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Like the ad or the brand? Marketing stimulates different electronic word-of-mouth content to drive online and offline performance☆

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ABSTRACT

Electronic word-of-mouth (eWOM) is often tracked in volume and valence metrics, but the topic of conversation may vary from the brand to its advertising to purchase statements. How do these different topics affect company performance? And which specific marketing communication (online, TV, radio, print) obtains most of its performance impact by stimulating eWOM topics?

This paper quantifies the dynamic interactions among marketing, eWOM content, search, and online and offline store traffic for an apparel retailer. While it yields a similar online store traffic lift, advertising-related eWOM yields only half the offline store traffic lift of brand-related eWOM and of neutral eWOM about purchasing at the retailer. Paid search shows the highest elasticity in stimulating online conversations, but drives less business than offline marketing actions. While TV is the main paid driver of online store traffic, print is the main paid driver of offline store traffic for the studied retailer. Over a third of the offline store traffic effects materialize indirectly through eWOM and organic search. To avoid undercounting the benefits of paid marketing, managers should therefore track how their actions induce specific eWOM content metrics and how much these in turn drive performance.

1. Introduction

Word of Mouth (WOM) has long been heralded as a more important driver of business success than paid marketing (Misner, 1999), and the worldwide popularity of online social media (surpassing 2 billion users) made it easier to send and receive it (Dellarocas, 2003; Statistica, 2015). As a result, many companies are moving their metrics from consumer impressions to expressions (Tripodi, 2011). Beyond monitoring such electronic WOM (eWOM), managers are keenly interested in how they can stimulate it with paid advertising, including offline actions (Godes et al., 2005; Onishi & Manchanda, 2012; Trusov, Bucklin, & Pauwels, 2009). To this end, managers need to know which eWOM content affects performance most and which specific marketing communication actions (e.g. online, TV, radio, print) stimulate these eWOM conversations.

Across disciplines, research on the impact of eWOM has focused on its quantity (i.e., volume), sentiment (i.e., valence) and dispersion, as summarized in recent meta-analyses (Babic, Sotgiu, de Valck, & Bijmolt, 2016, Floyd, Freling, Alhoqail, Cho, & Freling, 2014; You, Vadakkepatt, & Joshi, 2015). However, several important areas remain for future research, including "the analysis of the content of eWOM" (Babic et al., 2016, p.34) and the "differences in effectiveness of traditional media such as broadcasting and print advertising in generating eWOM" (You et al., 2015, p. 37).

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As to the content of eWOM, managers and investors nowadays can track metrics aggregating the rich information context of thousands or even millions of customer expressions (Hopkins & King, 2010; Tirunillai & Tellis, 2012). For instance, conversations about a company could concern its advertising (hereafter 'Ad eWOM'), its offering (hereafter 'Brand eWOM') or 'neutral' comments of purchase (hereafter 'Purchase eWOM').[1] Given their different places in the purchase funnel, Ad eWOM versus Brand eWOM should have different performance effects — just as they do in the offline world (Brown & Stayman, 1992). Indeed, Ad eWOM does not require purchase or consumption experience, while Purchase eWOM requires purchase and Brand eWOM is typically grounded in actual experience with the brand. Moreover, Ad eWOM may suffice to get a prospective customer to visit the company online, but not offline in the physical store, which requires more effort (Pauwels, Leeflang, Teerling, & Huizingh, 2011). However, no study has quantified such different performance effects of Ad eWOM versus Brand eWOM. Likewise, Purchase eWOM may have important performance implications because it offers potential customers the opportunity for 'observational learning' (Baxendale, Macdonald, & Wilson, 2015). In this regard, Sonnier, McAlister, and Rutz (2011) call for future research on the differential effects of the topic of online comments.

As to paid marketing actions, only a handful of studies have analyzed their effects on eWOM (Onishi & Manchanda, 2012; Pauwels & van Ewijk, 2013; Srinivasan, Rutz, & Pauwels, 2015). In each case, the authors show a stronger indirect than direct performance effect of TV advertising. However, none of these studies distinguished between eWOM content metrics nor compared the differential eWOM effects across different marketing actions.

This paper is the first to quantify the the differential impact of Ad, Brand and Purchase eWOM on business performance and the dynamic effects of different offline and online paid marketing actions on these eWOM content metrics. Our research questions are:

(1) How do Ad eWOM, Brand eWOM and Purchase eWOM affect online and offline business performance?
(2) How do paid marketing actions stimulate specific eWOM content, and how strong are these indirect performance effects for specific marketing actions?

To address these research questions, we gather data that combine eWOM content with online and offline marketing actions and online (i.e., website) and offline (i.e., brick and mortar) store traffic for a major apparel retailer. Our data are substantially richer than that used in previous eWOM research, both in terms of marketing actions (TV, radio, print, online) and in the broad coverage of blogs, forum messages, Facebook and Twitter. We show how specific marketing actions induce the specific content of eWOM conversations, which in turn convert to online store traffic and offline store traffic. The vector-autoregressive (VAR) model estimates the dynamic relationships among marketing, search, eWOM and performance without imposing a priori restrictions (Sims, 1980).

Our empirical application for a US retailer finds that that different eWOM content metrics have substantially different performance implications and that marketing actions with small direct effects can have large total effects by stimulating eWOM conversations.

2. Research background

Word-of-mouth has been called "the world's most effective, yet least understood marketing strategy" (Misner, 1999). Initially, researchers focused on messages that consumers received from opinion leaders (Katz & Lazarsfeld, 1955). About 30 years ago, the concept was extended to include "all informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods and services or their sellers" (Westbrook, 1987, p. 261). Importantly, this includes observing the actions of peers such as family, friends or simply other consumers (Childers & Rao, 1992; Godes et al., 2005; Narayan, Rao, & Saunders, 2011). For instance, we may learn about a jacket because an online friend just bought it, or we may be persuaded because she posted a positive review.

From the initial study by Katz and Lazarsfeld (1955), over 70 papers have used self-reports to demonstrate the high sales effectiveness of word-of-mouth (Godes & Mayzlin, 2004; Money, Gilly, & Graham, 1998). In their meta-analysis of antecedents and consequences of word-of-mouth, De Matos and Rossi (2008) call for more research on the effect of WOM on actual customer behavior (versus intention) and on the nature of eWOM. Table 1 reviews the publications that have done so, highlighting the performance variable, eWOM source, valence, content and interaction with paid marketing; the latter two constituting the main contribution of this paper to the literature.

As to our first research question, only a handful of studies model eWOM content, and of those only Onishi and Manchanda (2012) account for the indirect performance effects of paid marketing through eWOM (denoted as 'synergy' in Table 1). For movies in Japan, they find that 90% of advertising's performance effect is indirect (through blogging), but wonder whether this finding is "an anomaly" (p. 229) and call for further research. No previous study specifically considers Ad eWOM (column 4 of Table 1), though it is often included in positive eWOM — thus averaging its effect with that of Brand eWOM. As to our second research question, several studies investigate the complementary roles of paid marketing versus eWOM and find that the latter has a substantially higher performance impact (Goh, Heng, & Lin, 2013; Trusov et al., 2009). However, most of these studies consider only 1 marketing communication channel, such as marketer-generated content (Goh et al., 2013), paid events (Trusov et al., 2009), traditional publicity (Stephen & Galak, 2012) and TV advertising (Chintagunta, Gopinath, & Venkataraman, 2010; Srinivasan

[1] Throughout this paper, we don't consider negative WOM, which is the topic of many previous studies.

Table 1
Synthesis of past literature on eWOM performance effects and this study's contribution.

Study	Source of eWOM	eWOM Effect on	eWOM valence	eWOM content	Ad eWOM	Paid Marketing	Paid drives eWOM
Albuquerque, Pavlidis, Chatow, Chen, and Jamal (2012)	Referrals	Visitors, sales	✗	✗	✗	Promotions	✗
Chen et al. (2011)	Reviews, % buying	Sales rank	✓	✓	✗	✗	✗
Chevalier and Mayzlin (2006)	Ratings B&N vs. Amazon	Difference in sales rank	✓	✗	✗	✗	✗
Chintagunta et al. (2010)	Rating	Opening day revenues	✓	✗	✗	Advertising, distribution	✗
Decker and Trusov (2010)	Reviews	Preferences	✓	✓	✗	✗	✗
Dellarocas, Zhang, and Awad (2007)	ratings	sales	✓	✗	✗	Advertising, distribution	✗
Dhar and Chang (2009)	Reviews, blogs	Sales	✗	✗	✗	✗	✗
Godes and Mayzlin (2004)	Reviews	Episode rating	✓	✗	✗	✗	✗
Goh et al. (2013)	Facebook	Consumer expenditure	✓	✓	✗	Firm-gene-rated content	✗
Liu (2006)	Reviews	Revenues	✓	✗	✗	✗	✗
Moe and Trusov (2011)	Ratings	Ratings, sales	✓	✗	✗	✗	✗
Onishi and Manchanda (2012)	Blogs	Viewers, blogs	✓	✓	✗	Advertising	Synergy
Pauwels and van Ewijk (2013)	Not specified	Sales change	✓	✗	✗	TV, print	✓
Sonnier et al. (2011)	Comments	Sales	✓	✗	✗	✗	✗
Srinivasan et al. (2015)	Facebook	Sales	✓	✗	✗	TV	✓
Stephen and Galak (2012)	Publicity	Sales	✓	✓	✗	✗	✗
Sun (2012)	Ratings	Sales	✓	✗	✗	✗	✗
Tirunillai and Tellis (2012)	Reviews	Abnormal stock returns	✓	✓	✗	✗	✗
Trusov et al. (2009)	Referrals	Sign-ups	✗	✗	✗	Paid events	✓
Zhu and Zhang (2010)	Reviews	Sales change	✓	✗	✗	Price	✗
This study	Blogs, forums, Facebook, Twitter	Online and offline store traffic	✓	✓	✓	TV, print, radio, search	✓

et al., 2015). Pauwels and van Ewijk (2013) find that TV advertising is more effective than online marketing to increase positive eWOM, but do not distinguish Ad eWOM from Brand eWOM.

