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Competitive Spillover Elasticities of Electronic WOM:

An Application to the Soft Drink Industry

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Electronic word of mouth (eWOM), especially on online platforms such as Twitter, is a topic of interest for many C-suite Executives. Yet little is understood about competitive spillover effects in eWOM, especially among mature brands in FMCG markets. In this article we analyze the entire corpus of tweets of two main FMCG brands (Pepsi and Coke) and use dynamic factorial analysis to classify eWOM into topic categories in an unsupervised manner. We then analyze how these topics influence sales, taking account of traditional marketing mix elements and endogeneity concerns. Our results show that looking at eWOM in an aggregate manner (positive vs. negative valence) can be misleading and mask important effects. We see strong evidence for eWOM competitor spillover, depending on eWOM content diagnosticity (high vs. low). We also show the presence of asymmetric eWOM spillover effects depending on the typicality and directionality of brand associations.

Keywords: word of mouth; WOM; electronic word of mouth; eWOM; twitter; FMCG; soft drinks; dynamic factorial analysis; competition; spillover; diagnosticity; marketing mix

Introduction

Since the seminal work of Katz and Lazarsfeld in 1955, academics and practitioners alike have recognized the significant influence of word of mouth (WOM) on consumer behavior. The understanding of how social media and digital technologies impact purchase decisions has been cited as a key research priority (Marketing Science Institute 2018; Srinivasan, Rutz, and Pauwels 2016). In addition, many C-Suite Executives cite a better understanding of electronic WOM as a key business priority for their companies (WOMMA 2014).

In recent years, electronic WOM has received particularly widespread attention, as indicated by a series of meta-analyses and review articles on this topic (Babic Rosario, Sotgiu, De Valck, and Bijmolt 2016; King, Racherla, and Bush 2014; You, Vadakkepatt, and Joshi 2015). On an aggregate level, the positive relationship between electronic WOM and sales is well established. For example, Babic Rosario et al. (2016) report a positive and non-negligible relationship between electronic WOM and sales that is consistent across platforms and products. However, this relationship becomes less clear when analyzed at a more granular level. For example, electronic WOM valence's impact has a significant positive effect on sales in 248 studies (42%), a significant negative effect in 63 studies (11%), and no significant effect in 285 studies (48%). Such divergent findings suggest that our understanding of how electronic WOM impacts sales is still unclear, and underscores the need for more detailed studies on electronic WOM sales elasticities.

While many possible factors may explain these divergent findings, one aspect that has been cited as particularly important is the need to take competitor interactions into account when analyzing electronic WOM (Babic Rosario et al. 2016; Heerde 2016; Hewett, Rand, Rust, and van Pauwels, Aksehirli, and Lackman 2016; Tirunillai and Tellis 2012; You et al. 2015). This is important, as consumers frequently use online communities and forums to engage in discussions about competitive products. Furthermore, firms often employ advertising and social media strategies that may unintentionally stimulate electronic WOM toward competitive brands. For example, in Nike's *Kaepernick Campaign*, negative comments about Nike on Twitter and other social media might have benefited sales of Adidas (Taylor 2018). Similarly, the controversial Pepsi campaign involving Kendall Jenner triggered reminders of previous Coke advertising and showed unclear effects on both Pepsi's and Coke's performance (Nicholson 2017).

This phenomenon also applies to marketing mix initiatives beyond advertising. For example, distribution-related activities such new store openings (e.g., the recent Starbucks Roastery Reserve in Europe and China[1], or Primark in Germany[2]) can create buzz in social media. The same is true for (price) promotions like those of Domino's on Twitter[3] or Instagram, which may affect not only the focal brand, but also competitors. Thus, a wide range of comments about consumer brand experiences may affect a focal company as well as competitor performance, as exemplified by the Oxfam crisis, which harmed the entire non-profit sector[4]. This has also been supported by a series of in-depth interviews with executives from several multinational companies that we conducted in the context of this study (see details below). According thereto, understanding the competitive dynamics associated with WOM spillover effects is crucial for managers, as it helps brands to (a) more accurately assess their activities' results, (b) detect early and act on consumers' reactions, and (c) use social media as a strategic tool for effective brand promotion and product design.

Insights on spillovers are difficult to extract from previous studies in the form of meta-analyses due to the highly aggregated level at which electronic WOM has been studied.

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[1] *https://twitter.com/Eater/status/735939637424848896*

[2] *https://www.independent.ie/business/world/expansion-of-primark-stores-across-europe-helps-drive-revenue-rise-for-owner-ab-foods-37083127.html*

[3] *https://twitter.com/dominos/status/1067100785442529286?lang=en*

[4] *https://www.theguardian.com/global-development/2018/feb/13/toxic-effects-oxfam-scandal-weakened-us-aid-sector*

For example, a binary classification of positive vs. negative valence can mask or cancel out specific electronic WOM content elasticities, including those of competitors (Babic Rosario et al. 2016; King et al. 2014; Lovett, Peres, and Shachar 2013; Tirunillai and Tellis 2012). Consequently, we hear regular calls for studies to: (a) more thoroughly investigate how competitors strategically interact through electronic WOM (Babic Rosario et al. 2016; Hewett, Rand, Rust, and van Heerde 2016; Pauwels, Aksehirli, and Lackman 2016; Tirunillai and Tellis 2012) and (b) provide a deeper disaggregation of electronic WOM content related to competitors' attitudes and behaviors (Babic Rosario et al. 2016; de Matos and Rossi 2008; Kim and Hanssens 2017; King et al. 2014; Marchand, Hennig-Thurau, and Wiertz 2017; Tirunillai and Tellis 2012). Yet an analysis of how electronic WOM content from competing brands affects the sales of a focal brand is missing from the literature.

Our study's contribution to the existing literature on electronic WOM is twofold: First, we empirically explore, without any content restriction, electronic WOM content's competitive spillover elasticities, using two mature brands in the FMCG[5] industry; and second, we provide fresh perspectives regarding the interactions between the electronic WOM content generated and the focal brand, as well as competitors' marketing mix elasticities.

Using dynamic factorial analysis, we classify, in an unsupervised manner, the electronic WOM generated by two competitors in a mature FMCG market (Pepsi and Coke), according to the type of content observed in the electronic WOM. We build a model for each brand's sales that includes the electronic WOM content factors obtained and the traditional marketing mix variables from both competitive brands. The results show important positive and negative electronic WOM spillover effects on the competitors' sales. The unsupervised

[5] FMCG can be defined as frequently purchased, low-involvement products that are sold at relatively low cost (Nijssen 1999; Silayoi and Speece 2007; Cleeren et al. 2013), such as household products, food, alcoholic beverages, soft drinks, tobacco products, and personal care products (Koschate-Fischer et al. 2014; Olsen et al. 2014).

disaggregation of electronic WOM content allows for the identification of hitherto unrecognized spillover effects. In order to elucidate and gain further insights, we conducted eight in-depth interviews with marketing, media, and advertising executives.

We provide evidence that electronic WOM content's diagnosticity plays a crucial role in explaining such spillovers. We conceptualize diagnosticity as the degree of helpfulness of information (Chakravarti, and Biehal, 1990; Quiu, Pang, and Lim 2012; Dick). This allows us to respond to calls advocating the need for a deeper understanding of how the attributes consumers transfer across competing brands impact the posting and sharing of electronic WOM content (Chae, Stephen, Bart, and Yao 2017; Janakiraman et al. 2006). It also allows us to advance research demonstrating that various forms of WOM content can affect consumer behavior in varying ways (e.g., Gong, Zhang, Zao, and Jian 2017; Gopinath et al. 2014; Pauwels et al. 2016).

In addition to analyzing competitive spillover effects, we provide a holistic perspective on the interplay between electronic WOM content elasticities and traditional marketing mix elements. We provide novel insights into the elasticities such as that between pricing and electronic WOM as it relates to new product features. This allows firms to capture electronic WOM content's synergistic effects, as well as traditional marketing actions to strategically plan resource allocation (Kumar et al. 2017). It also enables us to provide tentative insights into new avenues wherein firms can proactively alter their marketing mix decisions to impact sales directly and indirectly through electronic WOM. These research findings offer important theoretical and managerial implications, as our interviews showed, related to the brand management of unstructured data; and electronic WOM's interaction with traditional marketing mix activity.

Related Literature

Despite the rich literature on WOM, almost no prior research has looked into electronic WOM content's competitive spillover elasticities. The only exception (see Table 1 for an overview of related literature), is the study of Borah and Tellis (2016) that tested the existence of negative spillover among four brands during a series of automobile recalls. The study found that spillover is extensive, occurring for nameplates within the same brand as well as across brands within the same segment; and that it affects brand sales and share price. The authors found stronger effects between brands from the same country and from a dominant brand to a less dominant brand than vice versa. They also found that apology advertising about recalls has a harmful effect.

Concerning potential spillover effects between traditional marketing mix elements and electronic WOM content, only a few studies have considered this interplay. Onishi and Manchanda (2012) were one of the first to analyze the relationship between traditional media (TV) and online blog content in the context of new product launches in the movie and cellular industry. Their analysis suggests that traditional media and blogs act synergistically with respect to market outcomes such as watching new movies and buying new cellular phone services. In another attempt to examine electronic WOM content's effects, Gopinath et al. (2014) measure electronic WOM content dimensions' average valence (i.e., attribute, emotion, recommendation content) for five brands in the cellular phone market. They find that the interaction of those dimensions and the type of ads differ for mature vs. new products, depending on the type of WOM and time. Pauwels et al. (2016) quantify the elasticities in online/offline store traffic of three pre-defined positive and neutral electronic WOM categories (i.e., advertising conversations, conversations on company offerings, and neutral comments on purchases) while controlling for TV GRPs and print investment, and find evidence for indirect effects of media on WOM and various effects over time of the three different WOM contents under study.

Insert Table 1 approximately here

Competitive Spillover Effects

Drawing on Ahluwalia et al. (2001), we define competitive spillover effects as situations wherein (a) information about a brand influences the beliefs of an individual about the brand's competitors where: (b) these changes in beliefs are not necessarily addressed in the communication from the focal brand. Competitive spillover effects can be explained through information processing theory (Bettman, 1979), as messages received by individuals radiate out to related elements within an interconnected cognitive structure, also called an *associative network* (Collins and Loftus, 1975). For example, a firm's marketing actions regarding a focal product (e.g., Pepsi) can cue thoughts about broader concepts related to the focal product, which in turn open up the possibility of thinking about other competitive products (e.g., Coca Cola, Berger and Schwartz 2011).

The retrieval of information from this associative network requires memory accessibility as well as some degree of perceived diagnosticity of the information (i.e., a message's perceived relevance and degree of helpfulness, Feldman and Lynch, 1988). Perceived diagnosticity has a strong effect on trial-based beliefs (Kempf and Smith, 1998), as consumers are more responsive to messages with high diagnosticity, which allow distinguishing between alternative assumptions, interpretations, and categorizations (Herr et al. 1991). A given type of electronic WOM communication is more diagnostic if it provides more information that consumers perceive to be helpful in familiarizing, understanding, and evaluating a product's quality and performance (Jiang and Benbasat 2007). For example, when studying online reviews and websites, the perceived diagnostic of visual and functional control (Jiang and Benbasat 2004) or informational and normative cues have been shown to influence consumer information adoption (Filieri 2015). Similarly, advertising is perceived as diagnostic when ads provide an individual with sufficient information to judge the quality of the product (Chang 2010).

Accessibility-diagnosticity theory has been used to explain both positive and negative spillover effects among competing brands (Borah and Tellis 2016; Janakiraman et al. 2009; Roehm and Tybout 2006). Broadly speaking, consumers comment on their experiences with brands, the information they receive about brands, and the marketing mix activities of brands (Fossen and Schweidel 2016; Kumar et al. 2016; Srinivasan et al. 2016). This renders an analysis of competitive spillover effects complex and their effects difficult to predict. Despite being the most common topic of conversation among consumers (Keller and Fay 2012), advertising is not the only possible source of electronic WOM spillover. It has been argued that consumers also exchange information on brand scandals (Trump and Newman 2017), brand rumors (Brunvand, 1981), brand promotions (Berger and Schwartz 2011), and new product launches (Keller and Libai 2009). Discussions thereof can generate electronic WOM that might in turn influence a competitor's sales.

Competitive spillover effects are more likely to occur when information is related to a typical brand or a typical brand attribute; and when brands share attribute-level similarities (Janakiraman et al. 2009). The specific effects depend upon the directionality and salience of associations between brands (Lei, Dawar, and Lemmink 2008) and the message's high/low construal level (Trump and Newman 2017). Generally, competitive spillover effects have been shown to be particularly relevant in the case of brand scandals and product recalls, as (a) negative information is more diagnostic about brand performance than is positive information (Chevalier and Mayzlin 2006; Herr, Kardes, and Kim, 1991; Tirunillai and Tellis 2012) and (b) highly negative information is more effective than is moderately negative information in categorizing a product, as the former is less ambiguous. For example, in our study we expect negative electronic WOM about a brand scandal to spill over to competitors and to negatively affect their sales, as electronic WOM is more trusted than are other traditional forms of communication (Evans 2010; Goldsmith and Horowitz 2006). Consistent with this expectation, in the case of product recalls, Borah and Tellis (2006) documented the presence of competitor spillover effects that are asymmetric and moderated by brand strength.

Electronic WOM Content Diagnosticity

We define electronic WOM content spillover effects as electronic WOM content's positive or negative influence on focal brand or competitor sales. To study such electronic WOM content spillover effects, we distinguish between two types of electronic WOM content *high* diagnostic, and *low* diagnostic. We posit that in mature markets, the impact of a given piece of electronic WOM content on brand choice depends on that content's level of diagnosticity, or perceived relevance.

In mature markets, consumers have high awareness of product category and brand characteristics, making them less prone to brand switching (Pauwels, Erguncu, and Yildirim 2013). According to Herr et al. (1991), WOM communication has a reduced effect on product judgment when a priori impressions of products are available in memory, and when anecdotal[6] vs detailed attribute information is posted. Following this line of thinking, we contend that in mature markets, a necessary condition for competitive spillover effects to occur is that some new information must be communicated to customers, as all else being equal, consumers will maintain their attitudes and preferences.

