Seeding as Part of the Marketing Mix:

Word-of-Mouth Program Interactions for Fast Moving Consumer Goods

September 18, 2018

(Accepted version. For final print version, go to: https://doi.org/10.1177/0022242918817000)

Florian Dost*, Ulrike Phieler, Michael Haenlein, and Barak Libai

The authors thank Erik Maier and Jens Sievert for helpful comments on a previous version of this manuscript, as well as the Dynamic Capabilities and Relationships (DCR) doctoral program for financial support. The authors also thank TRND AG for its help and support in gaining access to some of the data, brands, and interview partners. None of the companies or brands in this study had a role in empirical study design, analysis, decision to publish, or preparation of the manuscript.

*Corresponding author

Florian Dost is Associate Professor (Senior Lecturer) for Marketing Analytics, Management Science Department, Lancaster University Management School, LA1 4YX Lancaster, United Kingdom, f.dost@lancaster.ac.uk.

Ulrike Phieler is a doctoral candidate, European University Viadrina, Grosse Scharrnstrasse 59, 15230 Frankfurt (Oder), Germany, phieler@europa-uni.de.

Michael Haenlein is Professor, Marketing Group, ESCP Europe, 79 Avenue de la République, 75011 Paris, France, haenlein@escpeurope.eu.

Barak Libai is Professor, Marketing Group, Arison School of Business, Interdisciplinary Center, Herzliya, Israel, libai@idc.ac.il.

Seeding as Part of the Marketing Mix:

Word-of-Mouth Program Interactions for Fast Moving Consumer Goods

Seeded Marketing Campaigns (SMCs) have become part of the marketing mix for many Fast-Moving Consumer Goods (FMCG) companies. In addition to making large investments in advertising and sales promotions, these firms now encourage seed agents or micro-influencers to discuss brands with friends and acquaintances to create further value. The interaction of an FMCG seeding program with the traditional marketing tools is thus critical to understanding the effectiveness of such efforts. Surprisingly, however, the issue is still underexplored. The authors present the first empirical analysis of this question based on a rich data set collected on four brands from various European FMCG markets. They combine advertising and sales promotion data from FMCG brand managers with sales and retail variables from market research companies as well as firm-created word-of-mouth variables from SMC agencies. Using several analysis approaches and confronting challenges of endogeneity and multicollinearity, the authors observe two consistent findings: firm-created word of mouth via SMC programs interacts consistently negatively with all tested forms of advertising but consistently positively with promotional activities. This phenomenon has significant implications for understanding and managing SMCs. The analysis implies that SMCs may increase total sales by approximately 3%–18% over the course of the campaigns.

Keywords: Word-of-Mouth Program, Seeding Program, Product Seeding, Fast-Moving Consumer Goods, FMCG, Advertising, Sales Promotion, Marketing Mix Modeling, Marketing Mix

A fundamental development in the marketing landscape of the past two decades is the realization that word of mouth (WOM) should be viewed as part of the marketing mix and managed accordingly (Chen and Xie 2008; Rosen 2009). Consequently, a significant literature stream has emerged to explore issues such as the motivation for WOM and its effect on the audience, what brands people talk about, and how WOM can affect customer profitability (Berger 2014; Kumar et al. 2010; Lamberton and Stephen 2016; Lovett et al. 2013). Scholars have paid increasing attention to firms' emerging efforts to create programs that generate amplified WOM through tools such as seeding programs, influencer marketing, and referral reward programs (Godes et al. 2005; Haenlein and Libai 2017; Kumar et al. 2013).

Given that consumers are more likely to engage in social interactions on high-ticket, complex, high-involvement products (Berger 2014), one might wonder how relevant WOM programs are to fast-moving consumer goods (FMCG) such as groceries, household products, and beauty and health products. Firms seem to believe they are very relevant: in the past two decades, various FMCG marketers have, with the help of specialized agencies, regularly employed seeded marketing campaigns (SMCs), which use thousands of individuals who "buzz" about the product (Carl 2006; Godes and Mayzlin 2009). The idea is to select a certain number of customers as "seed agents" and to equip those agents with the product to be marketed (in the form of either actual products or samples) as well as additional brand information. The customers are then encouraged to engage with the product while also telling their peers about it. A handful of academic articles that address the effectiveness of such SMCs have demonstrated a positive impact on sales and the potential for substantial return on investment (Chae et al. 2017; Dost et al. 2016; Godes and Mayzlin 2009).

The move toward integrating WOM into the FMCG marketing mix should be considered in light of the shifts these trillion-dollar markets have been experiencing in recent years, including significant changes in consumer tastes, changes in the effectiveness of media channels, and the move to e-commerce. With the aim of adapting their brands to a changing world, FMCG marketers have been moving budgets to digital advertising and social media, although many open questions remain regarding the efficacy of such efforts (Neff 2017; Sloane 2016). Thus, it is unsurprising that many FMCG brands experimenting with additional ways to acquire customers have aimed to integrate WOM into the marketing mix via SMCs. As a result, according to a proprietary competition analysis that covered 348 campaigns across Europe during 2007–2011, more than 80% of all commissioned SMCs are for FMCG brands.

Still, the question of how to manage SMCs is largely open, and a source of confusion, as we discovered in a series of interviews with managers who run SMCs for consumer packaged-goods firms. One manager we interviewed ran three different SMCs of similar design, size, and cost for the same brand but saw estimated sales effects that differed by more than 150%. Yet she could not identify any apparent differences in those SMCs or the amplified WOM generated that could have explained these significant variations. We ultimately discovered that what differed among these campaigns were *other* planned marketing activities to which the SMC had been added. Another manager suspected that as the marketing plan becomes more complex, advertising increasingly cannibalizes firm-created WOM effects. Yet she did not have sufficient insights on the question of potential interaction effects between SMCs and traditional marketing communication measures, such as advertising and sales promotions, to explicitly take account of these effects in her decision making.

The question of the interaction among marketing mix elements is critical to marketing planning in general (Naik and Raman 2003; Naik et al. 2005) and specifically for FMCG marketers who are considering introducing an SMC program on the background of the current marketing mix. Where some marketing campaigns use WOM as the main vehicle to drive new product growth and seeding campaigns as a main tool to initiate the process (Libai et al. 2013), SMCs for supermarket brands must integrate into a world where massive budgets are spent on existing products using both advertising and promotion (Mela et al. 1997). Their profitability will thus depend on how they interact with existing media campaigns. The fundamental question is whether the additional WOM complements or substitutes for traditional marketing efforts such as advertising (Armelini and Villanueva 2010). The answer is vital to the ability to plan and justify SMC campaigns.

However, brand managers who aim to plan an informed use of SMCs have little research knowledge to draw on. One reason is that in FMCG environments, firm-created WOM tends to predominantly take place offline (Toubia et al. 2011). For example, one SMC agency we interviewed in the context of this study reported that over 90% of all measured conversations occur face-to-face. Yet given the prevalence of social media and the online influence in consumer markets, as well as researchers' ability to collect data on customer interactions through electronic means, the vast majority of recent knowledge about WOM and its effectiveness, including WOM programs, has come from programs geared toward online (notably social media) environments (Babic Rosario et al. 2016; Floyd et al. 2014; You et al. 2015). In addition, prior research has focused extensively on organic WOM, and firm-created WOM has received substantially less attention. See Table 1 for an overview of the few studies analyzing SMC in an FMCG setting.

(Insert Table 1 approximately here)

The issue is particularly challenging given consistent findings on the differences between online and offline WOM behavior, which may stem from the diverse nature of oral versus written communication channels and the size and makeup of the audience (Berger 2014). For example, online and offline environments differ with regard to people's motivations to share information (Berger and Iyengar 2013), willingness to retransmit WOM (Baker et al. 2016), and the role of customer loyalty in WOM transmission (Eelen et al. 2017). Furthermore, researchers have found that people tend to talk about different types of products online and offline (Fay and Larkin 2017) and, unsurprisingly, people tend to talk offline rather than online regarding low-involvement, less status-based supermarket goods (Berger 2014; Berger and Iyengar 2013; Lovett et al. 2013). Given these constraints, findings from the online-dominant world, such as those dealing with the integration of social media and traditional advertising (Hewett et al. 2016; Kumar et al. 2017; Trusov et al. 2009), may be of limited help to FMCG managers planning an SMC.

Some FMCG brand managers may have considered conducting an independent analysis of interaction effects for SMC campaigns—a nontrivial task. For such an analysis, diverse data across brands, campaign types, and media outlets are required to generalize the phenomenon. In addition, estimating sales and interaction effects of SMCs is challenging due to the inherently unplannable nature of the campaigns. The seed agents may self-select or be selected non-randomly into the campaign or react to unobserved market dynamics. The result is a potential endogeneity bias in sales model estimates, which demands a level of statistical analysis often not available to brand managers.

Taking up this challenge, we present the first empirical analysis on the integration of SMCs with other marketing mix activities that dominate the world of FMCG, namely, mass advertising and sales promotions. For our study, we collected a rich data set that combines advertising and promotion plans from FMCG brand managers with sales and retail variables from market research companies, as well as firm-created WOM variables from SMC agencies. In addition, our data set comprises different market situations to represent the wide variety of both FMCG products and SMCs. We focus on SMCs for four products (instant coffee, sensitive toothpaste, anti-age cosmetics, and organic chocolate) from three European markets. The cases we analyze feature different types of advertising (e.g., TV, digital, print) and/or promotional activities (e.g., point-of-sale stoppers and coupons, direct mail coupons) in their respective marketing plans. Furthermore, the data differ in their structure (i.e., weekly or monthly measurement and number of cross-sectional units) and operationalization of several variables (e.g., measures for amplified WOM).

To address endogeneity concerns, we collected additional external SMC data and population statistics and employed an instrumental variable (IV) modeling approach (Germann et al. 2015; Wooldridge 2010). We compare the estimates against several robustness models with panel internal instruments (Hausman and Taylor 1981; Villas-Boas and Winer 1999). For additional robustness, we consider variable transformations, measurement error, and collinearity in interaction effects. We also employ an equivalent control function approach (Petrin and Train 2010), which allows for an endogeneity correction in all estimated robustness models.

We find that despite the variation in data and models, the results still converge to consistent interaction effects between firm-created WOM from SMCs and other marketing variables, which suggests generalizability. First, our results indicate that firm-created WOM from SMCs incrementally increases sales in all cases. Second, we observe managerially relevant interaction effects between firm-created WOM and advertising/sales promotions. Specifically, for the FMCG products we analyzed, firm-created WOM consistently interacts *negatively* with all tested forms of advertising. In contrast, it consistently interacts *positively* with promotional activities. To put these empirical results into perspective, we calculate effect sizes and meta-analytically integrate them to compare with extant meta-analytic findings. Sales elasticities and sensitivity analyses help us explore the role and magnitude of marketing mix interactions, such that managers can use these findings to optimize their marketing plan.

