwell E. and Donald L. Shaw (1972), "The Agenda-setting Function of Mass Media," *Public Opinion Quarterly*, 36, 2, 176–87.

Moe, Wendy (2009), "How much does a good product rating help a bad product? Modeling the role of product quality in the relationship between online consumer ratings and sales." *Working Paper*. University of Mayland.

Mullen, Tony and Nigel Collier (2004), "Sentiment Analysis Using Support Vector Machines with Diverse Information Sources," *Proceedings of Conference on Empirical Methods in Natural Language Processing*, 412–8.

Pauwels, Koen (2004), "How Dynamic Consumer Response, Competitor Response, Company Support, and Company Inertia Shape Long-term Marketing Effectiveness," *Marketing Science*, 23, 4, 596–610.

———, Zeynep Aksehirli, and Andrew Lackmann (2016), "Like the Ad or the Brand? Marketing Stimulates Different Electronic Word-of-Mouth Content to Drive Online and Offline Performance," *International Journal of Research in Marketing*, 33, 3, 639–55.

Schouten, John W. and James H. McAlexander (1995), "Subcultures of Consumption: An Ethnography of the New Bikers," *Journal of Consumer Research*, 22, 1, 43–61.

Simon, Herbert A. (1971), "Designing Organizations for an Information-rich World," in *Computers, Communication, and the Public Interest.* Martin Greenberger, editor.

Srinivasan, Shuba, Marc Vanhuele, and Koen Pauwels (2010), "Mind-set Metrics in Market Response Models: An Integrative Approach," *Journal of Marketing Research*, 47, 4, 672–84.

———, Oliver J. Rutz, and ——— (2015), "Paths to and off Purchase: Quantifying the Impact of Traditional Marketing and Online Consumer Activity," *Journal of the Academy of Marketing Science*, 1-14.

Stephen, Andrew T. and Jeff Galak (2012), "The Effects of Traditional and Social Earned Media on Sales: A Study of a Microlending Marketplace," *Journal of Marketing Research*, 49, 5, 624–39.

Sullivan, Bob (2012), "Pouring Gas on a Fire? Firms' Deletion of Online Critiques Draws 'Censorship' Cries," *NBC News, September 4th* accessed September 10, 2016 at: http://redtape.nbcnews.com/_news/2012/09/04/13591835-pouring-gas-on-a-fire-firms-deletion-of-online-critiques-draws-censorship-cries.

Trusov, Michael, Randolph E. Bucklin, and Koen Pauwels (2009), "Effects of Word-of-Mouth versus Traditional Marketing: Findings from an Iinternet Social Networking Site," *Journal of Marketing*, 73, 5, 90–102.

van Doorn, Jenny, Katherine N. Lemon, Vikas Mittal, Stephan Nass, Doreen Peck, Peter Pirner, and Peter C. Verhoef (2010), "Customer Engagement Behavior: Theoretical Foundations and Research Directions," *Journal of Service Research*, 13, 3, 253–66.

Verhoef, Peter, Lemon Katherine, A. Parasuraman, Anne Roggeveen, Michael Tsiros, and Leonard Schlesinger (2009), "Customer Experience Creation: Determinants, Dynamics and Management Strategies," *Journal of Retailing*, 85, 1, 31–41.

Wilson, Andrew E., Michael D. Giebelhausen, and Michael K. Brady (2017), "Negative Word of Mouth Can Be a Positive for Consumers Connected to the Brand," *Journal of the Academy of Marketing Science*, 45, 4, 534–47.

You, Ya, Gautham G. Vadakkepatt, and Amit M. Joshi (2015), "A Meta-analysis of Electronic Word-of-Mouth Elasticity," *Journal of Marketing*, 79, 2, 19–39.