In mature markets, as well as in later stages of the product life cycle, general information channeled through advertising becomes less relevant (e.g., Parsons, 1975; Tellis and Fornell, 1988; Sethuraman, Tellis, and Briesch 2011) in determining a consumer's decision to switch brands (e.g., Raj, 1982; Tellis, 1988; D'Souza and Rao, 1995). As brand

[6] "Anecdotal" refers to judgments that do not add relevant information to the product.

consideration is consolidated and more difficult to overcome, memory of the advertising of familiar brands is less affected by exposure to competitive advertising (Kent and Allen, 1994). When high-diagnostic information is communicated, such as for example information on new prices, promotions, product launches, or new product characteristics, consumers might be more willing to switch (e.g., Abril and Sanchez 2016; Ailawadi and Neslin, 1998; Blattberg, Briesch, and Fox, 1995; Liu and Lopez 2016). Consequently, the electronic WOM generated might spill over to competitors and affect their sales. For instance, according to Liu and Lopez (2016), consumer conversations on social media about soft drink brands and their nutritional aspects have a significant impact on consumers' valuation of brand characteristics and on their choices of soft drinks impacting brand sales.

Electronic WOM content that informs consumers about relevant changes such as product news, new prices, or promotions is high diagnostic, as product-related attributes are perceived as more diagnostic, and enable consumers to obtain information about the product's characteristics, which is helpful for them to assess product performance (Qiu, Pang, and Lim 2012). In contrast, if electronic WOM content is on non-product-related topics, it reveals limited information about the product itself, and consumers will perceive such comments as less relevant, and consequently less diagnostic for product evaluation (Filieri 2015; Sen and Lerman 2007). We therefore consider such electronic WOM content as low diagnostic, as in mature markets, such comments do not add sufficient relevant information for consumers to reconsider their current brand relationship status. For example, when consumers tweet comments such as "*I've always loved Pepsi ads*" the level of diagnosticity for current Coke consumers is likely to be low, and consequently no electronic WOM spillover on Coke sales is expected. On the other hand, high-diagnostic electronic WOM content such as "*I tried new Pepsi formula, it is really awesome!*" might influence Coca Cola consumers to try the brand, and therefore generate some negative spillover effects on Coke sales.

Given this reasoning, we expect differing competitive spillover effects and elasticities depending on the diagnosticity of the electronic WOM content generated. Specifically, we expect that that high-diagnostic positive (negative) electronic WOM content generates (a) competitive spillover effects and negatively (positively) affects competitors' sales and (b) positive (negative) sales elasticity in the focal brand and positive interactions with focal brand marketing mix actions, as such actions extend the messages' reach. We set forth the logic for this argument in the next section.

Competitive Spillover Effects related to Marketing Mix

Regarding one of the most important traditional marketing mix elements – *advertising* – the findings on competitive spillover effects are inconclusive. Both Sahni (2016) and Anderson and Simester (2013) found positive spillover effects of competitor advertising on the sales of a focal brand. In addition, Lewis and Nguyen (2014) found that online advertising increases online search activity for competitor brands. However, Janakiraman et al. (2009) and Chae, Stephen, Bart, and Yao (2017) found no spillover effects of advertising across competitors.

These inconclusive results may be due to insufficient advertising recall of the focal brand, as well as differences in the content and execution of advertising messages of differing diagnosticity (Keller, 1987). They might also be related to the underlying markets' maturity. In the case of new products, positive competitive spillover effects have been documented consistently. Electronic WOM generated in new markets characterized by high-involvement products helps consumers to reduce uncertainty and to make informed decisions (Janakiraman et al. 2009; Libai, Muller, and Peres 2009; Krishnan, Seetharaman, and

Vakratsas 2012; Peres and Van den Bulte 2014). Conversely, in mature FMCG markets, which is the setting of our research, advertising spillover effects can vary dramatically across campaigns and products (Chen 2017), as customers are aware of brands; can easily purchase them; do not have to learn how to use the products; and may exhibit behavior that is determined by established preferences, habit, and inertia (Anderson and Simester 2013). In this situation of consumer learning, we speculate that electronic WOM content's effects vis-à-vis advertising will spill over to competitors' sales when the content of the message is high-diagnostic and therefore informative on product news, new prices, or promotions.

Regarding *pricing* and *promotion* activities, it is important to control for these when studying electronic WOM elasticities, as failing to do so may lead to biased coefficient estimates (Babic Rosario et al. 2016). It has been shown that consumers enjoy telling others about low prices (You et al. 2015), and are more likely to engage in conversations when they receive free products or gifts from brands (Berger and Schwartz 2011). These online conversations about prices of brands may spill over, influence competitors' associations, and in the process, affect consumer value perceptions of brands and ultimately consumer behavior toward competitive brands (Janakiraman, Meyer, and Morales 2006). For example, an aggressive coupon campaign for Pepsi might have a positive impact on Pepsi's sales and a negative spillover effect on Coke sales due to electronic WOM generated by the Pepsi action.

Similar effects can occur concerning (increased) *distribution* of brands, as a product's accessibility and its public visibility are important drivers of consumer conversations (Berger and Schwartz 2011). For example, spillovers have been documented on arrivals of retailers in cities or new openings of competitors' stores[7] (Wilson 2012; Yang 2012).

Beyond competitive spillovers, focal brand spillovers can also occur due to the focal brand's own marketing mix activity. Understanding the interplay between electronic WOM

[7] *https://www.cnbc.com/2017/02/27/how-one-teen-retailer-is-thriving-while-its-competitors-flounder.html*

content and traditional marketing mix elements is important, as both can serve as complements to each other (Chen and Xie 2008; Dost, Phieler, Haenlein and Libai 2018; Hogan, Lemon, and Libai; 2004; Keller 2007). Integrated marketing communications and generating earned media can have a multiplicative effect on expected sales (Batra and Keller 2016). Therefore, we expect positive elasticities from the interactions between electronic WOM content and marketing mix activities of the focal brands when dealing with high-diagnostic electronic WOM content.

Method

For our analysis, we use the soft drinks market as an empirical setting. According to Lovett et al. (2013), out of the 16 most-discussed categories, beverages ranked fifth (seventh) in the number of offline (online) brand mentions. The frequent use of the soft drinks market as an exemplary market for FMCG and mature products in several domains (e.g., Fosfurri and Giarratana 2009; Lopez, Liu, and Zhu (2015); Lovett et al. 2013; Sunder, Kumar, and Zhao 2016), enables us to respond to calls for empirical research on online media's impact on FMCG industries (Onishi and Manchanda 2012; Dost et al. 2018). In the social media domain, new products and online consumer reviews prevail, leading to several calls to further investigate FMCG industries (Babic Rosario et al. 2016).

The specific submarket we focus on is dominated by two well-known brands (Pepsi and Coke) that jointly represent approximately 90% of the market share. This duopoly has traditionally allowed researchers to investigate with high precision the effects of strategic actions and reactions on the two competitors (Fosfuri and Giarratana 2009) and enables a parsimonious analysis of competitive spillover effects (Borah and Tellis 2016; Joshi and Hanssens 2010; Tirunillai and Tellis 2012).

Our data cover two full years (2012 and 2013) of weekly activity in a major European market. Our model integrates two datasets: (a) a tweets database containing the number of tweets that mention either of the two brands in our study (Pepsi or Coke), and (b) a weekly marketing mix database over a two year-period (103 weeks), provided by Nielsen and Kantar Media.

Data

Tweets Database

We use Twitter as a platform to measure electronic WOM. Twitter data is a particularly useful proxy for social media (Hewett, Rand, Rust, and Van Heerde 2016) and has frequently been studied in the social media literature (Culotta and Cutler 2016; Gong, Zhang, Zhao, and Jiang 2017; Hennig-Thurau, Wiertz, and Feldhaus 2015; Ma, Sun, and Kekre 2015; Zhang, Moe, and Schweidel 2017). As one of the most important social media platforms, Twitter exhibits high penetration with a substantial share of tweets on product and brand recommendations. It is an active network with 80% of users following at least one brand (Nielsen 2017).

Our database contains nearly 170,000 tweets: 17,074 negative, and 15,618 positive tweets about Pepsi; and 46,187 negative and 88,514 positive tweets on Coke. Those tweets were collected by a third-party data provider contracted by one of the companies under study, and represent not a sample of tweets, but rather the *entire corpus* of positive and negative tweets mentioning either brand in 2012 and 2013, the two years of the study. In total, in the database provided us, Twitter accounted for 86% of all the social media electronic WOM in the time period studied. Note that within this period, we are addressing organic electronic WOM that occurs directly and without direct firm involvement (Libai et al. 2010; Haenlein and Libai 2017), as there were only a few firm-generated tweets from both companies.

Marketing Mix and Sales Database

For brand sales, we use the weekly sales volume for both brands over a period of 103 weeks across all SKU of each brand. The brands' sales, prices, and weighted distributions were provided by Nielsen (Scantrack) weekly retail panel data, while advertising investment in GRPs (gross rating points) was provided by Kantar media. According to the data provided at the time of the study, the market shares were around 20% for Pepsi and 70% for Coke. Table 2 provides descriptive statistics on our data. Regarding information on the marketing mix, we include the weekly average price paid per liter in euros; the weekly value-weighted distribution coverage; and the weekly advertising media measured in GRPs. Advertising GRPs show significant variance in their means and over time, as can be expected due to the seasonality of the category. In our data, more than 80% of the market investment was made in television.

Insert Table 2 approximately here

Model

Electronic WOM Content Analysis

Extracting content characteristics from electronic WOM is not yet a standardized process, and prior articles have used a variety of methods to accomplish this, including lexicon-based sentiment analysis (Bae and Lee 2012), semantic analysis based on naive Bayes classifiers (Chern, Wei, Shen, and Fan 2015), and product-specific dictionaries (Gopinath, Thomas, and Krishnamurthi 2014). Nevertheless, several studies provide insights into the fundamental principles of adequate modeling of electronic WOM content (Feldman 2013; Pauwels, Aksehirli, and Lackman 2016; Tirunillai and Tellis 2014; Zhang et al. 2017). For our study, we followed a six-step process for each brand (see Appendix for details): (1)

tweets preprocessing, (2) valence classification, (3) topic extraction, (4) weekly aggregation of topics, (5) dynamic/time series factor analysis, and (6) factor score extraction and unstandardization. This resulted in a list of 15 topics of electronic WOM content clustered by brand and valence, seven of which corresponded to Coke, and eight to Pepsi. Table 3 provides a brief description of the various factors.

Insert Table 3 approximately here

Demand Model

We use a Seemingly Unrelated Regression (SUR) demand model for each of the two brands (Zellner, 1962). In both models, the dependent variable is the weekly sales of the focal brand. We test two models: The first model includes aggregated electronic WOM by valence for the focal brand and the competitor brand as well as traditional marketing mix variables; the second model includes the 15 electronic WOM topic factors describing the electronic WOM content for the focal and the competitor brand as well as the traditional marketing mix variables. Given the cyclical nature of demand in this product category, we also include a series of dummy variables to account for seasonality. The SUR model states that there are *k* dependent variables (y_j, $j = 1 \ldots k$) specified as follows:

Aggregated model

(1) $\log y_j = \alpha_j + \sum_{i=1}^{4} \beta_{ij} \log f_{ij} + \sum_{i=1}^{4} \gamma_{ij} \log m_{ij} + \phi_j + \varepsilon_j$

and the stochastic component:

(2) $\varepsilon_j \sim \mathcal{N}(0, \sigma_j)$,

where y_j denotes the sales for the respective brand (Pepsi or Coke), f_i are the volume WOM variables (negative WOM volume and positive WOM volume for each brand), m_i are the marketing mix variables (i.e., the price gap between Pepsi and Coke, the weighted distribution of Pepsi, the advertising investment in Pepsi in GRPs, and the advertising investment in Coke in GRPs), ϕ is a seasonality dummy (trimesters), ε is the residual component, and β,γ are regression coefficients.

Disaggregated model

(3) $\log y_j = \alpha_j + \sum_{i=1}^{15} \beta_{ij} \log f_{ij} + \sum_{i=1}^{4} \gamma_{ij} \log m_{ij} + \phi_j + \varepsilon_j$

and the stochastic component:

(4) $\varepsilon_j \sim \mathcal{N}(0, \sigma_j)$,

where y is the sales for the respective brand (Pepsi or Coke), f_i are the electronic WOM topic factors extracted from the dynamic factor analysis, m_i are the marketing mix variables (i.e., the price gap between Pepsi and Coke, weighted distribution of Pepsi, advertising investment in Pepsi in GRPs, advertising investment in Coke in GRPs), ϕ is a seasonality dummy (trimesters), ε is the residual component, and β,γ are regression coefficients.

Note that in this product category and due to intense competition, the price gap between Pepsi and Coke is a more adequate variable than are the absolute prices of both brands. Additionally, as Coke shows a constant market distribution of 100%, it is not possible to include Coke's weighted distribution as a variable into the model. This specific log-log demand model allows for a direct interpretation and comparison of the estimated coefficients as elasticities, and accounts for decreasing returns. Consistent with prior research, we also account for the lagged effects of advertising (Berkowitz, Allaway, and D'Souza 2001)[8].

Endogeneity

[8] Other possible model specifications, such as a model in differences, were tested. A comparison between those alternative specifications shows that the main conclusions hold despite the dissimilarities in explanatory power. See table 9-A, appendix.

A common problem in demand models is the presence of endogeneity. Advertising budgets may be set or adapted as a function of (expected) sales (Aaker, Carman, and Jacobson, 1982; Hanssens, 1980), and electronic WOM may be affected by sales, as more sales may lead to more consumers talking about the brand. To correct for a potential endogeneity bias, we rely on the Durbin-Wu-Hausman test using instrumental variables (Durbin, 1954; Hausman, 1978; Wu, 1973) for both models (aggregated and disaggregated).