These results enrich our understanding of the integration of emerging WOM tools into the FMCG world. For managers, they provide insight into what to expect when introducing SMCs into this environment. Our findings support the importance of SMC to FMCG marketers: SMCs may increase total sales by approximately 3%–18% over the course of the campaigns, and sales elasticities are comparable to, or stronger than those previously reported for tools such as electronic word of mouth. Yet these elasticities decrease with a higher level of advertising, which calls for brand specific analyses to determine the optimal investment. Our analysis provides guidance to managers and consulting firms on how to conduct a rigorous analysis, possibly simulating specific brand conditions.

On the theoretical level, we provide evidence of how new tools such as SMCs integrate with more established tools of the marketing mix, which can help not only shed light on the dynamics of interactions but also provide some indication, as we subsequently discuss, of the mechanism by which SMCs contribute to the firm. In the context of FMCG, seeding campaigns may be better considered as substitutes for advertising, rather than complements, at least for certain consumers. Whereas in the prevailing view of word of mouth, which has been shaped in many cases by organic word of mouth, and largely in new product and social media contexts, advertising ignites the WOM process that later dominates sales, in the context of the supermarket it may be markedly different.

Background

The increasing connectivity of customers through online means, the realization of the power of online reviews, and the ability to track online connectivity have led to a rise in general interest in WOM activity. A significant body of research has examined WOM in consumer markets, investigating issues such as individuals' motivations to talk and listen (Berger 2014), which products people talk about (Berger and Schwartz 2011), and WOM effects on individual customer profitability (Kumar et al. 2010) and on sales in general (You et al. 2015).

A notable change during the past two decades is the growing realization that WOM not only is an organic part of customer interactions but can also be amplified via WOM programs (Godes et al. 2005). Indeed, cross-industry surveys among managers reveal that most plan to use campaign formats that leverage WOM, driven by the belief that WOM marketing is more effective than traditional marketing activities (WOMMA 2014b).

Haenlein and Libai (2017) highlight three types of such WOM programs: referral programs, which encourage and incentivize current customers to contribute to customer acquisition by helping to acquire new customers; online recommendation programs, which encourage individuals to spread the word to their close social network or a broader network such as in an online review website; and seeding programs, which aim to get products into the hands of some individuals (seeds) in the hope that the consequent social influence will help accelerate and expand the growth process. Seeding programs are our focus here, specifically SMCs in the

FMCG industry. To establish the context, we next describe the main insights from qualitative interviews regarding major European providers' planning and setup of SMCs.

SMCs: Practice and Measurement

When a marketing manager commissions an SMC at a specialized agency (e.g., BzzAgent, The Insiders, TRND), three key questions must be answered: First, how many seed agents should take part in the campaign (typically ranging from 100 to 20,000)? Second, when and how long should the campaign run (typically between 4 and 12 weeks)? And third, what exactly should be given to the seed agents (typically the full focal product, several smaller samples to share, and a brand information booklet)? Using these specifications, the SMC agency invites potential seed agents from its seed panel to apply for the campaign.

Subsequently, the agency selects the requested number of seed agents among the applicants using a set of proprietary selection criteria and sends the product to them. SMC agencies put considerable effort into which seed agents and how many to choose, which incentives to offer them, and the contents of the campaign material they receive. Selection criteria typically include demographics, prior campaign participation and performance, stated preferences for products and brands, stated personality measures, and perceived motivation judged from the open-text application form. Selection criteria deemed more critical, for example demographics that match the intended target group, very high stated liking of the brand, or a proven record of reported WOM volume in prior campaigns, are often balanced with selection criteria intended to maintain an agency's panel health. For example, seeds may be rotated such that every applicant regularly gets the opportunity to participate in a campaign.

Over the course of the campaign, the agency engages the seed agents and manages the evolving campaign process through a campaign-specific online platform. Typically, such SMC platforms include a project blog to facilitate inter-agent communication, messaging tools to directly contact the seed agents, and survey tools to track responses, requests, and WOM behavior. Seed agents then test the products; engage with the agency, the brand, and one another; and recommend the product to their peers. These incremental recommendations, or firm-created WOM, are the main intended outcome of the campaign. Such firm-created WOM predominately takes place offline (with some estimating that the share of offline conversations for these products exceeds 90%) and is overwhelmingly positive. One of our interview partners analyzed 43,000 receiver surveys from 36 SMCs and found that less than 3% of all WOM incidents were negative and over 90% positive. Therefore, WOM measurement focuses on volume, not valence, similar to traditional types of marketing communication (e.g., TV advertising gross rating points [GRPs]).

Issues of disclosure are pivotal to the ability to operate and benefit from SMC, in particular given growing concerns on the ethical behavior of brands. The agencies we collaborate with operate under comparable ethical terms which are made explicit to the agents. Specifically, seed agents (a) participate voluntarily; (b) are encouraged share their honest opinion about the products (though through phrasing the agency primes positive WOM); (c) do not receive additional financial rewards or payment besides what is included in the starter packages; and (d) should disclose their participation. In particular, given the European General Data Protection Regulation (GDPR), agencies are making additional efforts by highlighting, and even verifying where possible, appropriate disclosure. Interestingly, disclosure may even help the SMC efforts. Research in this area suggests that when disclosure occurred agents were rated as more credible, conversation partner had fewer negative feelings about the agent's corporate affiliation and told more people about the brand being discussed (Carl 2008).

Seeding, Networks, and Marketing Mix Interactions

An interesting issue relates to the relationship between customer loyalty and seeding effectiveness. Godes and Mayzlin (2009) suggest that loyal customers may be less effective as seeds than non-loyal ones, who are more likely to know equally unaware and untapped peers. However, this phenomenon depends on the type of product and may be different for really new products (Dost et al. 2016). Research provides some insights on the expected characteristics of agents who will engage more in WOM (Toubia et al. 2011) and how agents choose conversation partners (Groeger and Buttle 2016). Other research addresses the effect of spillover to other categories on brand-level WOM (Chae et al. 2017) and the importance of product interest and cuing from the environment as drivers of WOM (Berger and Schwartz 2011).

Yet most of the research on WOM seeding has been done in the context of networks and their effect on optimal seeding. Labeled in computer science and related fields as the *influence maximization problem*, the issue is generally considered one of the most important in network science in general, as evidenced by numerous efforts to develop efficient algorithms for a given network (Kempe et al. 2003; Morone and Makse 2015). Academic work in marketing and related fields typically takes a network-based approach, mostly examining markets for new products with a given network, in which organic WOM is expected to complement the seeding effort that will ideally ignite a further contagion process. Among the network issues related to seeding effectiveness are the importance of degree or betweenness centrality (Hinz et al. 2011), assortativity in customer lifetime value (Haenlein and Libai 2013), seed size (Aral et al. 2013), competition (Libai et al. 2013), and network characteristics such as relationship type or homophily (Chen et al. 2017; Nejad et al. 2015).

The question remains to what extent the network-related insights are relevant for seeding in FMCG markets. Although SMC agencies commonly look for individuals who are more connected and socially active when screening potential candidates, beyond that, the SMC operators we interviewed had little empirical knowledge on the social networks that existed in their markets or even on how information spreads further after the seeds communicate. Although some industry efforts have been made to follow information spread, these analyses are not easy to conduct, and estimations may be biased (Carl 2006).

What emerges as a key managerial concern is the need to better understand the interaction between SMCs and other marketing mix elements—particularly the two mostly widely used types for these products: advertising and sales promotions (Mela et al. 1997). In the FMCG industry, SMCs are typically conducted in an environment of mature categories, where the seeding campaign joins larger-scale efforts of advertising and sales promotion. In fact, firms commonly decide whether to conduct an SMC after the marketing plan for advertising and promotion has been finalized. As typically SMC are cheaper than traditional advertising activities, they are often added (or not) with the remains from a larger budget for a marketing plot or pulse. To justify the use of SMCs, managers must understand the extent to which seeding interacts with current efforts and whether it complements or substitutes them.

Scholars and practitioners widely agree on the need to manage marketing mix tools to increase brand equity and sales (Kotler and Keller 2012). Yet parts of the mix may interact and affect each other, and firms should consider interactivity trade-offs in planning their marketing-mix strategies (Naik et al. 2005). Much attention in this respect has been given to media synergies. Batra and Keller (2016) show that coordinated media campaigns among channels may lead to more favorable attitudes toward the brand. For example, in an attempt to take advantage of media mix synergy, marketers may increase the media budget and allocate more funds to the less effective activity (Naik and Raman 2003).

Adding WOM to the marketing mix adds complexity and challenges to managing marketing mix interactions. Given the availability of data and the rising importance of social media, recent examinations in this area have centered nearly exclusively on the context of mostly organic, online social interactions. The challenge is to untangle an "echoverse" in which online and offline social interactions and offline and online WOM affect each other (Hewett et al. 2016). What emerges from this growing literature is recognition of the power of online WOM, yet also the compound effects associated with it. These effects vary across platform, product, time, and metric factors (Babic Rosario et al. 2016; Kumar et al. 2017; You et al. 2015). Despite the potential heterogeneity underlying those findings, it is clear that WOM and advertising are expected to affect each other (Trusov et al. 2009). Thus, ignoring WOM when planning marketing campaigns can lead to suboptimal spending (Zubcsek and Sarvary 2011).

Interaction Effects Between SMCs and Advertising

The overall picture that emerges from previous work is that WOM mainly complements, rather than substitutes for, advertising (Armelini and Villanueva 2010). Researchers view WOM as a more effective and persuasive tool that can convince people to close a purchase, following the awareness created by advertising (Hanssens et al. 2015). From another angle, advertising is viewed as a first step of customer acquisition that will be followed by a ripple of customers acquired by WOM (Hogan et al. 2004). Furthermore, advertising stimulates conversation, both online and offline (Tirunillai and Tellis 2017). Industry studies suggest that about 25% of talks about brands involve discussions of an ad for that brand (Keller and Fay 2012).

If WOM complements advertising, then a positive interaction between them may be expected. Managers may be encouraged to invest more in SMCs in tandem with a larger investment in advertising. Yet it is not clear that this is indeed the case for FMCG seeding marketing campaigns, as there may be substantial differences in the power of WOM, and so in the dynamics of interactions. First, much of the literature on WOM effectiveness focuses on the effect of organic, and not firm-driven, WOM. Organic WOM may be more relevant for complex, novel, exciting, and risky products but less so for the supermarket goods SMCs often aim to promote (Armelini and Villanueva 2010; Berger 2014).

For new and complex products, a higher level of organic WOM helps to drive profitability because it follows the early adoption of the seeds, and together accelerates adoption and increases customer equity. Nevertheless, high levels of organic WOM also imply a fast penetration without the seeding processes (Haenlein and Libai 2013). For FMCG, on the other hand, organic WOM that follows the seeding may not be that large. However, the seeding process itself may be quite effective, as the organically occurring alternative is not that strong.

It should also be noted that much of the recent knowledge regarding WOM stems from an analysis of dynamics within social media, in which the intensity of WOM due to the audience size and large scale effects may be much stronger. Even though research shows referral effectiveness that is an order of magnitude stronger than advertising (Trusov et al. 2009), this finding may be less relevant to FMCG brand-related communication.

In the FMCG environment, advertising plays a major role in creating product awareness and familiarity (Vakratsas and Ambler 1999), and much information can be retrieved in front of the shelf. The seeding campaign may help more in awareness creation among customers than reducing risk and decreasing uncertainty. As a result, the incremental effect of firm-created WOM on awareness can be expected to be lower.

