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ORIGINAL EMPIRICAL RESEARCH

# Paths to and off purchase: quantifying the impact of traditional marketing and online consumer activity

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**Abstract** This study investigates the effects of consumer activity in online media (paid, owned, and earned) on sales and their interdependencies with the traditional marketing mix elements of price, advertising and distribution. We develop an integrative conceptual framework that links marketing actions to online consumer activity metrics along the consumer's path to purchase (P2P). Our framework proposes that the path to purchase has three basic stages–learning (cognitive), feeling (affective), behavior (conative)—and that these can be measured with novel online consumer activity metrics such as clicking on a paid search ads (cognitive) or Facebook likes and unlikes of the brand (affective). Our empirical analysis of a fast moving consumer good supports a know–feel–do pathway for the low–involvement product studied. We find, for example, that earned media can drive sales. However, we find that the news is not all good as it relates to online consumer activity: higher consumer activity on earned and owned media can lead to consumer disengagement in the form of unlikes. While traditional marketing such as distribution (60%) and price (20%) are the main drivers of sales variation for the studied brand, online owned (10%), (un)earned (3%), and paid (2%) media explain a substantial part of the path to purchase. It is noteworthy that TV advertising (5%) explains significantly less than online media in our case. Overall, our study should help strengthen marketers' case for building share in consumers' hearts and minds, as measured through consumer online activity and engagement.

**Keywords** Paid, owned, and earned media · VAR · FMCG · Path to purchase · Advertising

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## Introduction

The new marketing paradigms of the third millennium have made the notion of a linear consumer purchase process (i.e., funnel) obsolete and replaced it by a system-type network structure (e.g., Achrol and Kotler 2011), often collectively called the path to purchase (P2P). The growing prevalence of different forms of online media offers exciting new opportunities for marketers to interact with consumers along their path to purchase. In 2014, the two leading online media are search and social. The search engine Google alone provides 40,000 searches per second (or 3.5 billion searches per day, Internet Live Stats 2014) and has a market share of about 67% of the US search traffic as of 2014 (Comscore 2014). Recently Nielsen (2012) reported that 27% of US consumers have searched product information based on a TV advertisement and 22% have researched promotions advertised on TV. Ofcom (2013) reported that 16% of UK consumers have searched for product information or even posted to a social network about a television advertisement. Social media giant Facebook alone has 1.3 billion active users, 860 million daily log-ons and generates 4.5 million "likes" daily (Zephoria



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2014). Research shows that 26% of consumers have increased positive attitudes towards ads posted by friends and another 26% find ads targeted using their profile information acceptable (Nielsen 2012). Online media have made it possible to observe and leverage such behavior throughout the consumer's purchase decision journey. Marketers can now communicate with consumers through new channels and create a brand space that consumers can easily access and interact with. It also enables firms to monitor consumers' conversations, brand attitudes, consumer engagement and disengagement in a faster and cost-effective manner than classic surveys (De Matos and Rossi 2008; Pauwels and van Ewijk 2014).

A critical question is how these online media interact with each other and with traditional marketing mix actions such as price, distribution and offline advertising. The marketing literature has started to analyze the effectiveness of consumer activity metrics, but most often in stand-alone fashion without accounting for the effects of traditional media (Li and Kannan 2014; Onishi and Manchanda 2012; Wiesel et al. 2011). Moreover, these studies are typically either in high involvement product categories (e.g., cars, lodging, or furniture) or product categories that allow for online consumption (e.g., music, movies, books, or newspapers). Both of these factors may overstate the role of consumer activity on the path to purchase for more mundane consumer and business products, such as, typically low involvement and non-online consumable, fast moving consumer goods (FMCGs). This is reflected in the often-stated managerial opinion that "nobody looks online for toothpaste or paper clips" (Lecinski 2011, p. 37). If valid, this common wisdom implies that marketing communications for FMCGs do not drive higher online (paid, owned, and earned) consumer activity, which in turn will not drive brand sales. In contrast to survey-based attitude metrics (Srinivasan et al. 2010; Lautman and Pauwels 2009), online consumer activity metrics would therefore not drive (i.e., Granger-cause) brand sales and therefore not qualify as "leading performance indicators" for FMCGs. There is a lack of systematic empirical research on the role that consumer activity metrics play on the path to purchase that either refutes or confirms these managerial expectations for FMCG categories. Accordingly, our research questions are:

(1) Are online consumer activity metrics driven by FMCG marketing actions?
(2) Are FMCG brand sales driven by online consumer activity metrics?
(3) How large are the effects among marketing, online metrics, and FMCG brand sales?

A particular feature of our study is that we consider both the positive and negative sides of online consumer activity. Not only can consumers engage with brands online, e.g., by liking them on Facebook, they can also disengage with brands, e.g., by unliking them. What is currently unknown is whether such "unearned media" (typically by only a few consumers) translate into an overall sales dip and whether they are stimulated by marketing.

Overall, our contribution is threefold. First, we contribute by proposing and testing a conceptual framework of how online consumer activity reflected in online media interacts with the traditional marketing mix actions (price, distribution and advertising) in driving the path-to-purchase and ultimately translates into sales and consumer engagement. We establish this web of causal relations with Granger causality tests. We demonstrate that brand managers of mundane products can benefit from tracking online consumer activity as reflected in paid, owned, and earned media metrics. In so doing, we respond to the calls in previous research to offer new empirical evidence of online media impact in such categories (Onishi and Manchanda 2012).