This paper shares the above studies' objective of quantifying the effect of eWOM and paid marketing. However, our focus is on how different marketing actions drive specific eWOM content metrics with different performance benefits. Moreover, we show the extent of direct marketing effects versus indirect through organic search and eWOM — which differs for different offline and online marketing actions.

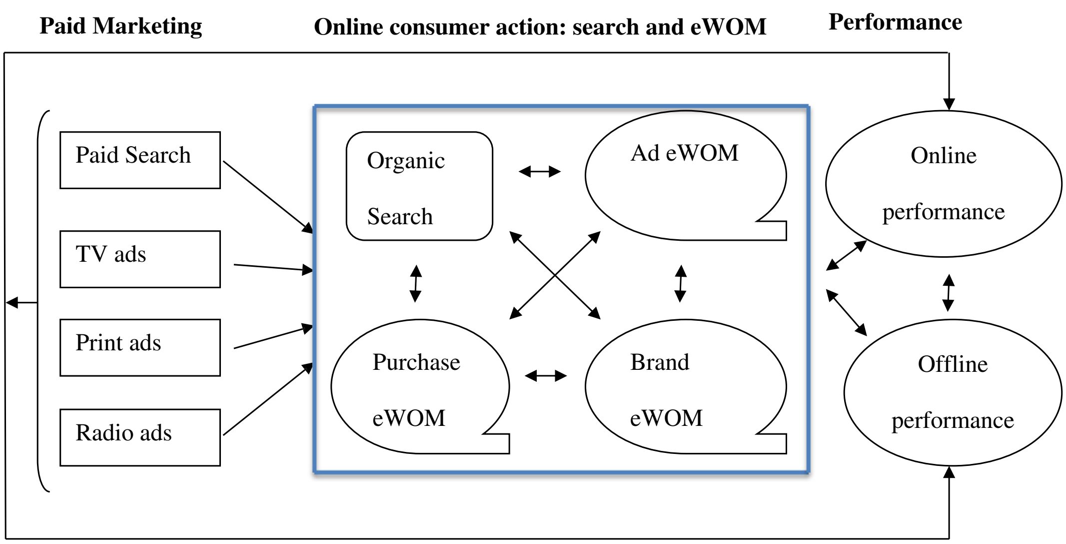

Fig. 1. Paid marketing communication, search, online WOM and company performance.

3. Conceptual framework

Based on previous literature, we acknowledge that marketing can both have direct performance effects and indirect performance effects by inducing action that nudges the customer closer to purchase (e.g. Srinivasan, Pauwels, & Vanhuele, 2010). The ‘upper funnel’ part of the online decision journey can be represented by organic search (indicating browsing interest) and Ad eWOM (indicating consumer attention to and liking for the brand's ads). The ‘lower funnel’ part can be represented by Purchase eWOM and Brand eWOM, which indicate respectively purchase and a positive evaluation of the brand (typically grounded in actual brand experience). Performance is often tracked separately online and offline; e.g. as online store traffic (website visits) and offline store traffic (physical store visits) for a bricks-and-clicks retailer like our data provider. Our framework in Fig. 1 visualizes the dynamic interactions among these key metrics.

Because organic and paid searches have seen plenty of research attention (Dinner, Van Heerde, & Neslin, 2014, Rutz & Bucklin, 2011; Yang & Ghose, 2010), we focus our conceptual discussion on the Ad, Brand and Purchase eWOM metrics. First, we explain their different nature and expected effects on offline and online performance (first research question). Next, we discuss how paid marketing can influence these different eWOM metrics.

First, the difference between Ad eWOM versus Brand eWOM has yet to see research in online settings. This is surprising given the extensive pre-Internet literature on the brand evaluation importance of attitude towards the ad (Brown & Stayman, 1992). Different effect configurations include the direct affect transfer, i.e. one-way causation of brand attitude by ad attitude (e.g. Shimp, 1981), a reciprocal relation, i.e. two-way causation (e.g. MacKenzie, Lutz, & Belch, 1986) and independent influences of ad attitude and brand attitude on purchase intention (e.g. Howard, 1977). In the former 2 configurations, positive ad attitude affects positive brand attitude and, in any configuration, positive ad attitude increases purchase intention (e.g. Mitchell & Olson, 1981). Extending these classic findings to the digitally connected consumer, we believe similar mechanisms operate for Ad eWOM and Brand eWOM. A reciprocal relation is likely because digitally connected consumers will not just strive to maintain their own cognitive balance (Heider, 1946) but also strive to project a consistent image to other consumers (Godes et al., 2005; Moe & Schweidel, 2012). Talking positively about a brand's advertising online is consistent with talking positively about the brand online.

Importantly, potential customers may need not only rely on what others say, they can also observe what others do (Asch, 1955; Narayan et al., 2011). This is a key and often overlooked component of eWOM, as a brand's apparent popularity with non-paid others may well impact the prospective consumer's “expected utility from that product or service” (Godes et al., 2005). Such “bandwagon effect” (Mcallister & Studlar, 1991) or “observational learning” (Bikchandani, Hirshleifer, & Welch, 1992) could arise because prospects perceive other customers' choice as more reliable than their own private information (Chen, Wang, & Xie, 2011). Risselada, Verhoef, and Bijmolt (2014) report a constant influence of recent adopters, plausibly because they are more enthusiastic or credible (Iyengar, van den Bulte, & Valente, 2011). Factors that drive such influence include compliance, identification and internalization (Kelman, 1958). In their recent meta-analysis, Babic et al. (2016) demonstrate “the dominance of the bandwagon effect over the persuasion effect”, as they find volume metrics of eWOM (which include those of ‘neutral’ valence) to have a larger performance effect than valence metrics. A direct comparison by Baxendale et al. (2015) finds higher brand consideration lifts from observational learning than from what others say.

Why would Ad eWOM, Brand eWOM and Purchase eWOM have different effects on offline and online performance metrics? First, offline customer action typically requires a considerable travel cost for the customer to visit a brick-and-mortar store during its opening hours (Bell, Ho, & Tang, 1998). In contrast, the online store is ‘just a click away’, available at all times, and thus seen as fast and convenient by consumers with broadband internet connection (Pauwels et al., 2011; Verhoef, Neslin, & Vroomen, 2007) Due to this difference, we expect prospective customers to require a greater expected benefit and/or lower perceived purchase risk for visiting the offline store (Pauwels & Neslin, 2015). Brand eWOM should do a better job than Ad eWOM of increasing the perceived benefits and decreasing the perceived risk. Likewise, Purchase eWOM tells the prospective customer that the WOM-generator has actually purchased the brand, instead of being wowed by its advertising. Therefore, *we expect Brand eWOM and Purchase eWOM to have a larger impact than Ad eWOM on offline store traffic.*

In contrast, Ad eWOM may be sufficient for prospective customers to visit the online store because of the relatively low cost of doing so. Therefore, we do not have a directional expectation on differential effects on online store traffic. Likewise, we see no convincing rationale to expect higher effects of Brand eWOM versus Purchase eWOM effects on offline or online store traffic: while Brand eWOM gives a more positive signal, Purchase eWOM may give a more credible signal. Actual purchase differs from ‘cheap talk’, which may also be generated by non-customers — note that Amazon recently sued ‘fake reviewers’ for leaving positive comments (Brand eWOM), not ‘neutral’ Purchase eWOM (Gani, 2015). Thus, we examine the performance effects of Brand eWOM versus Purchase eWOM in an exploratory fashion.

As to our second research question, how can marketing communication drive these eWOM metrics? For Ad eWOM, customers obviously need advertising to talk about (e.g. Brown & Stayman, 1992). Moreover, marketing communication may directly increase Brand eWOM and Purchase eWOM. Customers are more likely to spread Brand eWOM for highly visible brands (Berger & Schwartz, 2011), because they receive more social benefits, which are the main motivation to engage in eWOM (Lovett, Peres, & Shachar, 2013). For Purchase eWOM, talking about purchasing well-known brand gives customers more prestige and perceived expertise (Amblee & Bui, 2008).