Prior research on SMCs provides some support to this expectation: targeting firm-created WOM toward peers already aware of the product results in smaller sales effects (Dost et al. 2016), which explains why less loyal seed agents can achieve greater sales effects than more loyal ones (Godes and Mayzlin 2009). In addition, traditional advertising and firm-created offline WOM do not occur at the point of purchase, which limits any expected interaction effect due to recognition. This is different from online settings, where advertisements may directly link to an e-commerce website such that they benefit from improved familiarity (Pauwels et al. 2016).

Thus, the combined information from advertising and firm-created offline WOM is likely to be more substitutive than complementary. Substitutive information has a cannibalizing effect that reduces positive interactions and can even result in negative interaction effects across communication elements (Campbell and Keller 2003; Park and Lessig 1977). This phenomenon has been shown in the movie industry, in which the positive interaction between online reviews and advertising disappears over time (Bruce et al. 2012a), and in the negative interaction effects between publicity and print advertising for video games (Burmester et al. 2015). For the same reason, the integrated communication synergy potential is generally more limited for FMCG (Kumar et al. 2017) than for more complex products such as cars (Naik and Peters 2009). Given these factors, we expect to find *negative* interaction effects between firm-created WOM and advertising in an FMCG setting.

Interaction Effects Between SMC and Sales Promotions

Will the interaction direction with sales promotion be the same as with advertising? In the context of FMCG, advertising and sales promotions are perceived to contradict each other. Whereas sales promotions are focused on creating short-term sales, advertising is aimed at establishing long-term brand equity. Firms must thus find the optimal combination to drive long-term profits and be careful not to invest too much in the short run (Sriram and Kalwani 2007).

Sales promotions may create different interaction dynamics with SMCs. Although most types of promotions (e.g., coupons, in-store displays, features) provide little additional awareness, cues such as point-of-sale promotions can trigger the retrieval of SMC-induced memories in a purchase decision context and thus improve recognition and affective/heuristic choice for already familiar brands and products (Pauwels et al. 2016). Similar effects have been observed for traditional advertising, in which point-of-sale displays have been shown to be more effective when accompanied by a TV advertising campaign (Dickson 1972). We therefore expect firm-created WOM and point-of-sale promotions to exhibit similar recognition synergies at the point of purchase.

Furthermore, firm-created WOM provides information and reduces uncertainty about the product and the consumer's own preferences, which should lead to a steeper, more price-sensitive individual price response curve (Dost et al. 2014) and to more price-sensitive demand (Stigler 1961). In combination with the price discount that accompanies most promotions, the increase in demand (i.e., sales) from firm-created WOM should be more pronounced. Therefore, based on rational choice, we expect a positive interaction effect between firm-created WOM and promotions.

In combination, the mechanisms for recognition and information suggest a mutually supportive interaction between firm-created WOM and promotions. In our empirical study, we thus expect to find positive interaction effects between firm-created WOM and promotions.

Data

The data set used for our analysis represents four SMCs for four FMCG products in three European countries: instant coffee, sensitive toothpaste, anti-age cosmetics, and organic chocolate. We use sales as the dependent variable in our model. We compiled this data set by combining information from the SMC clients on the overall marketing plan (advertising and promotions) and other market variables (sales, distribution, price, and competitive advertising) with data from SMC agencies on firm-created WOM volumes.

Table 2 provides details on the specific product context, SMC setup and measures, marketing plan variables, and other market variables for each SMC. This overview shows that the data sets are heterogeneous on several dimensions, which allows us to obtain tentative insights into the generalizability of our findings. The seed agents used in our study were recruited from four different SMC agency panels in Europe, two of which were from the same European country. All campaigns were run by specialized SMC agencies between 2011 and 2014. The campaigns differed in size (between 1,500 and 7,500 seed agents) and duration (between eight and nine weeks). As specified above, agent screening procedures in the SMC agencies are not a function of the clients marketing mix spending.

(Insert Table 2 approximately here)

Brand marketing plans were set well in advance (typically 6–12 months ahead) and contained different forms of advertising and sales promotions to which the SMC had been added.

In addition, the instant coffee brand provided advertising data for its other independently positioned product variants as a competitive advertising control variable. The sensitive toothpaste brand obtained its estimated GRPs through a media data provider. Three of the products were sold through third-party retailers (which makes the level of distribution and average retail price relevant control predictors), while one (the cosmetics line) was sold in the brand's own stores, giving the brand full control over not only advertising and sales promotions but also distribution and price. All brands obtained retail sales (and price) data either through a scanner panel or directly from their own stores.

To measure firm-created WOM volume in the sensitive toothpaste, the anti-age cosmetics, and the organic chocolate cases, we use WOM conversations as reported by the seeds and captured by the agency's survey tools during the campaign. This is the standard measure for firm-created WOM volume used by most SMC agencies and in prior research. For the instant coffee case, we use the tracked number of seed agent visits to the campaign platform as a measure for firm-created WOM. While the relationship between seed agent activity on the platform (which may include mere reading and lurking) and the actually created WOM volumes is only correlational, the advantage of using this measure is that, compared with seed reports, the tracked platform activity does not require seed agents' attention and diligence, which may decrease over the course of the campaign. In addition, platform activity extends beyond the duration of the campaign: seed agents often remain active on the platform—and presumably in the actual market. To ensure comparability, we also obtained information on platform visits for the anti-age cosmetics and organic chocolate cases, which allows us to compare both measures. Web Appendix A summarizes both commonly used measures, their advantages and disadvantages, as well as their use in our data set and extant studies.

We determined the data set structure for the four cases using the dependent variable (sales), which provides a panel structure of regions measured over time. The chocolate data comprise several separate flavors as different stock keeping units (SKUs) in addition to the regions and month. Sampling intervals range from weekly (coffee, toothpaste, and cosmetics) to monthly (chocolate), and we matched all variables to their respective data set structure. Web Appendices B.1–B.4 include information on measurement units, descriptive statistics, and correlations. For our model, we use standardized variables to allow better comparison between cases.

Modeling Approach

We start by presenting some model-free evidence for potential interaction effects between firm-created WOM and advertising and sales promotions. Figure 1 shows sales over WOM against a backdrop of high or low levels of concurrent advertising and sales promotions for one of our cases (sensitive toothpaste). We scale the marketing variables to range from 0 to 100 and normalize the sales to a maximum of 100 in every regional cross-section of the data set. Three findings are of importance. First, sales for low levels of advertising are higher than for higher levels (54.5 vs. 48.3 and 59.9 vs. 53.0), consistent with our expectation of a negative interaction effect between firm-created WOM and advertising. Second, sales for high levels of promotions are higher than for lower promotion levels (50.5 vs. 48.3 and 59.9 vs. 52.3), consistent with our expectation of a positive interaction effect between firm-created WOM and sales promotions. Third, for the same level of advertising and sales promotions, sales are higher for high levels of WOM than for lower levels, indicating a direct positive impact of firm-created WOM on sales. This picture remains consistent when running linear regressions on the high/low marketing backdrop subsets of all points in the sales over WOM scatterplots (Figure 1, lower plots). To test these effects more formally, we next specify a comprehensive sales model to isolate and estimate the various effects.

(Insert Figure 1 approximately here)

Consistent with models used for similar questions in prior research (Godes and Mayzlin 2009; Naik and Raman 2003), we rely on a sales model that controls for carryover effects using a lagged dependent variable and includes fixed effects for seasonality and regional unobserved effects. In our short data sets, which feature mostly stable sales, the seasonal dummies capture time trends without an additional linear trend. Marketing activity and control variable effects are additional predictors, as well as the (multiplicative) interaction effects of interest. This base model can be formalized as follows:

$$(1) \quad Sales_{it} = Constant + \lambda_{it} Sales_{it-1} + \beta_{0it} WOM_{it} + \beta_{1it} Advertising_{it} + \beta_{2it} Promotions_{it} + \kappa_{1it} WOM_{it} \times Advertising_{it} + \kappa_{2it} WOM_{it} \times Promotions_{it} + \gamma_{jit} Controls_{it} + \delta_i R_i + \delta_t S_t + \varepsilon_{it} ,$$

where $Sales_{it}$ represents volume sales of region i in time period t, $Sales_{it-1}$ is the lagged dependent variable, WOM_{it} is the firm-created WOM volume, and $Advertising_{it}$ comprises the advertising and $Promotions_{it}$ the sales promotions concurrent with WOM in region i and time t. The vector $Controls_{it}$ includes other marketing plan elements (e.g., distribution, price, competitive advertising); regional effects appear within the vector R_i; and seasonal effects are in the vector S_t. Finally, ε_{it} denotes the error term.

Two points that require closer attention are a potential bias due to endogeneity concerns and problems resulting from (multi)collinearity. The following subsections explain how we addressed those issues. Table 3 provides detailed information on the relevant robustness checks.

(Insert Table 3 approximately here)

Endogeneity

It is widely known that endogeneity in marketing models can lead to biased coefficient estimates (Germann et al. 2015; Papies et al. 2017). Broadly speaking, endogeneity can result from reverse causality in observational data (or simultaneity), unobserved variables, or measurement error. A common way to correct for endogeneity involves using IVs that, in an ideal case, allow for unbiased estimates, which can be implemented through either two-stage least squares (2SLS) models that use estimated values from a first-stage regression for the possibly endogenous variable (Angrist and Pischke 2009; Germann et al. 2015; Wooldridge 2010) or an equivalent control function approach that includes the first-stage regression residuals as control variables in the main model (Petrin and Train 2010).

Current recommendations stress that researchers should first carefully exploit control variables and panel structures in the data sets (to control for unobserved effects) before deciding to use IVs (Germann et al. 2015; Papies et al. 2017; Rossi 2014). Our data set comes with a rich set of control variables: all cases are complete in their respective available marketing plan variables. Because the marketing plans in all cases were planned and commissioned in advance, they are independent of the later concurrent variations in the market. In addition, three cases (instant coffee, sensitive toothpaste, and premium chocolate) control for distribution and price, and two cases (instant coffee and sensitive toothpaste) control for some form of competitive advertising. In the cosmetics case, the data come from the brand’s own stores, which means distribution and price are under causal control of the brand. Therefore, a rich-data, fixed-effects regression approach that leverages the panel structure of the data sets to control for unobserved regional and seasonal effects should account for a significant part of the unobserved effects in the marketing plan variables (Germann et al. 2015; Papies et al. 2017). We provide these estimates in Web Appendix C.

However, it is still conceivable that firm-created WOM volumes may be subject to endogeneity bias, for the following three reasons. First, before the start of the SMC, invited prospective seed agents might self-select, and more agents might apply in regions where a brand is already perceived positively. As a result, we may observe more WOM in regions where the product already sells better. Second, SMC agencies may select seed agents with respect to the success measurement of the client brand, which creates an incentive to select more and better seed agents in regions where the brand focuses on. Third, the selected seed agents might react in their activity to some unobserved dynamics, resulting in a correlation between WOM or seed activity measure and the unobserved variables. We correct for such possible endogeneity bias in the WOM variable using an instrument as described next.