As our second, empirical, contribution, we quantify the role of online consumer activity measured by paid, owned, earned and unearned media metrics in driving sales within the context of traditional marketing mix variables price, distribution and advertising. We quantify the long-term impact of a change to each marketing mix element. Based on the Vector Autoregressive (VAR) model, we derive Generalized Forecast Error Variance Decompositions (GFEVD) and Generalized Impulse Response Functions (GIRF) to quantify the elasticity and relative influence of consumer activity and traditional marketing mix actions on sales. We show to what extent these different consumer activity metrics contribute to driving sales, as compared to the traditional marketing mix actions of price, distribution and advertising.

Our third contribution is to assess whether, and if so how, tracking online consumer activity through online media metrics improves prediction of brand sales, as Srinivasan et al. (2010) have done for traditional, survey-based mindset metrics. In addition, we add to the understanding on media effects by examining the impact of consumer activity metrics on consumer engagement and disengagement and assess the diagnostic value of these consumer activity metrics. First, we investigate whether these metrics allow managers to better evaluate their marketing efforts on the path to purchase. For example, to what extent do more Facebook likes translate into sales? Second, we consider whether these metrics can be used as early indicators of trouble. For example, do a (few) Facebook unlikes indicate a future sales decline? Beyond establishing online consumer activity metrics as leading sales indicators, our study also shows that even small changes to online engagement metrics can lead to sales declines. As a potential wellspring of strategic intelligence, tracking them could prove instrumental in expanding the role of marketing in corporate decision making in practice.

In sum, online consumer activity tracking through paid, owned, and earned media offers an important complement to previously relied upon survey-based metrics (i.e., mindset metrics) to better understand the consumer decision process and the consumer relationship with the brand (Court et al. 2009). What sets these new activity-based metrics apart is that they are behavior-based—they reflect what consumers actually do. Moreover, they offer potentially lower tracking costs (e.g., surveys are costly) and the opportunity for earlier warnings and more fine-grained data (e.g., surveys are often monthly). Lastly, understanding the consumer's decision journey and the role of the marketing mix are becoming increasingly important. Our paper addresses these needs by providing an overarching framework for the P2P and an integrated model of online media and marketing mix actions in a FMCG setting.

## Related literature

Our research is related to three streams of work: those focusing on offline P2P, offline and online P2P, and offline–online media synergy. The first research stream focuses on tracing the consumer's path to purchase in an offline setting. Srinivasan et al. (2010) analyze the path to purchase by examining the value of including consumer mindset metrics in a sales response model. They find that along the path to purchase survey-based metrics of awareness, consideration, and liking translate into sales performance and help explain sales even in a model that accounts for long-term effects of own and competitive marketing mix actions. Hanssens et al. (2014) informs financially focused executives on how consumer attitudes such as awareness, consideration, and liking influence the consumer's journey along the path to purchase. They quantify the conditions under which the influence is strong or weak, the extent of marketing's role in it, and hence how this knowledge can be used to make sound marketing resource allocation decisions.

A second stream of literature has worked to build better models to understand the cross-channel effects of online and offline marketing on both offline and online sales. Wiesel et al. (2011) investigate how consumers move through the purchase funnel in the B2B domain to find evidence of many cross-channel effects, in particular, offline marketing affects online funnel metrics and online funnel metrics affect offline purchases. Using individual level data on online marketing and purchases through multiple channels for a franchised hospitality firm, Li and Kannan (2014) find significant spillover effects from firm-initiated channels (i.e., display advertising and email) to consumer-initiated channels (i.e., search, website visits, referrals) at both the visit and purchase stages. Their use of individual level data, for a high-involvement service, on consumer touch points enables them to offer compelling insights about these spillover effects. Both Li and Kannan (2014) and Wiesel et al. (2011) consider paid and owned media, but not earned media. These papers that do model the effect of traditional media on online media study high-involvement products and services such as movies, automobiles, fashion, and hoteling services, which lend themselves easily to online debate and/or purchase (Li and Kannan 2014; Onishi and Manchanda 2012) and call for future research beyond their study's context. We respond to these calls with our study on FMCGs which are (still) mostly bought and discussed offline.

The third stream of research has focused on offline–online media synergy. Stephen and Galak (2012) investigate the effect of traditional and online earned media on lending volume on a micro-lending marketplace and find that online earned media affects lending volume. Naik and Peters (2009) investigate how offline (TV, radio, magazines) and online (website, banner ads) advertising drive sales for a car company in Germany. They find synergies within offline and online media as well as cross-media synergies between the offline and online media groupings. Danaher and Dagger (2013) use a single-source, consumer-level database of ten advertising media and retail sales for a large retailer to find that single-medium advertising elasticities were highest for catalogs, followed by direct mail, television, email and search, suggesting that direct-response traditional media are most effective at increasing short-term sales. Finally, several recent papers (e.g., Zigmond and Stipp 2011) have used online search data to show that search engine queries to Google and Yahoo! respond almost immediately to TV advertising but have not examined the impact on the consumers' subsequent P2P. Given the prominence of multiple media including, paid, owned, and earned media in the mix, it is important to marketers to investigate their roles as a part of the complete marketing mix and as proxy metrics for consumer online activity.

