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Dancing with the Enemy: Broadened Understanding of Engagement in Rival Brand Dyads

Behice Ilhan, Koen Pauwels, and Raoul Kübler

Report summary

Increasingly, brand fans are engaging and interacting with the touchpoints and fans of rival brands. These inter-brand and inter-communal practices provide immense opportunities for brand managers to respond to the competition, influence the rival brand's customers, and strengthen their own brand's message. Yet marketing efforts are usually limited to managing, measuring, and facilitating engagement with company-owned or operated social media accounts.

Here, Behice Ilhan, Koen Pauwels, and Raoul Kübler aim to broaden understanding of brand engagement that is facilitated and fostered by this growing practice – which they call "dancing with the enemy" (DwE) – and to empirically relate DwE to its triggers and consequences.

They combine content, sentiment, and time-series analysis to explore and describe this practice for rival brand dyads. They distinguish three types of DwE: *across*: where fans migrate and interact with the social media of both brands in the dyad; *discourse*, where rival brand fans communicate their thoughts through words on the central brand's social media; and *ripple*, where central brand fans react to rival brand fan's posts and words on the central brand's social media.

Findings show that (1) new products and brand communication trigger DwE, (2) DwE for one brand drives DwE for the rival brand, and (3) DwE substantially drives the volume and valence for both the originating brand and rival brand's Facebook comments.

In particular, their findings highlight the key role of fans posting *across* both rival brand pages. Because DwE across is a strong driver of page posts for each brand dyad, these fans are likely very engaged with and responsive to brand communications. Moreover, DwE across unlocks the full dynamics of discourse and ripple.

Overall, their findings give social media managers concrete and feasible metrics to drive DwE and relate the interactions to overall engagement. Their study shows that fans, even the rival ones, are not passive actors in a company's competitive strategies but rather active and proactive participants who can shape competition and rivalry between brands. In other words, competition is not a zero sum-game in the dynamic, multi-channel, social, and interdependent digital brandscape.

Behice Ilhan is Adjunct Professor of Marketing, Kellstadt Graduate School of Business, DePaul University. Raoul Kübler is Assistant Professor of Marketing and Koen Pauwels is Professor of Marketing, both at Özyeğin University, Istanbul, Turkey.

"People who buy Apple are always snobby people who think they are so great because they have a[n] [$]800 phone when in reality you have a[n] [$]800 paper weight lmfao… my Note 3 does more the[a]n Apple's mac books. Your [You're] paying for a name basically and get a product that doesn't do you any good. If you have a shot battery Apple has to replace it because if you open the phone it voids out the whole warranty. Talk about stupidity… with android phones you can replace it anytime you want."

-Samsung fan post on Apple's Facebook page

"I've had Samsung, htc, blackberry, Motorola, and Apple phones. Apple kills them all …in the 3 years I have had iPhones, never once have I had my phone freeze or have any problems. [T]heir computers are great as well…You should know you get what you pay for and Apple gives you your money's worth."

Apple fan's response to the Samsung Fan

Have you ever felt the desire to interact with the fans of the "opposing team," whether in sports, politics or other brand rivalries? Have you ever acted on this desire like the Samsung fan above? The above quotes concern the Apple-Samsung brand rivalry, where some Samsung fans travel to Apple's Facebook page to slam Apple's new products. Samsung fans' interaction with the "enemy" Apple brand and its fans at Apple's Facebook site reveals a new type of social media practice propelled by the eminent brand rivalry and by the connected consumers of the digital age who can easily access a number of platforms and other consumers to express their likes, dislikes, and their fanaticism. This engagement between rivalries is not limited to technology brands like Apple and Samsung, but can also be observed in political parties and presidential candidates (e.g., Obama- Romney; Hillary Clinton-Bernie Sanders), to consumer brands (e.g., Coca Cola-Pepsi; Nike-Adidas) and entertainment products (e.g., Marvel-DC Comics; Xbox-PS3 gaming systems). Our study is driven by real-life observations that fans of a brand engage and interact with the social media ecosystem – touchpoints and fans – of the rival brands, a behavior we refer to as *Dancing with the Enemy (DwE).* In the social media-boosted brandscape, these inter-brand and inter-communal practices become more common for consumers while providing immense opportunities for brand managers to respond to the competition, influence the rival brand's customers, and strengthen their own brand's message. Is DwE a social media practice that drives engagement with the brand and its rivals? If so, how does DwE facilitate engagement for the rival brand dyads? And how much does DwE impact online measures of brand engagement, such as the volume and valence of social media posts?

While consumer engagement with brands has received much recent research attention (Brodie, Hollebeek, and Ilic 2011; Isaac, Calder, and Malthouse 2015; Hollebeek 2011a,b, Doorn et al 2010), our knowledge studies have been limited to consumer engagement with one brand or one object. Consumer engagement is defined as a "state that occurs by virtue of interactive, co-creative customer experiences *with a focal agent/object (e.g. a brand)"* (Brodie et al. 2011, emphasis added). In the social media world, this focus often translates to an understanding of engagement that only considers the consumer activities and interactions with touchpoints operated by the brand (Trusov et al. 2009). Similarly, in practice, social media marketing and digital brand management efforts are limited to managing, measuring, and facilitating engagement with company-owned or operated social media accounts like Facebook, Instagram, or Twitter. For instance, Jeep, Coca Cola, and many other social media strong brands brag about the high number of "Likes" they garner on Facebook — sometimes approaching millions —and the high number of blog registrations they receive. These likes and positive interactions among existing customers may strengthen consumer loyalty for the brand, but do little to reach the rival brand's customers. This brand-specific focus of academics and managers alike ignores the 'Dancing with the Enemy' phenomenon, where the fans of a brand interact and engage with the brand's rivalry and its fans.

Even studies on 'brand wars' (Ewing Wagstaff, and Powell 2013; Phillips-Melancon and Dalakas 2014) typically collect data from the fans of one brand; thus, not lending themselves to a dyadic understanding of consumers' inter-brand migratory and inter-communal behaviors that DwE introduces. Moreover, the widely standard emphasis on competition (e.g., brand wars, brand warriors, oppositional loyalty) throughout study literature prevents the development of a synergy that rival brand sets could create for the brands. Van Doorn, et al. (2010, 258) also stress that "competitors and their actions could create a strong contextual force affecting customer engagement." Such cross-competitive effects (van Doorn, et al., 2010) and potential dynamic outcomes of customer engagement behavior are not yet understood (Verhoef, et al., 2009), as research has focused on cross-sectional studies (Brodie et al. 2014, p. 161), hampered by measurement challenges (Van Doorn et al. 2014). DwE could potentially increase engagement for both brands of the dyad much like competition helps build interest in a new product category (Libai, Muller, and Peres 2009).

Our study aims to broaden the brand-specific understanding of engagement that is facilitated and fostered by DwE and to empirically relate DwE to its triggers and to its consequences. Our empirical research questions are: (1) How does DwE manifest itself as an inter-brand and inter-communal practice? (2) What triggers DwE? (3) How prevalent is DwE? and (4) To what extent does DwE drive the brand's and the rival brand's volume and valence metrics of engagement? To the best of our knowledge, nobody has conceptually and empirically analyzed this inter-brand and inter-community social media practice and interaction. Combining qualitative and quantitative approaches, this multi-method, and multi context study seeks to explore and describe this novel and important phenomenon for the rival brand dyads. We distinguish three types of DwE: (a) *migratory*; i.e., fans interacting with the social media of both brands in the dyad (b) *discourse,* i.e. rival brand fans communicating their thoughts through words on the central brand's social media (as in our first opening quote); and (c) *ripple,* i.e. central brand fans reacting to rival brand fan's posts and words on the central brand's social media (as in our second opening quote).

Our analysis first identifies brand dyads that are likely to induce DwE behavior, and then proceeds to collect and analyze data for two brand dyads: Apple and Samsung as an example of a high-technology brand rivalry, and Coke and Pepsi as a low-technology brand rivalry. We dive through several years of data on the brands' official Facebook pages (or the largest unofficial Facebook page if an official page does not exist). Next, we operationalize variables by running a sentiment analysis on all posts and by classifying posts as Dancing with the Enemy. This classification shows that DwE is more prevalent in the low-technology brand rivalry (4.6% and 3.3% of all comments for Coke and Pepsi respectively) than in the high-technology brand rivalry (1.1% and 1.3% for Apple and Samsung respectively). Time series analysis shows that new product announcements and launches are key DwE triggers in the high-tech brand rivalry, while advertising, PR, and sponsorships are key DwE triggers in the low-tech brand rivalry. Consistent across all of the studied brands, the results show that (1) migration DwE drives other DwE behavior, (2) DwE for one brand drives DwE and social media engagement metrics for the rival brand, (3) DwE dynamically explains social media engagement metrics for several weeks, even when controlling for the new product, advertising and other triggers. Faced with a customer engagement behavior such as DwE, managers need a process to identify it, evaluate its consequences, and react to it (Van Doorn et al. 2014). This paper thus broadens the academic understanding of engagement and gives managers concrete and feasible metrics to track DwE in its prevalence and engagement implications and to influence it with new product announcement, launches, and brand communications.

Literature Review

Engagement: A Brand-Specific Consumer State?

DwE can be perceived as a new form of inter-brand and inter-communal social media practice and as interaction that facilitates consumer-brand engagement. Engagement has long been an interest to marketing and media consumption scholars and practitioners who strive to understand and manage consumers' experiences and relationships with brands, media, and media texts. There is a lot of disagreement and confusion on what engagement is and how it should be defined. Our objective in this study does not aim to introduce a new definition of engagement or another scale to measure it. Yet, in this section, we will review common approaches and assumptions relative to how engagement has been persistently understood across most of the academic and industry literature. We will also reflect on how these approaches, due to their assumptions, fail to understand and incorporate more contemporary media practices and social media interactions like *DwE (Dancing with the Enemy)*.

Engagement as a consumer state. Academic studies have predominantly understood engagement as a consumer state: a mental (Csikszentmihalyi 1991; Novak, Hoffman, and Duhachek 2003; Smith and Sivakumar 2004, Wang and Calder 2006), relational (Russell 2002), or motivational (Petty and Cacioppo 1979) consumer state. As a consumer state, engagement is treated a status or an outcome that consumers acquire as a result of their identity projects (Algesheimer, Dholakia, and Hermann 2005; Russell and Puto 1999;), social connections (De Valck, van Bruggen, and Wierenga 2009), passion and trust for the brand (Füller, Matzler, and Hoppe 2008), or driven by media narratives (Busselle and Bilandzic 2009) and market-designed experiences that create emotionally immersive interactions for customers (Calder, Malthouse, and Schaedel 2009; Higgins 2006; Mersey, Malthouse, and Calder 2010). Engagement manifests itself in various ways: affectively as an affinity for the brand (Calder and Malthouse 2008; Kozinets 2010a); cognitively as attention and mental activity (Smith and Gevins 2004); behaviorally as textual production (Jenkins 1992) or participation (Schroer and Hertel 2009; Sprott, Czellar, and Spangenberg 2009); holistically as a collection of logics (logics of entertainment, mastery, immersion, identification) (Askwith 2007) or as cognitive, affective, and behavioral activity (Hollebeek, Glynn and Brodie 2014).