A suitable instrument must be correlated with the focal variable (regional weekly WOM volumes) but independent of the dependent variable (regional weekly sales). To obtain such a variable, we collected similar WOM volume variable levels over time from similarly sized SMCs, run by the same agency but at different times and with different products. The weekly averages of these WOM volume levels provide typical aggregate WOM dynamics for comparable SMCs, which are unrelated to the focal SCM and do not affect the respective product sales, nor are they affected by the respective unobserved conditions. We weigh these typical WOM levels regionally by the regional share of population in the country. As a result, our instrument represents a typical firm-created WOM pattern, as would be expected if seed agents apply and are selected proportional to the general population. We use such an instrument for each case and each type of WOM volume measure in a 2SLS regression as our main model.

As a robustness check, we also design two panel internal instruments (Germann et al. 2015). As a regional panel internal instrument, we construct the weekly WOM averages of the three regions most similar in population size to the target region and re-estimate the models in Web Appendix D.1. This approach is similar to Hausman and Taylor (1981), in that it assumes that comparable cross-sections of the data set may be less affected by an unobserved variable in a focal section. As a temporal panel internal instrument, we use the two-week lag of the focal, regional WOM variable in Web Appendix D.2. This approach is similar to Villas-Boas and Winer (1999) in that it assumes that the potential unobserved variables are uncorrelated over time. We use a two-week lag because we have already included lagged sales in the main model. As a robustness check against endogeneity issues from measurement error, we employ a Kalman filter estimation in Web Appendix E, in which we correct for unobserved variables using the main model instrument and the control function approach (Petrin and Train 2010).

We also re-estimate the main models with interacting seasonal (e.g., monthly) and regional dummy variables to control for unobserved effects specific to a time and region (e.g., a local retailer reacting to the SMC) in Web Appendix F. We run additional models with square root–transformed advertising, promotion, and WOM variables to check for robustness to diminishing communication effectiveness at high levels of advertising pressure in Web Appendix G, although in fact none of our cases exhibits particularly high advertising pressures (i.e., the largest single TV advertising volume in all our data amounts to just 58 GRPs).

Collinearity

Models that include complex marketing plans run the risk of highly collinear variables, which can distort coefficient estimates—although they remain unbiased as the sample size approaches infinity. All our variables show low pairwise correlations, the strongest being $r = -.69$ between sales promotions and price for the toothpaste case (see Web Appendix A.2), suggesting generally low levels of collinearity. Adjusted generalized variance inflation factors (GVIF; Fox and Monette 1992) also signal low collinearity in models with only direct effects (average GVIF = 3.50, single largest GVIF = 5.02). Still, adding interaction effects in the main models will increase collinearity (average GVIF = 3.57, single largest GVIF = 12.01) with a potential increase in standard errors.

To address this problem, we estimate the main models with a random-effects instead of a fixed-effects specification and the control function approach (see Web Appendix H). Random-effects models are more efficient (i.e., smaller errors in the estimates) but do not correctly account for endogeneity from unobserved effects (Papies et al. 2017). We also apply a ridge regression (and control functions) with an automatically selected ridge parameter (Cule and Iorio 2012) that penalizes model fit and shrinks the estimated coefficients (Amemiya 1985) in Web Appendix I. These models trade smaller errors for biased estimates and lower model fit. Finally, we sequentially add all interaction terms to a direct-effects-only model in Web Appendices J.1–J.4 to determine whether the estimated parameters remain stable when adding possibly collinear interaction variables.

Results

Table 4 lists the estimated main model for the four cases. All cases show a good model fit, explaining over 80% of the variance in the respective sales data. The direct effect estimates are in the expected directions—positive for planned marketing activities and distribution levels, negative for price—and mostly significant. For firm-created WOM, the direct effect results indicate a consistent positive effect on sales. These direct WOM effects are larger in the main models that include interaction effects than in corresponding models with direct effects only (see the “Robustness Checks” section and Web Appendices J1–J.4). These results provide a first indication that the WOM effects on sales may be weaker on a backdrop of advertising.

(Insert Table 4 approximately here)

The interaction effects between firm-created WOM and either advertising or sales promotion consistently support our expectations. Firm-created WOM and advertising interact negatively, and all advertising-related interaction effects have a negative sign, irrespective of whether the advertising is TV, digital, or print. In contrast, all promotion-related interaction effects are positive and significant, again irrespective of whether promotions are point of sale or direct email. In addition, the chocolate model confirms that significant positive interactions between firm-created WOM and point-of-sale promotions exist even when no advertising is present, providing evidence that the effect does not result from more complex higher-dimensional interactions.

When comparing different measures of firm-created WOM, we observe that direct WOM effects as well as most interaction effects show larger coefficients when using seed agent reports than when using platform visits. This is particularly obvious in the cosmetics and the chocolate cases, in which both measures are available. This can be explained by WOM-unrelated seed activities, which are included in the platform visits measure but not in the seed reports.

Robustness Checks

We used several checks to test the robustness of our findings over different model choices. Table 5 summarizes the directions and significance levels of the interaction effect results and their robustness checks across all four cases.

(Insert Table 5 approximately here)

A comparison of the main model interaction effects with the results from a fixed-effects only model without IV correction (Web Appendix C) shows similar directions and significance levels of the negative interactions with advertising and the positive interactions with promotions. This finding indicates that our instrument does not fundamentally change the estimated coefficients. However, all estimated interaction coefficients are larger when using an instrument, pointing to the possibility of underlying endogeneity in the firm-created WOM that goes uncorrected when not using an instrument.

Comparing the panel external instrument used in the main models with the two panel internal instruments (Web Appendices D.1–D. 2) shows that overall, both alternative instrument robustness models have largely the same pattern of negative interactions of WOM with advertising and positive interactions with promotions. The results from the temporal panel internal instruments model (using two-week lag as the instrument) show inconsistent differences in parameter sizes for the interaction effects with advertising: the models with platform visits as WOM measure show insignificant coefficients, whereas the models with seed reports show much larger estimated interaction coefficients. Presumably, some of the advertising effects may not be contained within a single week, thereby violating the temporal independence assumption for the temporal panel internal instrument.

We also test for instrument strength and estimation consistency. All employed instruments can be considered strong as evidenced by significant partial F-tests ranging from F =

5.93 (cosmetics) to F = 24,289.29 (premium chocolate) (Bound et al. 1995). Furthermore, Wu–Hausman tests (Hausman 1978; Wu 1973) reject consistency of fixed effects estimates in most cases (with minimum $p < .10$), except in three instances (main and panel internal regional instrument for visits for anti-age cosmetics, and panel internal regional instrument for seed reports), which indicates that instrumented WOM estimates are consistent in the presence of endogeneity and should be preferred over fixed-effects estimates.

As a robustness check against endogeneity from measurement error, we also estimate the main models with a Kalman filter in Web Appendix E (Naik and Raman 2003), including our panel external instrument with the control function approach (Petrin and Train 2010). Again, the interaction effects show largely similar directions and strengths, although one interaction with advertising in the toothpaste model remains insignificant. In summary, we are confident that the interaction effects exist as expected and that they are not an artifact of the instruments used to correct for potential endogeneity in the WOM variables.

Using square root–transformed WOM, advertising, and promotion variables to account for possible diminishing marginal direct effects does not substantially alter the directions of the interaction effects when re-estimating the model with 2SLS (see Web Appendix G). Qualitatively, these results indicate interaction effects sufficiently strong to remain super- or sub-additive, even after reducing the influence of the larger marketing levels in the model.

Controlling for interacting monthly and regional unobserved effects when re-estimating the main model (see Web Appendix F) confirms that interaction effects remain in the same directions, providing evidence of robustness against an unobserved dynamic, specific to select regions (e.g., a regional retailer with special promotions). Only the positive interactions between WOM and promotions seem weaker compared with the main model, possibly indicating some unobserved regional retailers' actions. However, given that we find these weaker results mainly in the cases with the smallest sample sizes and fewest overlapping weeks with the WOM variables (coffee and cosmetics), the result might be an artifact of the higher collinearity from interacting control dummies and the resulting larger estimation errors. Recalling that the cosmetics case data come from the brand's own stores, which rules out unobserved retailer activity, we deem this explanation likely.

We confirmed this speculation using random effects models (Web Appendix H) and ridge regression models with control functions (Web Appendix I), both of which are more efficient than the fixed-effects models when faced with collinearity and produce smaller standard errors. None of these models shows substantially different results, only some changes in coefficient size for specific variables. Finally, sequentially adding the interaction effect of interest to a direct-effects-only model (Web Appendices J.1–J.4) again confirms that the expected negative interactions with advertising and positive interactions with promotions are all significant when estimating models with reduced collinearity.

Discussion

The question of how SMC effects behave in the presence of traditional communication tools and how these effects compare with the effects of advertising or sales promotion remains unanswered, especially in an FMCG context. Our study aims to provide an initial empirical analysis in this direction. The four product markets we analyze demonstrate converging evidence for consistent interaction effects. We demonstrate consistent negative interaction effects between firm-created WOM and various types of advertising (TV, digital banner, and print).

To put our estimated sales effects into perspective with prior research, we calculate partial correlation effect sizes, $r = \sqrt{[t^2/(t^2 + df)]}$, using the t-statistics of the estimated coefficients in our main models (Cohen 1988). Table 6, Panel A, lists all estimated effect sizes. Integrating all three WOM × advertising interactions—using the seed report measure where possible—with a random-effects meta-analysis (Cumming 2014), we identify an overall effect size of r = .187 (95% confidence interval [CI] = .083, .291). We also demonstrate consistent positive interaction effects between firm-created WOM and various kinds of promotions (point of sale and direct email), with an overall integrated effect size of r = .143 (95% CI = .117, .169). Such strong interactions of SMCs with other marketing effects can help explain the wide range of firm-created WOM sales effects perceived by our interview partners and the WOM industry (WOMMA 2014a).

(Insert Table 6 approximately here)

Generally, we see that the effect sizes illustrated in Table 6 are small to medium, ranging from r = .034 to r = .316. These values are in the range of the known sales effect sizes in prior studies with stand-alone SMCs of r = .148 (N=180; Godes and Mayzlin 2009) and r = .262 (N = 88; both calculated from Cohen's d in Dost et al. 2016). Integrating the effect sizes from our four cases and the two extant offline SMC effect sizes with random-effects meta-analyses, we identify an overall r = .156 (95% CI = .080, .232). Note that this effect is only slightly stronger than the sales effect of electronic WOM volume on sales identified by prior meta-analyses (r = .091 overall; r = .141 for WOM volume; Babic Rosario et al. 2016). We attribute this slightly stronger result to the rich face-to-face nature of most SMC-created WOM communication.

Given the negative interaction between firm-created WOM and advertising, one might wonder about the contribution of SMCs, given that FMCG companies typically employ large-scale investment in media. Our interviews with SMC users indicate that, unlike when promoting new products, which can be largely pushed in various social influence channels, SMCs for supermarket goods are not aimed to replace traditional communication methods but rather to add to them. For example, SMCs are conducted when marketers want to inform users about a new development in a current product line such as a line extension (e.g., a new flavor or form of the product). In this context, one can imagine that some FMCG consumers can be more easily reached by advertising than others. Here, SMCs can be an efficient method to reach consumers who are less exposed to traditional media or are skeptical of its content. The larger this group is, the greater the contribution of SMC. If in such a context a firm increases advertising spending, some (but not necessarily all) of the individuals may be affected even before the SMC starts, which may explain the negative interaction between advertising and SMCs.