On the aggregated model, we ran a series of 2SLS specifications (see Table 1-A and Table 2-A in the appendix). The two main sources of potential endogeneity are electronic WOM and advertising variables. Due to the potentially high number of endogenous variables, we tested each variable individually in order to avoid inaccuracies and overfitting (Hansen, Hausman, and Newey 2008; Roodman 2009). The instrument for electronic WOM variables is the number of active Twitter users, as this number might be correlated with the volume of brand mentions in Twitter, yet uncorrelated with the error term. For advertising variables, we followed a classical approach, using one-period lagged variables as an instrument (Arellano and Bover 1995). Table 3-A in the Appendix shows the Durbin and Wu-Hausman tests of endogeneity for each potentially endogenous variable in Pepsi's equation; and Table 4-A shows the same tests for Coke's equation. In every case, the null hypothesis of exogeneity cannot be rejected, and thus we did not find endogeneity problems.

Similarly, we controlled for potential endogeneity issues in the disaggregated model by estimating four 2SLS equations (see Table 5-A in the appendix). In this case, the possible endogenous variables are only those related to advertising efforts, as the specific electronic WOM content itself cannot be influenced by brand sales performance or by category sales as a whole. While it is possible that brand or category sales can have some impact on the volume of comments on social sites, generating electronic WOM on *specific* topics or themes (e.g., advertising, product taste, fake news) seems unlikely. Once again, we used one-period lagged variables as instruments. Tables 6-A and 7-A in the appendix show Durbin and Wu-Hausman tests of endogeneity for both brands. The tests show that the null hypothesis of exogeneity cannot be rejected.

Furthermore, we tested a more complex and efficient 3SLS specification to accommodate the IV estimation process to a SUR equation system (Oberhofer and Kmenta 1974, see Table 8-A in the appendix). The instrumental variables are the same as those we used in the 2SLS model specification, and the coefficients and standard errors are close to those obtained by the SUR equation system. Given these results, our final model will be the SUR specification with the additional interaction terms.

After estimating the two models (for Pepsi and Coke) with the inclusion of the instrumental variables, the Durbin-Wu-Hausman test fails to reject the null hypothesis of exogenous regressors.

Results

Aggregated Analysis of Competitor Spillover Effects

As a baseline, we first estimated a SUR model wherein electronic WOM appears in aggregated form only (i.e., the total number of positive and negative tweets by brand – see Equations 1 and 2). This model produced an adjusted R^2 of 0.667 and 0.683 for Pepsi and Coke respectively (see Table 4). Concerning the traditional marketing mix variables, we observed effects that are consistent with managerial intuition and prior research (Hanssens 2018; Srinivasan, Rutz, and Pauwels 2016). Regarding the price gap, we found a positive significant effect for the weaker brand (Pepsi, β =0.339, i.e., the wider the price gap, the greater the sales) and a corresponding negative significant effect for the stronger brand (Coke, β = -0.376). For Pepsi's weighted distribution, we found a direct and positive effect on Pepsi sales (β = 5.861) and a positive and significant spillover effect on Coke sales (β = 6.220), most likely due to category demand effects.

Concerning electronic WOM, we did not find statistically significant main effects of aggregated electronic WOM on sales except for the interaction between Coke advertising and positive Coke electronic WOM, which shows a positive effect on Coke sales (β = 0.0214) and a positive spillover effect on Pepsi sales (β = 0.0207). This spillover effect is most likely due to category demand effects. No significant effects (either direct or spillover) were found for any of the negative electronic WOM measures. This result is consistent with prior research that failed to detect a consistent relationship between electronic WOM valence and sales (Duan, Gu, and Whinston 2008; Liu 2006). In fact, no significant direct effect of WOM valence on sales has been found in nearly half of all studies analyzed by Babic Rosario et al. (2016).

As we assume that the absence of significant effects might be due to the use of two highly aggregated valence categories (positive vs. negative WOM) that may mask or cancel out more specific electronic WOM effects, we follow up this aggregated analysis with a disaggregated analysis of the electronic WOM content.

Insert Table 4 approximately here

Disaggregated Analysis of Competitor Spillover Effects

Table 5 shows the result of a disaggregated model as specified in Equations 3 and 4. Looking at the traditional marketing mix variables of price (gap), weighted distribution, and advertising GRPs, we observe results similar to those obtained from the aggregated model. In terms of electronic WOM content factors' competitive spillover effects, we observe considerable evidence for spillover elasticities that were absent from the aggregated model.

This supports our assumption that an aggregated analysis obscures important theoretical and managerial insights.

Insert Table 5 approximately here

Asymmetry in Competitive Spillover Effects

We confirm the presence of asymmetry in the competitive spillover effects. Specifically, we observe spillover effects from the weaker brand (Pepsi) to the stronger one (Coke), but not vice versa. This is consistent with prior research that has shown that interbrand spillover effects can be asymmetric depending upon the brand associations' strength and directionality (Lei, Dawar, and Lemmink 2008). In our case, these results support the assumption that Coke shows more differentiation (less similarity) from Pepsi than vice versa (Tversky, 1977). Note that those spillover effects from Pepsi to Coke show negative elasticities in three out of four cases, indicating the significant harm that some type of competitors' electronic WOM can represent for brand sales.

Electronic WOM Content Diagnosticity

We observe more significant competitive spillover effects for electronic WOM content that is more diagnostic. Table 6 includes a classification of electronic WOM content topics according to their perceived level of diagnosticity (high vs. low) and their significant effects on the focal brand's elasticity (F) and spillover to competitors (S). We classified comments related to product/packaging news (e.g., Pepsi taste, promotions, and fake news on product contamination; as well as new Coke products) as *high diagnostic*; and general or anecdotal topics (e.g., Coke Summer and general ads; Pepsi celebrity ads where the brand shows celebrities but no product news is communicated, company-related news/success) as *low diagnostic*, consistent with Herr et al. (1991).

Insert Table 6 approximately here

For both brands, we found that high-diagnostic product-related electronic WOM shows positive elasticities (β = 0.117 for Pepsi taste and β = 0.192 for Coke product news). Even the negative electronic WOM related to the taste of Pepsi has a positive elasticity on the Pepsi brand (β = 0.0221), suggesting the power of controversy (Chen and Berger 2013). Positive effects due to negative comments have been confirmed in prior studies (Berger, Sorensen, and Rasmussen 2010; Chen and Berger 2013; Wilson, Giebelhausen, and Brady 2017). Conversely, we did not find any significant spillover effects of electronic WOM low-diagnostic content related to advertising, such as comments related to celebrities, ads, or the brands in general. Together, these results confirm our expectation that electronic WOM content's degree of diagnosticity moderates the strength of competitive spillover effects.

Interestingly, we observe that the size of the spillover effect of extreme negative content (e.g., fake news related to Pepsi's formula contamination on Coke sales) is comparable to the other main effects (β = -0.0259). This is consistent with the moderating effect of brand typicality, as such Pepsi-negative WOM refers to a typical category attribute (i.e., its formula), and both brands are perceived as typical of the product category (Janakiraman, Sismeiro, and Dutta, 2009). Our results confirm previous studies' similar patterns concerning competitive spillover when negative information such as competitor's recalls occur (Borah and Tellis 2016).

Competitive Spillover Effects related to the Marketing Mix

Concerning competitive spillover effects of the marketing mix, we found that electronic WOM content related to Pepsi promotions and Pepsi product news exhibited a significant negative impact on Coke sales (β = -0.0185 and β = -0.0252). This result suggests that diagnostic electronic WOM content related to Pepsi news might be a source of competitive gains more powerful than Pepsi advertising itself. In fact, we found that Pepsi advertising spillover's positive category-related electronic WOM impacts Coke sales positively ($\beta = 0.0267$), consistent with publicity on a confounded brand recall of Pepsi affecting the lead brand's advertising (Sahni 2016).

We did not find as significant an effect of promotion-related comments as we expected. As the promotional marketing mix investment is not included in the model, we have limited data thereon. Nonetheless, we speculate that the high variance of promotional activity in the market and the fact that not all promotion types are equally diagnostic, might explain this result.

As consumers make sense of all communications received (Batra and Keller 2016; Finne and Gronroos 2017), it is important to understand any possible interactions between all elements of the marketing mix under study and the electronic WOM content generated. As cited above, we expected positive elasticities from the interactions between high-diagnostic electronic WOM content and marketing mix activities. We found a significant interaction of the Pepsi brand's price activity with the consumer electronic WOM about Pepsi taste ($\beta = 0.114$), yielding insights into firms' opportunity to capture social media's synergy with traditional marketing initiatives (Kumar et al. 2017). Note that this interaction's elasticity is the third strongest after those of price and distribution, suggesting the power of combined and synergistic marketing actions.

The second interaction we found refers to Coke advertising and electronic WOM regarding Coke's summer campaign – its most important of the year – which exhibited a modest yet positive elasticity on Coke sales ($\beta = 0.00186$). This suggests that low-diagnostic electronic WOM content might help the focal brand to reinforce its consumers' loyalty when combined with the adequate advertising awareness.

To obtain a more intuitive sense of spillover effects' importance, using the estimated SUR model as an input, we conducted a series of simulations. Figs. 1 and 2 show the simulated impact of changes in marketing mix elements and electronic WOM content on Pepsi and Coke sales.

Insert Figure 1 and Figure 2 approximately here

Regarding various electronic WOM content factors' elasticities, we observed fewer effects for Coke than for Pepsi. These results are consistent with the notion that high-equity brands are less elastic with respect to WOM (Ho-Dac, Carson, and Moore 2013). In particular, none of the negative electronic WOM factors was significant for Coke, confirming that consumers are resistant to negative comments about brands they like (East, Hammond, and Lomax 2008). The only positive elasticity of electronic WOM for Coke (0.0192) occurred with product-related electronic WOM related to Coke (classified as high-diagnostic). Note that this effect is similar in magnitude to that of Coke advertising's main effect on GRP sales (0.0162), indicating the importance of earned vs. paid media in driving sales and the importance of high-diagnostic messages in mature markets.

Additional analysis: In-depth interviews with executives

As an additional aid to complement and better interpret our results, we conducted eight in-depth interviews. The face-to-face, semi-structured interview was considered the most appropriate instrument to gather this kind of knowledge due to its flexibility and potentially deeper exploration of electronic WOM mechanics. This complementary qualitative approach can unveil new insights and elucidate additional, non-obvious explanations about electronic WOM's effect. Specifically, this approach was used (a) to obtain better understanding of how competitors' electronic WOM content is tracked, (b) to gather feedback from managers on the empirical results, and (c) to understand in more detail the use of integrated marketing mix models incorporating electronic WOM.

We selected interviewees using purposeful sampling procedures (Cresswell and Plano Clark 2011) as per the following criteria: (a) international scope (all were global companies), (b) industry variability (from fast food to non-profits), (c) differentiation of players (advertising agencies, media planning agencies, and consumer-oriented corporations), (c) highly competitive market environment, and (d) top marketing and communication decision makers with experience in social media management. See Table 7 for a detailed description of the interviewees' profiles.

Insert Table 7 approximately here

While the initial number of interviews (eight) was the starting point, the final number was determined by a classical saturation criterion (Guest, Bunce, and Johnson 2006). After analyzing each of the interviews sequentially, we found a high recurrence rate in most of the categories and topics, showing that the initial number of interviews was sufficient to satisfy the purpose of this qualitative complementary approach. Executives were recruited by personal invitation, and all accepted except one. The interviews lasted between 50 and 90 minutes, and were conducted between February and March 2019. Before showing them our empirical results, we asked the interviewees how their firms currently monitor electronic WOM content and marketing mix elasticities, in order to get their feedback.

Monitoring Competitor Electronic WOM Content

All firms interviewed recognize the importance of tracking electronic WOM content and its potential spillover effects. However, despite this agreed-upon importance, none of the firms we interviewed systematically measures competitors' electronic WOM content. At best, tracking is limited to the volume of positive and negative messages, mainly those generated by advertising campaigns (I4). Reasons therefor are a general limited knowledge on methodologies for tracking such information; the difficulty of extracting the right data; and the high cost of such tracking (I4).

We did, however, find some differences by type of industry (FMCG vs services), which is consistent with prior studies that have shown that product type (e.g., search vs. experience; hedonic vs. utilitarian) moderates the perceived helpfulness of consumer comments (Mudambi and Schuff 2010; Sen and Lerman 2007). For example, our interviewees in highly competitive FMCG industries (e.g., dairy products; soft drinks), focus most of their monitoring on offline activities, based on the assumption that competitive dynamics occur mainly at the point of sale (I2). This results in fewer resources available to track electronic WOM content (I3). In the case of FMCG firms that do analyze electronic WOM content, the purpose thereof is less to measure elasticities or spillover effects, and more to be informed about content that arouses a higher number of consumer conversations in order to design future communication strategies.

Our interviewees in service industries (i.e., insurance; non-profits) and the automotive sector, which can be considered experience products, recognize the importance of monitoring competitors' electronic WOM content, as it may significantly affect their brand's performance. However, they contend that holistic models to track these dynamics are difficult and costly to find (I6; I8).

Reactions with Respect to our Empirical Findings

When exposed to our empirical findings, some managers responded with anecdotal evidence wherein they recalled tracking electronic WOM spillover, and found this information very useful (I7). Interestingly, our interviews also provided additional insights into market factors that might make the monitoring of competitor spillover effects even more important. The two points discussed in this context are market size dynamics and direct-to-consumer brands (i.e., native online brands) that are frequently lie under their radar. Looking at market size dynamics, managers showed significant interest in tracking electronic WOM at the product category level. For instance, they mentioned the importance of tracking electronic WOM on sugar and sweeteners in the beverage category; as well as comments on proteins in the dairy market (I2). With respect to new competitors, tracking electronic WOM of emerging direct-to-consumer brands (e.g., online insurance or store brands/private labels), particularly those that have built their brand equity mostly through consumers' comments on social media (I7).

Integrated Marketing Mix Models and electronic WOM

Our interviewees in the media and advertising industry mentioned that they rarely build integrated marketing mix models, as they focus on reporting the performance of the actions under their purview: efficiency on media buying, and media mix selection. At best, their agencies track brand awareness and report a social listening study in their annual business reviews. Concerning competitor activities, measurement is usually limited to advertising investment (GRPs) and at most, number of mentions. Demand models used to not include interactions between traditional marketing mix elements and electronic WOM (I4). The key reason for the limited analysis of electronic WOM is the cost of outsourcing the modeling.