Which specific marketing actions should drive eWOM most? While empirical generalizations on marketing action effects on eWOM are lacking, we can speculate that online and TV advertising have the strongest effect, as they have a larger sales elasticity than radio and print (e.g. Jamhouri & Winiarz, 2009; Pauwels & van Ewijk, 2013; Srinivasan, Rutz & Pauwels, 2015). For online marketing, the channel fit with eWOM makes it very convenient for a consumer to spread the online world. Meanwhile, TV is

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Table 2
Descriptive statistics of variables included in the model.

	Mean	Median	Standard deviation	Minimum	Maximum
Store traffic	681,821	682,627	153,469	407,984	1,203,802
Online traffic	110,206	10,6476	33,999	52,653	269,087
Organic search	36	35	13	14	100
Brand eWOM	538	460	290	230	1678
Ad eWOM	1736	1355	1112	634	5623
Purchase eWOM	753	645	401	358	2511
Television GRPs	8	7	7	0	24
Radio GRPs	3	0	7	0	20
Print: number of circulars	384,089	0	897,440	0	2,908,555
Paid search impressions	672,267	645,553	212,767	283,846	1,268,048

a rich medium with high reach, and most US consumers are online while watching TV (Advertising Age, 2015). In contrast, radio is often listened to while driving (Shields, 2010), at which time spreading eWOM is inconvenient (and often illegal). Meanwhile, print also offers a rich medium in certain industries (such as the apparel retailer studied in our empirical application), and consumers typically consult it 'leaning back' in the comfort of their home or office, where online connection is easily available (Pauwels & Neslin, 2015).

Online marketing and offline marketing have been shown to each drive both online and offline sales in both B2B and B2C markets (Dinner et al., 2014; Wiesel, Pauwels, & Arts, 2011). In today's customer decision journey, customers may search for information online and then go to the offline store, which enables face-to-face interaction with salespeople, for touching and physically fitting the merchandise (Pauwels & Neslin, 2015). Likewise, customers may be exposed to offline marketing and then browse the online store for higher convenience, easy price comparison with competing store, etc. (Pauwels et al., 2011). We expect such cross-channel effects also for the impact of eWOM metrics on offline store traffic, as especially Brand and Purchase eWOM may induce prospective customers to visit the offline store (see above). Finally, offline and online store traffic are likely related, either negatively (a channel substitution effect) or positively, as prospective customer visit both the online and the offline store (Verhoef et al., 2007).

Previous findings and theory do not provide sufficient basis for hypotheses on which marketing actions have the highest elasticity on eWOM metrics, nor for a hierarchy among eWOM variables, mirroring the absence of a strict order in the traditional funnel (e.g. Srinivasan et al., 2010). Instead, we recognize the possibility of different paths in the "consumer journey", such as:

(1) paid advertising leading consumers to online search for more information, which brings them to the company's online store;
(2) paid advertising leading consumers to discuss their liking for the ad, which then prompts Brand eWOM and ultimately stimulates visits to the offline store; and
(3) Purchase eWOM alerts the consumer that an important other is frequenting a store, after which said consumer visits the same store;

Each of these paths has a dynamic nature, in that prospective consumers may need time to react to advertising (e.g., Little, 1979) and eWOM (e.g., Trusov et al., 2009). Moreover, once the effects materialize, they may last for a long time due to purchase reinforcement and the positive spiral of eWOM and customer acquisition (Trusov et al., 2009). As is typical in social sciences such as marketing and economics, existing theories are silent on when such effects materialize and how long they last (e.g., Sims, 1980; Dekimpe & Hanssens, 1999).

4. Data and variable operationalization

Addressing our research questions requires a longitudinal data set of marketing actions, company performance, online search and eWOM content metrics. These data come from three sources. First, a major US apparel retail brand provided weekly data on (online store) traffic and physical (offline store) traffic; the main performance indicators for this retailer, who generates substantial revenues from both channels. Second, we collected organic search data from Google. Next, weekly time series of eWOM volume, valence and content for this retail brand were provided by Crimson Hexagon. Finally, the retailer provided data on its 4 main media for marketing spending: TV, radio, print and paid search advertising. Television and radio advertisements were measured in Gross Rating Points (GRPs); print advertising as the number of circulars distributed, and paid search advertising in impressions. The combination yields complete data for July 4th 2010 to July 31st 2011 (55 weeks). Table 2 shows summary statistics for all variables included in the model.

Table 2 shows substantial variation in each variable, which allows us to estimate the effects of their changes in the tradition of time series econometrics.[2] Store traffic data were provided at the financial store level on a daily basis, and then aggregated to the

[2] The data do not allow us to track how specific individuals react to marketing, search or use eWOM While such individual-level data for representative samples are important in studying e.g. segmentation, heterogeneity in response and in fine-tuning marketing tactics, it is often unavailable to researchers (Onishi & Manchanda, 2012) due to cost and privacy issues. Moreover, senior managers typically make strategic budget allocation decisions at the aggregate level, where comparable metrics for online and offline marketing are available (e.g. Wiesel et al., 2011).

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national level on a weekly basis in order to be consistent with other measures. We gathered organic Google search data through Google Analytics, an online tool that provides data on search volume for key terms. Search data were provided in a weekly index of total number of searches through Google.com for the retailer, or the retailer's webpage. Organic search data showed a large spike around Christmas — a clear indication we should allow for seasonality, which we do through a seasonal retail mall index and a holiday dummy variable.

For eWOM, we aim to obtain comprehensive coverage of different online platforms, including Twitter, Facebook, blogs, forum messages, etc. The data provider indexes over 200 million social media posts per day, including blog posts,[3] forum messages, Facebook posts, and the entire Twitter fire hose of tweets (http://www.crimsonhexagon.com/new-data-sources-added-to-social-media-library/). This approach fits the paper's purpose of providing a general, non-platform specific assessment of the performance effects of different eWOM content. The content topics from these data are derived from Hopkins and King's (2010) content analysis.[4] From this statistical classification, three conversational themes are consistent with our conceptual distinction on eWOM content. The first conversation bucket is positive about the brand (Brand eWOM). The second bucket concerns sentiment–neutral posts about going to the store or making a purchase (Purchase eWOM). The last conversation bucket is posts about liking the brand's advertisements (Ad eWOM). Importantly, the company did not get any substantial negative mentions about either its brand or its advertising in the analyzed period. We do not claim that these 3 measures are exhaustive or the best among conversation topic metrics (an important area for future research) — our aim is to analyze whether they are useful in predicting brand performance and marketing effectiveness. As a first step, we show that these eWOM metrics have different time series patterns in Fig. 2.

Several observations stand out from Fig. 2. First, Ad eWOM posts are most numerous, followed by Purchase eWOM, and finally, Brand eWOM. These numbers illustrate the potential limitations of focusing only on Brand eWOM. The higher volume of brand neutral versus brand positive comments is typical in eWOM data (Godes & Mayzlin, 2004; Sonnier et al., 2011). Second, all three conversation threads show spikes around major events, such as Black Friday (November 2010). However, the conversation threads do not always follow each other: Ad eWOM shows a much higher peak than the others in February 2011, while Brand eWOM peaks in May 2011 and is trending upwards over the full data period. The correlation between Ad eWOM and Brand eWOM is 0.36 and of each with Purchase eWOM is 0.54, which indicates that multicollinearity is unlikely to pose problems. Moreover, the moderate correlation in these eWOM content metrics is similar to that reported in experimental research on ad liking and brand liking (e.g. 0.49 in Baumgartner, Sujan, & Padgett, 1997).

5. Methodology

Both the dynamic system in our conceptual framework and the aggregate longitudinal time series data suggest persistence modeling (Dekimpe & Hanssens, 1999) is appropriate. Moreover, You et al.'s (2015) and Babic et al.'s (2016) meta-analyses of word-of-mouth effect shows the importance of properly accounting for the lag structure. To this end, our modeling approach consists of three steps. First, we test for endogeneity and the possibility of long-term (permanent) effects of eWOM, paid marketing, offline store traffic and online store traffic. Next, we specify a Vector Autoregressive (VAR) model that is able to account for endogeneity, dynamic responses and interactions among variables (Dekimpe & Hanssens, 1999). Third, we estimate short- and long-run responses of store traffic and online traffic to paid marketing and eWOM in the form of elasticities and decompositions. Table 3 displays these analysis steps.

In the first step, a series of tests allow us to formulate the model specification. First, do we need to model a system of equations (explaining not only the retailer performance variables)? Granger causality tests show the temporal causality within each pair of variables (Granger, 1969).[5] The test results (available upon request) show substantial endogeneity among eWOM content topics (Ad eWOM, Brand eWOM and Purchase eWOM), between marketing and eWOM content (e.g. print and Ad eWOM), between eWOM metrics and store traffic metrics, and between marketing and store traffic metrics (e.g. TV and offline store traffic). Each variable in our framework is Granger caused by at least one other variable in the framework. This indicates the need for a dynamic system model (such as the VAR) to explain each variable by the other variables.