While academia is more interested in identifying the underlying processes or drivers, the industry struggles to find the best possible way to measure engagement without becoming preoccupied with how the engagement is labeled. Most industry metrics consider engagement as a function of viewer attitudes (feelings), viewer behaviors (persistence, loyalty), or viewer attentiveness (recall, recognition) (Askwith 2007, p.29). With television audiences, engagement in practice is mostly used as a decision criterion to judge whether engagement with the content would transfer to the viewers' attitudes, behaviors, or attentiveness about the brand (*transference*). Aligned with this approach, the early engagement scales used the number of TVs tuned in to a particular program (e.g. Nielsen ratings). Yet, over the years, the ways industry understands engagement have evolved. A recent Forrester framework, for example, takes the discussion beyond Nielsen's reach and frequency focus and adopts a more relational and holistic view where they identify the components of engagement as: involvement, interaction, intimacy, and influence (Forrester 2009).

Engagement as a target-specific consumer state. Regardless of the context and the theoretical approach of the study, engagement has always been understood as the intensity of the relation between the individual consumer and a *specific object*, be it a brand or brand community (Muniz and O'Guinn 2001; Ouwersloot and Odekerken-Schröder 2008), a media text like advertisements (Wang and Calder 2006), a TV series (Askwith 2007), Wikipedia posts (Schroer and Hertel 2009), a media platform like a website (Calder, Malthouse, Schaedel 2009), newspapers (Mersey et al. 2010), a service provider (Malthouse et al. 2013), a movement (Putnam 2000), or a corporation (VKumar 2013). Stressing the single object focus, the Advertising Research Foundation (ARF) defines engagement as 'turning on a prospect *to a brand idea* enhanced by the surrounding context' (ARF, 2006). Similarly, Hollebeek et al. (2014) conceptualize CE as " a positively valenced brand-related cognitive, emotional, and behavioral activity during or related to focal consumer/brand interactions" (p. 149).

Congruently, engagement in brand community literature is defined as the interaction of community members, called brand fans, with the specific brand as a result of their boosted community relations driven by social ties and identity projects (De Vlack et al. 2009; Kozinets 1999; Muñiz and O'Guinn 2001; McAlexander, Schouten, and

Koenig 2002). Due to this keen focus of the existing engagement frameworks on the single object, they do not provide the necessary insights to describe the engagement dynamics for consumers interacting with multiple or rival brands, as DwE entails.

Social media performance and consumer-brand engagement. With the increasing influence of Web 2.0, consumers' brand relations are becoming predominantly mediated by the social media efforts of the brands – the official Twitter, Facebook, or Instagram brand accounts, related hashtags, online brand challenges and campaigns (Adjei, Noble, and Noble 2012; Gensler et al. 2013; Hennig-Thurau et al. 2010; Rohm, Kaltcheva, and Milne 2013). The "consumer-brand engagement" concept has been heavily used to refer to the interactive relationship consumers have with brands through social media platforms (Calder, Malthouse, and Schaedel 2009; Hollebeek et al 2014; van Doorn et al. 2010; Singh and Sonnenburg 2012). As Hollebeek et al. (2014, p.1) state: "Consumer brand engagement (CBE) concept has been postulated to more comprehensively reflect the nature of consumers' particular interactive brand relationships, relative to traditional concepts, including 'involvement.'" Social media marketing has even been called "the next generation of business engagement" (Deepa and Deshmukh 2013, p.2461). As consumers become more active (Hoffman and Novak 1996; Pagani, Hofacker, and Goldsmith 2011; Prahalad 2004; Ramani and Kumar 2008) and connected (Kozinets et al. 2010b), the consumer-brand engagement becomes more relevant and fundamental to understand consumers' relation with and experience of brands. DwE, indeed, facilitates consumer-brand engagement as DwE reveals a form of these interactive brand relationships where the "consumer engagement concept centers on specific interactive consumer experiences.... between consumers and the brand, and/or other members of the community." (Brodie et al. 2011, pp. 2-3). Our study builds on Brodie et al. (2001) and Calder et al.'s (2009)'s multidimensional, iterative, and dynamic understanding of engagement that entails the consumers' collection of interactive experiences with the brand. Also, our approach aligns with Van Doorn et al. (2010)'s understanding of engagement that "goes beyond transactions, and may be specifically defined as a customer's behavioral manifestations" (250) that could be induced by competitive marketing actions. Yet, our study expands these frameworks, as DwE illustrates that these interactive experiences do not only take place within a specific virtual community or a specific brand, but also with the rival brands.

Although the existing literature has focused on a brand-specific and brand-driven engagement approach, the marketing field has long studied multi-brand scenarios. The next section will review these scenarios to establish a firm conceptual foundation to understand *DwE* as an inter-brand and inter-communal social media practice and interaction.

Brands: Friend or Foe?

In this section, we organize the brand management and brand community literature that iterates multiple brand scenarios into two streams. The *cooperative* stream entails studies of multiple brands that strive to work towards a common purpose or benefit, thus acting in conjunction and in mutual assistance (e.g., Aaker and Keller 1990). This stream mostly studies topics like consumers' attitude for and relationship with brand extensions, management of brand portfolios, brand fit, or co-branding. Although multiple brands are considered in this stream, these studies still emphasize the branding activities of one company, or, in some cases, multiple companies whose interests are aligned (like in co-branding). Engagement with one brand would drive the engagement with the cooperative brands, like brand extensions (e.g., movie sequels, Sood and Dreze 2006).

The brand community literature mostly aligns with this cooperative understanding where consumers interact with one brand at the center and all the related brands and products that further the prosperity of the focal brand. When brand extensions fail and the brand therefore does not deliver the desired self-presentation benefits, Avery (2006) shows that brand community members engage in face-saving meaning-making, which preserves the ties to the brand. McAlexander, Schouten, Koenig (2008) define the consumer's life experiences within the broadly construed brand – composed of the brand, other community members, the company, and the product – as *the integrated brand community*. The stronger the attachment to each of these touchpoints in this broadly construed brand is, the stronger the engagement in the brand community would be. Yet, this stream still does not provide enough conceptual foundation to study DwE that spans across two rival brands with agendas and synergies of competition.

In contrast, the *competitive* research stream focuses on the competition between independently acting brands and examines consumer behavior regarding brand wars, brand rivalry, brand avoidance, market leader competition, or first mover advantage (e.g., Srinivasan et al. 2010). Although brand rivalry is believed to have negative consequences and/or connotations and is seemingly avoided by brands (Fournier and Lee, 2009, p.108), there are studies that identify positive outcomes of the rivalry. Libai et al. (2009), for example, shows that the interplay between within-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.

Brand community literature conceptualizes competition as rivalry between communities where the community members derive their sense of distinction, we-ness, and belonging through exclusion of and rivalry with other brands (Muniz and O'Guinn 2001). Muniz and O'Guinn (2001, p.420) introduces "oppositional loyalty" as one of the differentiating characteristics of brand communities: "Through opposition to competing brands, brand community members derive an important aspect of their community experience, as well as an important component of the meaning of the brand. This serves to delineate what the brand is not, and who the brand community members are not."

Building on this prominent work, scholars have found evidence for the existence of oppositional loyalty for rival brand communities like Coke vs. Pepsi (Muñiz and Hamer 2007), Mac vs. PC users (Hickman and Ward 2007), Ford vs. Holden (Ewing, Wagstaff, and Powell 2013), sports teams (Berendt and Uhrich, 2015; Hickman and Ward 2007) and for the splitting role of oppositional loyalty in consumption communities (e.g., snowboarders vs. skiers, Edensor and Richards, 2007).

Although both DwE and oppositional loyalty deal with the fans' relation with rival brands, they differ. Oppositional loyalty is an *attitude* that creates a belonging and we-ness for the members of the community while it distances the community members collectively away from the rival brand(s). Whereas DwE facilitates engagement across communities and rival brands, oppositional loyalty is more likely to discourage community members to interact with rival brands. From the oppositional loyalty perspective, the interactions with rival brands violate communal identity, and dishearten through a common attitudinal stand. Thus, oppositional loyalty is an attitude of brand community members that suggests disengagement.

Oppositional loyalty has been established as the attitude that drives the polarization of the brand and consumption communities where its existence (Muñiz and Hamer 2007), its role in initiating inter-communal conflict (Ewing, Wagstaff, and Powell 2013; Siraj-Aksit 2015), and its possible outcomes (Thompson and Sinha 2008; Libai et al. 2009) have been studied. Yet, cultivating the single brand focus, most of these studies iterate the oppositional loyalty concept and its outcomes *within the boundaries of a specific community*, typically through the accounts of the members of that community expressed for the rival brand community and its rival consumers. This lacking inter-communal focus prevents the exploration of the interactions of different brand fans and also their possible impacts on the involved brands and related performances. Muñiz and Hamer (2007), as an exception, study how the rivalry between Coke and Pepsi fans take place in a Pokemon video gaming community – rather than within one of the brand communities – after the members of both brand fans are prompted by a Diet Coke ad placed within the game, a neutral brand medium for both fan groups. Yet, none of these papers have actually studied the inter-communal clash and inter-brand interactions of multiple brand fans where rival brand fans engage in a conversation or migrate across platforms to engage with the rival brand community as it happens in real-life brand rivalry cases. In the existing studies, the monadic unit of analysis – driven by the existing conceptualization of competition favoring the welfare of a single brand at the expense of other brands – and reliance on fan accounts of one brand community do not explore and describe a fan's actual interaction behavior with rival brands, what we call *Dancing With* *the Enemy (DwE)*. To our knowledge, our study is the first one that actually iterates the inter-brand and inter-communal engagement and its effects driven by consumers' interaction with the rival brands. Our dyadic approach helps us uncover the interdependency between rival brand dyads as well as the communication, conversation, and clash between their fans. In real-life cases, fans of rival brands interact with each other and these interactions produce conversations and discourses. The failure to use a dyadic approach will limit the data on how one set of fans talks about a rival set. As such, only measuring and exploring attitude, applies to oppositional loyalty, but not DwE.