Discussion

Theoretical Implications

From a theoretical perspective, our main contribution is threefold: First, we provide novel evidence of the importance of incorporating competitive spillover effects into the study of electronic WOM content elasticities. Our findings suggest that in mature markets, the level of diagnosticity (high vs. low) of electronic WOM content moderates such spillover effects. These effects are critically important to uncovering marketing communication's effectiveness even in mature markets.

Second, we extend findings from previous studies analyzing electronic WOM's elasticities, which have suggested that not all electronic WOM is identical (Gopinath et al. 2014). We provide evidence for the benefits of examining electronic WOM in a disaggregated manner. Firms should therefore be cautious of tracking aggregated measures, such as electronic WOM volume or volume broken down by high-level valence dimensions, as this tracking may mask to a considerable degree individual-level effects. Our findings also have implications for WOM program design (Haenlein & Libai, 2017), as they show that not all forms of electronic WOM have an equal effect on sales. If firms want to engage in the amplification of organic electronic WOM, it is of crucial importance that they take the specific content of electronic WOM into account.

Third, by analyzing electronic WOM content's and traditional marketing mix elements' impact on sales simultaneously, we contribute to understanding social media's synergistic effect with traditional marketing (Kumar et al. 2017), a relationship rarely analyzed in the literature (Srinivasan et al. 2015). The significant interaction between price activity and electronic WOM on product taste suggests product activities' superior effectiveness in generating electronic WOM in some instances. For example, for brands that exhibit a lower elasticity with respect to advertising, a promising strategy might be to devote resources to generating certain types of electronic WOM, such as those related to informed and more diagnostic content, which might deliver the strongest electronic WOM elasticities.

Managerial Implications

The in-depth interviews combined with our empirical findings provide clear indication of competitive spillover effects, and by consequence, underscore the need to actively monitor competitors' electronic WOM. We therefore advise brands to systematically track competitors' electronic WOM. Specifically, negative electronic WOM that refers to a typical product attribute can substantially harm focal brand sales. We thus advocate a disaggregated approach.

In the mature FMCG market that we study, our findings indicate spillover effects comparable in size to the effects of the focal brand's own electronic WOM, and larger in magnitude than the direct effect of advertising. Being aware of these effects of electronic WOM will help managers to enhance their companies' investment and communications strategies. For example, in such markets, earned media strategies such as seeded communication should be linked to diagnostic messages, as our results suggest that consumer-generated electronic WOM is expected to have more impact on competitive gains sales than do either non-diagnostic or anecdotal messages.

Secondly, we underscore the importance of an integrated perspective on electronic WOM content and other traditional marketing mix actions to appropriately assess marketing initiatives' effectiveness. We recommend that brand managers leverage traditional marketing mix elements besides advertising, such as point-of-sale activities and product news, as effective and powerful tools for generating electronic WOM content. Such a wholistic approach can help to make sense of less elastic marketing activities and promote positive electronic WOM for their brands. For example, we found that although Pepsi advertising shows no effect on Pepsi sales, the elasticity of Pepsi positive electronic WOM on taste (β = 0.117) is significant and comparable in size to the elasticity of Coke advertising (β = 0.019). This effect suggests an opportunity to leverage consumers' electronic WOM about product news as an alternative competitive strategy to advertising in mature markets.

Finally, our approach demonstrates a method for brand managers to address unstructured data (Balducci and Marinova 2018) such as electronic WOM, and to integrate it with competitor activities and traditional marketing mix elements. As shown by our interviews, such models are highly needed by firms. While the lack of integrated approach to measuring marketing mix's and WOM's effects despite the size of investment and talent of the firms interviewed might appear surprising, there is a high recognition in the markets in general of the difficulty of managing and measuring WOM (Bughin, Doogan, and Vetvik 2010). As a WOMMA study found, only 6% of marketers consider themselves experts in word of mouth. That reticence is due to their discomfort in finding relevant metrics (Cardona 2015)[9].

As managers recognize the difficulty in finding models for adequately measuring their actions, our research suggests new avenues for how firms can proactively alter their marketing mix decisions to impact sales directly and indirectly through electronic WOM.

Limitations and Areas of Future Research

Overall, our results show that there is no simple answer to the fundamental questions that managers face when managing electronic WOM: What types of comments provide the most effective competitive advantage, and how do these messages interplay with the traditional marketing mix? Rather, our findings suggest that electronic WOM content has a complex relationship with sales, with various possible effects depending upon the message's and the marketing mix interplay's levels of diagnosticity. Importantly, we suggest that the appropriate modeling of electronic WOM likely depends upon the particular brand positioning vis-a-vis that of the competitors. This in turn results in the need to model and

[9] *https://www.cmo.com/features/articles/2015/2/25/talk_aint_cheap_word_of_mouth.html#gs.c3o574*

track electronic WOM content at a granular level to gain understanding of each brand’s particularities.

Our study is limited to the soft drink cola market as a representative example of mature FMCG markets. This limitation of analyzing one industry is shared by several comparable studies such as that of Borah and Tellis (2016), who focused on automobiles; and Pauwels et al. (2016) who analyzed the retail sector. Nevertheless, it would be worthwhile to investigate our findings’ generalizability to other FMCG markets with a broader competitive setting. In the same vein, the focus on Twitter as the main source of electronic WOM does not allow us to distinguish content or sentiment differences between platforms such as Facebook, blogs, or visual platforms such as Instagram.

Moreover, an analysis of possible brand and industry boundary conditions on the spillover relationships we identified appears to be a fruitful avenue of future research. For example, do the same patterns of spillover effects occur in markets involving less dominant competitors? Do industries with high/low rivalry exhibit higher or lower spillover effects? Research exploring these questions would enable understand of the extent to which spillovers are more or less uniform in their impact, and whether some firms may be insulated from competitive spillovers while others are not.

Table 1: Comparison of Selected Prior Research on electronic WOM Content Competitor Spillover Effects

Article	Source of electronic WOM	Dependent variable	Positive electronic WOM	Negative electronic WOM	Type of eWOM content investigated	Competitor's spillover	Marketing mix interactions with eWOM content	Product type	Key findings
Onishi and Manchanda (2012)	Blogs	Views, Subscribers Pre/post launch	Yes	Yes	Selected keywords: "Award", "Advertising", "Interesting", "Viewed"	No	Advertising	Movies, Cellular phones	Synergies between blogs and traditional media
Gopinath et al. (2014)	Online forum	Sales	Yes (weighted average)	Yes	Predefined and aggregated into "Attribute", "Emotion" and "Recommendation"	No	Price, distribution, number and type of ads	Cellular phones	WOM and advertising interaction depends upon mature vs new products
Pauwels et al. (2016)	Blogs, online forum, Twitter, Facebook	In-store traffic	Yes	No	Predefined and aggregated into: advertising, brand, purchase eWOM	No	Advertising, print impressions, paid search	Retail outlets	Positive/neutral WOM interacts with traditional media in attracting store traffic
Borah and Tellis (2016)	Forums, blogs, review sites	Monthly sales	No	Yes	Product recalls, chatter	Yes	Advertising	Cars	Negative spillover of WOM when brand recalls occur
This study	**Twitter**	**Weekly sales**	**Yes**	**Yes**	**Any type of content, not predefined (unsupervised)**	**Yes**	**Advertising price, distribution**	**Soft drinks**	**Competitors Spillover Elasticities for positive and negative eWOM content, depending on high/low level of the content's diagnosticity; Interactions with the marketing mix**

Table 2: Descriptive Statistics

	Variable *	Mean	Maximum	Minimum	Std. Dev.
Pepsi	Sales (thousand liters)	1,563.56	2,171.68	1,230.12	201.60
	Price (EUR/ liter)	0.63	0.69	0.57	0.03
	Weighted Distribution (%)	98.01	99.00	96.00	0.65
	GRPs/ week	30.47	365.00	0.00	80.46
Coke	Sales (thousand liters)	9,715.27	14,425.77	7,633.45	1,563.87
	Price (EUR/ liter)	0.94	1.02	0.85	0.04
	Weighted Distribution (%)	100.00	100.00	100.00	0.00
	GRPs/ week	116.53	876.20	0.00	160.83

* All variables are measured on a weekly basis.

Table 3: Topics of Electronic WOM Content

Name	Brand	Valence	Topic	Description	*Illustrative Tweet*
Pepsipos1	Pepsi	Positive	Product/Package news	Promotions	*My idol is that person who wears Pepsi pajamas and promotes Pepsi*
Pepsipos2	Pepsi	Positive	Company-related news	Category news	*Whatever possible could be very good. It could be Pepsi's Latest Pepsi campaign.*
Pepsipos3	Pepsi	Positive	Product/Package news	Taste	*Too strong a taste to call ourselves ZERO. Great message from Pepsi Max in USA OMG!*
Pepsipos4	Pepsi	Positive	Advertising	Celebrities	*One Direction has signed a multimillionaire contract to sponsor Pepsi!*
Cokepos1	Coke	Positive	Company-related news	Success	*Coca Cola success: unresolved enigma? http://t.co/tWjZvCfx*
Cokepos2	Coke	Positive	Product/Package News	Promotions	*Drinking Coca Cola Zero. It is cool to promote it.*
Cokepos3	Coke	Positive	Advertising	New ads	*Terrific @coca cola campaign targeted to young people @MTV Spain experience*
Cokepos4	Coke	Positive	Advertising	Summer Campaign	*Welcome to summer! Coca cola and tapas to enjoy!*
Cokepos5	Coke	Positive	Product/Package news	New products	*#goodads Fantastic last Coca cola Zero Ad*
Pepsineg1	Pepsi	Negative	Fake news	Fake news (formula)	*Did you know that @Pepsi researches aborted fetuses? According to them they produce "greater taste and less calories in soft drinks" #boycott*
Pepsineg2	Pepsi	Negative	Fake news	Fake news (cancer)	*Pepsi needs to include cancer warnings on their labels*
Pepsineg3	Pepsi	Negative	Product/Package news	Taste	*Pepsi taste continues to be bad!*
Pepsineg4	Pepsi	Negative	Advertising	Advertising (general)	*@Pepsi should get information before doing such terrible campaigns #pepsisnotcool*
Cokeneg1	Coke	Negative	Advertising	Advertising (general)	*I don't like at all the spot with @ATM and @Coca cola*
Cokeneg2	Coke	Negative	Company-related news	General	*We should boycott all big brands to show them some pain. Coca cola NO THANKS!*

Table 4: Aggregated WOM SUR Model

	(1) Pepsi	(2) Coke
Constant	-18.87*	-19.58*
	(8.115)	(9.602)
Price gap	0.339***	-0.376***
	(0.0751)	(0.0888)
Distribution	5.861***	6.220**
	(1.749)	(2.070)
Grps Pepsi	0.00645	0.00655
	(0.00477)	(0.00564)
Grps Coke	-0.123***	-0.122**
	(0.0366)	(0.0434)
Grps Coke (t-1)	0.00874**	0.0108**
	(0.00326)	(0.00386)
Negative WOM Pepsi	-0.0187	-0.0187
	(0.0191)	(0.0227)
Positive WOM Pepsi	0.0260	0.0258
	(0.0172)	(0.0204)
Positive WOM Coke	-0.0800*	-0.0927*
	(0.0321)	(0.0380)
Negative WOM Coke	0.0262	0.0465
	(0.0265)	(0.0314)
Grps Coke x Positive Ewom Coke	0.0207***	0.0214**
	(0.00552)	(0.00653)
R squared	0.667	0.683
Adjusted R squared	0.617	0.636
F	13.99	13.99
Model *df*	13	13
Residual *df*	87	87
Observations	101	101

Standard errors in parentheses
Dependent variable: Brand sales in equivalent units
Seasonal dummies not shown
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Disaggregated WOM SUR Model

	(1) Pepsi	(2) Coke
Constant	-26.22***	-22.26**
	(7.435)	(8.268)
Price gap	0.233**	-0.481***
	(0.0833)	(0.0923)
Distribution	7.359***	6.706***
	(1.617)	(1.799)
Grps Pepsi	0.00269	0.00518
	(0.00461)	(0.00516)
Grps Coke	0.0134***	0.0162***
	(0.00331)	(0.00368)
Grps Coke (2-lagged)	0.0103**	0.00724
	(0.00315)	(0.00390)
Neg. Pepsi [Fake News (Formula)]	-0.0259***	-0.0268**
	(0.00778)	(0.00866)
Neg. Pepsi [Fake News (Cancer)]	0.00889	0.00584
	(0.00499)	(0.00553)
Neg. Pepsi [Taste]	0.0221*	0.0203
	(0.00964)	(0.0108)
Neg. Pepsi [Advertising]	0.00486	0.00995
	(0.00612)	(0.00681)
Pos. Pepsi [Promotions]	-0.0118*	-0.0185**
	(0.00597)	(0.00665)
Pos. Pepsi [Category news]	0.0180*	0.0267**
	(0.00882)	(0.00981)
Pos. Pepsi [Taste]	0.117**	-0.0252*
	(0.0446)	(0.0125)
Pos. Pepsi [Celebrities]	-0.00320	-0.00262
	(0.00510)	(0.00567)
Neg. Coke [Advertising]	-0.00239	0.00152
	(0.00549)	(0.00611)
Neg. Coke [General]	-0.00489	0.000197
	(0.00604)	(0.00671)
Pos. Coke [Success]	0.00165	0.00288
	(0.00569)	(0.00633)
Pos. Coke [Promotions]	0.00693	0.00541
	(0.00744)	(0.00829)
Pos. Coke [New ads]	-0.00334	-0.00358
	(0.00631)	(0.00701)
Pos. Coke [Summer campaign]	0.0104	0.00400
	(0.00563)	(0.00667)
Pos. Coke [New products]	0.00945	0.0192**
	(0.00566)	(0.00632)
Price Gap x Taste	0.114**	
	(0.0367)	
Grps Coke x Summer campaign		0.00186*
		(0.000852)
R squared	0.724	0.768
Adjusted R squared	0.725	0.725
F	18.93	18.93
Model *df*	24	24
Residual *df*	76	76
Observations	101	101