Next, how should each variable be included in the model: in levels or in differences? To address this question, we estimate unit root and cointegration tests. As to the unit root test, we perform both the Augmented Dickey–Fuller (ADF) test and the KPSS test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992). Both tests show that offline Store Traffic, Brand eWOM and Paid Search are evolving (unit root), while the other variables are stationary. Evolving variables need to be differenced to avoid spurious regression

[3] The data provider starts its list with 8 public and 2 private blog directories, including www.globeofblogs.com, http://truthlaidbear.com, www.nycbloggers.com and http://dir.yahoo.com/Computers, a list of blogs provided by blogrolling.com, and 1.3 million additional blogs made available to them by Blogpulse.com. The technology then continuously crawls out from the links or "blogroll" on each of these blogs, adding seeds along the way from Google and other sources, to identify the target population of blogs.

[4] This automated content analysis is publicly available at http://gking.harvard.edu/readme.The technology does not rely on keyword counts, but on statistical classification algorithms that identify patterns of words used in conversations and then recognize information from the conversation that is relevant to the user's chosen topics. The reported accuracy rate on these classifications is 97% with a margin of error of +/− 3%. Thus, the technology's coding matches human coding in more than 90% of cases analyzed. This accuracy rate is confirmed in independent tests by the Pew Research Center, which 'spent more than 12 months testing Crimson Hexagon and its own tests comparing coding by humans and the software came up with similar results' (Pew Research Center, 2013, p.2).

[5] Because we are applying these tests to investigate the need for modeling a full dynamic system, we are not interested in whether variable X causes variable Y at a specific lag, but in whether we can rule out that X Granger causes Y at any lag. Therefore, we run the causality tests for lags up to 13 (i.e., one quarter of 13 weeks) and report the results for the lag that has the highest significance for Granger causality.

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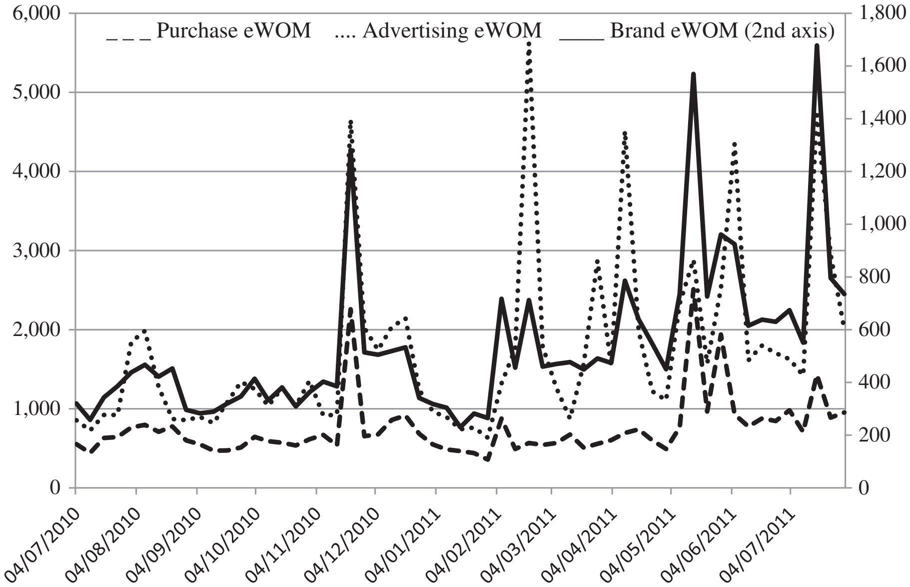

Fig. 2. Electronic word-of-mouth content metrics of purchase, advertising and brand.

issues (Granger & Newbold, 1974), unless they are tied in a long-term equilibrium. We test for such equilibrium with cointegration tests (Johansen, Mosconi, & Nielsen, 2000), but found no evidence for cointegration. Therefore, we include the evolving variables in first differences in the model. This is important for the interpretation of our results: e.g. impulse response functions show the effect of a variable on Offline Store Traffic Growth, and a significant effect on this first-differenced variable thus implies a permanent effect on Offline Store Traffic, the performance variable we are actually interested in (see Trusov et al., 2009).

Comparing eWOM/marketing effects in the presence of both stationary and evolving variables is thus a challenge, which previous papers have dealt with in several ways: (a) omit the evolving variables from the analysis, (b) separately report the non-permanent and the permanent effects for the evolving variables, (c) calculate the net present value of the permanent effects, and (d) accumulate the non-permanent and permanent effects for a given period (such as 13 weeks, i.e. 1 quarter), so that this accumulated effect on an evolving variable is comparable with the accumulated effect on a stationary variable for the same period (Slotegraaf & Pauwels, 2008). Note that options (a) and (b) do not allow an easy direct comparison of the effect magnitude on stationary variables (in our case online store traffic, Ad eWOM and Purchase eWOM) and evolving variables (in our case offline store traffic and Brand eWOM). Meanwhile, calculating the Net Present Value of permanent effects (option c) is desirable when decision makers have an easier time agreeing on the discount rate than on the period under consideration. In our case,

Table 3
Analysis steps.

Methodological step	Relevant literature	Research question
1. Endogeneity and evolution tests		
Granger causality test	Granger (1969)	What is the temporal causality among variables?
Augmented Dickey–Fuller Test	Kwiatkowski et al. (1992)	Are variables stationary or evolving?
KPSS unit root test		Are the unit root results robust to null hypothesis?
Cointegration test	Johansen et al. (2000)	Are evolving variables in long-run equilibrium?
2. Model of dynamic interactions		
Vector autoregressive model VAR in differences Vector error correction model	Dekimpe and Hanssens (1999); Pauwels, Hanssens, and Siddarth (2002)	How do endogenous variables interact in the long run and the short run, accounting for the unit root and cointegration test results?
3. Policy simulation analysis		
Generalized impulse response function	Evans and Wells (1983)	What is the immediate and dynamic effect of an impulse, without imposing a causal ordering?
Short-run (immediate) and long-run (cumulative) elasticities	Pauwels et al. (2002)	By what % does performance change as a result of a 1% change in marketing or in eWOM?
Restricted policy simulation	Pauwels (2004)	How much of the cumulative performance elasticity is direct and how much is indirect?
Forecast error variance decomposition	Srinivasan et al. (2010)	How much of performance variation is explained by past marketing &WOM changes (dynamic R^2)

management believed it was unlikely that the model-calculated permanent effects would really be permanent, given the volatility in the environment. Because management is evaluated on quarterly results, we agreed on option (d) and a period of 13 weeks (i.e. one quarter) to accumulate permanent effects into a long-term elasticity, which can be compared to the long-term elasticities of stationary variables in the same period (Slotegraaf & Pauwels, 2008).

In the second step, the Granger-Causality, evolution and cointegration tests allow us to finalize the model specification in Eq. (1). The vector of endogenous variables includes: Traffic to the retailer's offline stores (T), Online store traffic (O), Google organic search (G), Brand eWOM (B), Purchase eWOM (P), Ad eWOM (A), Television GRPs (TV), print as the number of Circulars distributed (C), Radio GRPs (R), and paid Search impressions (S). Each variable is included in logs to capture diminishing returns. Thus, the estimated effects are directly interpretable as elasticities (Nijs, Dekimpe, Steenkamp, & Hanssens, 2001). The vector of exogenous variables includes for each endogenous variable i) an intercept, ii) a 'seasonal retail index' to control for seasonality (SRTI), and iii) a holiday dummy variable (D) to capture unusually high marketing efforts and traffic around Christmas. Store traffic, Brand WOM conversations, and paid search impressions are first differenced (denoted by d) in order to correct for evolution:

$$\begin{bmatrix} d(T_t) \\ O_t \\ G_t \\ d(B_t) \\ P_t \\ A_t \\ TV_t \\ C_t \\ R_t \\ d(S_t) \end{bmatrix} = \begin{bmatrix} C_{d(T)} \\ C_O \\ C_G \\ C_{d(B)} \\ C_P \\ C_A \\ C_{TV} \\ C_C \\ C_R \\ C_{d(S)} \end{bmatrix} + \begin{bmatrix} \delta_{d(T)} \\ \delta_O \\ \delta_G \\ \delta_{d(B)} \\ \delta_P \\ \delta_A \\ \delta_{TV} \\ \delta_C \\ \delta_R \\ \delta_{d(S)} \end{bmatrix} \times SRTI + D \begin{bmatrix} \theta_{d(T)} \\ \theta_O \\ \theta_G \\ \theta_{d(B)} \\ \theta_P \\ \theta_A \\ \theta_{TV} \\ \theta_C \\ \theta_R \\ \theta_{d(S)} \end{bmatrix} + \sum_{j=1}^{J} \begin{bmatrix} \phi^j_{1\,1} & \cdots & \phi^j_{1\,10} \\ \vdots & \ddots & \vdots \\ \phi^j_{10\,1} & \cdots & \phi^j_{10\,10} \end{bmatrix} \times \begin{bmatrix} d\left(T_{t-j}\right) \\ O_{t-j} \\ G_{t-j} \\ d\left(B_{t-j}\right) \\ P_{t-j} \\ A_{t-j} \\ TV_{t-j} \\ C_{t-j} \\ R_{t-j} \\ d\left(S_{t-j}\right) \end{bmatrix} + \begin{bmatrix} \varepsilon_{d(T),t} \\ \varepsilon_{O,t} \\ \varepsilon_{G,t} \\ \varepsilon_{d(B),t} \\ \varepsilon_{P,t} \\ \varepsilon_{A,t} \\ \varepsilon_{TV,t} \\ \varepsilon_{C,t} \\ \varepsilon_{R,t} \\ \varepsilon_{d(S),t} \end{bmatrix} \tag{1}$$

where t indexes weeks, J equals the number of lags, C, δ, θ, γ and ϕ are the parameters to be estimated and ε_T are white-noise disturbances distributed as $N(0, \sum)$.The full residual variance–covariance matrix Σ contains the short-term (same-week) effect of each endogenous variable on the others, as interpreted in the third step. We assess the number of lags and the in-sample fit with the Akaike Information criterion, which balances model accuracy with parsimony (Akaike, 1974; Burnham & Anderson, 2004). We leave out July 2011 as a hold-out sample to calculate the forecast error and mean absolute percentage error (MAPE).