For promotion, the story is different. Marketers invest in promotions to convince buyers to take advantage of price deals. The higher the intensity of the price deals, the better the ability of the SMC to contribute to sales—thus the positive interaction with promotion efforts.

One of the interesting aspects of these results relates to how researchers approach amplified WOM programs in comparison to organic WOM. While originally the term "word of mouth" referred to organic talks among individuals, the growing involvement of firms in managing their customer interactions has blurred the distinction such that WOM effects may refer to both organic and amplified forms (Berger and Schwartz 2011; Godes et al. 2005). Yet it may be necessary to differentiate among various forms of WOM: firm-created WOM from SMC programs for supermarket goods may work as a substitute to advertising, whereas organic WOM for complex produces may work best instead of, or in addition to, advertising. Examining the interactions of WOM with other marketing tools can help in the quest to understand the role of WOM in specific markets.

Managerial Implications

It is the central assumption of all research on integrated marketing communication that different types of marketing communication and activities interact with one another (Batra and Keller 2016; Naik and Raman 2003; Smith et al. 2006; Stammerjohan et al. 2005). For a marketing manager commissioning an SMC, it is important to know how the additional firm-created WOM interacts with the firm's other advertising and promotional activities. Our results offer managers the opportunity to compare firm-created WOM sales effects from SMCs with sales effects from other marketing activities. To facilitate comparisons, we calculate elasticities of each marketing variable for each period and region with a nonzero value and then average them. For the calculation, we increase the variables by 1% and all affected interaction effects accordingly. In addition, we simulate how sensitively the firm-created WOM elasticities would react to marginal changes in advertising or promotion variables. We base the following managerial recommendations on these calculations and comparisons with elasticities from extant literature.

The SMC effect. Similar to previous SMC studies, we find evidence for a positive effect of SMCs on FMCG sales. Our analysis implies that SMCs may increase total sales by approximately 3%–18% over the course of the campaigns. The firm-created WOM elasticities ε shown in Table 6, Panel B, range from $\varepsilon = .03$ to $\varepsilon = .20$. These values are comparable to or stronger in size than extant meta-analytic sales elasticities for electronic WOM volume of $\varepsilon = .026$, when including advertising in the sales model, and $\varepsilon = .014$, when including a lagged sales variable in the sales model (You et al. 2015). They are also comparable in absolute values to the average sales elasticity ($\varepsilon = .12$) and the median ($\varepsilon = .05$) advertising elasticity for TV advertising in prior meta-analyses (Sethuraman et al. 2011). These numbers thus indicate that SMCs, which frequently cost well below 100,000€, likely generate incremental sales that are greater than their costs. It is important to note, however, that these numbers reflect relatively small sized SMC with no known simultaneous SMC by competitors. As the use of SMC widens and the market matures, we expect these elasticities to decline over time.

Managing SMCs with promotion and advertising. Table 7 shows how firm-created WOM elasticities change as a result of marginal increases or decreases in advertising or promotion. The relative changes can be interpreted as cross-elasticities between media. The results show that firm-created WOM elasticities decrease by –.6% to –2.2% for every 1% increase in concurrent advertising activities. Over the course of an SMC, similar reductions in total sales effects can be expected, which means that by reducing other advertising in the marketing plan, an SMC could substantially increase its total sales impacts, with the optimal mix being a function of media cost. An obvious implication of this finding is that firms should refrain from adding SMCs to the "big bang" marketing plan, as one of our interviewees put it. When temporally disentangling SMCs and advertising, we anticipate an order effect (Schultz et al. 2012) in favor of running the SMC first, followed by advertising later, because SMCs have smaller reach but likely richer information. In theory, this allows high-reach advertising to still inform unaware consumers and possibly recall SMC-induced memories of those already informed. In contrast, SMCs seem to combine well with promotion activities. The sensitivity analyses demonstrate higher firm-created WOM sales elasticities of +.3% to +1.1% for each 1% increase in promotional activities.

(Insert Table 7 approximately here)

Limitations and Areas of Future Research

Other marketing and market conditions for firm-created WOM synergy. Our study is limited to the analysis of offline firm-created WOM in the FMCG industry. Still, other forms of SMC do exist, and it is unclear whether our findings also hold in those cases. Online reviews as a form of electronic WOM, for example, occur at the (electronic) point of purchase. As such, they may benefit from easier recall due to familiarity from paid media or firm-created WOM. Digital advertising forms that directly link to a shopping site, such as search ads, may benefit from SMC or advertising-induced familiarity (Pauwels et al. 2016). Relatedly, forms of organic or firm-created WOM that are less information rich, such as ratings on review sites (Moon et al. 2010) or short social media network posts (Kumar et al. 2017), may offer more potential for complementary information and positive interaction effects with other marketing communication than face-to-face firm-created WOM. Future research could systematically vary the closeness of firm-created WOM or other marketing communication to points of consumer activity and reinvestigate the impacts on cross-media interaction effects.

Further, more complex products may allow for more information complementarity between marketing communications and thus promise more potential for synergy (Naik and Peters 2009). In such cases communication may also be more focused on sales promotions rather than the more brand related advertising in FMCG. In a business-to-business marketing environment with more customized and complex product solutions, personal selling—which ought be information rich and adaptive, similar to face-to-face WOM—exhibits positive instead of negative synergies with TV advertising (Gatignon and Hanssens 1987; Gopalakrishna and Chatterjee 1992). Future research could reinvestigate WOM-related media interaction effects in various product, market, or media channel contexts. The results could explain systematic differences between online and offline forms of marketing.

Individual level analysis. Future research may enhance our results with individual-level analysis to understand the process that creates the interactions between SMC and advertising/promotion in the context of FMCG. Customer heterogeneity is of particular interest. The interaction of SMC with the marketing mix elements can partly be explained by the existence of segments that react differently to the communication tools. If such segments can be identified, and possibly targeted, then managers can use the more precise targeting offered by SMC to mitigate the negative interaction with advertising. Field experiments may be a promising tool to disentangle segment-dependent reactions to SMC and the other communication tools.

Firm-created WOM impacts on organic WOM. A common assumption is that advertising spawns organic WOM, which then amplifies the sales effect (Hogan et al. 2004). Although researchers have analyzed this finding in the context of organic WOM, it has not yet been studied in the context of firm-created WOM. In this light, failing to consider the downstream consequences of interacting SMCs and advertising on organic WOM might represent a limitation on our effect estimates, because some portions of the interaction effect may be attributable to organic WOM from advertising. Although recent research challenges the notion that advertising effects are mediated by organic WOM (Lovett et al. 2017), the relationship would be worthwhile to analyze in more detail.

***Integrating communication content*.** Our study does not consider the qualities or differences in communication content, and it is conceivable that matching content in firm-created WOM and advertising could affect their interaction effects. In this light, a shift to "strategic" rather than "tactical" content integration could become beneficial for marketers (Sheehan and

Doherty 2001). This may be more complicated than it appears, considering that consumer-created content is inherently uncontrollable and even SMC seed agents do not just parrot the information that a brand or agency gives them (Kozinets et al. 2010). One option to design complementary content that propagates firm-created WOM is to offer trustworthy, unique, valuable stories (Berger 2014). Another avenue to create complementary content is to monitor a wide variety of ongoing organic conversations and then suggest careful additions between, not within, the separate topics, such that the content bridges separate conversations. Such content bridging then helps form a comprehensive communication "trellis" (Bail 2016) across the separate topics and increases information complementarity—and synergy.

Conclusion

Interacting in a market environment in which consumers pay increasingly less attention to traditional media and are notoriously difficult to reach through previously effective channels represents a challenge for most companies. Although firms increasingly realize that managing customer relationships in this context is substantially different from doing so in the past (Haenlein 2017), they still struggle with the day-to-day implementation of new strategies. If WOM programs are to become part of the marketing mix, we should understand their applicability to different types of markets and their interaction with other tools. The consistent results we found across scenarios suggest that, at least for FMCG, one can form expectations in the direction of the effects. We believe such analysis can help FMCG firms, as well as other markets, continue to explore the opportunity of SMCs and manage them as another marketing mix tool used in the marketing plan.

TABLE 1
Overview of Selected Studies Analyzing Seeding Marketing Campaigns for FMCGs

Authors	Firm-Created WOM Channel	Dependent Variable	Marketing Plan Interaction	Major Findings
Chae et al. (2017)	Online	WOM volume	—	Seeding increases WOM about the focal brand among non-seeds and decreases WOM about other brands in the same category
Berger and Schwartz (2011)	Offline	WOM volume	—	More interesting products create immediate WOM, publically visible or cued products create immediate and ongoing WOM
Toubia et al. (2011)	Offline	WOM volume	—	More social seed agents generate more WOM
Groeger and Buttle (2014)	Offline	Reach	—	Reach is lower than total WOM volume due to multiple exposures and channel overlap
Groeger and Buttle (2016)	Offline	Reach	—	Only half of firm-created WOM reaches its target group, but this share is higher when embedded in everyday conversation
Dost et al. (2016)	Offline	Sales	—	SMCs show sales effect; seeding through high-value customers or reaching high-value peers increases sales effect for unknown products
Godes and Mayzlin (2009)	Offline	Sales	—	SMCs show sales effect; WOM from non-loyal seeds drives incremental sales, because it reaches more unaware peers
Current study	Offline	Sales	Advertising (TV, digital, print) Promotions (point-of-sale, direct email)	For SMC WOM volume, consistent negative interaction with advertising and positive interaction with promotion is evident across different environments

TABLE 2
Case and Data Description

SMC Case	Instant Coffee	Sensitive Toothpaste	Cosmetics	Premium Chocolate
Product and campaign context	Major coffee brand, reintroduction of a variant from a product family in a southern European country	Well-known dental care brand, support for mature product in a western European country	High-end cosmetics brand, support for mature product in brand-owned retail stores in a central European country	Small premium organic chocolate brand, support for stable retail sales in a western European country
SMC characteristics	7,500 seeds from SMC agency panel, 8 weeks campaign duration WOM data over 12 weeks	7,500 seeds of WOM agency panel, 9 weeks campaign duration WOM data over 9 weeks	1,500 seeds of WOM agency panel, 8 weeks campaign duration WOM data over 13 weeks	5,000 seeds of WOM agency panel, 8 weeks campaign duration, WOM data over 3 months
WOM variables	• SMC platform visits	• Seed reports	• SMC platform visits • Seed reports	• SMC platform visits • Seed reports
Marketing plan variables	• Advertising (TV): GRPs • Promotion (point of sale): Number of supermarkets with tasting events and discounts • Promotion (direct email)[a]: Online coupons, emails sent (in thousands) • Promotion (sampling)[a]: Product samples in newspapers, copy (in thousands)	• Advertising (digital): large (500,000€) digital banner campaign, banner views (in thousands) • Promotion (point-of-sale): percentage of supermarkets with stopper displays and promotion shelves	• Advertising (print): brand–owned magazine, estimated circulation with focal product support • Promotion (direct email): Promotion coupons sent by email, emails sent (in thousands)	• Promotion (point-of-sale): Supermarkets with promotional activities, percentage points
Other variables	• Distribution: weighted • Price: euros (per pack) • Competitive advertising (TV): TV advertising for other variant of the brand family, GRPs	• Distribution: weighted • Price: euros (per pack) • Competitive advertising (TV): TV advertising for major competitor, GRPs	• Price: euros (per unit)	• Distribution: weighted • Price: EUR (per SKU)
Variables under brand control	Preplanned marketing plan activities, including competitive advertising for variant	Preplanned marketing plan activities	All observed variables under full brand control due to brand-owned retail stores	Preplanned marketing plan activities
Dependent variables	Volume sales, packs sold	Volume sales, packs sold	Volume sales, units sold	Volume sales, packs (per SKU)
Data structure	Panel (national level): 84 weeks ×8 regions: N = 672	Panel (national level): 36 weeks ×9 regions: N = 324	Panel (national level): 37 weeks ×7 cities: N = 259	Panel (national level): 12 months × 20 regions × 19 variants: N = 4,560
Descriptive statistics	Web Appendix B.1	Web Appendix B.2	Web Appendix B.3	Web Appendix B.4

[a] Not concurrent with WOM.