Broadened Understanding of Engagement

The field assumes and converges on the idea and practice that engagement is a brand-specific consumer state and is limited with the brand owned, facilitated, or operated touchpoints (e.g., website, social media accounts, brand communities). In academia and in practice, consumer-brand engagement and online brand performance are measured or assessed using consumers' activities and practices interacting with the specific brand's media platforms and social media accounts. This perspective isolates the engagement, the brand, and brand's related performance from those of the other brands in the marketplace. However, due to the exponential rise of social media that provide consumers proliferated ways and easier access to media platforms to voice their opinions, a brand with a highly identified and dedicated fan base could have a far-reaching impact on a rival brand in the social universe (Melancon and Dalakas 2014).

In sum, we propose to embrace the interdependency and the synergy of rival brands to understand consumer-brand engagement in the connected, digitalized, and social media driven mediascape. To this end, we introduce a ***broadened understanding***

of engagement that is not limited by the individual consumer interactions with a specific brand and/or brand owned touchpoints; but one that is facilitated by the interactive consumer behavior across rival brand dyads, and the subsequent ripple reactions, which we label Dancing with the Enemy (DwE). Figure 1 visualizes our conceptualization of engagement as broadened by the three types of DwE. (Tables and figures follow References.)

Instead of isolated brand pyramids with engaged fans at the top, Dancing with the Enemy bridges the rival brand's fan communities through across, discourse and ripple interactions – which in turn may drive higher engagement among fans (the upward arrow in Figure 1). We next turn to our empirical evidence for the presence of DwE, its triggers, and its consequences for the rival brand dyads.

Method

This is a multi-method and multi-context paper that combines qualitative and quantitative approaches. In the first, qualitative phase, we explore and describe types of Dancing with the Enemy. In the second phase, we collect Facebook comments to perform sentiment analysis in order to classify DwE, and to distinguish volume and valence of the overall brand Facebook page. In our third phase, we address our research questions of whether, how much, and for how long DwE is driven by brand triggers and drives the volume and valence of social media metrics of engagement. Based on the literature review, we choose the brand rivalries of Coke-Pepsi (Muñiz and Hamer 2007) and Apple-Samsung (Berendt and Uhrich 2015; Sponga 2013;) as an example in a respectively low-technology and a high-technology industry. These rather different contexts are likely to reveal some differences in the prevalence, triggers and consequences of DwE, given that our empirical analysis cannot feasibly examine DwE for all known brands. As the first paper to study DwE, moving beyond a single brand rivalry example shows that DwE manifests itself in different product categories.

Data Collection

We collect digital data via a customized social media web crawler that collects all publicly available information – without any time restrictions – from an accessible Facebook page. The crawler uses R in Version 3.2.1 to access Facebook through the Application Programming Interface (API) and the open Facebook Graph API Explorer. The crawler can access and extract the posts, number of likes and shares for each post, all publicly available information about the poster, all comments of each post, the number of likes for each comment, and all publicly available information about the commenting person. Wherever and whenever necessary, mostly used in the first phase, we relied on netnography (Kozinets 2002, 2010) to explore and get a richer understanding of the DwE practice by immersing ourselves in the publicly available information in company websites, social media sites, and related Apple, Samsung, Coke, and Pepsi online brand communities. Our netnographic efforts started with the ideation stage in 2012 and persisted throughout the full study.

Data Set

We extract social media data from the high-traffic Apple, Samsung, Pepsi, and Coke Facebook pages. For each of these brands, our data set is composed of posts, comments, the date of the post/comment, poster ID number, post ID number, and number of likes on their respective Facebook pages. Our social media data helps us capture the way that fans of both brands in the dyad talk to one another and let us observe "the behavior and communications of fans in a naturally occurring, social setting, one that is very similar in structure to conversational discourse" (MacKinnon 1995, as cited in Muñiz and Hamer 2001, 356). Since the Facebook pages for the brand dyads – Apple-Samsung and Coke-Pepsi – have been initiated at different dates, we establish the data set to the period where the Facebook sites were active for both brands of the dyad. Please refer to Table 1 for Facebook data details.

First Phase: Exploring DwE

Our first phase is exploratory as our first research questions ask how DwE manifests itself as an inter-brand and inter-communal practice, and what triggers DwE.

Data analysis. Throughout the first phase, we predominantly used qualitative approaches and netnographic principles (Kozinets 2002, 2010c) to comb through the brand landscape and explore brand rivalries and also the related brand triggers that might facilitate and intensify DwE. We utilized secondary resources, social media sites, brand communities, news articles, online forums, brand websites, blogs about the dual brand couplings, and brand Facebook pages. In addition to Pepsi-Coke and Apple-Samsung dyads**,** our netnographic insights for the first phase are driven by the several rival brand dyads listed on Table 1. To be able to investigate drivers and triggers of DwE, we additionally collected all available public data for each brand in the analysis. Via netnographic procedures, we gathered the trigger timelines for each brand where we have crawled events back in time corresponding to the time frame of collected social media data for each brand. This was achieved by crawling the company's official press releases, online business databases and news websites to capture all relevant company news, which may affect social media chatter. The query identified 626 events for Apple, 533 events for Samsung, 72 for Coke, and 240 for Pepsi. The different time frames on each brand's Facebook data explains the differences in number of identified events for each brands. Events were classified into different categories to give a better understanding of the drivers and to distinguish between different trigger forms. Table A1 in the Appendix gives more explanation about the identified triggers.

Additionally, we have conducted interpretive analysis on the relevant Facebook data sets to understand the ways DwE manifest itself between the rival brand dyads. We have coded the Facebook data for common themes and patterns using a process of induction, iteratively across data and theory, until some interpretive strength is reached (Katz 2001). As a result of this inductive analytic process, we identify three types of DwE: Migration (posting on both brand sites of the dyad), Discourse, (within the central brand's page), and Ripple (on the central brand's page reacting to rival brand fans), as we explain in detail in the findings section.

Second Phase: Sentiment Analysis and Content Analysis for Valence and DwE

Building on the first phase, the second phase classifies different types of DwE and also the valence (sentiment) of all comments on the brands' Facebook pages.

Sentiment analysis. The sentiment analysis classifies text in categories, such as positive or negative emotions. As exhibited in the Appendix A1, we choose for the Machine Learning Approach with Support Vector Machines (SVM), which combines human coding of a training sample with machine coding of the millions of other comments.

To train the SVM, we randomly select 500 comments from each social media data set (Apple, Samsung, Pepsi, and Coke). For each data set, we use a sample of 50 M-Turk specialists to classify comments as positive, negative or neutral. Each comment is classified by at least three coders. To test the classification power of the algorithm, a subset of 100 positive and 100 negative comments is generated for each data set to train our SVM. After training the remaining 50 positive and 50 negative comments from the M-Turk set, comments are classified with the help of the SVM integrated in the "RTextTools" R-package (Version 1.4.2). For all data sets, the prediction-hit-rate is above 90%. Overall, this can be considered as highly satisfactory. Next, we re-train the SVM with the full M-Turk training set for each brand and classify all extracted posts and comments by our crawler. Table 2 exhibits the MTurk classification, prediction hit rates, number of posts, and number of positive/negative comments for each brand.

Content analysis. In addition to the sentiment analysis, identification and categorization, DwE requires a content analysis of all specific brands in the Facebook comments and posts. The method has commonly been used attain a condensed description or the categorization of the phenomenon of interest (Berelson 1952; Kassarjian 1977; Kolbe and Burnett 1991; Krippendorff 1980) and also in marketing studies (e.g., Humpreys 2010, Kübler and Albers 2010). We created all possible scenarios of brand mentions, driven by the findings of the previous research that stresses the role and type of conversation between fans of the rival dyad, and combined them with the sentiment analysis to obtain the categorization matrix shown in Table A2 in the Appendix.

A research assistant, extensively trained in structured content analysis, classify the data into the different types of DwE interactions (Burnard 1996; Weber 1990).

Disagreements, only observed in a handful of posts, are solved by consensus after discussion with the first author. Next, we give more details on each type of DwE.

For *DwE Across*, we identify fans that have posted in both rival brand's pages. For Coke-Pepsi, for example, we found the common poster IDs on both Coke and Pepsi pages and labeled the posts by those ID numbers as DwE Across. To identify the *DwE Discourse* and *DwE Ripple*, we curated the possible scenarios of brand mentions – of the focal brand, enemy brand, and third brands – and identified keywords as well as their written versions and inaccuracies to allow us to classify the Facebook comments that fulfill the criteria. Table A3 in the Appendix shows the keywords for DwE Brand Mention Coding.

Third Phase: Dynamic Interactions Among Triggers, DwE, Volume and Valence

Now we have (1) identified specific comments as DwE behavior and (2) calculated the positive and negative sentiment of each brand's overall comments, we address the remaining research questions on the extent DwE is driven by triggers and drives the volume and valence online metrics that brand managers use to measure engagement. These metrics have been quantitatively linked to brand attitudes, sales and even company stock market performance in several recent papers (see Yu et al. 2015 for review and meta-analysis). Therefore, in absence of actual brand sales data (as is the case in our research), we refer to those papers to make this final link with performance.

Time series analysis. We deploy persistence modeling (e.g. Dekimpe and Hanssens 1999; Trusov et al. 2009). First, we use Granger Causality tests with lags from 1 to 14 (days) to investigate the *temporal causality* among DwE and online sentiment.

Next, we quantify the relations among these variables with dynamic system models; i.e. Vector Autoregressive (VAR) or Vector Error Correction (VEC) models depending on the outcome of unit root and co-integration tests (Dekimpe and Hanssens 1999). Specifically, we include as endogenous variables the daily time series of (1) brand triggers, (2) DwE types, (3) volume and valence for both involved brands in the category. From these models, we derive the forecast error variance decomposition (FEVD) and the generalized impulse response functions (GIRF). The FEVD quantifies the extent to which a variable is dynamically explained by the other variables in the model – thus addressing our last two research questions. The GIRF quantifies the magnitude and timing of the DwE effect on volume and valence metrics, which provides us with concrete managerial implications from stimulating DwE activity.