In the third step, we derive the Generalized Impulse Response Functions (GIRFs) and Forecast Variance Error Decompositions from the VAR estimates. Note from Eq. (1) that the VAR model captures immediate as well as lagged and direct as well as indirect interactions among the endogenous variables. Based on all these estimated reactions, the impulse response function estimates the net result of a shock to one variable (e.g., TV) on the other variables relative to their baselines (i.e., their expected values in the absence of the shock). To tease out which of the variables is responsible for a same-week shock, we estimate GIRFs with the simultaneous-shocking approach by Evans and Wells (1983). This approach derives the vector of expected immediate shocks from the residual variance–covariance matrix in Eq. (1). For instance, the expected immediate shock of Purchase eWOM on online store traffic equals the covariance between Purchase eWOM and online store traffic, divided by the variance of Purchase eWOM (Dekimpe & Hanssens, 1999). Standard errors are also obtained with the Generalized Impulse Response Function approach, as in e.g. Dekimpe and Hanssens (1999) and Nijs et al. (2001). As to statistical significance, short-term and long-term elasticities are obtained by comparing each GIRF estimate with its standard error, and only retaining those with a t-value higher than unity (Pesaran, Pierse, & Lee, 1993; Sims & Zha, 1999). We use this criterion to maintain comparability with past VAR-modeling literature. Finally, we disentangle direct and indirect performance effects with restricted impulse response functions (Pauwels, 2004).

While the GIRFs allow us to calculate the performance effect of a unit change in the log-transformed marketing or eWOM variable, managers also want to know its overall importance in driving performance. Based on the same VAR-estimates, Forecast Variance Error Decomposition (FEVD) measures the relative impact over time of shocks initiated by each of the individual endogenous variables. Akin to a dynamic R^2, it calculates the percentage of variation in performance that can be attributed to present and past changes in each variable of Eq. (1). Recently, Srinivasan et al. (2010) used FEVD to show that specific offline (survey-based) metrics of the purchase funnel are important sales drivers compared to marketing activity.

6. Empirical results

6.1. Model estimation, fit and forecasting accuracy

We estimated the VAR model in Eq. (1) with one lag to balance forecasting accuracy and model parsimony, with the acceptable model fit (Akaike Information Criterion) of 18.87. Note that this lag length is typical in VAR applications in marketing, and allows for complicated wear-in and wear-out patterns that can last for several weeks (Kireyev, Pauwels, & Gupta, 2015; Srinivasan et al., 2015; Wiesel et al., 2011). The observation-to-parameter ratio is 4.1 (53 observations for 13 parameters), which is close to the 4.2 ratio in Srinivasan et al. (2015). The explanatory power (R^2) for each equation's dependent variable is 0.47 (growth in offline store traffic), 0.59 (offline store traffic), 0.82 (organic search), 0.57 (growth in Brand eWOM), 0.71 (Purchase eWOM), 0.68 (Ad eWOM), 0.61 (TV Ads), 0.55 (Print Ads), 0.52 (Radio Ads) and 0.51 (growth in Paid Search). Moreover, the model's forecast error in the estimation sample is 7.00%, with a MAPE of 9.72%. We additionally assess the out-of-sample forecasting ability of the model by holding out July 2011, re-estimating the model and forecasting the 4 weeks in July 2011 with static updating (i.e. based on the predicted, not the realized values from the previous week). In the hold-out sample, the forecast error of the model is 7.57%, and the MAPE is 10.04%.

6.2. From short-term to long-term traffic elasticities of eWOM content and paid marketing

Based on the generalized impulse response function, Table 4 shows the short-term (same-week) impact of each variable on the other variables in the model.

The sign and magnitude of the short-term traffic elasticities are consistent with recent research and meta-analyses. First, all three eWOM metrics significantly drive both offline store traffic (column 2) and online store traffic (column 3). The magnitude of the Brand eWOM elasticities (0.216 and 0.274) is similar to the average eWOM volume elasticity of 0.236 in You et al. (2015) and within the most common 0 to 0.5 range for online review volume and valence elasticities (Floyd et al., 2014). Interestingly, Purchase eWOM elasticities (0.256 and 0.208) are of similar magnitude. In contrast, the Ad eWOM elasticity of offline store traffic is only 0.126, while that of offline store traffic is 0.207. This expected difference may reflect the lower threshold/effort for prospects to move from online exposure (in this case to Ad eWOM) to the online store, instead of visiting the offline store (Pauwels et al., 2011). Likewise, organic search has about double the elasticity on online store traffic (0.517) versus offline store traffic (0.227). These magnitudes are similar to the organic search elasticities reported in Demirci, Pauwels, Srinivsana, and Yildirim (2014). Finally, marketing-performance elasticities are substantially smaller than those for eWOM and for search, consistent with previous literature (Trusov et al., 2009; You et al., 2015). TV and paid search stimulate both offline and online store traffic, while radio and print mostly stimulate offline traffic. Adding dynamic effects to the same-week impact, the elasticities in the longer term of 13 weeks (one quarter) are shown in Table 5 and visualized for the eWOM effects on offline and online store traffic in Fig. 3.

Long-term traffic elasticities show an even greater offline *store traffic* benefit of eWOM conversations over marketing, reflecting the longer carry-over of eWOM (Trusov et al., 2009). These long-term elasticities are higher than the (short-term) valence elasticities of 0.417 for eWOM (You et al., 2015) and of 0.69 for online reviews (Floyd et al., 2014). Consistent with empirical generalizations (Hanssens, 2009; Tellis, 2009), the marketing communication elasticities of offline store traffic are between .088 and .181. Radio obtains the highest elasticity; managers believed this medium has not yet hit diminishing returns due to its low occurrence in the data period (Table 2). The long-term store traffic benefits of eWOM are an order of magnitude higher, from 1.635 for Ad eWOM to 3.549 for Brand eWOM.

In contrast, *online store traffic* does not always benefit more from eWOM than from paid marketing. Its eWOM long-term elasticities are rather small, and identical to the short-term elasticity, as we find no significant carry-over benefits. Paid Search Marketing has a similar (statistically indifferent) long-term elasticity compared to each of the eWOM content variables. Moreover, organic search has by far the largest online store traffic elasticity. The likely explanation is that visiting a physical store requires considerable effort from consumers, and eWOM is particularly powerful in helping them decide that the effort may be worth it. In contrast, the online store is just a click away, and an organic search result or marketing push is all that is needed for many consumers to take a look (Verhoef et al., 2007; Wiesel et al., 2011).

Table 4
Short-term elasticities of the row variable on the column variable (standard errors[a]).

	Offline store traffic	Online store traffic	Organic search	Brand WOM	Ad eWOM	Purchase eWOM
Offline store traffic		0.259 (0.123)	0.343 (0.110)	0.649 (0.155)	0.671 (0.211)	0.844 (0.169)
Online store traffic	0.159 (0.076)		0.479 (0.155)	0.506 (0.155)	0.677 (0.205)	0.420 (0.177)
Organic search	0.227 (0.073)	0.517 (0.110)		0.146 (0.144)	*0.167* (0.195)	*0.160* (0.177)
Brand eWOM	0.216 (0.052)	0.274 (0.084)	0.375 (0.072)		0.846 (0.133)	0.836 (0.161)
Ad eWOM	0.126 (0.040)	0.207 (0.062)	0.241 (0.055)	0.475 (0.075)		0.415 (0.089)
Purchase eWOM	0.256 (0.051)	0.208 (0.006)	0.375 (0.074)	0.762 (0.095)	0.674 (0.145)	
TV	0.008 (0.004)	0.007 (0.004)	*0.005* (0.006)	*0.007* (0.008)	*0.008* (0.011)	0.011 (0.009)
Print	0.007 (0.002)	0.004 (0.004)	0.004 (0.003)	0.006 (0.005)	0.010 (0.007)	*0.003* (0.006)
Radio	0.014 (0.005)	*0.003* (0.008)	*0.005* (0.007)	*0.001* (0.010)	*0.002* (0.014)	0.015 (0.012)
Paid search	0.070 (0.026)	0.082 (0.042)	0.089 (0.038)	0.154 (0.055)	0.201 (0.073)	0.095 (0.063)

[a] The elasticities that do not significantly differ from zero (t-value < 1, Sims and Zha, 1999) are indicated in *italics*.