TABLE 3
Robustness Checks

Model	Description	Reason	Related literature
Main model *External typical SMC IV*	Instrumental variable approach, 2SLS, IV: Average firm-created WOM of similar, but unrelated SMCs (Table 4)	Correcting for a potential endogeneity bias stemming from unobserved variables on firm-created WOM	(Angrist and Pischke 2009; Germann et al. 2015; Wooldridge 2010)
Fixed effects	Main model with seasonal and regional dummies (no instruments) (Web Appendix C)	Controlling for unobserved regional and seasonal effects	(Papies et al. 2017)
Panel internal regional IV	Instrumental variable approach, 2SLS, IV: average firm-created WOM of similarly populated regions within the panel data (Web Appendix D1)	Correcting for a potential endogeneity bias stemming from unobserved variables on firm-created WOM	(Hausman and Taylor 1981)
Panel internal temporal IV	Instrumental variable approach, 2SLS, IV: 2-week lag of WOM activity (Web Appendix D2)	Correcting for a potential endogeneity bias stemming from unobserved variables on firm-created WOM	(Villas-Boas and Winer 1999)
Kalman filter	Main model applying Kalman filtering with additional control function (Web Appendix E)	Controlling for potential endogeneity bias stemming from measurement error	(Naik and Raman 2003; Petrin and Train 2010)
Month × Region	Main model with interacting monthly and regional effects (Web Appendix F)	Controlling for unobserved effects specific to a certain time and region	(Papies et al. 2017)
Square root	Main model with squared advertising and WOM variables (Web Appendix G)	Accounting for diminishing effects of advertising and WOM variables	(Bruce et al. 2012b)
Random effects	Main model allowing for seasonal and regional individual effects, with additional control function (Web Appendix H)	Addressing potential unobserved heterogeneity	(Papies et al. 2017)
Ridge regression	Main model with ridge parameter penalizing model fit and coefficient size, with additional control function (Web Appendix I)	Addressing potential collinearity by shrinking estimate errors	(Amemiya 1985; Cule and Iorio 2012)
Sequentially adding interactions	Adding single interaction terms to the direct effects only model (Web Appendix J1 –J4)	Controlling for potential collinearity by sequentially adding single interaction terms to direct effects only model	

TABLE 4
Estimation Results of Main Model (2SLS – External Typical SMC IV)

	Instant Coffee	**Sensitive Toothpaste**	**Cosmetics**		**Premium Chocolate**	
	Weekly Sales (Units)	*Weekly Sales (Units)*	*Weekly Sales (Units)*		*Monthly Sales (SKU)*	
	Visits	Seed Reports	Visits	Seed Reports	Visits	Seed Reports
Constant	$.456^{***}$	$.964^{***}$	$–.385^{**}$	$–.321^{*}$	–.009	.011
	(.137)	(.233)	(.142)	(.153)	(.051)	(.051)
$DV_{t–1}$	$.373^{***}$	$.234^{***}$	.100	–.012	$.645^{***}$	$.644^{***}$
	(.033)	(.052)	(.070)	(.097)	(.011)	(.011)
WOM	$.090^{*}$	$.450^{**}$	$.237^{***}$	$.399^{***}$	$.034^{*}$	$.081^{***}$
	(.046)	(.161)	(.049)	(.084)	(.015)	(.016)
Advertising (TV)	$.055^{+}$					
	(.029)					
Advertising (digital)		$.237^{***}$				
		(.061)				
Advertising (print)			$.148^{**}$	$.159^{**}$		
			(.050)	(.059)		
Promotion (point-of-sale)	$.075^{**}$	$.547^{***}$			$.022^{**}$	$.029^{***}$
	(.026)	(.067)			(.008)	(.008)
Promotion (direct email)	$.139^{***}$		.002	.099		
	(.027)		(.054)	(.062)		
Promotion (sampling)	$.094^{***}$					
	(.019)					
Distribution	$.270^{***}$	$.142^{***}$			$.123^{***}$	$.130^{***}$
	(.060)	(.037)			(.011)	(.011)
Price	$–.453^{***}$	$–.295^{***}$	–.009	–.022	$–.060^{***}$	$–.061^{***}$
	(.036)	(.035)	(.033)	(.036)	(.014)	(.014)
Competitive advertising (TV)	$–.118^{*}$	.022				
	(.046)	(.057)				
WOM × Advertising (TV)	$–.115^{*}$					
	(.045)					
WOM × Advertising (digital)		$–.343^{***}$				
		(.080)				
WOM × Advertising (print)			$–.228^{***}$	$–.300^{**}$		
			(.051)	(.090)		
WOM × Promotion	$.097^{*}$	$.237^{***}$			$.082^{***}$	$.080^{***}$
(point-of-sale)	(.040)	(.068)			(.008)	(.008)
WOM × Promotion			$.071^{*}$	—[a]		
(direct email)			(.028)	—[a]		
Observations	672	324	259	259	4,560	4,560
R^2	.832	.953	.924	.910	.898	.897

$+p < .1$; $*p < .05$; $**p < .01$; $***p < .001$
Notes: Standard errors are in parentheses. All variables are standardized. Seasonal and regional effects are not shown for brevity. [a] Seed report WOM measure does not overlap with promotions in the cosmetics case.

TABLE 5
Direct and Interaction Firm-Created WOM Effects Across Modeling Choices

	Model	Instant Coffee	Sensitive Toothpaste	Cosmetics		Premium Chocolate		Summary
		Visits	*Seed Reports*	*Visits*	*Seed Reports*	*Visits*	*Seed Reports*	
Direct effect firm-created WOM	Direct effects only model—external IV (Web Appendix J.1–J.4)	.017$^{(n.s.)}$	.307***	.054$^{(n.s.)}$	.239***	.046**	.098***	+ *positive*
	Main model—external IV (Table 4)	.090*	.450**	.237***	.399***	.034*	.081***	
Firm-created WOM × advertising	Fixed effects—no IV (Web Appendix C)	–.175***	–.072$^{(n.s.)}$	–.222***	–.156***			– *negative*
	Main model—external IV (Table 5)	–.115*	–.343***	–.228***	–.300**			
	Panel internal regional IV (Web Appendix D.1)	–.164***	–.176*	–.205***	–.140**			
	Panel internal temporal IV (Web Appendix D.2)	–.086$^{(n.s.)}$	–.531*	–.131$^{(n.s.)}$	–.502***			
	Kalman filter (Web Appendix E)	–.159*	–.065$^{(n.s.)}$	–.308*	–.243*			
	Month × region (Web Appendix F)	–.072^{+}	–.268***	–.283***	–.413***			
	Square root (Web Appendix G)	–.082$^{(n.s.)}$	–.290***	–.155***	–.187^{+}			
	Random effects (Web Appendix H)	–.140***	–.268***	–.238***	–.278***			
	Ridge regression (Web Appendix I)	–.060*	–.060**	–.140***	–.118***			
	Sequentially added interaction (Web Appendix J.1–J.4)	–.081*	–.380***	–.234***	–.300**			
Firm-created WOM × promotions	Fixed effects – no IV (Web Appendix C)	.071**	.158**	.075**	—	.048***	.048***	+ *positive*
	Main model—external IV (Table 5)	.097*	.237***	.071*	—	.082***	.080***	
	Panel internal regional IV (Web Appendix D.1)	.076**	.200**	.071*	—	.032*	–.071$^{(n.s.)}$	
	Panel internal temporal IV (Web Appendix D.2)	.118***	.300***	.146***	—	.058***	.073***	
	Kalman filter (Web Appendix E)	.086*	.135*	.090*	—	.078*	.082*	
	Month × region (Web Appendix F)	.044$^{(n.s.)}$	.101^{+}	.008$^{(n.s.)}$	—	.018^{+}	.040**	
	Square root (Web Appendix G)	.078^{+}	.082$^{(n.s.)}$	.070*	—	.083***	.073***	
	Random effects (Web Appendix H)	.100**	.244***	.070**	—	.083***	.080***	
	Ridge regression (Web Appendix I)	.072*	.160***	.065**	—	.082***	.080***	
	Sequentially added interaction (Web Appendix J.1–J.4)	.072*	.242***	.081**	—	.082***	.080***	

$^{+}p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$; $^{(n.s.)}$Not significant.

TABLE 6
Effect Sizes and Marketing Variable Elasticities
Panel A: Estimated Direct and Interaction Effect Sizes

	Instant Coffee (Visits) **r**	**Sensitive Toothpaste** (Seed Reports) **r**	**Cosmetics** (Visits) **r**	**Cosmetics** (Seed Reports) **r**	**Premium Chocolate** (Visits) **r**	**Premium Chocolate** (Seed Reports) **r**
Firm-created WOM	.080	.167	.316	.312	.034	.076
Advertising (TV)	.076					
Advertising (digital)		.229				
Advertising (print)			.202	.182		
Promotion (point-of-sale)	.117	.443			.043	.058
Promotion (direct email)	.208		.002	.109		
Promotion (sampling)	.196					
Distribution	.182	.227			.160	.168
Price	.459	.456	.019	.043	.063	.064
Competitive advertising (TV)	.103	.023				
WOM × Advertising (TV)	.103					
WOM × Advertising (digital)		.253				
WOM × Advertising (print)			.296	.224		
WOM × Promotion (point-of-sale)	.099	.206			.152	.143
WOM × Promotion (direct email)			.175			

Notes: r represents the partial correlation effect sizes of the estimated variables.