Findings: Dancing with the Enemy (DwE)

Findings from Phases 1 and 2: DwE Manifestation, Types and Triggers

As a result of our exploratory phase, we have a deeper understanding of the DwE practice, its triggers, and the ways this new social media interaction manifests itself. Building on the framework of consumer engagement (Van Doorn et al. 2014), we considered antecedents related to the customer- (such as identity and perceived costs/benefits), the firm (such as brand characteristics and firm reputation) and the context (such as the competitive nature and the technological information environment, like a brand Facebook page). Although brand rivalry might happen between any brands, DwE is more common and more prominent for brands that offer comparable products (Thompson and Sinha 2008), have vibrant and dynamic brand communities displaying a common oppositional attitude for similar brands (Muniz and O'Guinn 2001), and display a certain type of polarized competition and fan base (Luo, Wiles, Raithel 2013). Customers engaging in DwE are likely to have category and brand involvement, a strong perceived benefit from self-enhancement (e.g. Hennig-Thurau et al. 2004), and a low perceived cost of time (Van Doorn et al. 2010).

Brand triggers. Our netnographic process and interpretive analysis identified four emergent categories of brand triggers that might facilitate DwE: new product related, brand related, and company related. Table A1 in the Appendix shows details and examples of brand triggers, all compiled from information available to the public.

Types of DwE. Our exploratory phase revealed that consumers engage and interact with rival brands in different ways. We identified three ways that this new social media interaction manifests itself: Across, Discourse, and Ripple. DwE Across is the migratory aspect of the phenomenon where fans actually interact with both Facebook pages of the brand dyad. By using consumers' Facebook IDs, we have identified the consumers who have posted on both brand pages for each dyad and labeled those posts as DwE Across. Most existing social media interaction studies acknowledge that consumers become more active and nomadic across brands and media touchpoints as a result of the intensifying role of digital media and mobile technologies. DwE Across reflects this nomadic and mobile behavior of digital age consumers while they are interacting with the rival brands.

DwE Discourse, on the other hand, looks at the consumers who come to the Facebook page of a brand to show their loyalty, fanaticism, and support for the rival brand through their posts. In our case, for example, we have identified various ways Samsung fans could engage with the Apple's Facebook page and vice versa. The existing research on how rival fans speak about each other supports our DwE Discourse classification criteria as one of the three layers. Although the existing research doesn't study the two-way dialogues between rival fans, it states that when fans of a brand speak of rival fans, the rhetoric is mostly hostile, playful, sarcastic, stereotyping, cruel, and sometimes insulting (Ewing, Wagstaff, and Powell 2013; Hickman and Ward 2007; Seraj-Aksit 2015). We used the categorization matrix to code DwE Discourse for each brand on the dyad.

Through our exploratory phase, it becomes evident for us that DwE Discourse influences the ways fans of the central brand respond to DwE within comments, extending and lengthening the role of DwE and its impact on the social media performance of and engagement of both brands of the dyad. In this rein, we identify DwE Ripple to understand the reactions of fans to the DwE Discourse on the central brand's site. In sum, we have identified the components of DwE as Migration, Discourse, and Reaction, facilitating a broadened understanding of engagement. Please see Table 3 for the details on DwE manifestations for each brand.

Table 3 shows that DwE is more prevalent in the low technology brand rivalry (4.6% and 3.3% of all comments for respectively Coke and Pepsi) than in the low-technology brand rivalry (1.1% and 1.3% for respectively Apple and Samsung). Within this DwE behavior, migration is most prevalent for challenger brands – i.e., brands with comparably less brand equity – Pepsi (61%, discourse 28%, ripple 11%) and Samsung (49%, discourse 34%, ripple 17%), while ripple is most prevalent for Coke (51%; discourse is 12%) and discourse for Apple (58%, ripple is 16%). We infer that fans of the challenger brands may be more active and nomadic across social media to compensate for the difference in brand equity between the rival brand dyads.

This classification has revealed that the inter-brand and inter-communal interaction cannot be explored only through the rhetoric of one community towards the other as detailed by the existing studies. When rival fans and rival communities clash, there are several other ways of interacting for rival fans, including interacting with both brands or engaging with the rival brands at their own site. Along the same lines, DwE Ripple illustrates that this inter-brand and inter-communal interaction impacts the way fans of a brand respond to the interaction of the rival fans. Yet, the dyadic data is essential to uncover these inter-brand conversations and migrations.

Findings from Phase 3: Correlation and Causality

Tables A4 and A5 in the Appendix shows the mean, standard deviation and the variable correlations used in the time series analysis of Coke-Pepsi and Apple-Samsung. Note that we combine DwE Discourse and DwE Ripple (which are highly correlated) as DwE Within to save degrees of freedom in our analysis. For the Coke-Pepsi data, the highest correlations are for CokeDwEAcross: 0.92 with Coke Posts and 0.84 with CokeDwEWithin. Pepsi posts are correlated 0.69 with PepsiDwEAcross and 0.63 with PepsiDwEWithin. All other correlations are below 0.42. For the Apple-Samsung data, the highest correlations are for Apple Posts with AppleDwEWithin (0.78) and with AppleDwEAcross (0.68) and of both AppleDwE types with each other (0.54). Brand trigger Apple Other Events is correlated 0.76 with Apple new product announcements and 0.59 with Apple Launch. All other correlations are below 0.42.

The Granger causality tests reveal several interesting causality patterns (at $p < 0.05$), which are visually summarized in Figures 2 and 3 for respectively Coke-Pepsi and Apple-Samsung.

Consistent for both rival brand dyads, the leading brand's (i.e., the brand with comparably with higher brand equity) DwEAcross drives not only its own Posts and Valence, but also the challenger brand's DwEAcross. In turn, challenger brand's DwE Across drives leading brand's DwE Within. These cross-brand page interactions clearly demonstrate the *power of DwE to transcend a specific brand community.*

Regarding *cross-brand engagement effects*, either Volume or Valence in the brand community is driven by the rival brand's DwE or its Volume. Coke Volume is driven by Pepsi DwE Across , while Pepsi Valence is driven by Coke Volume. Apple Volume is driven by Samsung DwE Within, while Samsung Valence is driven by Apple Posts, and in turn drives Apple DwE Within. Coke Volume is driven by Pepsi DwE Across, while Pepsi Valence is driven by Coke Volume. In both brand dyads, dual causality exists among their Valence metrics.

Which brand triggers drive DwE, and thus have the power to jump-start the positive spirals uncovered in the Granger causality tests? Apple DwE is driven by Apple new product announcements, while Samsung DwE is driven by Apple new product launches and by Samsung Other News, which includes acquisitions.

Importance of DwE as a dynamic explanatory power of engagement. Because unit root tests show all variables are stationary (results upon request), we estimate a Vector Autoregressive (VAR) model for each rival brand dyad. Please see appendix for model variables, lag length selection, explanatory power and observation-to-parameter ratios.

Based on the selected model, the FEVD reveals how much a variable is dynamically explained by its own past and the current and past of the other endogenous variables in the model (see Srinivasan et al. 2010 for a recent marketing application). Like Srinivasan et al. (2010), our main objective for the FEVD is to determine whether performance (volume and valence) is mainly driven by DwE activity versus the brand triggers. To provide an acid test for DwE, we causally order all brand triggers before DwEAcross, followed by DwE Within and the Volume and Valence metrics. For instance, Figure 4 shows the FEVD of Apple Volume (Posts) for 14 days (2 weeks).

Apple new product announcements explain 13% of its Facebook page Volume on day 1, but influence is reduced to 10% the next day and 9% in the long run. In contrast, Apple DwE Across grows in explanatory performance from 16% in day 1 to 36% after a week, surpassing even the own past of Apple Volume Posts (which is typically the main driver of a marketing performance time series). Apple DwE Within grows from 19% to 22% in the same time. Thus, Apple DwE activity dynamically explains 58% of the changes to Apple Volume (Posts), despite representing only 1% of all posts!

Evaluating all results at day 14, we obtain the main drivers of DwE in Appendix Tables A6 and A7 for respectively Coke-Pepsi and Apple-Samsung. As usual for marketing time series, the main driver is the series' own past ('inertia' in Nijs et al. 2007; Srinivasan et al. 2008). The exceptions are Apple Volume Posts, Coke Volume Posts and Pepsi Volume posts, which are mainly driven by their DwE Across activity. In all cases, DwE activity is a "Top 3" driver of both Volume and Valence. Thus, the FEVD results are consistent with our contention that *DwE is a substantial dynamic driver of both Volume and Valence* metrics of engagement (despite the fact that we prioritized brand triggers by putting them earlier in the causal ordering). Thus, DwE is not simply a conduit for brand trigger effects. Moreover, the FEVD of DwE shows that (1) *DwE Across largely feeds on itself* (most of its variance explained by its own past) and then by brand *triggers* and (2) *DWE Within is mostly driven by DwE Across.*

Interesting differences for the brands suggest boundary conditions that can become the focus of future research. Leading brand's Coke DwE Across is driven more by own brand triggers than by the rival brand's triggers, while Pepsi DwE Across is more driven by Coke DwE Across and Coke triggers than by Pepsi triggers. Compared to the Apple/Samsung high-technology rivalry, we observe that both own and rival brand triggers explain a larger portion of DwE for the low-technology Coke-Pepsi rivalry.

Sign, magnitude and timing of DwE effects on Volume and Valence metrics. Based on the same VAR model, the Generalized Impulse Response Functions (GIRF) show the sign, magnitude and timing of 1 unit increase in DwE activity on Volume and Valence Metrics. For instance, Figure 5 shows the response of Coke Volume Posts to respectively Coke DwE Across and Pepsi DwE Across, with the typical 1-standard error bands (e.g. Trusov et al. 2009).

While Coke DwE Across has its peak impact on the same day, Pepsi DwE 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. In table 4, we summarize the effect of Coke DwE Across has a cumulative (immediate) effect of 138.07 (42.91), a wear-in of 1 day and a wear-out of 5 days for a total duration of 6 days. Likewise, Pepsi DwE Across has a cumulative (immediate) effect of 212.91 (24.75), a wear-in of 2 days and a wear-out of 4 days.

In all cases, the effect of DwE (Across and Within) is positive on Volume, but negative or insignificant on Valence. Coke Volume and Coke and Pepsi Valence see the peak effect of Pepsi DwE in the second day. All effects have died out within eight days. The largest cumulative effects are *cross-brand*, from Pepsi DwE on Coke Volume. For the Apple-Samsung dyad, table 5 displays the volume and valence effects.

In the Apple-Samsung dyad, Volume is driven by own DwE Across, not by that of the rival brand. Compared to Samsung, Apple sees much higher and much longer Volume effects: up to 28 days (four weeks). Both brands see Valence decrease with Apple DwE Across, but increase with Samsung DwE Within. The highest Valence is Samsung DwE Across on Samsung valence (6% higher positive to overall posts).