## A framework to trace the consumers' path to purchase

Our framework builds upon the idea of a path to purchase sequence (Srinivasan et al. 2010) which holds that consumers proceed through a series of stages on the path to purchase (P2P) beginning with awareness and knowledge-building (cognition or thinking) to liking and preference (affect or feeling) to conviction and purchase (conation or doing). Consumers, of course, do not necessarily follow the above sequence. Multiple pathways can exist for the consumer's path to purchase (Vakratsas and Ambler 1999). In addition, the consumer can choose to exit the path to purchase at any time. Figure 1 links marketing actions to online consumer activity metrics along the consumer's path to purchase (P2P) in terms of consumer engagement and identifies the mechanisms by which online consumer activity metrics affect the consumer purchase decision journey. Specifically, it includes both direct effects of marketing actions on performance and indirect

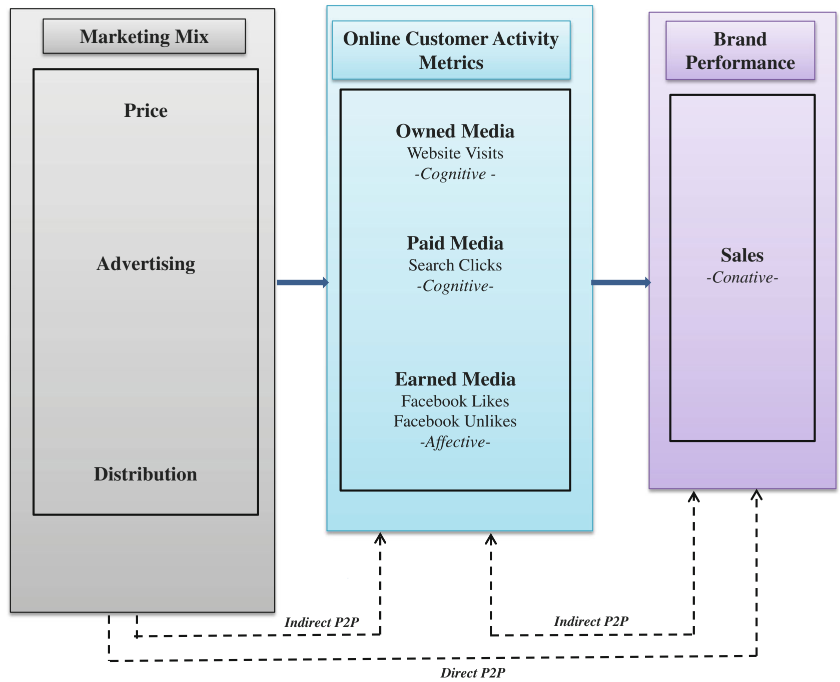


**Fig. 1** Customer's path to and off purchase

effects, where marketing actions influence online consumer activity metrics such as paid search, which in turn move the consumers along the path to purchase.

Our goal is to take advantage of the explicit electronic tracing of paid search clicks, website visits, and Facebook like/unlikes, combined with traditional offline marketing mix data and data for brand sales, to examine, via an econometric model, which pathways are present and determine the magnitude of the effect size associated with each one. Specifically, learning/cognitive components of the attitude towards the brand are measured by paid search clicks and visits to the firm's website. The feeling/affective components of attitude are measured by consumer engagement in the form of both positive and negative sentiments on social media (e.g., Facebook likes and unlikes). The behavioral/conative component is measured by brand sales. The rationale for our classification is the following. The overt actions required by the consumer to search and click-through as well as the overt actions required to browse to a specific website (whether accessed by URL, bookmark, or click-through) reflect awareness and knowledge-building and, accordingly, indicate a cognitive process at work. The likes and unlikes consumers post for brands (or other entities) on Facebook are overt expressions of positive and negative sentiment, representing feelings towards the brand. Lastly, brand sales reflect the aggregate actions of consumers in their purchase conversion.

Kotler and Keller (2012) argue that the path to purchase of learning/knowledge to feelings to action is appropriate when consumers have high involvement with highly differentiated product categories (e.g., automobiles, movies) while the action to feelings to learning path is more probable when consumers have high involvement but with less differentiated product categories (e.g., airline tickets). In addition, they argue the knowledge to action to feelings path to purchase is most likely when consumers have low involvement and there is little differentiation among brands (e.g., batteries, bathroom tissue). A key reason is the low expected benefit and the comparatively high effort needed from consumers to get a "second opinion" about the product. For example, the cost-benefit tradeoff involved in identifying and asking another consumer who cares enough about the product category to have/share her (strong) opinions. However, online media have substantially lowered this threshold as (even the very few) consumers who care, can provide an easily accessible and permanently available record of their likes and dislikes (Godes et al. 2005).

In our set-up, the classic knowledge to feelings to action path holds that paid search clicks and own website visits would lead to likes and unlikes, and in turn, likes and unlikes to brand sales. Similarly, the knowledge to action to feelings sequence holds that paid search clicks and own website visits would lead to brand sales, and in turn, to consumer engagement with the brand through earned media. It is important to note that the possibility of multiple pathways exists for advertising to influence sales and we adopt this perspective. Our goal is to ascertain which pathways are supported by the data and measure the effect sizes associated with each possible pathway. As such, we aim to offer insights for advertising managers and brand managers who want to assess the effects of TV advertising via consumer online activity metrics. Together with the direct sales effect of advertising, this allows an assessment of how effective television advertising is in the entire P2P journey.

In our empirical study, we examine a lower involvement FMCG product category which would presumably draw few, if any, cognitive resources. Thus, the classic knowledge to action to feelings path to purchase seems unlikely at first glance. However, if some consumers seek to learn more about the brand (e.g., prompted by TV, friends, social connections, or other stimuli) a different path from learning to sales or from learning to feelings to sales might coexist. To the extent that online media lower search costs, they also lower the costs for consumers to learn about low-involvement products online. Likewise, while few people are likely to talk about great experiences with a mundane product category, e.g., toothpaste, at a cocktail party or another offline WOM opportunity, they may do so online by simply clicking "like."

Additionally, online consumer activity metrics measured via paid, owned, and earned media can serve as early signals of performance successes and problems for brands (Srinivasan et al. 2010; Ambler 2003). If marketing actions move consumers closer to the buying decision in a series of steps on the path to purchase, then tracking and interpreting these customer activity metrics can provide early evaluation signals. Specific actions that strengthen the competitive position of the brand in consumers' "hearts and minds" may not translate into sales immediately but the online activity metrics can verify that marketing moves consumers in the right direction (Keller and Lehmann 2006). In the case of performance problems, the consumer may not react immediately by switching to another brand, but tracking consumer attitudes may diagnose declining interest and offer a chance for remedial action before sales are affected.