Table 5
Long-term elasticities of the row variable on the column variable (standard errors[a]).

	Offline store traffic	Online store traffic	Organic search	Brand eWOM	Ad eWOM	Purchase eWOM
Offline store traffic	1.594	0.259	0.343	1.762	0.671	1.062
	(0.152)	(0.123)	(0.110)	(0.422)	(0.211)	(0.399)
Online store traffic	2.138	1.575	1.211	6.572	0.680	0.420
	(0.982)	(0.366)	(0.506)	(2.018)	(0.205)	(0.177)
Organic search	3.057	0.787	2.103	9.686	2.259	1.327
	(0.946)	(0.240)	(0.651)	(1.867)	(1.089)	(0.514)
Brand eWOM	3.428	0.274	0.811	10.956	1.580	1.277
	(0.820)	(0.084)	(0.348)	(1.318)	(0.667)	(0.387)
Ad eWOM	1.635	0.207	0.588	6.181	1.527	0.708
	(0.514)	(0.062)	(0.264)	(0.969)	(0.476)	(0.293)
Purchase eWOM	3.334	0.208	0.698	9.911	1.645	1.675
	(0.667)	(0.088)	(0.289)	(1.241)	(0.887)	(0.525)
TV	0.105	0.018	*0.005*	*0.085*	*0.010*	0.011
	(0.050)	(0.014)	(0.006)	(0.106)	(0.011)	(0.009)
Print	0.088	0.004	0.004	0.149	0.010	*0.003*
	(0.030)	(0.004)	(0.003)	(0.127)	(0.007)	(0.006)
Radio	0.181	*0.003*	*0.005*	*0.205*	*0.002*	0.015
	(0.063)	(0.008)	(0.007)	(0.264)	(0.013)	(0.012)
Paid search	0.108	0.210	0.089	0.237	0.201	0.095
	(0.062)	(0.136)	(0.039)	(0.081)	(0.074)	(0.059)

[a] The elasticities that do not significantly differ from zero (t-value < 1, Sims and Zha, 1999) are indicated in *italics*.

In sum, the impulse response function analysis shows that company performance lifts are higher for eWOM content metrics than for paid marketing, with the one exception that paid search is as effective as eWOM in increasing online traffic. Brand eWOM especially pays off for offline store traffic, with a short-term elasticity 3 times higher, and a long-term elasticity 30 times higher, than the most effective paid marketing effort. Of course, it may be much easier for managers to change paid marketing (e.g., spend 10% more) than to increase eWOM by the same amount. Likewise, some variables show more changes than others, as evident from Table 2. Thus, we next analyze the importance of each variable's variation (all changes over the data period) in driving performance variation with forecast error variance decomposition.

6.3. Relative importance of eWOM and paid marketing as a store traffic driver

Forecast error variance decomposition (FEVD) measures the relative importance of all present and past changes to a variable in driving store traffic. Given our conceptual framework in Fig. 1, we order the variables as paid marketing, eWOM metrics, organic search, online store traffic and offline store traffic growth. We retain the FEVD after 13 weeks (one quarter). Figs. 4 and 5 display the FEVD of Offline Store Traffic Growth and Online Store Traffic, respectively.

Of all variation in offline store traffic growth, 40% is driven by its own past changes; thus establishing the 'baseline' in the absence of other influences. The next big bucket is paid marketing, which drives 35% of offline store traffic growth. The three eWOM content metrics together account for 24% of the variation in offline store traffic growth. Thus, while any given change in eWOM has a high elasticity, the many changes to paid search impressions, print, radio and TV make marketing responsible for a large part of the variation in store traffic. As to specific variables, print drives most offline store traffic growth variation, followed by Brand eWOM. In contrast, online traffic and Google search explain only a small amount of store traffic variation.

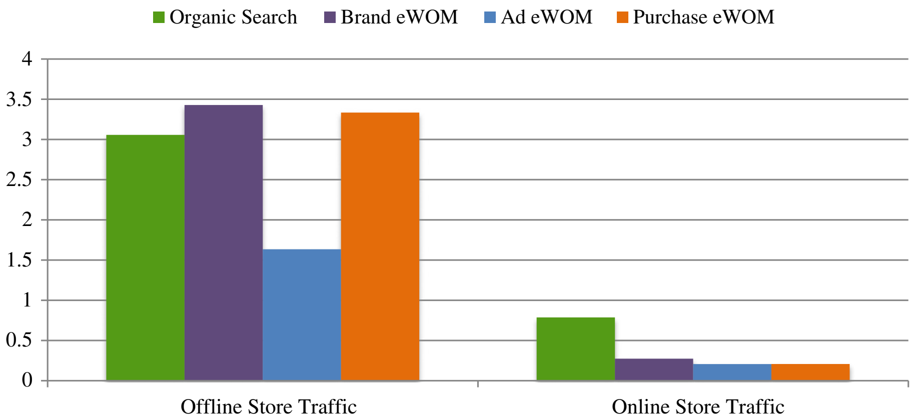

Fig. 3. Long-term elasticity of offline and online store traffic to search and eWOM content.

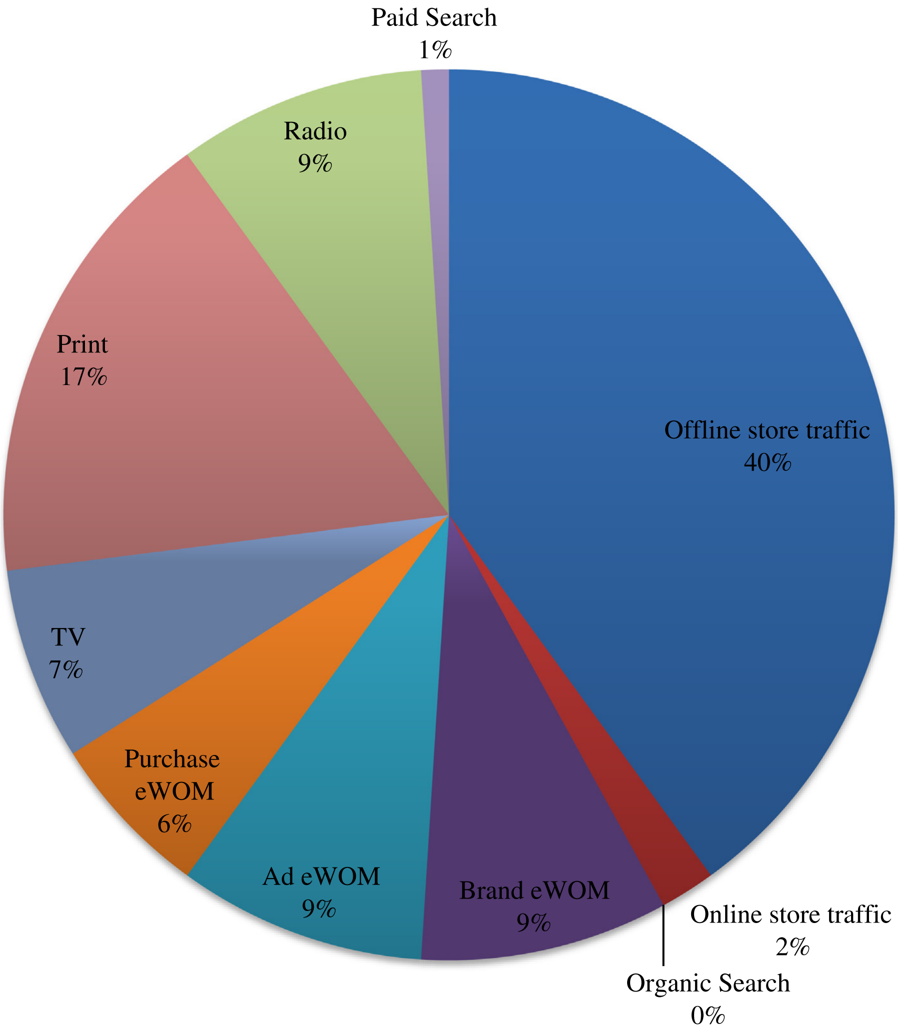

Fig. 4. Forecast error variance decomposition (FEVD) of offline store traffic growth.

Online store traffic variation is mostly driven by own past changes (56% baseline), followed by Google organic search (17%). Across 36 brands, Pauwels and van Ewijk (2013) find that 5% of sales variation is due to Google search — our paper shows the importance of distinguishing the large importance of organic search for online traffic (17%) versus offline traffic (.01%). Contrary to offline store traffic, we find that eWOM drives more online store traffic variation (14%) than paid marketing does (12%). Ad eWOM is the most important eWOM driver of online traffic (remember that the prevalence of Advertising eWOM is 3 times that of Brand eWOM), while TV is the main paid marketing driver.