Standard errors in parentheses
Dependent variable: Brand sales in Equivalent Units
Seasonality dummies not shown.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6. Description of Topics Extracted

Classified by Level (high/low) of Diagnosticity

	High-diagnostic Positive	**Low-Diagnostic Positive**	**High-diagnostic Negative**	**Low-Diagnostic Negative**
Pepsi	Promotions[*FS]	Category News[*FS]	Fake News[*FS]	Advertising (general)
	Taste[*FS]	Celebrities Advertising	Taste[*F]	
Coke	New product[*F]	(Company) Success		Advertising (general)
	Promotions	Summer ads		Company news (general)
		Advertising (general)		

F: significant effect for the focal brand
S: significant spillover effect for the competitor brand

Table 7. Description of the Executives interviewed

Industry	Company	ID	Interviewer	Exemplary quote
Advertising agency	Leading global corporation	I1	Social Media Manager	*"These insights would allow us to measure electronic WOM ROI more efficiently."*
Dairy products	Leading European multinational	I2	General Manager	*"In product categories where new demand can be created, understanding the electronic WOM content is really important"*
Soft drinks	Leading American multinational	I3	Insights and Media Manager	*"Given our competitive situation, we can´t react to lead brand actions as we don't have enough resources …but we are creating a Global Center for Digital Excellence and probably in the future this [the electronic WOM content analysis] will change"*
Media Planning	Leading advertising agency	I4	General Manager	*"We outsource this type of study, and every time we slightly change a variable, a three-figure budget is added"*
Insurance	Leading European multinational	I5	Marketing Manager	*"Negative comments about our category are common on Social Media and I'm sure it's something that hurts us badly. However, we don't know exactly how much it hurts and how to counteract it"*
Non-profit	European NGO	I6	Media Manager	*"Online WOM comments are very important for our market (NGO), even more so than our own advertising, as what others believe about NGOs will foster or prevent individuals from affiliating….but we still haven't found a reliable system for exploring and managing all the information"*
Fast Food	Leading American multinational	I7	Media Strategy	*"…how to account for the activity of native brands on line? We have a burger chain competitor that invests only in social media. We should use your model to get to know the impact of their strategy"*
Automobile	Leading multinational	I8	Digital Manager	*"While online WOM is paramount to us, we still haven't found a reliable system for exploring and managing all that information"*

Figure 1: Simulated Impact of Changes in Marketing Mix Elements and electronic WOM content on Pepsi sales

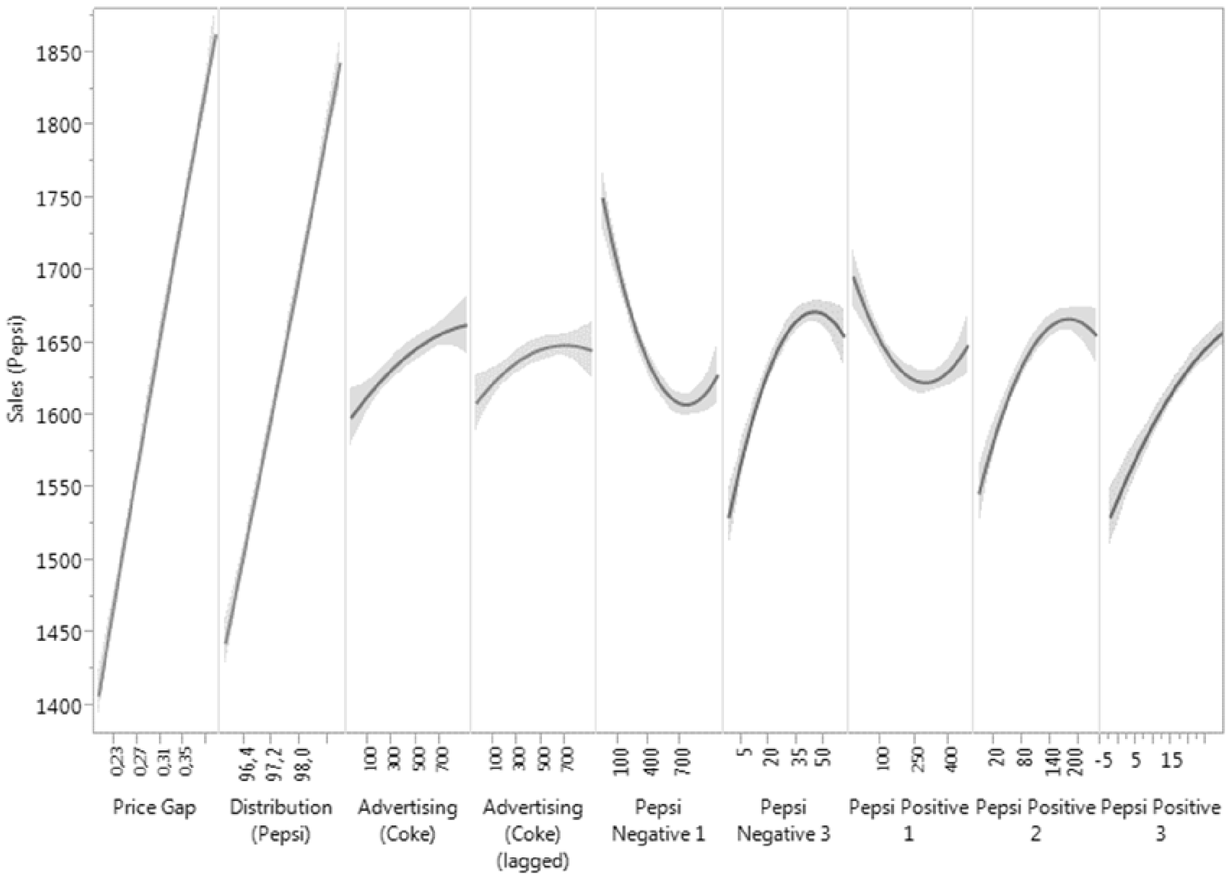
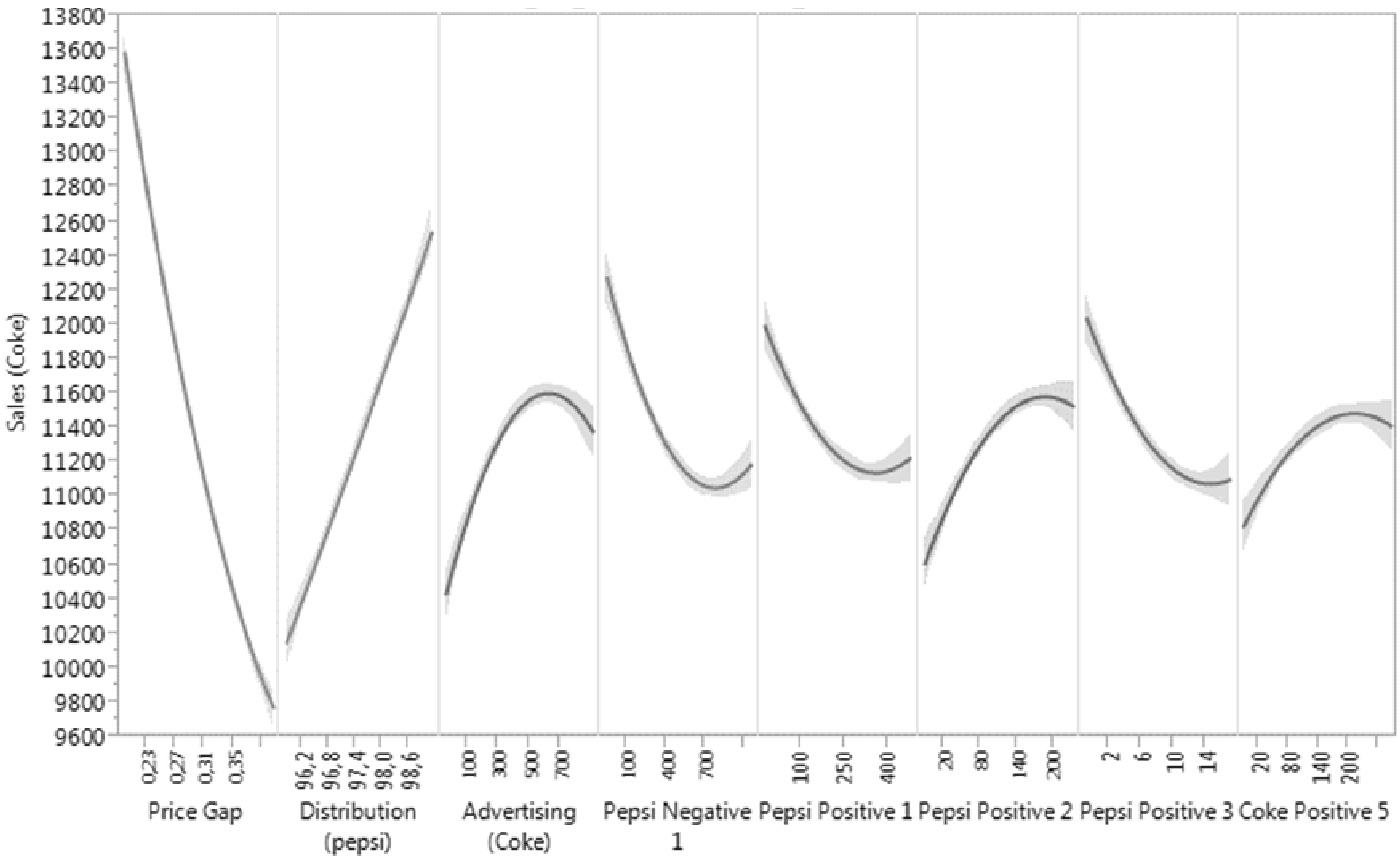


Figure 2: Simulated Impact of Changes in Marketing Mix Elements and electronic WOM content on Coke sales



References

Aaker, D. A., Carman, J. M., & Jacobson, R. (1982). Modeling advertising-sales relationships involving feedback: A time series analysis of six cereal brands. Journal of Marketing Research, 19(1), 116–125.

Abril, C. & Sanchez, J. (2016). Will they return? Getting private label consumers to come back: Price, promotion, and new product effects. Journal of Retailing and Consumer Services, 31, 109–116.

AMA/WOMMA Survey. (2014). The state of word of mouth marketing: A survey of marketers. Chicago.

Anderson, E. T. & Simester, D. (2013). Advertising in a competitive market: The role of product standards, customer learning, and switching costs. Journal of Marketing Research, 50(4), 489–504.

Arellano, M. & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. Journal of Econometrics, 68(1) 29–51.

Babic Rosario, A., Sotgiu, F., De Valck, K., & Bijmolt, T. H. A. (2016). The effect of electronic word of mouth on sales: A meta-analytic review of platform, product, and metric factors. Journal of Marketing Research, 53(3) 297–318.

Bae, Y. & Lee, H. (2012). Sentiment analysis of twitter audiences: Measuring the positive or negative influence of popular twitterers. Journal of the Association for Information Science and Technology, 63(12) 2521–2535.

Balducci, B. & Marinova, D. (2018). Unstructured data in marketing. Journal of the Academy of Marketing Science, 1–34.

Batra, R. & Keller, K. L. (2016). Integrating marketing communications: New findings, new lessons, and new ideas. Journal of Marketing, 80(6), 122–145.

Berger, J. & Schwartz, E. M. (2011). What drives immediate and ongoing word of mouth? Journal of Marketing Research, 48(5), 869–880.

Berger, J., Sorensen, A. T., & Rasmussen, S. J. (2010). Positive effects of negative publicity: When negative reviews increase sales. Marketing Science 29(5), 815–827.

Berkowitz, D., Allaway, A., & D'Souza, G. (2001). Estimating differential lag effects for multiple media across multiple stores. Journal of Advertising, 30(4), 59–65.

Bettman, J. R. (1979). Memory factors in consumer choice: A review. Journal of Marketing, 37–53.

Borah, A. and Tellis, G. J. (2016). Halo (spillover) effects in social media: Do product recalls of one brand hurt or help rival brands? Journal of Marketing Research, 53(2), 143–160.

Bughin, J., Doogan, J., & Vetvik, O. J. (2010). A new way to measure word-of-mouth marketing. McKinsey Quarterly 2, 113–116.

Chae, I., Stephen, A. T., Bart, Y., & Yao, D. (2017). Spillover effects in seeded word-of-mouth marketing campaigns. Marketing Science, 36(1), 89–104.

Chang, C. (2010). Message framing and interpersonal orientation at cultural and individual levels: Involvement as a moderator. International Journal of Advertising 29(5), 765–794.

Chen, Z. & Berger, J. (2013). When, why, and how controversy causes conversation. Journal of Consumer Research, 40(3), 580–593.

Chen, Y. & Xie, J. (2008). Online consumer review: Word of mouth as a new element of marketing communication mix. Management Science, 54(3), 477–491.

Chern, C.-C., Wei, C.-P., Shen, F.-Y., & Fan, Y.-N. (2015). A sales forecasting model for consumer products based on the influence of online word of mouth. Information Systems and e-Business Management, 13(3), 445–473.

Chevalier, J. A. & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. Journal of Marketing Research, 43(3), 345–354.

Cleeren, K., van Heerde, H. J., & Dekimpe, M. G. (2013). Rising from the ashes: How brands and categories can overcome product-harm crises. Journal of Marketing, 77, 58–77.

Collins, A. M. & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. Psychological Review, 82(6), 407.

Creswell, J. W. & Plano Clark, V. L. (2011). Designing and conducting mixed method research, 2nd edition. Thousand Oaks, CA: Sage. 201.

Culotta, A. &Cutler, J. (2016). Mining brand perceptions from Twitter social networks. Marketing Science, 35(3), 343–362.

D’Souza, G. & Rao, R. C. (1995). Can repeating an advertisement more frequently than the competition affect brand preference in a mature market? Journal of Marketing, 59(2), 32–42.

de Matos, C. A. & Rossi, C. A. V. (2008). Word-of-mouth communications in marketing: A meta-analytic review of the antecedents and moderators. Journal of the Academy of Marketing Science, 36(4), 578–596.