## Modeling approach

In this section, we describe our approach to modeling the effects of online consumer activity metrics and traditional marketing on brand performance. As our conceptual framework shows, we require a methodology that accounts for dual causality and thus for indirect and feedback effects among online consumer activity metrics (paid, owned, and earned), the traditional marketing mix (price, distribution, and TV advertising), and brand performance. For instance, an increase in online consumer activity through paid search clicks may induce web users to visit the brand's website and subsequently purchase the brand, which increases brand revenues and, in turn, leads the firm to increase paid search (a feedback effect). We anticipate a similar pattern of causality for traditional marketing activity and brand sales. It is likely that TV advertising will stimulate consumers to engage in paid search (Nielsen 2012) and website visits leading to another indirect effect on sales. We also include lagged effects of traditional marketing, online consumer activity, and brands sales to account for varying wear-in and wear-out effects likely for communication activity. The Vector Autoregressive (VAR) model is specified as:

$$Y_t = A + \sum_{i-1}^{p} \Phi_i Y_{t-i} + \Psi X_t + \Sigma_t,\ t = 1, 2, \ldots T, \qquad (1)$$

where $Y_t$ is an $(8\times1)$ vector of the endogenous variables consisting of online consumer activity consisting of paid (i.e., paid search clicks), owned (i.e., website visits), and earned media (i.e., Facebook likes and unlikes), traditional marketing mix (i.e., price, distribution, and TV advertising) and brand sales, $A$ is a $(8\times1)$ vector of intercepts, $\Sigma_t \sim N\left(\vec{0}, \Omega\right)$,and $A, \Phi, \Psi, \Omega$ are parameters to be estimated and the optimal lag length $p$ is selected by the Bayesian Information Criterion. VAR models are estimated equation-by-equation: because all right hand side variables are identical across equations, Seemingly Unrelated Regression (SUR) does not improve efficiency (Hanssens et al. 2001).

Next, we compare the predictions of the full VAR model with the two alternative benchmark models. In addition to this "full model," we estimated two benchmark models nested within the full model. The first is the model with only marketing mix where we estimate a 4-equation VAR model obtained by deleting the online consumer activity consisting of paid (i.e., paid search clicks), owned (i.e., website visits), and earned media (i.e., Facebook likes and unlikes) media equations from the full VAR model. The second is the model with only online consumer activity variables where we estimate a 5-equation VAR model obtained by deleting the traditional marketing mix on brand sales (i.e., price, distribution, and television advertising). We compare the performance of these nested models with the full model to assess the improved explanatory power of the different models.

The links represented in the conceptual framework can be tested by investigating which variables Granger-cause other variables (e.g., Hanssens et al. 2001). In essence, Granger causality implies that knowing the history of a variable X helps explain a variable Y, beyond Y's own history. This temporal causality is the closest proxy for causality that can be gained from studying the time series of variables (i.e., in the absence of manipulating causality in controlled experiments). We perform a series of Granger-causality tests on each pair of key variables. If indeed brand sales Granger-cause (some of) the consumer activity metrics and traditional marketing variables, we need to capture the complex interactions of Fig. 1 in a full dynamic system. Next, we test for potential permanent effects of online consumer activity metrics and traditional marketing on brand sales.[1] In the case of permanent effects,

[1] We use both the Augmented Dickey-Fuller test, which maintains evolution as the null hypothesis and the KPSS test which maintains stationarity as the null hypothesis (e.g., Pauwels and Weiss 2008).

the time series for brand sales would be classified as evolving. The opposite classification, that of stationary, implies that sales has a fixed mean and that changes (including those caused by marketing actions) do not have a permanent impact (e.g., Dekimpe and Hanssens 1995).

In addition, based on the VAR parameters, we also estimate the short-term and long-term responses of sales to online consumer activity metrics and traditional marketing actions and compute the corresponding elasticities. The impulse response function estimates the net result of a shock to one variable on the time path of another other variable relative to its baseline. Specifically, we estimate Generalized IRFs (GIRF) with the simultaneous-shocking approach (Evans and Wells 1983; Dekimpe and Hanssens 1999). This approach does not require researchers to specify a causal ordering among variables to obtain their immediate (same-period) interactions. Instead, the GIRF estimates, given a one-unit shock to variable $i$, the expected value for shocks occurring simultaneously to the other variables $j$ ($i \neq j$) is shown in Eq. (2)

$$\mathrm{E}\left[u_j \mid u_i = 1\right] = \sigma_{ij}/\sigma_{ii}; \text{with } \sigma_{\mathrm{ij}}, \sigma_{\mathrm{ii}} \text{ elements of } \Sigma \qquad (2)$$

(from Eq. 1).

Thus, we obtain the immediate (same-period) effect of, e.g., TV advertising on brand sales as the expected value of the contemporaneous sales change for a one-unit change to TV advertising. Summing up all significant impulse response coefficients,[2] we obtain the long-term unit effects of one endogenous variable (the impulse variable) on another (the response variable). When the response variable is evolving, we derive the long-term unit effect on the level (versus the change) in the variable by calculating accumulated impulse response functions and their standard errors. Finally, we apply the procedure in Trusov et al. (2009) to derive long-term elasticities from the unit effects.