In sum, the FEVD analysis shows a more nuanced picture of the total influence of WOM and paid marketing: both are important drivers of offline and online store traffic. Consistent with the elasticity results, Brand eWOM is most important among the eWOM conversations, while different marketing actions drive store and online traffic to a different degree. This leaves us with the question: to what extent do different marketing actions affect performance directly, versus working indirectly by stimulating search and eWOM conversations?

6.4. Indirect versus direct performance effects of paid marketing

Beyond marketing's direct effect on traffic, it can also have an indirect effect through eWOM or search. For example, print stimulates Ad eWOM, which in turn lifts store traffic (Table 5). In the long-term elasticity calculation, such indirect effect can be set to 0 by restricting the impulse response function (Pauwels, 2004). Doing so for all indirect effects yields the direct cumulative effect, after which we allow for each significant indirect effect to estimate its impact. Table 6 compares indirect and direct effects for each marketing action on offline store traffic.

For television, the significant indirect effects by stimulating online store traffic (22% of the total effect) and Purchase eWOM (10%) together constitute 32% of the total cumulative effect of 0.105 (Table 5). In contrast, radio only has an indirect effect through

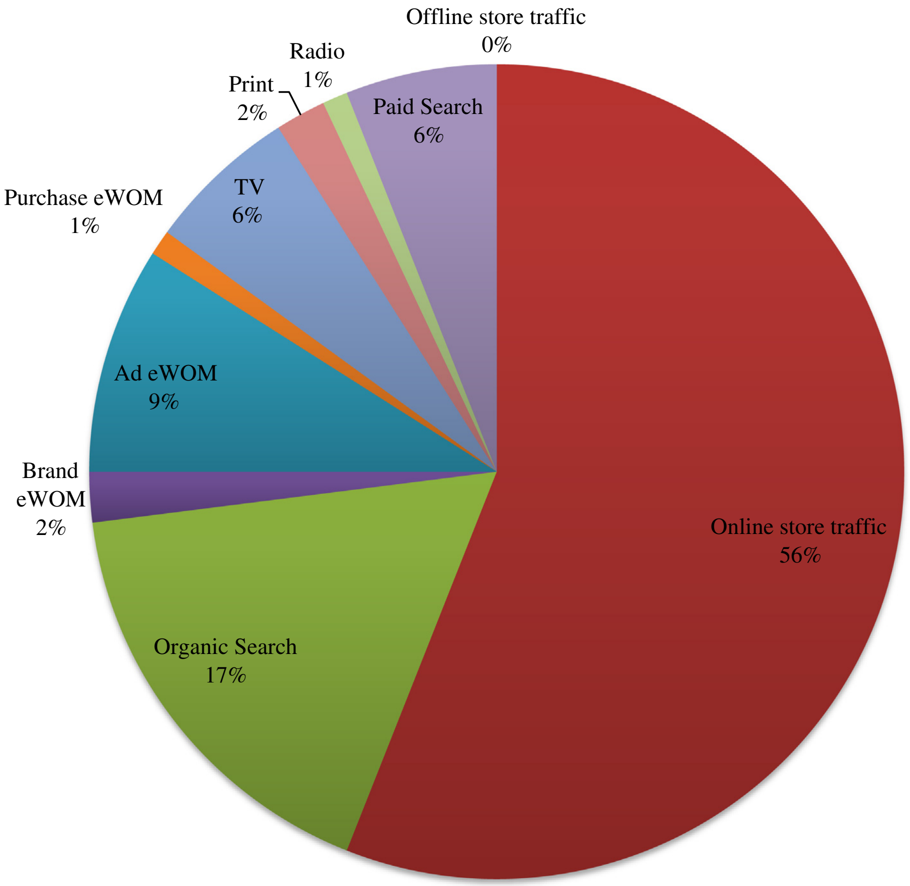

Fig. 5. Forecast error variance decomposition (FEVD) of online store traffic.

Purchase eWOM, which adds 23% to the direct effect. Print works indirectly through online store traffic, Brand eWOM and Ad eWOM, yielding 43% of the total effect. Finally, paid search works through organic search and all eWOM variables. The indirect effects represent 69% of the total effect and thus exceed the direct effect on store traffic.

On average, the indirect offline store traffic effect of paid marketing is 42% of the total. Thus, managers substantially underestimate marketing effectiveness if they consider only the direct effects on offline performance. This result is consistent with our conceptual argument that prospective consumers need a stronger push to visit the physical store (and thus incur a travel cost). Paid marketing actions by themselves are often insufficient; but they can be reinforced through eWOM conversations and organic search in the echoverse of the connected consumer (Hewett, Rand, Rust, & van Heerde, 2015).

As to online store traffic, indirect effects are not significant for three out of four marketing actions (Table 5). For the television impact on online store traffic, the indirect effects are 17% through offline store traffic and 11% through Purchase eWOM; together 28% of the total cumulative elasticity of 0.018. Averaging this 28% with the 0% of the other 3 marketing actions yields only 7% of the total marketing impact created by indirect effects. This is consistent with our conceptual argument that it is relatively straightforward to induce prospective consumers to visit the retailer's online store, which is only a click away. Even for online store traffic though, we observe indirect effects of TV through offline store traffic (likely reflecting multi-channel shopping behavior) and Purchase eWOM, which has the power to drive more traffic to the retailer's website. In contrast to previous studies though, these indirect effects are not stronger than the direct performance effects of TV advertising (Onishi & Manchanda, 2012; Pauwels & van

Table 6
Decomposition of offline store traffic impact in direct and indirect marketing effects.

	Offline store traffic	Online store traffic	Organic search	Brand eWOM	Ad eWOM	Purchase eWOM	Total Effect
TV	68%	22%	0%	0%	0%	10%	0.0105
Print	57%	8%	10%	14%	11%	0%	0.088
Radio	77%	0%	0%	0%	0%	23%	0.181
Paid search	31%	10%	13%	17%	15%	14%	0.108
Average	58%	10%	6%	8%	7%	12%	

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Ewijk, 2013; Srinivasan et al., 2015). Beyond the difference in analyzed categories, the likely reason is that our performance variable, store traffic, is still higher up the purchase funnel than the actual sales studied in these three previous papers.

In sum, managers underestimate marketing effectiveness if they consider only the direct performance effects of their marketing actions. Marketing actions differ in how they induce organic search and specific eWOM conversations, and these indirect effects are important to understand when evaluation total marketing effectiveness.

7. Conclusion

7.1. Summary of the findings and academic insights on the research questions

While the seminal paper by Godes and Mayzlin (2004) already called for online word-of-mouth measures to capture the "potentially valuable content of the conversations", this paper is the first to quantify how brand- versus advertising and purchase related eWOM content are driven by specific marketing and in turn drive performance. Our findings include:

- Ad eWOM only has *half* the long-term elasticity on *offline store traffic* than Brand eWOM and Purchase eWOM have;
- in contrast, Ad eWOM has about the same long-term elasticity on *online store traffic* than Brand and Purchase eWOM have;
- *dual causality* exists among eWOM metrics, and brand eWOM shows hysteresis;
- while *brand*-related content is the main eWOM driver of offline store traffic, *advertising*-related content is the main eWOM driver of online store traffic;
- while *paid marketing* is a more important than eWOM in driving offline store traffic, *eWOM* is more important than paid marketing in driving online store traffic;
- while *TV* is the main paid driver of online store traffic, *print* is the main paid driver of offline store traffic for the studied retailer; and
- over a third of the long-term offline performance effects of *TV and print* materialize indirectly through eWOM and organic search, while *radio* mostly works directly.

As to our first research question, these findings highlight the importance of tracking eWOM content and including separate metrics for Brand, Ad and Purchase eWOM. Thus, we empirically validate the intuition of Sonnier et al. (2011) and Babic et al. (2016) that more research on eWOM content generates important insights. Ad eWOM and Brand eWOM show dual causality,