Dick, A., Chakravarti, D., & Biehal, G. (1990). Memory-based inferences during consumer choice. Journal of Consumer Research, 17(1), 82–93.

Duan, W., Gu, B., & Whinston, A. B. (2008). Do online reviews matter? An empirical investigation of panel data. Decision Support Systems, 45(4), 1007–1016.

Dost, F., Phieler, U., Haenlein, M., & Libai, B. "Seeding as part of the marketing mix: Word-of-mouth program interactions for fast-moving consumer goods", Forthcoming, Journal of Marketing

Durbin, J. (1954). Errors in variables. Revue de l'Institut International de Statistique / Review of the International Statistical Institute 22(1/3) 23–32.

East, R., Hammond, K., & Lomax, W. (2008). Measuring the impact of positive and negative word of mouth on brand purchase probability. International Journal of Research in Marketing 25(3) 215–224.

Evans, D. (2010). Social media marketing: The next generation of business engagement. John Wiley & Sons.

Feldman, J. M. & Lynch, J. G. J. (1988). Self-generated validity and other effects of measurement on belief, attitude, intention, and behavior. Journal of Applied Psychology, 73(3), 421–435.

Feldman, L. B. (2013). Morphological aspects of language processing. Psychology Press.

Filieri, R. (2015). What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM. Journal of Business Research, 68(6), 1261–1270.

Finne, Å. & Grönroos, C. (2017). Communication-in-use: Customer-integrated marketing communication. European Journal of Marketing, 51(3), 445–463.

Fosfuri, A. & Giarratana, M. S. (2009). Masters of war: Rivals' product innovation and new advertising in mature product markets. Management Science, 55(2), 181–191.

Fossen, B. L. & Schweidel, D. A. (2016). Television advertising and online word-of-mouth: An empirical investigation of social TV activity. Marketing Science, 36(1), 105–123.

Gong, S., Zhang, J., Zhao, P., & Jiang, X. (2017). Tweeting as a marketing tool: A field experiment in the TV industry. Journal of Marketing Research, 54(6), 833–850.

Goldsmith, R. E. & Horowitz, D. (2006). Measuring motivations for online opinion seeking. Journal of Interactive Advertising, 6(2) 2–14.

Gopinath, S., Thomas, J. S., & Krishnamurthi, L. (2014). Investigating the relationship between the content of online word of mouth, advertising, and brand performance. Marketing Science, 33(2) 241–258.

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. Field Methods, 18(1), 59–82.

Haenlein, M. & Libai, B. (2017). Seeding, referral, and recommendation: Creating profitable word-of-mouth programs. California Management Review, 59(2), 68 –91.

Hanssens, D. M. (1980). Bivariate time-series analysis of the relationship between advertising and sales. Applied Economics, 12(3), 329–339.

Hanssens, D. M. (2018). The value of empirical generalizations in marketing. Journal of the Academy of Marketing Science, 46(1), 6–8.

Hansen, C., Hausman, J., & Newey, W. (2008). Estimation with many instrumental variables. Journal of Business and Economic Statistics 26(4), 398–422.

Hausman, J. A. (1978). Specification tests in econometrics. Econometrica, 46(6), 1251 –1271.

Hennig-Thurau, T., Wiertz, C., & Feldhaus, F. (2015). 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), 375–394.

Herr, P. M., Kardes, F. R., & Kim, J. (1991). Effects of word-of-mouth and product-attribute information on persuasion: An accessibility-diagnosticity perspective. Journal of Consumer Research, 17(4), 454–462.

Hewett, K., Rand, W., Rust, R. T., & van Heerde, H. J. (2016). Brand buzz in the echoverse. Journal of Marketing, 80(3), 1–24.

Ho-Dac, N. N., Carson, S. J., & Moore, W. L. (2013). The effects of positive and negative online customer reviews: Do brand strength and category maturity matter? Journal of Marketing, 77(6), 37–53.

Hogan, J. E., Lemon, K. N., & Libai, B. (2004). Quantifying the ripple: Word of mouth and advertising effectiveness. Journal of Advertising Research, 44(3) 271–280.

Janakiraman, N., Meyer, R. J., & Morales, A. C. (2006). Spillover effects: How consumers respond to unexpected changes in price and quality. Journal of consumer research, 33(3), 361–369.

Janakiraman, R., Sismeiro, C., & Dutta, S. (2009). Perception spillovers across competing brands: A disaggregate model of how and when. Journal of Marketing Research, 46(4), 467–481.

Jiang, Z. & Benbasat, I. (2004). Virtual product experience: Effects of visual and functional control of products on perceived diagnosticity and flow in electronic shopping. Journal of Management Information Systems 21(3), 111–147.

Jiang, Z. & Benbasat, I. (2007). The effects of presentation formats and task complexity on online consumers' product understanding. MIS Quarterly, 475–500.

Joshi, A. & Hanssens, D. M. (2010). The direct and indirect effects of advertising spending on firm value. Journal of Marketing, 74(1) 20–33.

Katz, E. & Lazarsfeld, P. F. (1955). Personal influence: The part played by people in the flow of mass communications. Glencoe, IL: The Free Press.

Keller, E. & Fay, B. (2012). The face-to-face book: Why real relationships rule in a digital marketplace. Free Press.

Keller, K. L. (1987). Memory factors in advertising: The effect of advertising retrieval cues on brand evaluations. Journal of Consumer Research, 14(3), 316–333.

Keller, E. (2007). Unleashing the power of word of mouth: Creating brand advocacy to drive growth. Journal of Advertising Research, 47(4), 448–452.

Keller, E. & Libai, B. (2009, May). A holistic approach to the measurement of WOM. ESOMAR Worldwide Media Measurement Conference, Stockholm.

Kempf, D.S. & Smith, R.E. (1998) Consumer processing of product trial and the influence of prior advertising: A structural modeling approach. Journal of Marketing Research, 35, 3, 325–337.

Kent, R. J. & Allen, C. T. (1994). Competitive interference effects in consumer memory for advertising: The role of brand familiarity. Journal of Marketing, 58(3), 97–105.

Kim, H. & Hanssens, D. M. (2017). Advertising and word-of-mouth effects on pre-launch consumer interest and initial sales of experience products. Journal of Interactive Marketing, 37, 57–74.

King, R. A., Racherla, P., & Bush, V. D. (2014). What we know and don't know about online word of mouth: A review and synthesis of the literature. Journal of Interactive Marketing 28(3), 167–183.

Krishnan, T. V., Seetharaman, P. B. S., & Vakratsas, D. (2012). The multiple roles of interpersonal communication in new product growth. International Journal of Research in Marketing 29(3) 292–305.

Koschate-Fischer, N., Cramer, J., & Hoyer, W. D. (2014). Moderating effects of the relationship between private label share and store loyalty. Journal of Marketing, 72, 69–82.

Kumar, V., Choi, J. B., & Greene, M. (2017). Synergistic effects of social media and traditional marketing on brand sales: Capturing the time-varying effects. Journal of the Academy of Marketing Science, 45(2) 268–288.

Lei, J., Dawar, N., & Lemmink, J. (2008). Negative spillover in brand portfolios: Exploring the antecedents of asymmetric effects. Journal of Marketing, 72(3), 111–123.

Lewis, R. & Nguyen, D. (2015). Display advertising's competitive spillovers to consumer search. Quantitative Marketing and Economics, 13(2), 93–115.

Libai, B., Muller, E., & Peres, R. (2009). The role of within-brand and cross-brand communications in competitive growth. Journal of Marketing, 73(3), 19–34.

Lovett, M. J. & Staelin, R. (2016). The role of paid, earned, and owned media in building entertainment brands: Reminding, informing, and enhancing enjoyment. Marketing Science, 35(1), 142–157.

Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. Journal of Marketing, 70(3), 74–89.

Lopez, R. A., Liu, Y., & Zhu, C. (2015). TV advertising spillovers and demand for private labels: The case of carbonated soft drinks. Applied Economics, 47(25) 2563–2576.

Liu, Y. & Lopez, R. A. (2016). The impact of social media conversations on consumer brand choices. Marketing Letters 27(1), 1–13.

Lovett, M. J., Peres, R., & Shachar, R. (2013). On brands and word of mouth. Journal of Marketing Research, 50(4), 427–444.

Ma, L., Sun, B., & Kekre, S. (2015). The squeaky wheel gets the grease: An empirical analysis of customer voice and firm intervention on Twitter. Marketing Science, 34(5), 627–645.

Marchand, A., Hennig-Thurau, T., & Wiertz, C. (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), 336–354.

Marketing Science Institute. (2018). 2018 - 2020 Research Priorities: A guide to MSI research programs and procedures. Cambridge: Marketing Science Institute.

Mudambi, S. & Schuff, D. (2010). What makes a helpful online review? A study of customer reviews on Amazon.com. MIS Quarterly, 34(1), 185–200.

Nichoolson, R. (2017) https://www.theguardian.com/business/2017/apr/05/from-cokes-flower-power-to-kendall-jenners-pepsi-ad-how-ads-co-opt-protest last access 15th Nov 2018.

Nielsen (2017) Nielsen Social Media report https://www.nielsen.com/us/en/insights/reports/2017/2016-nielsen-social-media-report.html last access 15th Nov 2018.

Nijssen, E. J. (1999). Success factors of line extensions of fast-moving consumer goods. European Journal of Marketing, 33, 450–474.

Oberhofer, W. & Kmenta, J. (1974). A general procedure for obtaining maximum likelihood estimates in generalized regression models. Econometrica: Journal of the Econometric Society, 579–590.

Olsen, M. C., Slotegraaf, R. J., & Chandukala, S. R. (2014). Green claims and message frames: How green new products change brand attitude. Journal of Marketing, 78, 119–137.

Onishi, H. & Manchanda, P. (2012). Marketing activity, blogging and sales. International Journal of Research in Marketing 29(3) 221–234.

Pauwels, K., Erguncu, S., & Yildirim, G. (2013). Winning hearts, minds and sales: How marketing communication enters the purchase process in emerging and mature markets. International Journal of Research in Marketing, 30(1), 57–68.

Pauwels, K., Aksehirli, Z., & Lackman, A. (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), 639–655.

Peres, R. & Van den Bulte, C. (2014). When to take or forgo new product exclusivity: Balancing protection from competition against word-of-mouth spillover. Journal of Marketing, 78(2), 83–100.

Qiu, L., Pang, J., & Lim, K. H. (2012). Effects of conflicting aggregated rating on eWOM review credibility and diagnosticity: The moderating role of review valence. Decision Support Systems, 54(1), 631–643.

Raj, S. P. (1982). The effects of advertising on high and low loyalty consumer segments. Journal of Consumer Research, 9(1), 77–89.

Richins, M. L. & Root-Shaffer, T. (1988). The role of involvement and opinion leadership in consumer word-of-mouth: An implicit model made explicit. In M. J. Houston (Ed.), Advances in consumer research (Vol. 15, pp. 32–35). Provo, UT: Association for Consumer Research.

Roehm, M. L. & Tybout, A. M. (2006). When will a brand scandal spill over, and how should competitors respond? Journal of Marketing Research, 43(3), 366–373.

Roodman, D. (2009). Estimating fully observed recursive mixed-process models with cmp.

Sahni, N. S. (2016). Advertising spillovers: Evidence from online field experiments and implications for returns on advertising. Journal of Marketing Research, 53(4), 459–478.

Sen, D. (2007). Lerman, why are you telling me this? An examination into negative consumer reviews on the web. Journal of Interactive Marketing 21 (4) 76–94.

Sethuraman, R., Tellis, G. J., & Briesch, R. A. (2011). How well does advertising work? Generalizations from meta-analysis of brand advertising elasticities. Journal of Marketing Research, 48(3), 457–471.

Silayoi, P. & Speece, M. (2007). The importance of packaging attributes: A conjoint analysis approach. European Journal of Marketing, 41, 1495–1517.

Srinivasan, S., Rutz, O. J., & Pauwels, K. (2016). Paths to and off purchase: Quantifying the impact of traditional marketing and online consumer activity. Journal of the Academy of Marketing Science, 44(4), 440–453.

Sunder, S., Kumar, V., and Zhao, Y. (2016). Measuring the lifetime value of a customer in the consumer packaged goods industry. Journal of Marketing Research (JMR), 53(6), 901–921.

Taylor, K. (2018) https://www.businessinsider.es/nike-colin-kaepernick-ad-sparks-boycott-2018-9?r=USandIR=T last access 15th Nov 2018.

Tellis, G. J. (1988). Advertising exposure, loyalty, and brand purchase: A two-stage model of choice. Journal of Marketing Research 25(2), 134–144.

Tirunillai, S. & Tellis, G. J. (2012). Does chatter really matter? Dynamics of user-generated content and stock performance. Marketing Science, 31(2), 198–215.

Trump, R. K. & Newman, K. P. (2017). When do unethical brand perceptions spill over to competitors? Marketing Letters 28(2) 219–230.

Tversky, A. (1977). Features of similarity. Psychological Review, 84(4), 327–352.

Wilson, A. E., Giebelhausen, M. D., & Brady, M. K. (2017). Negative word of mouth can be a positive for consumers connected to the brand. Journal of the Academy of Marketing Science, 45(4), 534–547.

Wu, D.-M. (1973). Alternative tests of independence between stochastic regressors and disturbances. Econometrica, 41(4), 733–750.

Yang, N. (2012). Burger King and McDonald's: Where's the spillover? International Journal of the Economics of Business, 19(2) 255–281.

You, Y., Vadakkepatt, G. G., & Joshi, A. M. (2015). A meta-analysis of electronic word-of-mouth elasticity. Journal of Marketing, 79(2), 19–39.

Zhang, Y., Moe, W. W., & Schweidel, D. A. (2017). Modeling the role of message content and influencers in social media rebroadcasting. International Journal of Research in Marketing, 34(1), 100–119.

Zellner, A. (1962). An efficient method of estimating seemingly unrelated regression equations and tests for aggregation bias. Journal of the American Statistical Association 57: 348–368.