In addition, based on the VAR parameters, we derive GFEVD estimates to investigate whether, and to what extent, consumer activity metrics explain brand sales performance beyond the impact of marketing mix actions (Pesaran and Shin 1998). GFEVD estimates are derived using the following equation:

$$\theta^g_{ij}(n) = \frac{\sum_{l=0}^{n}\left(\psi^g_{ij}(l)\right)^2}{\sum_{l=0}^{n}\sum_{j=0}^{m}\left(\psi^g_{ij}(l)\right)^2}, i, j = 1, \ldots m. \qquad (3)$$

where $\psi^g_{ij}(l)$ is the value of a Generalized Impulse Response Function (GIRF) following a one-unit shock to variable $i$ on variable $j$ at time $l$. GFEVD quantifies the dynamic explanatory value on sales of each endogenous variable akin to a "dynamic $R^2$." More specific, GFEVD provides a measure of the relative impact over time of shocks initiated by each of the individual endogenous variables in a VAR model, without the need for the researcher to specify a causal ordering among these variables. Importantly, the GFEVD attributes 100% of the forecast error variance in sales to either (1) the past values of the other endogenous variables or (2) the past of sales itself, also known as "purchase inertia." The former (e.g., a past change in earned media drives current sales) is more managerially and conceptually interesting than the latter (i.e., a past change in sales drives current sales). Therefore, we assess the dynamic explanatory value of the online consumer activity metrics by the extent to which they increase the sales forecast error variance explained by the potential drivers of sales (i.e., other endogenous variables) in the model, and thus reduce the percentage explained by past sales. The relative importance of the drivers is established based on the GFEVD values at 6 months, which reduces sensitivity to short-term fluctuations. [3]

## Data

We obtained data from a large consumer packaged goods manufacturer in the US marketing a leading brand of a low-involvement, paper-based product with over 99% category penetration.[4] The transactions data are obtained from A.C. Nielsen for the entire US. The online consumer activity metrics in terms of paid, owned, and earned media data are obtained from MindShare, also for the entire US, for the period of January 2010 to October 2010 (40 weeks). As the focal brand performance measure, we use sales volume aggregated across all SKUs of the brand, on average 408 K units of the product are sold per week. For the marketing mix, our data include weekly average price paid, weekly value-weighted distribution coverage, and weekly offline advertising media in Gross Rating Points (GRPs). The average weekly price was $7.15 per unit. For distribution coverage, a value-weighted overall distribution presence is calculated at the brand level in the form of a percentage. Stores are weighted for their sales in the product category, and each UPC is weighted for its contribution to sales. TV advertising data are provided by an advertising audit service on a national level. On average, the firm has 78 GRPs in TV advertising per week.

[2] We use the one standard error criterion to judge the statistical significance of each impulse response coefficient (Pesaran and Shin 1998). Standard errors are calculated using a Monte Carlo simulation approach with 1,000 runs in each case (see Horváth 2003).

[3] To evaluate the accuracy of our GFEVD estimates, we obtain standard errors using Monte Carlo simulations (see Benkwitz et al. 2001).

[4] Our non-disclosure agreement with the data provider does not allow us to specifically name the product category and brand.

**Table 1** Descriptive statistics of sales, marketing mix, and online consumer activity variables

| | Weekly metric | Mean | Maximum | Minimum | Std. dev. |
|---|---|---|---|---|---|
| Brand sales | Units | 408,502 | 727,792 | 280,128 | 89,152 |
| Price | $ | 7.15 | 7.70 | 6.12 | 0.40 |
| Distribution | VWODP[1] | 93.34 | 96.00 | 91.00 | 1.06 |
| TV advertising | GRP[2] | 78 | 366 | 0 | 111 |
| Paid search clicks | # Clicks | 8,194 | 23,168 | 2,656 | 3,892 |
| Website visits | # Visit | 60,064 | 436,399 | 9,376 | 74,099 |
| Facebook likes | #Likes | 36,003 | 71,766 | 7,670 | 10,414 |
| Facebook unlikes | #Unlikes | 43 | 95 | 4 | 16 |

[1] Distribution is measured by using a value-weighted overall distribution presence. It is calculated at the brand level in the form of a percentage. Stores are weighted for their sales in the product category, and each UPC is weighted for its contribution to sales

[2] GRP stands for Gross Rating Points

After discussion with the data provider, we capture the different types of online consumer activity (paid, owned, and earned) as follows: *Paid media* was measured by paid search click-throughs (on average, 8 K clicks per week), *Owned media* by the number of weekly website visits by consumers (on average, 60 K visits per week), and *Earned media* as Facebook likes (on average, 36 K per week) and unlikes (on average, 43 per week). During the observation period, the manufacturer initiated a major nationally televised engagement campaign, inviting consumers to upload videos, share (and engage with) consumer-generated content, and engage in conversations about this brand and the category overall on company websites, Facebook, and other social media websites. This campaign created a mechanism and platform for consumers to engage with the brand on multiple online forums (e.g., website, paid search, Facebook).

Our data set, with coverage of the entire US, with comprehensive measures for the marketing mix, and paid, owned, and earned consumer online activity metrics, is uniquely suited to address our research questions on the impact of online consumer activity on brand performance. Table 1 provides descriptive statistics on our data. We observe sufficient variation in each of the paid, earned and owned activity metrics over time to relate it to both marketing actions and to brand sales.

## Empirical findings

We start by discussing the results of the unit root, cointegration, and Granger Causality tests. Next, we compare the performance of the full model with that of the marketing mix only model (no online consumer activity metrics) and the online consumer activity variables only model (no marketing mix) and discuss the relative importance of marketing mix and online consumer activity in explaining volume over time leveraging the GFEVD estimates. Finally, we discuss the long-term elasticities and unit effects, based on the GIRF results.