In sum, the GIRF analysis across the four studied brands reveals *the important managerial implications* of DwE Activity: 1 more DwE Across comment on the brand's Facebook page increases the overall volume of posts by respectively six (Samsung), 65 (Pepsi), 138 (Coke) and 532 (Apple). Likewise, one more DwE Within comment on the brand's Facebook page increases the overall volume of posts by respectively two (Samsung), 40 (Coke), 88 (Pepsi) and 174 (Apple). These higher benefits for Apple may be due to the unofficial nature of its page, allowing more free conversation. The GIRFs of brand triggers on DwE and Volume (available upon request) show that own brand triggers are most powerful in driving the Facebook page's DwE. In the cola category, Pepsi *Advertising* and Coke and Pepsi *Public Relations/Sponsorships* are the main drivers of DwE activity. In contrast, *product innovation* is key in the Apple-Samsung rivalry: *Announcements* for Apple and the actual *Launch* for Samsung. Cross-brand trigger effects exist but are relatively small and short-lived. Coke DwE responds to Pepsi Ads and PR on the second day, while Pepsi DwE responds right away to Coke PR. Apple DwE responds to Samsung Launch on the second day, while Samsung DwE responds right away to Apple New Product Launch. Thus, DwE activity can be influenced by variables (largely) under managerial control.

Discussion

First and foremost, our study provides a reformist perspective by asserting and demonstrating that fans of a specific brand also interact with the rival brands and rival fans, impacting the social media performance of the rival brand dyads and thus cultivating overall engagement. In our field, the existing understanding of social media interactions is very limited and mostly focuses on the social information transmission (namely, word of mouth) (MSI in Social Interactions and Social Media Marketing Call for Papers 2014). We expand and enrich this literature through the introduction of an inter-brand and inter-community social media interaction, which we call Dancing with the Enemy (DwE). We also show the triggers and dynamics that facilitate these interactions; thus bolstering social media performance and engagement. Our study thus introduces DwE, explores its triggers and layered manifestations, its role in driving engagement for rival brands, and also its impact that persists for the rival brand dyad.

Our study directly contributes to the existing understanding of consumer-brand engagement, a very popular and common performance metric and a brand objective, as it is understood, conceptualized, and practiced in our fields (Calder, Malthouse, and Schaedel 2009; Brodie et al 2001; Hollebeek et al 2014; van Doorn et al. 2010). The proposed inter-brand and inter-communal understanding of engagement broadens the scope of the engagement concept to include: (1) fan interactions with rival brands; (2) the migratory and nomadic behavior of fans across brands, interacting with multiple and rival brands; and also (3) the impact zone and ripple effects of those inter-brand practices on the rival brand dyad and respective brand communities.

The three layers of DwE – migration, discourse, and ripple – call attention to their differences and dynamic interactions. Although existing research has established that the conversations between the fans of rival brands can take several forms, from insults to jokes, our study clarifies the role of this discursive element of the inter-brand and inter-communal social media interaction. Our study also illustrates how this discursive aspect should facilitate or be facilitated by other manifestations of DwE to bolster overall consumer brand-engagement.

Our findings highlight the key role of fans posting *across* both rival brand pages. Because DwE Across is a strong driver of page posts for each brand dyad, these fans are likely very engaged with and responsive to brand communications. Moreover, DwE Across unlocks the full DwE dynamics of Discourse and Ripple. DwE Across mostly feeds on itself and brand triggers. In other words, DwE Across respond to the triggers and does not depend on any other manifestation of DwE to bolster the DwE dynamics.

Our aggregate time series analysis shows that, similar to the pre-purchase mindset metrics in Srinivasan et al. (2010), DwE activity represents an important missing link in the relationship between the brand marketing triggers and online metrics of engagement.

We also contribute to a new understanding of competition in rival brand dyads and in their respective brand communities. Our findings support that rival brands would benefit from a collaboratively and synergistically competitive mindset where they can utilize the prominence of DwE for fostering their own social media performance and consumer-brand engagement. Our study indicates that fans, even the rival ones, are not passive actors in a company's competitive strategies but rather active and proactive participants and important assets and agents that could shape competition and rivalry between brands. We clearly illustrate that competition is **not a zero sum-game** in the dynamic, multi-channel, social, and interdependent digital brandscape.

Thus, our findings contribute to and expand the studies that have explored the synergistic competition between brands and across brand communities where rivalry is deemed to have positive effects. Our research aligns with the similar interest of academic marketing researchers who are interested in the productive aspect of competition in brand wars (e.g., Libia et al. 2009) and also in brand communities (e.g., Berendt and Uhrich 2015), but it additionally provides triggers and a mechanism to unlock the benefits of the brand rivalry for a specific goal, i.e., bolstering overall brand engagement.

In sum, the contribution of this research for both marketing managers and scholars is to show that the fans of a rival brand could impact the brand performance of the brands in a brand rivalry and also foster consumer-brand engagement. Our study empirically elucidates what engagement in social media-driven brand landscape could be, its triggers, dynamics, and consequences for each rival brand.

Limitations of our study include the choice of rival brand dyads and the Facebook page-only collection of data. Moreover, future research should compare our choice of sentiment analysis and Valence (as the ratio of positive to all comments) with alternative approaches. This may well affect our observation that DwE sometimes reduces Valence (which may be due to the stronger increase in neutral versus in positive comments).

Finally, an individual-level analysis should uncover answers to additional research questions such as: (1) which type of fans engage (most) in DwE behavior; (2) what motivates them to do so; and (3) how influential fans are in the brand communities; and how DwE behavior is perceived by other community members.

Implications

Dancing with the Enemy in rival brand dyads has substantial managerial implications in brand management, digital marketing, and integrated marketing communications. Our study points to the need for a new engagement metric that integrates the migratory and nomadic behavior of the consumers. Currently, there is no social media performance metric or a method to measure engagement based on the rivalry dynamics. Managers do sometimes perform brand audits to understand social media performance of competing brands, but mostly use these to benchmark individual brand performance, rather than envision an integrative and layered approach as we detail through DwE.

The online marketing industry wholeheartedly adopts the Forrester framework — owned, paid, earned media classification — to explore and assess the social media activities and performances of the brands. This framework still assumes that these three — owned, paid, and earned — are the possible classifications of touchpoints that can be used by a single brand or portfolio of brands to facilitate social media performance, thus the engagement. Yet, our study strongly supports that the brands and digital managers experiencing a brand rivalry should consider and also leverage the competitive dynamics facilitated by the mobilized and migratory rival fan behavior.

The industry also glorifies the use and role of marketing analytics to understand and predict the consumers' social media interactions and behavior. The analytics report and manage the participation at particular touchpoints like company website, Twitter, Facebook. Based on our findings, we recommend brands utilize data on the conversations between fans and rival fans. Our study highlights that the rival brand dyads are uneven in terms of the brand equity the two brands possess. Our study also analyzes the differential impact the brands with comparably higher brand equity impose on the rival brand dyad and also on the mechanisms and triggers of DwE.

Our study identifies a new "influencer" segment whose cross-media practice better lends itself to facilitating strategic performance in addition to impacting engagement dynamics. The fans who interact with the rival brands not only foster engagement for these brand dyads but also highly engaged consumers themselves. The existing literature has firmly established that highly "engaged fans are more responsive to advertising (Cunningham, Hall, and Young 2006; DePelsmacker, Geuens, and Anckaert 2002; Gallagher, Foster, and Parsons 2001; Wang, 2006), more apt to support viral content (Brodie et al. 2013), or even expedite strategic performance (Kumar and Mirchandani 2012; Malthouse, Vandenbosch, and Kim 2013). Rather than the existing set of criteria to identify influencers based on their attitude or behavior with your brand, our findings offers an alternative approach to further your brand, social media, and even strategic goals by reaching out to the rival fans and leverage their strength in this polarized brand rivalry and audience base. Identifying various interactions between consumers and the fans of the rival brand also crystallize the WOM dynamics within and across brands.

Appendix

A1 Choice of sentiment analysis

Sentiment analysis has a rich tradition in linguistic and computer science as a data analysis method. Both fields developed a set of computer-based tools to automatically analyze and assess text content, which is commonly referred to as Natural Language Processing (NLP). Despite the rich opportunities of text processing with online and social media data, so far NLP tools have only recently seen adoption in marketing research. Current applications focused on measuring brand performance with the help of social media data (Schweidel and Moe 2014; Tirunillai and Tellis 2014), analyzing social media reactions to product recalls (Abhishek and Tellis 2015), and measuring shareholder reactions to online chatter (Tirunillai and Tellis 2012).

NLP distinguishes between two major forms of text processing: lexicon based and machine learning based sentiment analysis. Lexicon based approaches use word lists, which represent e.g. positive and negative sentiments (Pennebaker and King 1999; Pennebaker, Booth, and Francis 2007). Lexicon-based-algorithms then count the occurrence of words from each list. For each text document a score of positive minus negative sentiments is computed. Contrary to lexicon-based approaches, machine-learning-based sentiment analyses utilizes sets of hand-coded sentiments, instead of pre-prepared lists, that are used to train algorithms to classify texts in categories (Pang, Lee, and Vaithyanathan 2002). The algorithm uses the text and the hand coded classification information to calculate the likelihood of a positive or negative feeling given a combination of words in the training set. This brings several advantages. First, through hand-coding training sets can be specifically tailored to the topic and research question

(Mullen and Collier 2004). Second, instead of only counting single words, machine learning allows accounting for co-occurrences of words. This is especially important in case of short texts such as social media posts or comments. A comment such as "*freaking awesome*" would be miss-classified by most basic lexicon based approaches. Whereas "*freaking*" would be classified to be negative, and "*awesome*" to be positive – resulting in a neutral (1pos – 1neg) overall classification – a machine learning based algorithm accounts for the co-occurrence of both words and classifies the comment correctly as positive. Machine learning based sentiment analysis uses different types of classification algorithms like Naïve-Bayes classificators, Maximum Entropy classificators, Decision-Tree-Systems or Support Vector Machines (SVM) (Pang, Lee, and Vaithyanathan, 2002). Latest NLP research shows that SVM deliver best classification results in case of short texts like social media posts, comments or tweets (Go, Bhayani, and Huang 2009). Being faster and more efficient, SVM are especially suited for larger sets of texts. Therefore, we apply a SVM approach to sentiment analyze our aggregated data.

Similar to other NLP approaches (see e.g. Tirunillai and Tellis 2014), we transform each post and comment into a machine process able text corpus by first transferring all text into small letters and deleting all signs (such as e.g. , . ! "; etc.). We also stem the words (i.e., convert to the root form—e.g., "like" for "likable," "liked," and "liking") using Porter's (1997) stemming algorithm. Then we remove all stop words (e.g., "the," "and," "when," "is," "at," "which," "on," "in") that are used for connection and grammar but are not required for meaning.