Panel B: Marketing Variable Elasticities

	Instant Coffee (Visits) **ε**	**Sensitive Toothpaste** (Seed Reports) **ε**	**Cosmetics** (Visits) **ε**	**Cosmetics** (Seed Reports) **ε**	**Premium Chocolate** (Visits) **ε**	**Premium Chocolate** (Seed Reports) **ε**
Firm-created WOM	.028	.201	.066	.149	.068	.138
Advertising (TV)	.005					
Advertising (digital)		.002				
Advertising (print)			.094	.104		
Promotion (point-of-sale)	.072	.282			.124	.128
Promotion (direct email)	.234		.027	.145		
Promotion (sampling)	.175					
Distribution	.825	.852			.326	.344
Price	–2.205	–2.070	–.051	–.131	–.662	–.680
Competitive advertising (TV)	–.111	.014				

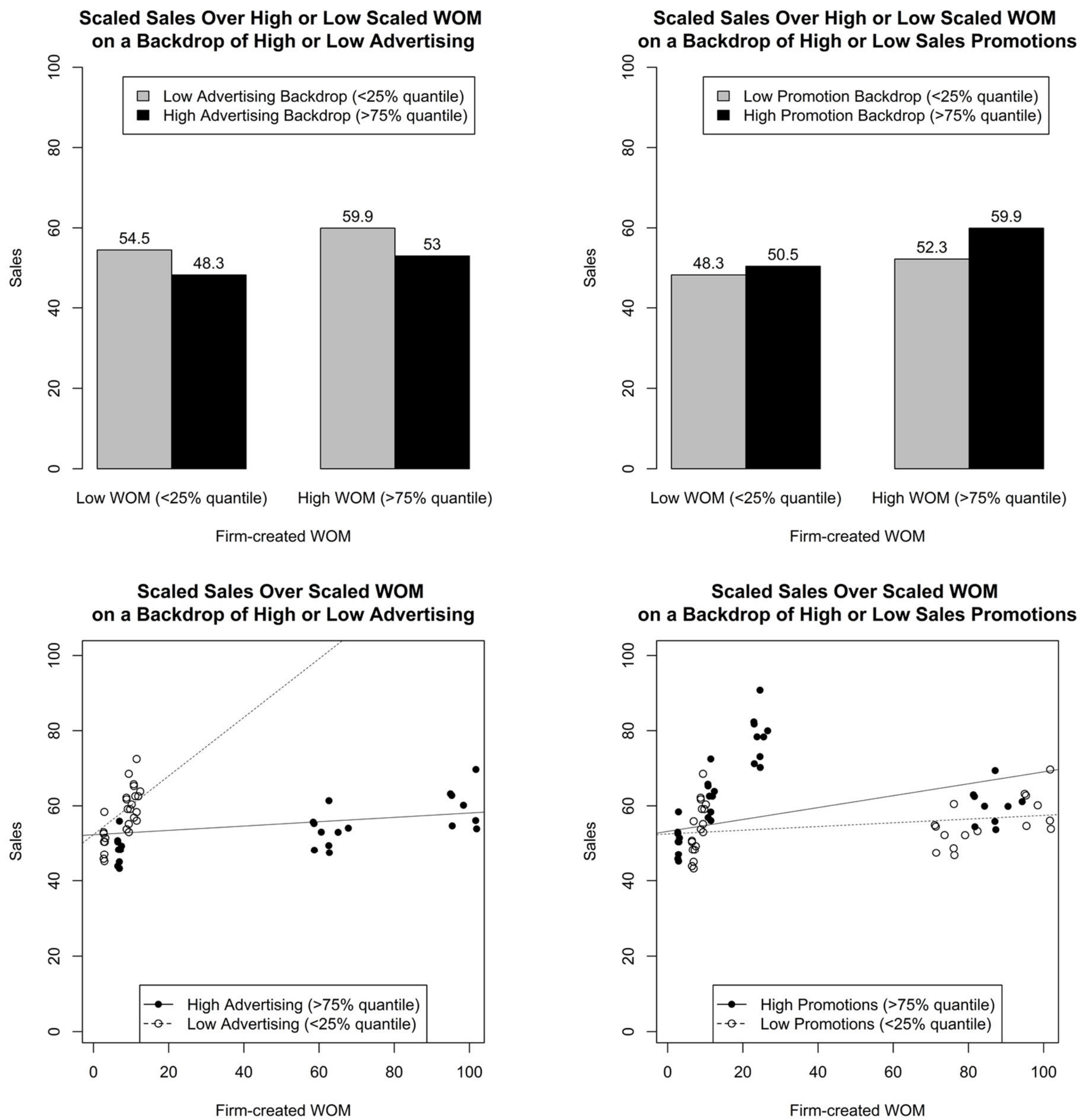
Notes: ε indicates sales elasticities (signup elasticity for online service), based on marginal changes in marketing variables (including interaction effects).

TABLE 7
Sensitivity of Firm-Created WOM Elasticities to Advertising and Promotion Changes

	Instant Coffee (Visits)		Sensitive Toothpaste (Seed Reports)		Cosmetics (Visits)		Cosmetics (Seed Reports)		Premium Chocolate (Visits)		Premium Chocolate (Seed Reports)	
	ε	**Relative Change**	**ε**	**Relative Change**	**ε**	**Relative Change**	**ε**	**Relative Change**	**ε**	**Relative Change**	**ε**	**Relative Change**
WOM elasticity	.028		.201		.066		.149		.068		.138	
With +1% advertising (TV)	.028	–2.16%										
With +1% advertising (digital)			.200	–.61%								
With +1% advertising (print)					.064	–2.31%	.147	–1.40%				
With +1% promotion (point-of-sale)	.029	+ 1.06%	.201	+.29%					.069	+ .47%	.138	+ .29%
With +1% promotion (direct email)					.066	+ .39%						

Notes: ε indicates elasticities based on marginal changes in marketing variables.

FIGURE 1
Model-Free Evidence for Interactions Between Firm-Created WOM and Other Marketing



Notes: Sales, advertising, promotion, and firm-created WOM scaled by region to regional maximum of 100. Upper plots show scaled sales mean values per WOM quartile, and lower plots show scatterplots and linear regression lines.

References

Amemiya, Takeshi (1985), Advanced Econometrics. Cambridge, MA: Harvard University Press.

Angrist, Joshua and Joern-Steffen Pischke (2009), Mostly Harmless Econometrics: An Empiricist's Companion: Princeton University Press;.

Aral, Sinan, Lev Muchnik, and Arun Sundararajan (2013), "Engineering social contagions: Optimal network seeding in the presence of homophily," *Network Science*, 1 (2), 125 - 53.

Armelini, Guillermo and Julian Villanueva (2010), "Marketing Expenditures and Word-of-Mouth Communication: Complements or Substitutes?," *Foundations and Trends in Marketing*, 5 (1), 1 - 53.

Babic Rosario, Ana, Francesca Sotgiu, Kristine De Valck, and Tammo H.A. Bijmolt (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.

Bail, Christopher Andrew (2016), "Combining natural language processing and network analysis to examine how advocacy organizations stimulate conversation on social media," *Proceedings of the National Academy of Sciences*, 113 (42), 11823–28.

Baker, Andrew M., Naveen Donthu, and V. Kumar (2016), "Investigating How Word-of-Mouth Conversations About Brands Influence Purchase and Retransmission Intentions," *Journal of Marketing Research*, 53 (2), 225 - 39.

Batra, Rajeev and Kevin Lane Keller (2016), "Integrating Marketing Communications: New Findings, New Lessons, and New Ideas," *Journal of Marketing*, 80 (6), 122 - 45.

Berger, Jonah (2014), "Word of mouth and interpersonal communication: A review and directions for future research," *Journal of Consumer Psychology*, 24 (4), 586 - 607.

Berger, Jonah and Raghuram Iyengar (2013), "Communication Channels and Word of Mouth: How the Medium Shapes the Message," *Journal of Consumer Research*, 40 (3), 567 - 79.

Berger, Jonah and Eric M. Schwartz (2011), "What drives immediate and ongoing word-of-mouth?," *Journal of Marketing Research*, 48 (5), 869-80.

Bound, John, David A. Jaeger, and Regina M. Baker (1995), "Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogeneous

Explanatory Variable is Weak," *Journal of the American Statistical Association*, 90 (430), 443 - 50.

Bruce, Norris I., Natasha Zhang Foutz, and Ceren Kolsarici (2012a), "Dynamic Effectiveness of Advertising and Word of Mouth in Sequential Distribution of New Products," *Journal of Marketing Research*, 49 (4), 469–86.

Bruce, Norris I., Kay Peters, and Prasad A. Naik (2012b), "Discovering How Advertising Grows Sales and Builds Brands," *Journal of Marketing Research*, 49 (6), 793 - 806.

Burmester, Alexa B., Jan U. Becker, Harald J. van Heerde, and Michel Clement (2015), "The impact of pre- and post-launch publicity and advertising on new product sales," *International Journal of Research in Marketing*, 32 (4), 408–17.

Campbell, Margaret C. and Kevin Lane Keller (2003), "Brand familiarity and advertising repetition effects," *Journal of Consumer Research*, 30 (2), 292–304.

Carl, Walter J. (2008), "The role of disclosure in organized word-of-mouth marketing programs," *Journal of Marketing Communications*, 14 (3), 225 - 41.

---- (2006), "What's all the buzz about? Everyday communication and the relational basis of word-of-mouth and buzz marketing practices," *Management Communication Quarterly*, 19 (4), 601 - 34.

Chae, Inyoung, Andrew T. Stephen, Yakov Bart, and Dai Yao (2017), "Spillover Effects in Seeded Word-of-Mouth Marketing Campaigns," *Marketing Science*, 36 (1), 89–104.

Chen, Xi, Ralf van der Lans, and Tuan Q. Phan (2017), "Uncovering the Importance of Relationship Characteristics in Social Networks: Implications for Seeding Strategies," *Journal of Marketing Research*, 54 (2), 187 - 201.

Chen, Yubo and Jinhong Xie (2008), "Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix," *Management science*, 54 (3), 477 - 91.

Cohen, J. (1988), "The effect size index: d," *Statistical power analysis for the behavioral sciences*, 2, 284–88.

Cule, Erika and Maria de Iorio (2012), "A semi-automatic method to guide the choice of ridge parameter in ridge regression," *arXiv preprint arXiv:1205.0686*.

Cumming, Geoff (2014), "The New Statistics Why and How," *Psychological science*, 25 (1), 7–29.

Dickson, John P. (1972), "Coordinating images between media," *Journal of Advertising Research*.

Dost, Florian, Jens Sievert, and David Kassim (2016), "Revisiting firm-created word of mouth: High-value versus low-value seed selection," *International Journal of Research in Marketing*, 33 (1), 236 - 39.

Dost, Florian, Robert Wilken, Maik Eisenbeiss, and Bernd Skiera (2014), "On the Edge of Buying: A Targeting Approach for Indecisive Buyers Based on Willingness-to-Pay Ranges," *Journal of Retailing*, 90 (3), 393–407.

Eelen, Jiska, Peren Özturan, and Peeter W. J. Verlegh (2017), "The differential impact of brand loyalty on traditional and online word of mouth: The moderating roles of self-brand connection and the desire to help the brand," *International Journal of Research in Marketing*, 34 (4), 872 - 91.