Both unit root tests detect evolution in volume, price and distribution. Inspection of the time series reveals "trend turnarounds" (Pauwels and Hanssens 2007), with volume and distribution declining and then rebounding and prices depicting the opposite pattern. This provides an important context against which online consumer activity measured through paid, owned, and earned media may help to turn around the volume decline. Beyond these stochastic trends, we detected no significant deterministic trend nor seasonality, as the product is used year-around in steady consumption amounts. Cointegration was not detected among the evolving variables, so we first difference the evolving variables (hereafter "volume change" etc.).

Considering the results for each row (i.e., the variable that is Granger caused) in Table 2, we first observe that volume change is Granger Caused by each variable at the 5% significance level. Moreover, distribution change is Granger Caused by volume change, price change and by online consumer activity in terms of paid search clicks. Paid search clicks in turn are driven by TV advertising, by website visits and by (Facebook) likes. Website visits are driven by paid search clicks and by likes, while likes are driven by clicks, website visits and unlikes (−). Finally, unlikes are Granger Caused by likes[5] and by website visits. Thus, we observe dual causality among cognitive and affective metrics in the online space, consistent with the literature in the offline space (e.g., Vakratsas and Ambler 1999). This dual causality also highlights the need for modeling these variables in a dynamic system.

We estimate three VAR-models explaining volume change with (1) *all* variables (full model with both marketing mix and online consumer activity metrics), (2) *offline* marketing mix

[5] Because only consumers that like a brand, can unlike it later, this causal relation is similar to that of marriage Granger causing divorce.

**Table 2** Granger causality tests: lowest p-value for the null hypothesis of no Granger causality

| Column variable is causing row variable | Sales | Marketing mix | | | Online consumer activity | | | |
|---|---|---|---|---|---|---|---|---|
| | Volume change | Price change | Distribution change | TV advertising | Paid search clicks | Website visits | New likes | New unlikes |
| Volume change | | **0.00** | **0.00** | **0.02** | **0.00** | **0.03** | **0.05** | **0.02** |
| Price change | 0.17 | | 0.37 | 0.55 | 0.54 | 0.45 | 0.86 | 0.54 |
| Distribution change | **0.02** | **0.04** | | 0.11 | **0.00** | 0.22 | 0.13 | 0.29 |
| TV advertising | 0.18 | 0.92 | 0.33 | | 0.10 | 0.32 | 0.17 | 0.14 |
| Paid search clicks | 0.40 | 0.50 | 0.13 | **0.05** | | **0.00** | **0.03** | 0.40 |
| Website visits | 0.10 | 0.14 | 0.66 | 0.89 | **0.05** | | **0.04** | 0.26 |
| New likes | 0.21 | 0.42 | 0.18 | 0.12 | **0.00** | **0.00** | | 0.09 |
| New unlikes | 0.10 | 0.19 | 0.28 | 0.17 | 0.11 | **0.04** | **0.01** | |

P-values 0.05 and below appear in bold face

variables only (and no online consumer activity metrics, offline-only model) and (3) *online* consumer activity metrics only (and no marketing mix, online-only model). The observation-to-parameter ratio of these models is 4.2 for the full model,[6] 7.6 for the offline-only model and 6.3 for the online-only model. Figure 2 shows the $R^2$ and adjusted $R^2$ for each model in explaining volume change.

As expected, the online-only model does a poor job of explaining volume changes for this FMCG ($R^2$ of 9% and adjusted $R^2$ of 7%). However, adding the online activity metrics to the offline-only model substantially increases the explanatory power from 27% ($R^2$ of offline-only model) to 33% ($R^2$ of full model), and the adjusted $R^2$ from 25 to 30%.

Next, we consider the "dynamic $R^2$," i.e., the GFEVD of volume change in each model. In their assessment of the importance of offline funnel metrics, Srinivasan et al. (2010) compare the percentage of volume variance that is explained by the past of volume (sales inertia) versus by the past of other variables. For our models, sales inertia decreases as we move from the online-only model (no marketing mix, 86%) to offline-only model (no online consumer activity metrics, 51%) to the full model (marketing mix and online consumer activity metrics, 42%). The GFEVD of the full model also allows us to directly compare the relative influence of marketing mix and consumer activity variables in explaining volume change over time. Figure 3 shows the part that each variable plays among the sales volume drivers (excluding sales inertia).

As expected for a FMCG, distribution is the major driver of sales, explaining 60% of the volume change variance (note that the analyzed major brand is an interesting case in which distribution does vary in the data period). Price comes next with 20%. Thus, 80% of volume change variance is accounted for by distribution and price, consistent with the low-involvement nature of the product category. The surprise is in the remaining 20%: TV accounts for only 5% while the online consumer activity variables account for 15% of volume change variance. Many FMCG companies continue spending the majority of their communication budgets on TV advertising to brand and differentiate their, often low-involvement and mundane, products. Our results point to potential to redistribute spending towards online media even for these products, which might be more cost-effective as compared to national TV advertising. For the analyzed brand with respect to these online activity variables, owned media (website visits) is key at 10%, while earned media (2%), paid media (2%) and unearned media (1%) are less important. The effect of website visits on purchases is twice that of paid and earned media combined, suggesting that website visits can be critical even for low-involvement products in driving purchases. Our analysis thus finds market-level empirical evidence against the often-stated managerial opinion that "nobody looks online for toothpaste or paper clips" (Lecinski 2011, p. 37).

Summing up, even for this mundane FMCG, using online consumer activity metrics on the path to purchase sheds light on previously unexplained variation in sales – both in terms of (adjusted) $R^2$ and in terms of dynamic explanatory power (GFEVD). To the best of our knowledge, our analysis is the first to show this sales-explanatory power of online consumer activities on the path to purchase journey. Interestingly, our analysis indicates a similar "dynamic $R^2$" performance for online consumer activity metrics (15%) as Srinivasan et al. (2010) found for mindset metrics variables (16%). Moreover, we also find a dominance of cognitive (learning) consumer online metrics: 12% for paid search clicks and website visits

[6] Each equation requires estimation of 9 parameters (the intercept and 1 lag of each endogenous variable). While we have 40 observations, we need to use 1 to take first differences and 1 to include lags, leaving 38 observations for parameter estimation.