APPENDIX

Table 1-A: SUR and 2SLS Estimation (Pepsi)

	SUR System		2SLS Estimation					
	(1) Pepsi	(2) Coke	(3) Instrumented: Pepsi Neg. eWOM	(4) Instrumented: Pepsi Pos. eWOM	(5) Instrumented: Coke Pos. eWOM	(6) Instrumented: Coke Neg. eWOM	(7) Instrumented: Grps Pepsi	(8) Instrumented: Grps Coke
Constant	-18.87*	-19.58*	-13.74	-18.14*	-15.53	-20.91*	-22.84**	-18.38
	(8.115)	(9.602)	(13.05)	(8.506)	(10.22)	(9.441)	(8.750)	(9.650)
Price gap	0.339***	-0.376***	0.396**	0.325***	0.351***	0.311**	0.339***	0.337***
	(0.0751)	(0.0888)	(0.134)	(0.0824)	(0.0788)	(0.0962)	(0.0760)	(0.0787)
Distribution	5.861***	6.220**	4.777	5.678**	5.165*	6.303**	6.721***	5.768**
	(1.749)	(2.070)	(2.784)	(1.842)	(2.177)	(2.037)	(1.887)	(2.017)
Grps Pepsi	0.00645	0.00655	0.0109	0.00609	0.00667	0.00545	-0.000927	0.00670
	(0.00477)	(0.00564)	(0.00998)	(0.00498)	(0.00482)	(0.00540)	(0.00741)	(0.00547)
Grps Coke	-0.123***	-0.122**	-0.146*	-0.0964	-0.143**	-0.131**	-0.118**	-0.145
	(0.0366)	(0.0434)	(0.0595)	(0.0622)	(0.0528)	(0.0423)	(0.0373)	(0.239)
Grps Coke (2-lag)	0.00874**	0.0108**	0.00811*	0.00970*	0.00869**	0.00766	0.00831*	0.00843
	(0.00326)	(0.00386)	(0.00364)	(0.00382)	(0.00329)	(0.00402)	(0.00331)	(0.00464)
Neg. WOM Pepsi	-0.0187	-0.0187	-0.0836	0.00773	-0.0200	-0.00281	-0.0105	-0.0209
	(0.0191)	(0.0227)	(0.126)	(0.0536)	(0.0194)	(0.0367)	(0.0204)	(0.0302)
Pos. WOM Pepsi	0.0260	0.0258	0.0563	-0.0198	0.0310	0.0352	0.0253	0.0288
	(0.0172)	(0.0204)	(0.0610)	(0.0881)	(0.0196)	(0.0254)	(0.0174)	(0.0344)
Pos. WOM Coke	-0.0800*	-0.0927*	-0.0859*	-0.0604	-0.120	-0.0180	-0.0781*	-0.0886
	(0.0321)	(0.0380)	(0.0358)	(0.0496)	(0.0807)	(0.124)	(0.0325)	(0.0982)
Neg. WOM Coke	0.0262	0.0465	0.0477	0.0371	0.0446	-0.0659	0.0237	0.0251
	(0.0265)	(0.0314)	(0.0498)	(0.0342)	(0.0431)	(0.180)	(0.0269)	(0.0290)
Grps Coke x Pos. eWOM Coke	0.0207***	0.0214**	0.0241**	0.0169	0.0239**	0.0218***	0.0199***	0.0240
	(0.00552)	(0.00653)	(0.00875)	(0.00916)	(0.00809)	(0.00619)	(0.00562)	(0.0359)
R squared	0.667	0.683	0.629	0.643	0.661	0.627	0.659	0.665
Adj. R squared			0.573	0.590	0.611	0.571	0.608	0.615
Model df	13	13	13	13	13	13	13	13
RSS	0.526	0.737	0.586	0.563	0.534	0.589	0.539	0.528
RMSE	0.0722	0.0854	0.0762	0.0747	0.0727	0.0764	0.0730	0.0723
Chi-square	201.9	217.7	180.9	186.6	195.0	179.6	195.5	190.4
Observations	101	101	101	101	101	101	101	101

Standard errors in parentheses
Dependent variable: Log of brand sales in Equivalent Units
Seasonal dummy variables not shown
Instrumental variables: Log of active Twitter users and one period lagged endogenous variables
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2-A: SUR and 2SLS Estimation (Coke)

	SUR System		2SLS Estimation					
	(1) Pepsi	(2) Coke	(3) Instrumented: Pepsi Neg. eWOM	(4) Instrumented: Pepsi Pos. eWOM	(5) Instrumented: Coke Pos. eWOM	(6) Instrumented: Coke Neg. eWOM	(7) Instrumented: Grps Pepsi	(8) Instrumented: Grps Coke
Constant	-18.87*	-19.58*	-8.623	-18.03	-12.44	-23.94	-23.57*	-21.32
	(8.115)	(9.602)	(17.14)	(10.79)	(12.30)	(12.45)	(10.32)	(11.58)
Price gap	0.339***	-0.376***	-0.256	-0.408***	-0.351***	-0.437***	-0.377***	-0.369***
	(0.0751)	(0.0888)	(0.176)	(0.105)	(0.0948)	(0.127)	(0.0896)	(0.0944)
Distribution	5.861***	6.220**	3.899	5.827*	4.731	7.164**	7.082**	6.552**
	(1.749)	(2.070)	(3.657)	(2.337)	(2.620)	(2.687)	(2.226)	(2.421)
Grps Pepsi	0.00645	0.00655	0.0161	0.00577	0.00702	0.00441	-0.000855	0.00566
	(0.00477)	(0.00564)	(0.0131)	(0.00632)	(0.00581)	(0.00712)	(0.00874)	(0.00657)
Grps Coke	-0.123***	-0.122**	-0.172*	-0.0656	-0.166**	-0.140*	-0.117**	-0.0430
	(0.0366)	(0.0434)	(0.0781)	(0.0789)	(0.0635)	(0.0557)	(0.0439)	(0.287)
Grps Coke (2-lag)	0.00874**	0.0108**	0.00949*	0.0129**	0.0107**	0.00853	0.0104**	0.0119*
	(0.00326)	(0.00386)	(0.00479)	(0.00485)	(0.00396)	(0.00531)	(0.00391)	(0.00557)
Neg. WOM Pepsi	-0.0187	-0.0187	-0.158	0.0378	-0.0215	0.0153	-0.0104	-0.0109
	(0.0191)	(0.0227)	(0.166)	(0.0679)	(0.0234)	(0.0484)	(0.0240)	(0.0363)
Pos. WOM Pepsi	0.0260	0.0258	0.0906	-0.0722	0.0364	0.0455	0.0251	0.0159
	(0.0172)	(0.0204)	(0.0801)	(0.112)	(0.0235)	(0.0335)	(0.0206)	(0.0413)
Pos. WOM Coke	-0.0800*	-0.0927*	-0.105*	-0.0509	-0.179	0.0399	-0.0908*	-0.0618
	(0.0321)	(0.0380)	(0.0470)	(0.0629)	(0.0971)	(0.164)	(0.0384)	(0.118)
Neg. WOM Coke	0.0262	0.0465	0.0924	0.0697	0.0859	-0.151	0.0440	0.0503
	(0.0265)	(0.0314)	(0.0655)	(0.0434)	(0.0519)	(0.237)	(0.0317)	(0.0348)
Grps Coke x Pos. eWOM Coke	0.0207***	0.0214**	0.0287*	0.0133	0.0282**	0.0237**	0.0205**	0.00960
	(0.00552)	(0.00653)	(0.0115)	(0.0116)	(0.00974)	(0.00817)	(0.00663)	(0.0430)
R squared	0.667	0.683	0.565	0.610	0.667	0.559	0.678	0.673
Adj. R squared			0.500	0.552	0.617	0.493	0.630	0.624
Model df	13	13	13	13	13	13	13	13
RSS	0.526	0.737	1.011	0.905	0.774	1.024	0.749	0.761
RMSE	0.0722	0.0854	0.100	0.0947	0.0875	0.101	0.0861	0.0868
Chi-square	201.9	217.7	159.1	176.2	204.9	155.4	212.8	203.3
Observations	101	101	101	101	101	101	101	101

Standard errors in parentheses
Dependent variable: Log of brand sales in Equivalent Units
Seasonal dummy variables not shown
Instrumental variables: Log of active Twitter users and one period lagged endogenous variables
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3-A. Durbin and Wu-Hausman tests of endogeneity. Base Aggregated Model – [PEPSI equation]

Brand	Instrumented variable	Durbin test		Wu-Hausman test		Equation number
		Score	p	F(1, 86)	p	(on Table 1-A)
Pepsi	Negative eWOM [Pepsi]	0.3017	0.5828	0.2576	0.6130	(3)
	Positive eWOM [Pepsi]	0.3017	0.5828	0.2576	0.6130	(4)
	Grps [Pepsi]	1.7631	0.1842	1.5282	0.2197	(7)
Coke	Negative eWOM [Coke]	0.3017	0.5828	0.2576	0.6130	(6)
	Positive eWOM [Coke]	0.3017	0.5828	0.2576	0.6130	(5)
	Grps [Coke]	0.0087	0.9254	0.0074	0.9314	(8)

Table 4-A. Durbin and Wu-Hausman tests of endogeneity. Base Aggregated Model – [COKE equation]

Brand	Instrumented variable	Durbin test		Wu-Hausman test		Equation number
		Score	p	F(1, 86)	p	(on Table 2-A)
Pepsi	Negative eWOM [Pepsi]	0.9859	0.3207	0.8477	0.3598	(3)
	Positive eWOM [Pepsi]	0.9859	0.3207	0.8477	0.3598	(4)
	Grps [Pepsi]	1.2667	0.2604	1.0922	0.2989	(7)
Coke	Negative eWOM [Coke]	0.9859	0.3207	0.8477	0.3598	(6)
	Positive eWOM [Coke]	0.9859	0.3207	0.8477	0.3598	(5)
	Grps [Coke]	0.0793	0.7781	0.0676	0.7954	(8)

Table 5-A. SUR and 2SLS Model estimation

	SUR system		2SLS (Pepsi)		2SLS (Coke)	
	(1) Pepsi	(2) Coke	(3) Instrumented: Grps Pepsi	(4) Instrumented: Grps Coke	(5) [Instrumented: Grps Pepsi	(6) Instrumented: Grps Coke
Constant	-26.22***	-22.26**	-28.60***	-27.48***	-27.18**	-24.63**
	(7.435)	(8.268)	(8.015)	(7.810)	(9.163)	(8.684)
Price gap	0.233**	-0.481***	0.240**	0.272**	-0.468***	-0.446***
	(0.0833)	(0.0923)	(0.0855)	(0.0909)	(0.0943)	(0.0979)
Distribution	7.359***	6.706***	7.881***	7.646***	7.782***	7.235***
	(1.617)	(1.799)	(1.744)	(1.700)	(1.995)	(1.891)
Grps Pepsi	0.00269	0.00518	-0.00296	0.00189	-0.00488	0.00380
	(0.00461)	(0.00516)	(0.00730)	(0.00478)	(0.00913)	(0.00550)
Grps Coke	0.0134***	0.0162***	0.0130***	0.00536	0.0157***	0.00780
	(0.00331)	(0.00368)	(0.00338)	(0.00665)	(0.00376)	(0.00731)
Grps Coke (2-lagged)	0.0103**	0.00724	0.0103**	0.0108***	0.0105	0.00896
	(0.00315)	(0.00390)	(0.00317)	(0.00326)	(0.00578)	(0.00563)
Neg. Pepsi [Fake News (Formula)]	-0.0259***	-0.0268**	-0.0265***	-0.0262**	-0.0271**	-0.0274**
	(0.00778)	(0.00866)	(0.00793)	(0.00805)	(0.00886)	(0.00895)
Neg. Pepsi [Fake News (Cancer)]	0.00889	0.00584	0.0102	0.00858	0.00870	0.00629
	(0.00499)	(0.00553)	(0.00536)	(0.00523)	(0.00601)	(0.00571)
Neg. Pepsi [Taste]	0.0221*	0.0203	0.0235*	0.0195	0.0243*	0.0184
	(0.00964)	(0.0108)	(0.00985)	(0.0101)	(0.0114)	(0.0114)
Neg. Pepsi [Advertising]	0.00486	0.00995	0.00588	0.00524	0.0120	0.0107
	(0.00612)	(0.00681)	(0.00628)	(0.00631)	(0.00710)	(0.00702)
Pos. Pepsi [Promotions]	-0.0118*	-0.0185**	-0.0109	-0.0131*	-0.0166*	-0.0199**
	(0.00597)	(0.00665)	(0.00609)	(0.00622)	(0.00691)	(0.00695)
Pos. Pepsi [Category news]	0.0180*	0.0267**	0.0178*	0.0195*	0.0261**	0.0279**
	(0.00882)	(0.00981)	(0.00890)	(0.00912)	(0.00998)	(0.0101)
Pos. Pepsi [Taste]	0.117**	-0.0252*	0.102	0.0639	-0.0278*	-0.0241
	(0.0446)	(0.0125)	(0.108)	(0.113)	(0.0128)	(0.0129)
Pos. Pepsi [Celebrities]	-0.00320	-0.00262	-0.00239	-0.00226	-0.00170	-0.00161
	(0.00510)	(0.00567)	(0.00521)	(0.00529)	(0.00584)	(0.00590)
Neg. Coke [Advertising]	-0.00239	0.00152	-0.00323	-0.000142	0.00000318	0.00371
	(0.00549)	(0.00611)	(0.00562)	(0.00587)	(0.00631)	(0.00648)
Neg. Coke [General]	-0.00489	0.000197	-0.00604	-0.00710	-0.00260	-0.00318
	(0.00604)	(0.00671)	(0.00637)	(0.00658)	(0.00714)	(0.00731)
Pos. Coke [Success]	0.00165	0.00288	0.00197	0.00213	0.00379	0.00387
	(0.00569)	(0.00633)	(0.00579)	(0.00590)	(0.00647)	(0.00654)
Pos. Coke [Promotions]	0.00693	0.00541	0.00771	0.00234	0.00789	0.00119
	(0.00744)	(0.00829)	(0.00757)	(0.00831)	(0.00867)	(0.00927)
Pos. Coke [New ads]	-0.00334	-0.00358	-0.00469	0.0000183	-0.00580	-0.000450
	(0.00631)	(0.00701)	(0.00660)	(0.00694)	(0.00733)	(0.00755)