Fay, Brad and Rick Larkin (2017), "Why Online Word-of-Mouth Measures Cannot Predict Brand Outcomes Offline: Volume, Sentiment, Sharing, and Influence Metrics Yield Scant Online–Offline WOM Correlations," *Journal of Advertising Research*, 57 (2), 132 - 43.

Floyd, Kristopher, Ryan Freling, Saad Alhoqail, Hyun Young Cho, and Traci Freling (2014), "How Online Product Reviews Affect Retail Sales: A Meta-analysis," *Journal of Retailing*, 90 (2), 217–32.

Fox, John and Georges Monette (1992), "Generalized Collinearity Diagnostics," *Journal of the American Statistical Association*, 87 (417), 178 - 83.

Gatignon, Hubert and Dominique M. Hanssens (1987), "Modeling marketing interactions with application to salesforce effectiveness," *Journal of Marketing Research*, 247–57.

Germann, Frank, Peter Ebbes, and Rajdeep Grewal (2015), "The Chief Marketing Officer Matters," *Journal of Marketing*, 79 (3), 1 - 22.

Godes, David and Dina Mayzlin (2009), "Firm-created Word-of-Mouth communication: Evidence from a field test," *Marketing science*, 28 (4), 721 - 39.

Godes, David, Dina Mayzlin, Yubo Chen, Sanjiv Das, Chrysanthos Dellarocas, Bruce Pfeiffer, Barak Libai, Subrata Sen, Mengze Shi, and Peeter Verlegh (2005), "The firm's management of social interactions," *Marketing letters*, 16 (3/4), 415 - 28.

Gopalakrishna, Srinath and Rabikar Chatterjee (1992), "A communications response model for a mature industrial product: Application and implications," *Journal of Marketing Research*, 29 (2), 189.

Groeger, Lars and Francis Buttle (2016), "Deciphering word-of-mouth marketing campaign reach: everyday conversation versus institutionalized word of mouth," *Journal of Advertising Research*, 56 (4), 368 - 84.

---- (2014), "Word-of-mouth marketing: Towards an improved understanding of multi-generational campaign reach," *European Journal of Marketing*, 48 (7/8), 1186 - 208.

Haenlein, Michael (2017), "How to date your clients in the 21st century: Challenges in managing customer relationships in today's world," *Business Horizons*, 60 (5), 577 - 86.

Haenlein, Michael and Barak Libai (2017), "Seeding, Referral and Recommendation: Creating Profitable Word-of-Mouth Programs," *California Management Review*, 59 (2), 68 - 91.

---- (2013), "Targeting revenue leaders for a new product," *Journal of Marketing*, 77 (3), 65 - 80.

Hanssens, Dominique M., Julian Villanueva, and Shijin Yoo (2015), "Word-of-Mouth and Marketing Effects on Customer Equity," in *Handbook of Research on Customer Equity in Marketing*, V. Kumar and Denish Shah, eds.: Elgar.

Hausman, J. A. (1978), "Specification Tests in Econometrics," *Econometrica*, 46 (6), 1251 - 71.

Hausman, Jerry A. and William E. Taylor (1981), "Panel Data and Unobservable Individual Effects," *Econometrica*, 49 (6), 1377 - 98.

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

Hinz, Oliver, Bernd Skiera, Christian Barrot, and Jan U. Becker (2011), "Seeding strategies for viral marketing: An empirical comparison," *Journal of Marketing*, 75 (6), 55 - 71.

Hogan, John E., Katherine N. Lemon, and Barak Libai (2004), "Quantifying the ripple: Word-of-mouth and advertising effectiveness," *Journal of advertising research*, 44 (3), 271 - 80.

Keller, Ed and Brad Fay (2012), The Face-to-Face Book: Why Real Relationships Rule in a Digital Marketplace: Free Press.

Kempe, David, Jon Kleinberg, and Eva Tardos (2003), "Maximizing the spread of influence through a social network," *SIGKDD '03 Washington, DC, USA*.

Kotler, Philip and Kevin Lane Keller (2012), Marketing management: Pearson.

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

Kumar, V., Lerzan Aksoy, Bas Donkers, Rajkumar Venkatesan, Thorsten Wiesel, and Sebastian Tillmanns (2010), "Undervalued or Overvalued Customers: Capturing Total Customer Engagement Value," *Journal of service research*, 13 (3), 297 - 310.

Kumar, V., Vikram Bhaskaran, Rohan Mirchandani, and Milap Shah (2013), "Creating a Measurable Social Media Marketing Strategy: Increasing the Value and ROI of Intangibles and Tangibles for Hokey Pokey," *Marketing Science*, 32 (2), 194 - 212.

Kumar, V., JeeWon Brianna Choi, and Mallik Greene (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), 268–88.

Lamberton, Cait and Andrew T. Stephen (2016), "A Thematic Exploration of Digital, Social Media, and Mobile Marketing: Research Evolution from 2000 to 2015 and an Agenda for Future Inquiry," *Journal of Marketing*, 80 (6), 146 - 72.

Libai, Barak, Eitan Muller, and Renana Peres (2013), "Decomposing the Value of Word-of-Mouth Seeding Programs: Acceleration Versus Expansion," *Journal of Marketing Research*, 50 (2), 161 - 76.

Lovett, Mitchell J., Renana Peres, and Ron Shachar (2013), "On Brands and Word of Mouth," *Journal of Marketing Research*, 50 (4), 427 - 44.

Lovett, Mitchell J., Renana Peres, and Linli Xu (2017), "There's No Free Lunch Conversation: The Effect of Brand Advertising on Word of Mouth," *working paper*.

Mela, Carl F., Sunil Gupta, and Donald R. Lehmann (1997), "The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice," *Journal of Marketing Research*, 34 (2), 248 - 61.

Moon, Sangkil, Paul K. Bergey, and Dawn Iacobucci (2010), "Dynamic Effects Among Movie Ratings, Movie Revenues, and Viewer Satisfaction," *Journal of marketing*, 74 (1), 108 - 21.

Morone, Flaviano and Hernán A. Makse (2015), "Influence maximization in complex networks through optimal percolation," *Nature*, 524, 65 - 68.

Naik, Prasad A. and Kay Peters (2009), "A Hierarchical Marketing Communications Model of Online and Offline Media Synergies," *Journal of Interactive Marketing*, 23 (4), 288–99.

Naik, Prasad A. and Kalyan Raman (2003), "Understanding the impact of synergy in multimedia communications," *Journal of Marketing Research*, 40 (4), 375–88.

Naik, Prasad A., Kalyan Raman, and Russell S. Winer (2005), "Planning Marketing-Mix Strategies in the Presence of Interaction Effects," *Marketing Science*, 24 (1), 25–34.

Neff, Jack (2017), "CPG now spends more on digital than traditional ads, but shoppers doubt they work," in http://adage.com/article/cmo-strategy/study-cpg-spends-digital-traditional-advertising-combined/308077/.

Nejad, Mohammad G., Mehdi Amini, and Emin Babakus (2015), "Success Factors in Product Seeding: The Role of Homophily," *Journal of Retailing*, 91 (1), 68 - 88.

Papies, Dominik, Peter Ebbes, and Harald J. van Heerde (2017), "Addressing endogeneity in marketing models," in *Advanced Methods for Modeling Markets*: Springer.

Park, C. Whan and V. Parker Lessig (1977), "Judgmental rules and stages of the familiarity curve: Promotional implications," *Journal of Advertising*, 6 (1), 10–16.

Pauwels, Koen, Ceren Demirci, Gokhan Yildirim, and Shuba Srinivasan (2016), "The impact of brand familiarity on online and offline media synergy," *International Journal of Research in Marketing*, 33 (4), 739–53.

Petrin, Amil and Kenneth Train (2010), "A control function approach to endogeneity in consumer choice models," *Journal of marketing research*, 47 (1), 3 - 13.

Rosen, Emanuel (2009), The anatomy of buzz revisited: Real-life lessons in Word-of-Mouth marketing. New York: Crown Business.

Rossi, Peter E. (2014), "Even the Rich Can Make Themselves Poor: A Critical Examination of IV Methods in Marketing Applications," *Marketing Science*, 33 (5), 655 - 72.

Schultz, Don E., Martin P. Block, and Kaylan Raman (2012), "Understanding consumer-created media synergy," *Journal of Marketing Communications*, 18 (3), 173–87.

Sethuraman, Raj, Gerard J. Tellis, and Richard A. Briesch (2011), "How well does advertising work? Generalizations from meta-analysis of brand advertising elasticities," *Journal of Marketing Research*, 48 (3), 457–71.

Sheehan, Kim Bartel and Caitlin Doherty (2001), "Re-weaving the web: Integrating print and online communications," *Journal of Interactive Marketing*, 15 (2), 47–59.

Sloane, Garett (2016), "Why P&G decided Facebook ad targeting often isn't worth the money," in http://adage.com/article/digital/p-g-decided-facebook-ad-targeting-worth-money/305390/.

Smith, Timothy M., Srinath Gopalakrishna, and Rabikar Chatterjee (2006), "A three-stage model of integrated marketing communications at the marketing–sales interface," *Journal of Marketing Research*, 43 (4), 564–79.

Sriram, S. and Manohar U. Kalwani (2007), "Optimal Advertising and Promotion Budgets in Dynamic Markets with Brand Equity as a Mediating Variable," *Management Science*, 53 (1), 46 - 60.

Stammerjohan, Claire, Charles M. Wood, Yuhmiin Chang, and Esther Thorson (2005), "An empirical investigation of the interaction between publicity, advertising, and previous brand attitudes and knowledge," *Journal of Advertising*, 34 (4), 55–67.

Stigler, George J. (1961), "The economics of information," *Journal of political economy*, 69 (3), 213–25.

Tirunillai, Seshadri and Gerard J. Tellis (2017), "Does Offline TV Advertising Affect Online Chatter? Quasi-Experimental Analysis Using Synthetic Control," *Marketing Science*, 36 (6), 862 - 78.

Toubia, Olivier, Andrew T. Stephen, and Aliza Freud (2011), "Viral marketing: A large-scale field experiment," *Economics, Management, and Financial Markets*, 6 (3).

Trusov, Michael, Randolph E. Bucklin, and Koen Pauwels (2009), "Effects of Word-of-Mouth versus traditional marketing: Findings from an Internet social networking site," *Journal of Marketing*, 73 (5), 90 - 102.

Vakratsas, Demetrios and Tim Ambler (1999), "How advertising works: What do we really know?," *Journal of marketing*, 63 (1), 26 - 43.

Villas-Boas, J. Miguel and Russell S. Winer (1999), "Endogeneity in brand choice models," *Management science*, 45 (10), 1324 - 38.

WOMMA (2014a), "Return on Word of Mouth." Chicago.

---- (2014b), "The State of Word of Mouth Marketing: A Survey of Marketers." Chicago.

Wooldridge, Jeffrey M. (2010), Econometric Analysis of Cross Section and Panel Data: MIT Press.

Wu, De-Min (1973), "Alternative Tests of Independence between Stochastic Regressors and Disturbances," *Econometrica*, 41 (4), 733 - 50.

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

Zubcsek, Peter Pal and Miklos Sarvary (2011), "Advertising to a social network," *Quantitative Marketing and Economics*, 9 (1), 71 - 107.