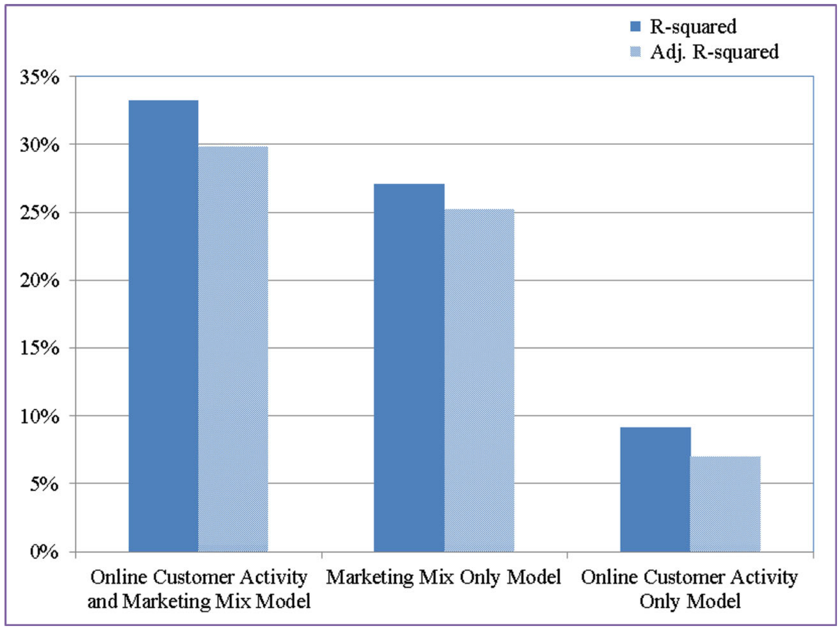


**Fig. 2** Explanatory power ($R^2$ and adjusted $R^2$) across models

versus 12% for advertising awareness and brand consideration in Srinivasan et al. (2010). Affective online consumer metrics, in contrast, explain only 3% (earned media Facebook likes and unlikes) in our study, similar to the 4.5% effect of brand liking in Srinivasan et al.'s (2010) study.

Based on the generalized impulse response functions, the long-term elasticities of the Granger-causing variables are displayed in Table 3, and the long-term unit effects in Fig. 4.

In Table 3 (in the first row with estimates), the traditional marketing mix shows sales elasticities of −3.53 for price, 2.73 for distribution and 0.03 for TV advertising, each in line with empirical generalizations (e.g., Hanssens 2009; Tellis 2004). As to the new contribution of our study, the clicks elasticity of TV advertising is 0.10 (see Table 3), indicating that doubling TV spending increases online consumer activity in the form paid search clicks by 10% for the analyzed brand. Such an impact of offline marketing on online marketing has also been confirmed by related research (e.g., Li and Kannan 2014; Wiesel et al. 2011). These paid search clicks translate into boosting the other two online consumer activity metrics as well: site visits increase with an elasticity of 0.72, and paid search clicks and consumer site visits in turn have a high elasticity impact on engagement in the form of likes (2.42 and 2.72 respectively). The reverse causality elasticities are smaller, respectively 0.09, 0.05 and 0.25. Increased online consumer activity is not all good news though: likes and web site visits increase unlikes (elasticities of 0.18 and 0.38), indicating that at least some people may be turned off by the brand's campaign. Such differential social media reactions have been recently documented with Twitter data: positive and negative tweets are strongly correlated in time (Pauwels and van Ewijk 2014). We find new evidence that (1) such disengagement significantly reduces company-wide sales and (2) that higher consumer activity on paid and owned media also leads to consumer disengagement in the form of unlikes.

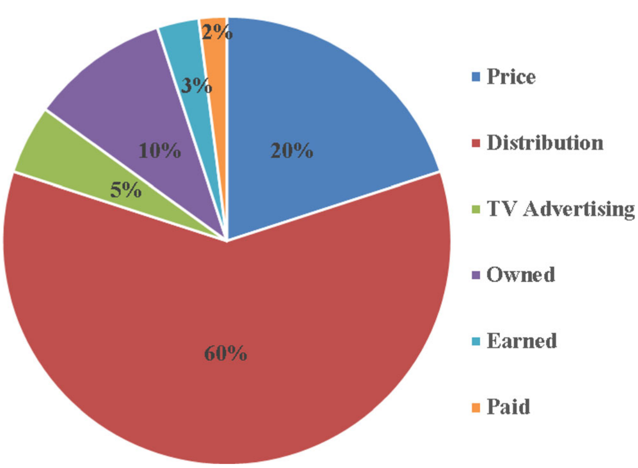


**Fig. 3** Variance decomposition of volume change, excluding sales inertia

How do the online consumer activity metrics translate into sales volume changes? In terms of these online activity metrics, paid search clicks have the highest elasticity (0.81), followed by likes (0.16), site visits (0.13) and unlikes (−0.01). These elasticities reflect the increase in sales as the number of clicks, the number of likes of the brand, the number of site visits and the number of unlikes increase, respectively. As such, the estimates reflect the elasticity of sales to these online consumer activity metrics. The low elasticity of site visits is almost certainly linked to the nature of the analyzed product: the brand does not sell online, so consumers have to