A2 VAR Model Specifications

For each brand dyad, we include an intercept and day-of-week dummies as exogenous variable, and the triggers, DwEAcross and DwE Within for each brand and the volume and valence metrics for each brand as endogenous variables. The Schwartz Information Criterion suggests 1 lag as optimal for both models, whereas the Aikake Information Criterion suggest 1 lag for the Coke-Pepsi model, and 2 lags for the Apple-Samsung model. For comparison purposes, we proceed with 1 lag for both models, which yields an observation-to-parameter ratio of 5.4 for the Coke-Pepsi model, and 23.8 for the Apple-Samsung model, both above the minimum suggested in Leeflang et al. (2014). Omitting the 6 day-of-week dummy variables (whose effects are insignificant in 96% of all cases) increases these observation-to-parameter ratios to respectively 19.7 and 33.3 without changing any of the substantive results (results available upon request). Likewise, estimating a 2-lag model for Apple-Samsung yields the same explanatory power (up to 2 digits) and substantive results (available upon request)

For the full, 1-lag model, the explanatory power (R^2) for each key variable is shown in Appendix Table A8 (see below).

In each rival brand dyad, the model explains substantially more variance of DwE 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 DwE metric.

Table A1: Details on Brand Triggers

Types of Triggers	*Events*	Examples			
		Apple	**Samsung**	**Coke**	Pepsi
New Product Related	***Announcements***	Apple Introduces iPhone 5	First Smartphone-Powered Virtual Reality Experience Available Early Dec. in U.S.	Coca-Cola Produces World's First PET Bottle Made Entirely From Plants	Diet Pepsi Responds To U.S. Consumer Demand For Aspartame-Free Diet Cola
	Previews	Apple Watch In-Store Preview & Online Pre-Order Begin Friday	Galaxy S5, Gear 2 and Gear Fit available for pre-order and hands-on demos in more than 61 markets to celebrate Samsung’s global flagship launch	N/A	N/A
	Launches	iPad mini with Retina Display Available Starting Today	The new flagship smartphone and wearables are now available in 125 markets	Coca-Cola Life Arrives On Shelves Nationwide	N/A
	Product Updates	Apple Updates MacBook Air With Next Generation Processors, Thunderbolt I/O & Backlit Keyboard	Samsung is planning to deliver regular security updates around once a month to Galaxy devices	Sprite Brings Back Popular Flavor Created With LeBron James	Stacy's Pita Chips Announces Special-Edition Salted Caramel Holiday Flavor Sure To Impress The Most Sophisticated Of Paletes

Integrated Marketing Communications Related	***Advertising Campaigns***	N/A	Samsung Partners with GQ to Create Global Fashion Native Campaign Featuring Samsung Galaxy S6 and S6 edge	Coke Zero™ Tips Off Drinkable Advertising Campaign at NCAA® Men's Final Four® In Indianapolis	PepsiCo's Doritos Brand Issues Last Call For Fans Around The World To Create Doritos Ads For A Shot At A $1 Million Grand Prize And Universal Pictures Dream Job
	PR/Sponsorship / Advertorial	Apple Awarded $30 Million iPad Deal From LA Unified School District	Refining the idea of the smart wearable	Coca-Cola Invests In Women Who Advance The World	PepsiCo Joins Calls for Action on Climate Change; Announces Goal to Phase Out HFC Equipment by 2020; and Reports Progress on Sustainability Goals
Brand Related	***Co-Branding***	IBM MobileFirst for iOS Apps	Samsung and Marvel team up to bring the Galaxy S6 edge a new Super Hero makeover	N/A	N/A
	Retail	Apple Store Grand Central Opens Friday, December 9	An innovative destination inviting customers to experience Samsung's smart mobile devices	N/A	N/A
	Strategic Partnerships / Collaborations	Verizon Wireless & Apple Team Up to Deliver iPhone 4 on Verizon	Samsung and Oculus collaborate to create an immersive new dimension of mobile life with the first widely available mobile VR headset optimized for Galaxy Note 4	The Coca-Cola Company, SABMiller And Coca-Cola SABCO To Form Coca-Cola Beverages Africa	PepsiCo Beverages Become Official Soft Drink Of Live Nation

	Discontinuations	iPod Touch (5th gen) (16 GB)	N/A	N/A	N/A
Company Related	***Performance***	iPhone 5 First Weekend Sales Top Five Million	Four GALAXY S4 smartphones sold every second	The Coca-Cola Company Grows Roster of Billion-Dollar Brands to 20	PepsiCo Declares 43rd Consecutive Annual Dividend Increase
	Acquisitions	OttoCat-Search engine	Samsung to Acquire LoopPay, Transformative Digital Wallet Platform	Coca-Cola China Offers to Acquire Xiamen Culiangwang Beverage Technology Co., Ltd	Worldwide Growth in Stevia Products & Natural Sweeteners Leads to Acquisitions, New Patents and Multi-Million Dollar Purchase Orders
	Leadership	Sue Wagner Joins Apple's Board of Directors	Former Coca-Cola marketing executive to help advance the company's global marketing initiatives	The Coca-Cola Company Announces Chief Marketing and Commercial Officer Joe Tripodi to Retire; Marcos De Quinto to Become Chief Marketing Officer	PepsiCo Elects David C. Page to Company's Board of Directors
	Ethical/ Legal Issues	Apple's filing in Apple v. Samsung	N/A	Statement on FIFA Investigation	New Facility Location, Philanthropic Initiatives, Favourable Court Rulings, Financial Results, and Promotions Research Reports on Tesla, P&G, Pepsico, Foot Locker and Johnson Controls

Table A2 DwE Categorization Matrix for Structured Content Analysis

<table>
<tr><th>Categorization Matrix</th><th>How can we find them?</th><th>Ways to identify DwE</th><th>Sentiment</th><th>Type of DwE</th></tr>
<tr><td>ACROSS
[Cross posters]</td><td>People who actually posts on both pages</td><td>Find the common poster ids on both brand pages</td><td></td><td>Migration (ACROSS)</td></tr>
<tr><td rowspan="18">WITHIN CENTRAL PAGE: DISCOURSE
&
RIPPLE</td><td rowspan="18">Mention brands in the comments</td><td rowspan="3">Central Brand [&related]</td><td>Neutral</td><td></td></tr>
<tr><td>Positive</td><td></td></tr>
<tr><td>Negative</td><td></td></tr>
<tr><td rowspan="3"><u>only</u> Enemy Brand [&related]</td><td>Neutral</td><td></td></tr>
<tr><td>Positive</td><td>Discourse</td></tr>
<tr><td>Negative</td><td>RIPPLE</td></tr>
<tr><td rowspan="3">Enemy <u>and</u> Central Brand [&related]</td><td>Neutral</td><td></td></tr>
<tr><td>Positive for Enemy (Negative For Central)</td><td>Discourse</td></tr>
<tr><td>Negative for Enemy (positive for Central)</td><td>RIPPLE</td></tr>
<tr><td rowspan="3">only third brand</td><td>Neutral</td><td></td></tr>
<tr><td>Positive</td><td></td></tr>
<tr><td>Negative</td><td></td></tr>
<tr><td rowspan="3">Central brand and third brand</td><td>Neutral</td><td></td></tr>
<tr><td>Positive for Third Brand</td><td></td></tr>
<tr><td>Negative For Third Brand</td><td></td></tr>
<tr><td rowspan="3">Enemy brand <u>and</u> third brand</td><td>Neutral</td><td>Discourse</td></tr>
<tr><td>Positive For both or Enemy</td><td>Discourse</td></tr>
<tr><td>Negative for</td><td>RIPPLE</td></tr>
</table>

			both or enemy	
		Third brand <u>and</u> both of the Central <u>and</u> enemy brands [<u>three brands</u>]	Neutral	**Discourse**
			Positive	**RIPPLE**
			Negative	**Discourse**
	No Mention of any brands	**No brand mention**	Neutral	
			Positive	
			Negative	
			Other	

Table A3: Keywords for DwE categorization

Brands	Keywords for Brand mentions		
	Umbrella Brand	***Brand***	***Extensions***
Coke (USA)	Coke, Coca Cola, Coca, coka, kaka, C.O.K.E, Coke-a-Cola	sprite, zero, Sprte, Spryte, Spryt, Zyro, Diet Coke, Fanta, vanilla, vanila, cherry coke	powerade, dasani, danon, inca, zico, fuze
Pepsi (USA)	pepsi, peps, pespi, peepsi, PepsiCo	gatorade, g2, Tropicana, Naked	Diet Pepsi, 7Up, 7 Up, Mt dew, Dew, Fanta, Pepsi Max, Mist
Third Brand	Pepper, Dr pepper, Diet Dr Pepper, peper	RC, RC cola	Vitamin water
	Operating System	***Brand***	***Device***
Apple (USA)	ios,operating,itunes, appstore, app store	apple, appel, aple	Iphone, iphon, iphne, ipad, ipod, 6plus, 6s, 5c, 5s, imac, 6 plus, 6+, apple iwatch
Samsung (USA)	android, andrd, androd	samsung, samsun, samsong	galaxy, s5, s6, note, nexus, galaxy note, gear, samsung watch, samsug edge, neo, 6 plus, 6+
Third Brand	Microsot, Microsoft, Microsoft band, Microsoft surface	nokia, noka, lumia	Motorola, Motorolla, HTC

Appendix A4: Data descriptives of variables used in the time series analysis

Table A3: Mean, standard deviation and correlations for the Coke-Pepsi data

	COKE TRIG PR	COKE TRIG PERF	COKE TRIG OTHER	PEP TRIG PR	PEPSi TRIGA D	PEPSI TRIG PERF	PEPSI TRIG OTHER	COKE DWE ACROSS	PEPSI DWE ACROSS	COKE DWE WITH IN	PEPSI DWE WITHI N	COKE POSTS	COKE VALEN CE	PEPSI POSTS	PEPSI VALEN CE
Mean	0.06	0.04	0.05	0.19	0.08	0.06	0.18	5.39	1.83	9.03	1.19	313.87	0.15	91.52	0.19
Maximum	1	1	1	2	1	1	2	49	13	146	6	4169	0.61	629	0.61
Std. Dev.	0.24	0.20	0.22	0.49	0.28	0.24	0.46	9.19	2.43	22.75	1.47	669.72	0.15	111.21	0.13