Table 5-A. SUR and 2SLS Model estimation

	SUR system		2SLS (Pepsi)		2SLS (Coke)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Pepsi	Coke	Instrumented: Grps Pepsi	Instrumented: Grps Coke	[Instrumented: Grps Pepsi	Instrumented: Grps Coke
Pos. Coke [Summer campaign]	0.0104	0.00400	0.00929	0.0105	0.00703	0.00625
	(0.00563)	(0.00667)	(0.00584)	(0.00590)	(0.00873)	(0.00876)
Pos. Coke [New products]	0.00945	0.0192**	0.00941	0.0118	0.0182**	0.0213**
	(0.00566)	(0.00632)	(0.00570)	(0.00605)	(0.00654)	(0.00683)
Price Gap x Pepsi's Taste	0.114**		0.102	0.0676		
	(0.0367)		(0.0913)	(0.0951)		
Grps Coke x Summer campaign		0.00186*			0.000228	0.00132
		(0.000852)			(0.00227)	(0.00215)
R squared	0.724	0.768	0.720	0.709	0.761	0.756
Adj. R squared			0.632	0.617	0.685	0.679
Model df	24	24	24	24	24	24
RSS	0.435	0.539	0.442	0.460	0.557	0.567
RMSE	0.0657	0.0731	0.0661	0.0675	0.0742	0.0749
Chi-square	273.7	339.0	261.1	236.7	323.5	300.6
Observations	101		101	101	101	101

Standard errors in parentheses

Dependent variable: Brand sales in Equivalent Units

Seasonality dummies not shown

Instrumental variables: one period lagged endogenous variables

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6-A. Durbin and Wu-Hausman tests of endogeneity. Disaggregated model – [PEPSI equation]

Instrumented variable	Durbin test		Wu-Hausman test		Equation number
	Score	p	F(1, 75)	p	(on Table 5-A)
Advertising [Pepsi]	1.0388	0.3081	0.7794	0.3801	(3)
Advertising [Coke]	2.0589	0.1513	1.5607	0.2154	(4)

Table 7-A. Durbin and Wu-Hausman tests of endogeneity. Disaggregated model – [COKE equation]

Instrumented variable	Durbin test		Wu-Hausman test		Equation number
	Score	p	F(1, 75)	p	(on Table 5-A)
Advertising [Pepsi]	1.7725	0.1831	1.3397	0.2508	(5)
Advertising [Coke]	1.9194	0.1659	1.4529	0.2319	(6)

Table 8-A. SUR and 3SLS Model estimation

	SUR system		3SLS Model estimation	
	(1)	(2)	(3)	(4)
	Pepsi	Coke	Pepsi	Coke
Constant	-26.22***	-22.26**	-30.16***	-27.74**
	(-3.53)	(-2.69)	(-3.71)	(-3.05)
Price gap	0.233**	-0.481***	0.266**	-0.444***
	(2.79)	(-5.21)	(3.00)	(-4.50)
Distribution	7.359***	6.706***	8.231***	7.915***
	(4.55)	(3.73)	(4.65)	(4.00)
Grps Pepsi	0.00269	0.00518	-0.00324	-0.00382
	(0.58)	(1.00)	(-0.44)	(-0.46)
Grps Coke	0.0134***	0.0162***	0.00603	0.00856
	(4.04)	(4.41)	(0.93)	(1.18)
Grps Coke (2-lagged)	0.0103**	0.00724	0.0108***	0.00836*
	(3.28)	(1.86)	(3.30)	(2.04)
Neg. Pepsi [Fake News (Formula)]	-0.0259***	-0.0268**	-0.0272***	-0.0283**
	(-3.33)	(-3.10)	(-3.37)	(-3.14)
Neg. Pepsi [Fake News (Cancer)]	0.00889	0.00584	0.0104	0.00826
	(1.78)	(1.06)	(1.94)	(1.38)
Neg. Pepsi [Taste]	0.0221*	0.0203	0.0214*	0.0206
	(2.29)	(1.88)	(2.09)	(1.79)
Neg. Pepsi [Advertising]	0.00486	0.00995	0.00634	0.0121
	(0.79)	(1.46)	(0.99)	(1.68)
Pos. Pepsi [Promotions]	-0.0118*	-0.0185**	-0.0123	-0.0185**
	(-1.98)	(-2.78)	(-1.94)	(-2.60)
Pos. Pepsi [Category news]	0.0180*	0.0267**	0.0189*	0.0273**
	(2.05)	(2.72)	(2.06)	(2.67)
Pos. Pepsi [Taste]	0.117**	-0.0252*	0.112*	-0.0259*
	(2.62)	(-2.02)	(2.36)	(-1.98)
Pos. Pepsi [Celebrities]	-0.00320	-0.00262	-0.00152	-0.000559
	(-0.63)	(-0.46)	(-0.28)	(-0.09)
Neg. Coke [Advertising]	-0.00239	0.00152	-0.00132	0.00215
	(-0.43)	(0.25)	(-0.22)	(0.32)
Neg. Coke [General]	-0.00489	0.000197	-0.00861	-0.00444
	(-0.81)	(0.03)	(-1.30)	(-0.60)
Pos. Coke [Success]	0.00165	0.00288	0.00272	0.00425
	(0.29)	(0.45)	(0.46)	(0.64)

Table 8-A. SUR and 3SLS Model estimation

	SUR system		3SLS Model estimation	
	(1)	(2)	(3)	(4)
	Pepsi	Coke	Pepsi	Coke
Pos. Coke [Promotions]	0.00693	0.00541	0.00387	0.00293
	(0.93)	(0.65)	(0.46)	(0.31)
Pos. Coke [New ads]	-0.00334	-0.00358	-0.00204	-0.00298
	(-0.53)	(-0.51)	(-0.29)	(-0.38)
Pos. Coke [Summer campaign]	0.0104	0.00400	0.0101	0.00415
	(1.84)	(0.60)	(1.71)	(0.59)
Pos. Coke [New products]	0.00945	0.0192**	0.0114	0.0210**
	(1.67)	(3.04)	(1.88)	(3.09)
Price Gap x Pepsi's Taste	0.114**		0.109**	
	(3.10)		(2.80)	
Grps Coke x Summer campaign		0.00186*		0.00156
		(2.19)		(1.66)
R squared	0.724	0.768	0.707	0.753
Model df	24	24	24	24
RSS	0.435	0.539	0.462	0.575
RMSE	0.0657	0.0731	0.0676	0.0755
Chi-square	273.7	339.0	241.6	297.6
Observations	101		101	

t statistics in parentheses
Dependent variable: Log of brand sales in equivalent units
Seasonality dummies not shown
Endogenous variables: Grps Pepsi, Grps Coke
Instrumental variables: one period lagged endogenous variables
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9-A SUR System in Differences

	(1)	(2)
	Pepsi (First differences)	Coke (First differences)
Constant	0.0115	0.0159
	(0.0148)	(0.0161)
Price gap	0.119	-0.366**
	(0.119)	(0.129)
Distribution	2.243	1.173
	(1.766)	(1.917)
Grps Pepsi	0.0131*	0.0105
	(0.00600)	(0.00649)
Grps Coke	0.00834*	0.00980*
	(0.00411)	(0.00445)
Grps Coke (2-lagged)	0.00293	0.000171
	(0.00385)	(0.00455)
Neg. Pepsi [Fake News (Formula)]	-0.0151*	-0.0211**
	(0.00666)	(0.00720)
Neg. Pepsi [Fake News (Cancer)]	0.00864	0.00837
	(0.00487)	(0.00524)
Neg. Pepsi [Taste]	0.00464	-0.00106
	(0.00813)	(0.00881)
Neg. Pepsi [Advertising]	-0.00193	0.00382
	(0.00522)	(0.00565)
Pos. Pepsi [Promotions]	-0.00807	-0.0160**
	(0.00473)	(0.00514)
Pos. Pepsi [Category news]	0.0116	0.0198**
	(0.00701)	(0.00759)
Pos. Pepsi [Taste]	0.0803*	-0.0145
	(0.0381)	(0.00950)
Pos. Pepsi [Celebrities]	0.00205	0.00418
	(0.00419)	(0.00453)
Neg. Coke [Advertising]	-0.00343	0.000456
	(0.00499)	(0.00541)
Neg. Coke [General]	-0.0108*	-0.00723
	(0.00540)	(0.00585)
Pos. Coke [Success]	0.00282	0.00162
	(0.00449)	(0.00487)
Pos. Coke [Promotions]	0.00627	0.00714
	(0.00601)	(0.00655)
Pos. Coke [New ads]	0.00133	0.00257
	(0.00569)	(0.00616)
Pos. Coke [Summer campaign]	-0.00153	-0.00722
	(0.00505)	(0.00613)
Pos. Coke [New products]	0.00192	0.00833
	(0.00506)	(0.00548)
Price Gap x Taste	0.0766*	
	(0.0316)	
Grps Coke x Summer campaign		0.00182*
		(0.000902)
R squared	0.319	0.385
Log-likelihood	316.1	316.1
Sum of squares	0.247	0.390
Residual sum of squares	0.526	0.622
Model df	24	24
Observations	100	100

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Dependent variable: Brand sales in Equivalent Units
All independent variables in first differences
Seasonality dummies not shown

Electronic WOM Content Analysis

For our study, we followed a six-step process for each brand: (1) tweets preprocessing, (2) valence classification, (3) topic extraction, (4) weekly aggregation of topics, (5) dynamic/time series factor analysis, and (6) factor score extraction and unstandardization.

In the first step, we follow a standard process for text preprocessing, namely, stop-words filtering, tokenization, normalization, and noise removal.

In the second step, according to their valence, we classify all tweets into two categories (positive and negative) by using a hybrid process of semiautomatic classification as per Sadegh, Ibrahim, and Othman (2012). Although some classifications other than valence are possible (e.g., by type of emotion), they are mostly experimental. Following this automatic classification, we manually inspected a random sample of 1,000 tweets to assess the valence classification's accuracy. This approach resulted in a correct classification rate of 80.7%, which compares well with prior studies (80% for Borah and Tellis 2016; 90.2% for Hennig-Thurau et al. 2015; 71.8% to 89.5% for Tirunillai and Tellis 2012). At the end of this process, we obtained 17,074 negative and 15,618 positive tweets about Pepsi and 46,187 negative and 88,514 positive tweets about Coke.

In the third step, using a Latent Dirichlet Allocation (LDA) algorithm (Tirunillai and Tellis 2014; Zhang et al. 2017), we subsequently extracted the common topics of the tweets. To minimize errors due to irony, ambiguity, and other contextual factors, we considered morphological rules (i.e., grammatical units), syntax rules (i.e., the combination of words to build sentences), and semantic dictionaries. The outcome of this classification was a list of 64 topics. This relatively high number of topics may in part be driven by the diverse set of conversations on Twitter compared to those on other, more focused social media forums; and in part due to the well-known problem of overfitting in LDA classification (Zhang et al. 2017). Overall, the topics evolve around (a) advertising (e.g., music, content, celebrity endorsements), (b) product and packaging news, (c) company-related news (e.g., awards) and (d) fake news (e.g., alleged product contamination or cancer risks).

In the fourth step we carried out a weekly aggregation of tweets by topic in order to match the scanner market data structure provided by Nielsen (weekly brand sales, weighted distribution, and price) and the advertising investment (GRPs) provided by Kantar Media. This weekly aggregation resulted in 64 electronic WOM time series (topics) measuring the weekly number of times each brand is mentioned on each topic.

In the fifth step, we performed a dynamic factor analysis (Du and Kamakura 2015; Molenaar, 1985) on the aggregated set of 64 topics in order to analyze their underlying structure. This allowed us to take into account the fact that some of those 64 topics refer to the same concept (e.g., the topics "*commercial*" and "*campaign*" may both measure the same topic, i.e., "*advertising*"). Dynamic factor analysis is an adaptation of traditional factor analysis that accounts for the dynamic nature of time series data through an autoregressive component. Formally, dynamic factor analysis models *n* time series starting from a linear combination of *m* trends ($m < n$). The dynamic specification of factors is determined by:

$$(1) \qquad y_{it} = f_{i1}\varphi_{1t} + f_{i2}\varphi_{2t} + K + f_{iM}\varphi_{Mt} + \varepsilon_{it},$$

where y_{it} is the value of the time series *i* at time *t*, φ_{jt} is the common trend *j*, f_{ij} are factor loadings, and ε_{it} the residuals of the model. The application of dynamic factor analysis yielded a 15-factor solution clustered by brand and valence, seven of which corresponded to Coke, and eight to Pepsi. Table 3 provides a brief description of the various factors.

In the final step, we extracted the factor scores for each period to complete the dataset structure for the demand model, and unstandardized them back to volume units (i.e., number of tweets in a given week) for a more intuitive interpretation[1].

References

Du, R. Y. & Kamakura, W. A. (2015). Improving the statistical performance of tracking studies based on repeated cross-sections with primary dynamic factor analysis. International Journal of Research in Marketing, 32(1), 94–112.

Molenaar, P. C. M. (1985). A dynamic factor model for the analysis of multivariate time series. Psychometrika, 50(2), 181–202.

Sadegh, M., Ibrahim, R., & Othman, Z. A. (2012). Opinion mining and sentiment analysis: A survey. International Journal of Computers and Technology 2(3), 171–178.

Tirunillai, S. & Tellis, G. J. (2014). Mining marketing meaning from online chatter: Strategic brand analysis of Big Data using latent Dirichlet allocation. Journal of Marketing Research, 51(4), 463–479.

[1] The unstandardization was carried out using the following expression:

$$V_{ft} = \left(F_{ft} \cdot \sigma_{ift}\right) + \mu_{ift}$$

where:

$V_{ft} =$ volume conversion of factor f at time t; $F_{ft} =$ factor f scores at time t; $\sigma_{ift} =$ standard deviation of the i items of factor f at time t; $\mu_{ift} =$ mean of the i items of factor f at time t.