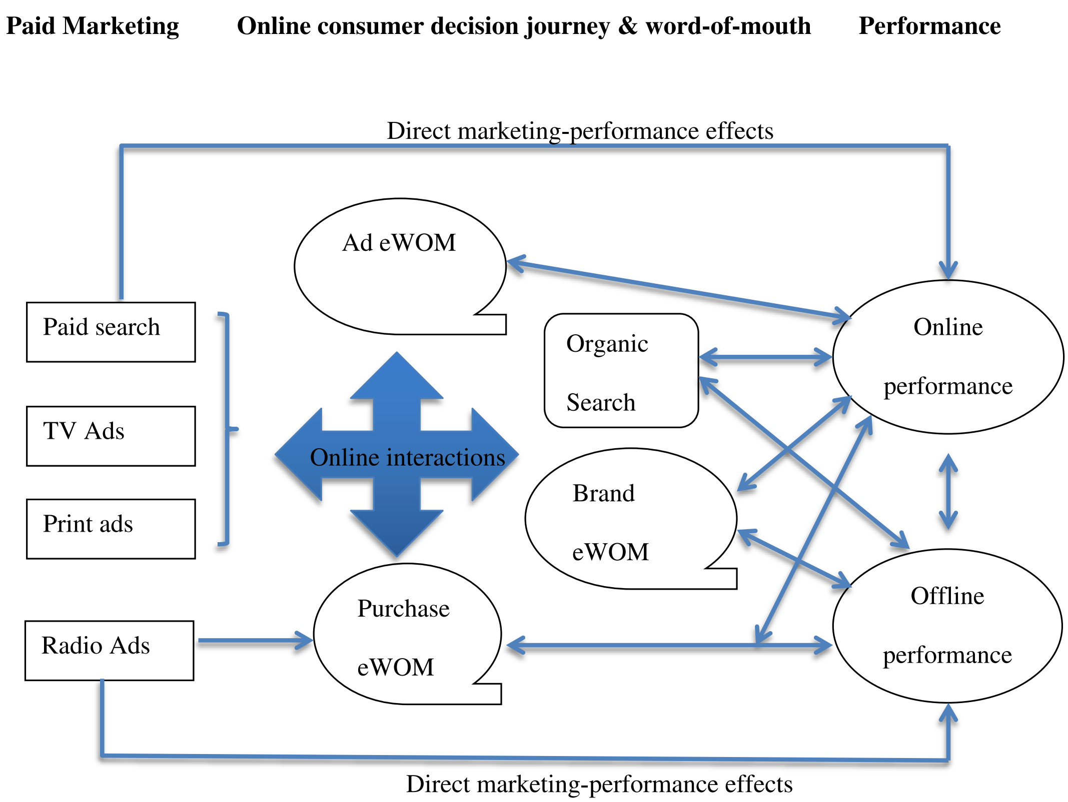

Fig. 6. Towards a model of marketing, eWOM content, and online & offline performance.

just as they do in the offline world (MacKenzie et al., 1986). Moreover, the strong effect of Purchase eWOM demonstrates the 'bandwagon effect' of observational learning, consistent with Baxendale et al. (2015). We call for future research to examine Ad, Brand and Purchase eWOM in other contexts, because Babic et al. (2016) show that eWOM performance effects are lower for social media platforms (as in our data) than for ecommerce sites.

As to our second research question, our findings show that paid marketing derives between 23% (for radio) and 69% (for paid search) of its offline store traffic impact through organic search and eWOM. How large are these indirect effects as compared to previous papers? While substantial, they do not amount to the 90% found for Japanese movies (Onishi & Manchanda, 2012). We do not believe their findings are "an anomaly" (ibid., p. 229) but instead that they are driven by the combination of (a) the product category (movies see even more WOM than retail in Keller, 2007), (b) the culture (WOM is a more important purchase driver in collectivist cultures, e.g. Aaker & Maheswaran, 1997), and (c) the performance variable (store traffic versus actual sales). Future research across categories, cultures, and performance metrics is needed to obtain a more complete understanding of the importance of the direct effect of paid advertising (the "one-step flow" theory) versus the indirect effects through WOM (the "two-step flow" theory). While the relative importance of indirect effects differs across settings, we confirm Onishi and Manchanda's (2012) 'multiplier effect' of paid marketing through eWOM.

Updating our a priori conceptual framework with these findings, we suggest Fig. 6 as a next step towards a model for how the online consumer decision journey and word-of-mouth dynamically relates to paid marketing efforts and company performance. Compared to our a priori framework in Fig. 1, we organized the online journey metrics to show that Ad eWOM mainly drives online performance, while Brand eWOM and Purchase eWOM have the stronger impact on offline performance. Moreover, radio only increases offline performance, both directly and indirectly through Purchase eWOM, while the other three marketing actions also stimulate either organic search or Ad eWOM, which typically represent the upper part of the online consumer decision journey.

Our research gives rise to several questions for future empirical and conceptual development. First, why, how and under which conditions does *online* marketing stimulate eWOM conversations and brand equity? Many researchers and practitioners believe that online marketing converts instead of builds brand equity; i.e. "*You cannot build a brand simply on the Internet. You have to go offline*" (J.G. Sandom, Co-founder and former director of Ogilvy) However, we find that paid search increases traffic in offline stores, not just through search but also through each of our 3 studied eWOM metrics. One reason may be the medium fit among electronic advertising and electronic word-of-mouth (Verhoef et al., 2007). However, our result is also reflected in the high correlation between online advertising and offline WOM across 35 brands in 5 categories (Graham & Havlena, 2007). Is this correlation causal, or due to a third variable? Future research should directly conceptualize and investigate the relationship between online marketing and brand equity. Such relationship would indicate power of online marketing to build brands, or at least to increase the salience of brand associations (Keller, 1993).

Second, the differential and dynamic effects of eWOM content deserve further scrutiny. Under which circumstances would Ad eWOM and Purchase eWOM have *stronger performance effects*, even higher than Brand eWOM? And is it in general the case that *increases to Brand eWOM are permanent* (as shown in the unit root tests), while those to Ad eWOM and Purchase eWOM are temporary? We find this result intuitive, because specific stimuli induce Ad eWOM and Purchase eWOM (respectively advertising and purchase). Therefore, the amount of Ad eWOM should decrease when the stimulus is retracted (consistent with our finding that the Ad eWOM time series is stationary). Purchase eWOM could remain high for frequently purchased products or services, but will strongly vary over the year for more seasonal items. It is key to understand what drives consumers to talk online about their purchases (Amblee & Bui, 2008). In contrast, Brand eWOM can remain high even when consumers are not currently buying or even in the market for a product — think about Apple and BMW, which are highly visible brands (Berger & Schwartz, 2011). Thus, we call for closer attention to eWOM content in the current research stream on the motivations and benefits for consumers to engage in eWOM.

7.2. Managerial implications

For managers, several findings stand out. First, we find that Brand eWOM persists; i.e., it maintains itself at the new level without the need for further stimuli. Thus, setting brand-related eWOM in motion is key — afterwards it can be the gift that keeps on giving. In contrast, Ad WOM and Purchase WOM require further stimuli to sustain a temporary lift. Stimulating specific content of eWOM thus becomes an important managerial objective, and we encourage managers to experiment with new tools and techniques to get consumers to talk about the brand, its communication and their purchases.

Second, the current attention to eWOM and online marketing may give the impression that *offline marketing* no longer has a place in the manager's marketing mix. Our research shows that this is not the case. Offline marketing does not only directly increase performance, but also increases organic search and eWOM, which in turn drive both online and offline store traffic. However, it makes a big difference whether the company cares most about online versus offline performance. For the analyzed retailer, *offline marketing is more important than all online factors combined* (organic search, eWOM and online traffic) in driving offline store traffic. In contrast, offline marketing is less important than online metrics in explaining online store traffic — instead organic and paid searches stand out. Thus, if the main objective is to stimulate online traffic in the short run, managers are expected to focus on online marketing, with its higher performance elasticity. However, such online "funnel vision" appears myopic in the light of the strong impact of offline marketing on offline performance (see also Pauwels & van Ewijk, 2013).

Third, *which paid marketing actions* are best at stimulating eWOM for the studied retailer? Print and paid search stand out in stimulating Brand eWOM and Ad eWOM. Print is popular for loyal retail shoppers due to its high-quality visual information and its permanent and shareable nature (Alreck & Settle, 2002; Pauwels & Neslin, 2015). Meanwhile, online ads and purchases have gained popularity in recent years, especially for retail shoppers that find it inconvenient to visit the offline store (Pauwels et al., 2011). In contrast, the retailer's TV and radio ads do not significantly lift Brand eWOM (in the studied data period). Instead, *TV* stimulates organic search and Purchased WOM, while *radio* has mostly a direct effect on offline traffic and then on Purchased WOM. Thus, when the studied retailer needs an immediate performance boost, radio drives offline store traffic and Purchase eWOM, which in turn quickly translates into traffic. In contrast, when longer-term benefits are important, print stimulates Brand eWOM, which has the highest long-term store traffic elasticity.

7.3. Limitations and avenues for future research

We acknowledge several limitations of our work related to the data and the methodology. First, the data come from one large US retailer, and do not include the retailer sales, margin, competitive information, negative eWOM, offline WOM nor other WOM antecedents, such as product quality, satisfaction, brand loyalty, customer commitment, trust and perceived value (de Matos & Rossi, 2008). This is typical for the recently published studies on eWOM, but observing both the "new" and the "classic" antecedents of WOM is crucial to integrate online and offline WOM research streams. As to methodology, our eWOM content classification derives from the work of Hopkins and King (2010), which is one of many content analysis approaches (e.g. Sonnier et al., 2011; Tirunillai & Tellis, 2012). To further scientific progress in this field, it is paramount to compare these different approaches in a marketing context. Moreover, the classification does not distinguish content or sentiment differences between platforms, such as blogs, tweets, Facebook posts etc. (Smith, Fischer, & Yongjian, 2012). Finally, our VAR model identifies and quantifies the dynamic interactions among paid marketing, eWOM and performance based on past data. Extrapolation and recommendations are subject to the assumption that the basic data-generating process does not change (Franses, 2005).

In sum, our quantitative analysis shows that eWOM conversation topics are relevant for managers aiming to drive business performance and evaluate the indirect effects of paid marketing. As eWOM is engaging larger audiences across countries and age groups (Statistica, 2015), its importance for marketing and business is only expected to grow.

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