Table A4-1: Correlations for Coke-Pepsi data

Correlations	COKE TRIG PR	COKE TRIG PERF	COKE TRIG OTHER	PEP TRIG PR	PEPSi TRIG AD	PEPSI TRIG PERF	PEPSI TRIG OTHER	COKE DWE ACROSS	PEPSI DWE ACROSS	COKE DWE WITHIN	PEPSI DWE WITHIN	COKE POSTS	COKE VALENCE	PEPSI POSTS	PEPSI VALENCE
COKETRIGPR		-0.05	-0.06	0.34	-0.08	0.24	-0.02	-0.01	0.00	0.01	0.07	-0.06	-0.06	-0.03	0.05
COKETRIGPERF	-0.05		0.14	-0.08	-0.06	-0.05	0.01	0.04	-0.04	0.04	-0.17	-0.02	-0.07	-0.14	0.14
COKETRIGOTHER	-0.06	0.14		-0.09	-0.07	-0.06	-0.09	0.16	0.05	0.21	0.05	0.12	-0.09	-0.04	0.01
PEPTRIGPR	0.34	-0.08	-0.09		0.13	0.19	0.07	0.06	0.01	0.15	0.03	0.08	-0.03	0.07	-0.02
PEPTRIGAD	-0.08	-0.06	-0.07	0.13		0.05	0.08	0.08	0.03	0.17	0.04	0.11	0.04	-0.05	0.07
PEPTRIGPERF	0.24	-0.05	-0.06	0.19	0.05		0.06	-0.05	-0.04	0.01	-0.06	-0.05	0.03	-0.05	0.23
PEPTRIGOTHER	-0.02	0.01	-0.09	0.07	0.08	0.06		0.03	0.04	-0.02	-0.02	-0.03	0.11	0.00	-0.10
COKEDWEACROSS	-0.01	0.04	0.16	0.06	0.08	-0.05	0.03		0.37	0.84	0.18	0.92	-0.18	0.35	-0.11
PEPDWEACROSS	0.00	-0.04	0.05	0.01	0.03	-0.04	0.04	0.37		0.22	0.45	0.29	-0.24	0.69	-0.24
COKEDWEWITHIN	0.01	0.04	0.21	0.15	0.17	0.01	-0.02	0.84	0.22		0.13	0.83	-0.12	0.21	-0.06
PEPDWEWITHIN	0.07	-0.17	0.05	0.03	0.04	-0.06	-0.02	0.18	0.45	0.13		0.16	-0.12	0.63	-0.25
COKEPOSTS	-0.06	-0.02	0.12	0.08	0.11	-0.05	-0.03	0.92	0.29	0.83	0.16		-0.18	0.30	-0.13
COKEVALENCE	-0.06	-0.07	-0.09	-0.03	0.04	0.03	0.11	-0.18	-0.24	-0.12	-0.12	-0.18		-0.25	0.15
PEPPOSTS	-0.03	-0.14	-0.04	0.07	-0.05	-0.05	0.00	0.35	0.69	0.21	0.63	0.30	-0.25		-0.40
PEPVALENCE	0.05	0.14	0.01	-0.02	0.07	0.23	-0.10	-0.11	-0.24	-0.06	-0.25	-0.13	0.15	-0.40	

Table A5: Mean and standard deviation for the Apple-Samsung data

	APP NP ANNOUNCE	APP NP LAUNCH	APP TRIGR OTHER	SAM NP ANNOUNCE	SAM NP LAUNCH	SAM TRIG OTHER	APP DWE ACROSS	SAM DWE ACROSS	APP DWE WITHIN	SAM DWE WITHIN	APP POSTS	APP VALENCE	SAM POSTS	SAM VALENCE
Mean	0.03	0.07	0.14	0.06	0.10	0.23	0.94	0.25	2.70	0.27	331.52	0.67	39.07	0.35
Maximum	4	5	11	4	7	11	23	8	72	13	4438	1	715	0.824
Std. Dev.	0.292	0.423	0.765	0.283	0.528	0.707	2.264	0.783	6.862	0.925	592.030	0.214	48.7012	0.168

Table A5-1: Correlations for the Apple-Samsung data

	APP NP ANNOUNCE	APP NP LAUNCH	APP TRIGR OTHER	SAM NP ANNOUNCE	SAM NP LAUNCH	SAM TRIG OTHER	APP DWE ACROSS	SAM DWE ACROSS	APP DWE WITHIN	SAM DWE WITHIN	APP POSTS	APP VALENCE	SAM POSTS	SAM VALENCE
APPNPANNOUNCE		0.39	**0.76**	0.03	0.01	0.07	0.12	0.02	0.28	-0.03	0.26	-0.03	0.03	0.00
APPNPLAUNCH	0.39		0.59	0.03	0.02	0.08	0.08	0.09	0.06	0.04	0.07	-0.02	0.08	0.07
APPTRIGGEROTHER	0.76	0.59		0.00	-0.01	0.11	0.11	0.10	0.19	0.01	0.18	-0.05	0.08	0.02
SAMNPANNOUNCE	0.03	0.03	0.00		-0.01	0.07	-0.04	0.03	-0.06	0.00	-0.08	0.00	0.38	0.10
SAMNPLAUNCH	0.01	0.02	-0.01	-0.01		-0.01	0.02	-0.05	-0.01	0.11	0.00	0.02	-0.01	-0.01
SAMTRIGGEROTHER	0.07	0.08	0.11	0.07	-0.01		-0.05	-0.01	-0.03	-0.02	-0.04	0.04	0.05	0.00
APPDWEACROSS	0.12	0.08	0.11	-0.04	0.02	-0.05		0.02	0.54	-0.01	0.68	-0.13	-0.02	-0.08
SAMDWEACROSS	0.02	0.09	0.10	0.03	-0.05	-0.01	0.02		0.10	0.16	0.01	-0.01	0.37	0.22
APPDWEWITHIN	0.28	0.06	0.19	-0.06	-0.01	-0.03	0.54	0.10		-0.01	0.78	-0.12	-0.03	-0.09
SAMDWEWITHIN	-0.03	0.04	0.01	0.00	0.11	-0.02	-0.01	0.16	-0.01		-0.03	0.07	0.41	0.10
APPPOSTS	0.26	0.07	0.18	-0.08	0.00	-0.04	0.68	0.01	0.78	-0.03		-0.07	-0.04	-0.04
APPVALENCE	-0.03	-0.02	-0.05	0.00	0.02	0.04	-0.13	-0.01	-0.12	0.07	-0.07		0.09	0.11
SAMPOSTS	0.03	0.08	0.08	0.38	-0.01	0.05	-0.02	0.37	-0.03	0.41	-0.04	0.09		0.36
SAMVALENCE	0.00	0.07	0.02	0.10	-0.01	0.00	-0.08	0.22	-0.09	0.10	-0.04	0.11	0.36	

Table A6: Forecast Error Variance Decomposition of Coke-Pepsi Dancing with the Enemy

Column variable explained (%) by	Coke DwE Across	Coke DwE Within	Pepsi DwE Across	Pepsi DwE Within
1st Driver	Own past (69%)	Coke DwE Across (52%)	Own past (78%)	Own past (67%)
2nd driver	Coke Other News (9%)	Own Past (17%)	Coke DwE Across (7%)	Pepsi DwE Across (16%)
3rd driver	Pepsi Posts (4%)	Coke Other Events (10%)	Coke Other Events (4%)	Pepsi Posts (3%)
4th driver	Pepsi Ads (4%)	Pepsi Ads (4%)	Pepsi Ads (2%)	Coke DwE Across (2%)
5th driver	Coke Posts (3%)	Pepsi Other Events (4%)	Coke Posts (2%)	Coke PR (2%)

Table A7: Forecast Error Variance Decomposition of Apple-Samsung Dancing with the Enemy

Column variable explained (%) by	Apple DwE Across	Apple DwE Within	Samsung DwE Across	Samsung DwE Within
1st Driver	Own past (86%)	Own past (51%)	Own past (96%)	Own past (91%)
2nd driver	Apple Posts (3%)	Apple DwE Across (23%)	Apple Trigger Other (1%)	Samsung Other Events (3%)
3rd driver	Apple Announce (2%)	Apple Announce (17%)	Apple Launch (1%)	Samsung DwE Across (3%)
4rd driver			Samsung Launch (1%)	Samsung Launch (1%)

Table A8: Explanatory power (R^2) for DwE , Volume and Valence for the studied brands

	DwE Across	DwE Within	Volume (Posts)	Valence
Coke	0.60	0.62	0.61	0.31
Pepsi	0.22	0.29	0.42	0.41
Apple	0.41	0.57	0.60	0.36
Samsung	0.06	0.12	0.06	0.18

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TABLES

Table 1: Facebook Data Details Across Brand Contexts as Extracted by the Crawler

Page	Start Date	End Date	Days of Observation	Crawling Date	# of Posts
Apple	9/11/13	1/13/15	489	1/15/2015	165773
Samsung	11/18/09	1/15/15	1884	1/15/2015	92191
Coke	11/20/2014	3/17/15	118	3/17/2015	37,027
Pepsi	4/20/12	9/01/15	1229	2/09/2015	94,011
Adidas	3/22/11	3/04/15	1443	3/13/2015	115,565
Nike	10/14/10	3/12/15	1610	3/12/2015	78,688
McDonalds	5/10/10	3/12/15	1767	3/13/2015	76,221
Burger King	4/12/14	3/04/15	326	3/12/2015	132,616
Marvel	8/01/12	3/02/15	943	3/2/2015	294,621
DC	9/29/09	2/04/15	1954	3/2/2015	307,566

Table 2: Sentiment Analysis Results for Coke, Pepsi, Apple, and Samsung.

	Coke (USA)	Pepsi (USA)	Apple (USA)	Samsung (USA)
MTurk Training Classification				
Positive	160	155	150	160
Negative	140	155	150	140
Neutral	200	190	200	200
Prediction Hit Rate	96%	97%	95%	93%
Total Number of Comments	37,027	94,011	165,773	92,191
Positive	19,277	61,554	107,273	43,883
Negative	2,651	10,323	6,404	11,045
Neutral	15,099	22,134	52,096	37,263

Table 3: Details on DwE manifestations: Across, Discourse, Ripple, and Total DwE

	DwE Across			DwE Within			DwE Ripple			DwE Total		
Facebook Pages		%DwE Total	%Total Posts		%DwE Total	%Total Posts		%DwE Total	%Total Posts		%Total Posts	#Total posts
Coke (USA)	636	37%	1.7%	866	51%	2.3%	199	12%	0.5%	1701	4.6%	37027
Pepsi (USA)	468	36%	1.7%	648	50%	2.3%	186	14%	0.7%	1302	4.6%	28272
Coke-Pepsi		Start:	21/11/14	End:	17/03/15							
Apple (USA)	473	26%	0.3%	1058	58%	0.6%	293	16%	0.2%	1824	1.1%	165773
Samsung (USA)	274	28%	0.4%	501	51%	0.7%	211	21%	0.3%	986	1.3%	76505
Apple-Samsung		Start:	11/9/13	End:	13/01/15							

Table 4: Cumulative Effect of 1 DwE increase on Volume and Valence for Coke & Pepsi

	Coke Volume	**Coke Valence**	**Pepsi Volume**	**Pepsi Valence**
Coke DwE Across	138.07	-0.26	6.23	-0.29
(Same-day effect)	(42.91)	(0)	(2.68)	(-0.17)
(WearIn, *WearOut***)**	(**1**, *5* days)	(**2**, *1* day)	(**1**, *2* days)	(**1**, *1* day)
Pepsi DwE Across	212.91	-3.97	64.86	-3.34
Same-day effect)	(24.75)	(-0.94)	(27.79)	(-0.71)
(WearIn, *WearOut***)**	(**2**, *4* days)	(**2**, *5* days)	(**1**, *7* days)	(**2**, *5* days)
Coke DwE Within	39.80	0	0	0
Same-day effect)	(13.22)			
(WearIn, *WearOut***)**	(**1**, *5* days)			
Pepsi DwE Within	266.37	0	88.25	-4.26
Same-day effect)	(0)		(33.80)	(0)
(WearIn, *WearOut***)**	(**2**, *3* days)		(**1**, *5* days)	(**2**, *3* days)

Table 5: Effect of a 1 unit increase in DwE on Apple & Samsung's Volume and Valence

	Apple Volume	**Apple Valence**	**Samsung Volume**	**Samsung Valence**
AppleDwE Across	532.25	-2.44	0	-0.42
(Same-day effect)	(76.25)	(-0.61)		(0)
(WearIn, *WearOut***)**	(**2**, *26* days)	(**1**, *4* days)		(**3**, *1* day)
Samsung DwE Across	0	0	27.13	5.92
(Same-day effect)			(23.05)	(4.73)
(WearIn, *WearOut***)**			(**1**, *1* day)	(**1**, *1* day)
AppleDwE Within	173.86	0	0	0
(Same-day effect)	(36.13)			
(WearIn, *WearOut***)**	(**1**, *27* days)			
SamsungDwE Within	0 (0)	1.08	30.27	2.00
(Same-day effect)		(1.08)	(20.43)	(2.00)
(WearIn, *WearOut***)**		(**1**, *0* days)	(**1**, *1* day)	(**1**, *0* days)

FIGURES

Figure 1: Dancing with the Enemy as inter-brand, inter-communal engagement

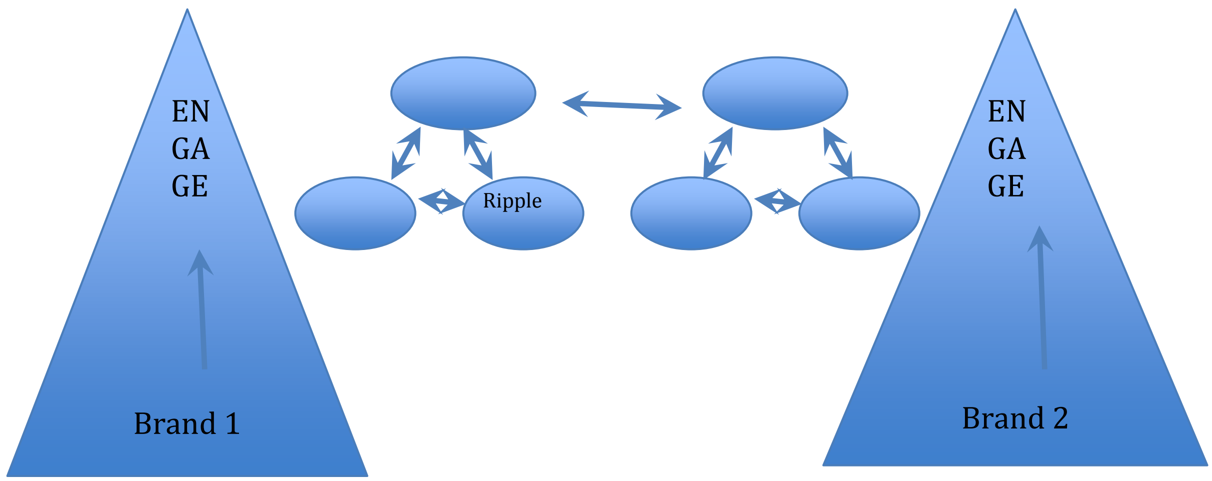

Figure 2: Granger Causalities between DwE, Posts and Valence for Coke-Pepsi

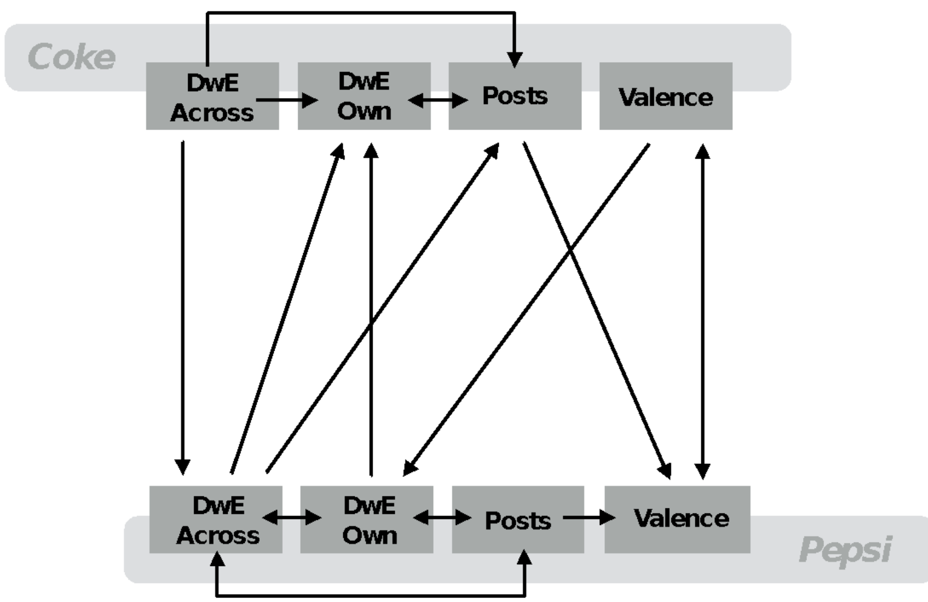

Figure 3: Granger Causalities between DwE, Posts and Valence for Apple and Samsung

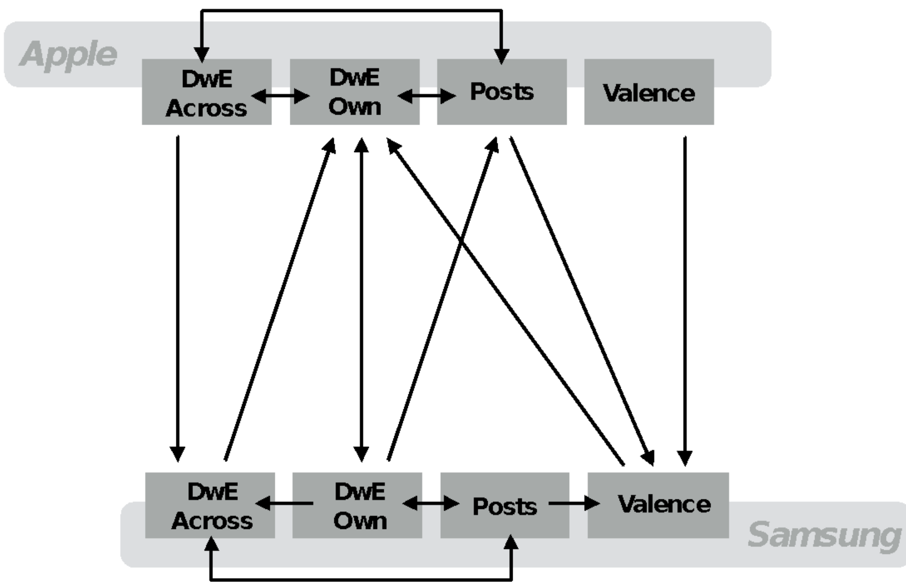

Figure 4: Forecast Error Variance Decomposition (FEVD) for Apple Volume (Posts)

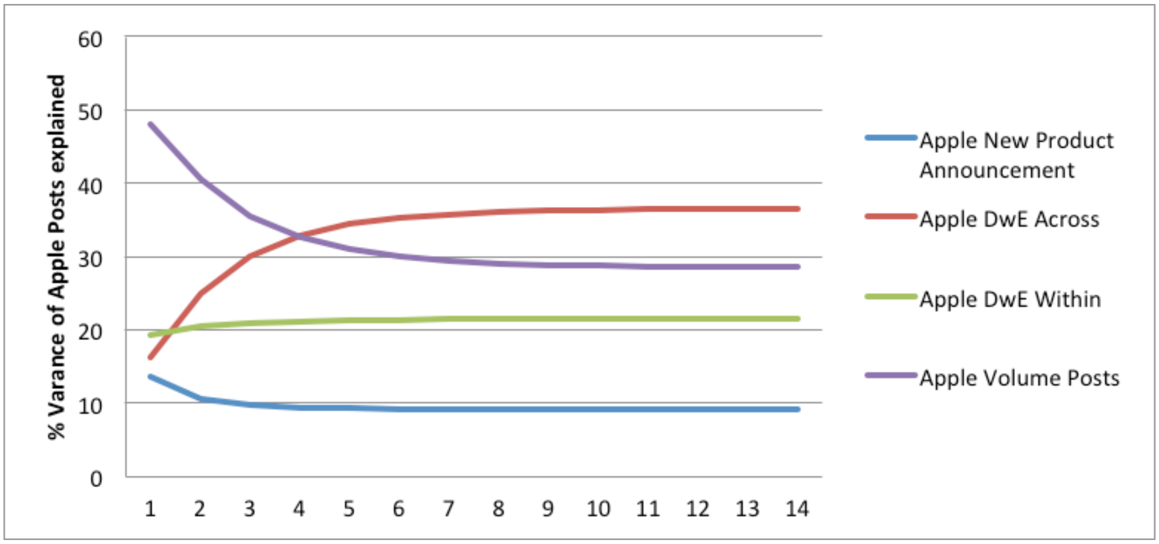

Figure 5: Coke volume (posts) unit effects of a 1 unit increase in DwE Across