**Table 3** Long-term elasticities based on generalized impulse response functions (effects of only 'Granger-causing' column variables reported; standard errors in parentheses)

| Effect of column variable to row variable | Sales | Marketing mix | | | Online consumer activity | | | |
|---|---|---|---|---|---|---|---|---|
| | | Price | Distribution | TV advertising | Paid clicks | Website visits | New likes | New unlikes |
| Sales | | **−3.530** (1.598) | **2.727** (.820) | **0.032** (.014) | **0.813** (.255) | **0.126** (.053) | **0.157** (0.064) | **−0.007** (.003) |
| Distribution | **0.040** (.014) | **0.068** (.031) | – | – | **0.006** (.002) | – | – | – |
| Paid clicks | – | – | – | **0.096** (.039) | – | **0.088** (.046) | **0.050** (.021) | – |
| Website visits | – | – | – | – | **0.718** (.311) | | **0.248** (.038) | – |
| New likes | – | – | – | – | **2.419** (1.177) | **2.716** (.241) | – | – |
| New unlikes | – | – | – | – | | **0.375** (.058) | **0.178** (.040) | – |

1. Each row represents the elasticity of the row variable with regards to the column variables, i.e., the elasticity of sales with regards to price is −3.53 (row Sales, column Price)

2. Bold estimates are significantly different from zero

3. Price and TV advertising do not appear in the rows since they are not Granger caused by another variable

4. "—"denotes that the corresponding column variable does not Granger-cause the row variable in that cell

remember to buy it in a physical store. Interestingly, the online consumer activity metric of paid search clicks is a leading indicator of distribution in addition to sales feedback and price (higher prices typically also mean higher retailer margins). The size of the elasticity is not large (0.006): doubling paid search clicks is needed to increase distribution by 0.6 points. This improvement appears plausible because paid search clicks range from the mid 2000s to the mid 20,000 s and distribution ranges from 91 to 96 ACV (Table 2). Thus, retailer distribution decisions appear to be based on brand popularity metrics reflected by consumer activity on the path to purchase. As retailers were not willing to answer our questions on this subject, we do not know whether and how well such online consumer activity metrics are tracked by retailers, or whether changes to paid search clicks are indicative of a broader change in popularity, on which retailers act by improving product availability and distribution.

Figure 4 displays the long-term unit effects, i.e., the impact of a 1-unit change in a variable. This is especially critical for our understanding given the low base of several online consumer activity variables (Table 1) and tracking the unit effect of marketing spending is of key managerial relevance. Increasing TV by 1 GRP yields 137 more sales units directly, but also increases paid search clicks by 9 units, each of which in turn yields 40 more sales units. Moreover, each paid search click yields 5 more site visits in the long run, and half a like.

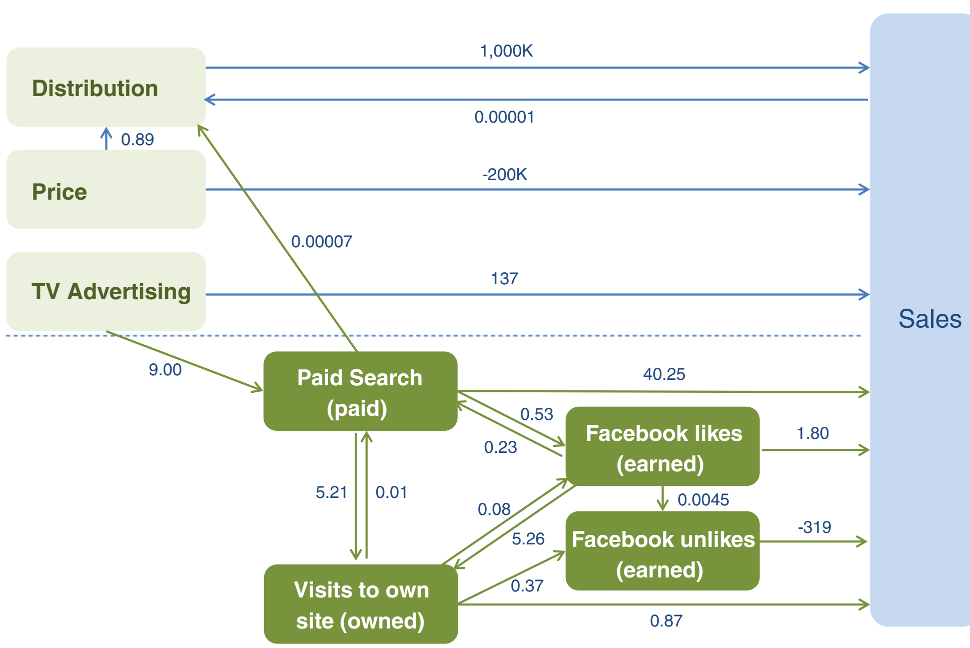


**Fig. 4** Long-term unit effects based on generalized impulse response functions

Especially strong in magnitude are the impact of a like on site visits (5.26) and of an unlike on sales (−319). The latter is unlikely to come from reduced purchases only of the person who unliked the brand. Instead, we believe an unlike is part of a larger problem of negative word-of-mouth for the brand. Thus, "unearned" media, similar to earned media, appears to serve as a useful proxy for general word-of-mouth behavior, which has proven difficult and/or expensive to track in its entirety. Overall, by investigating the effects of online consumer activity metrics on consumer (dis)engagement in the form of (un)likes, we shed new light on consumer's path to purchase and off purchase journey.

Our results thus indicate that online consumer activity metrics interact with each other, are affected by traditional communication activities, and convert into sales. We find a predominant flow of TV advertising influencing the cognitive metrics (e.g., clicking on a paid search to find out more), then the affective metrics (e.g., liking the brand on Facebook) and finally conative (increase brand purchase). Displaying the generalized impulse response functions for the unit effect, Fig. 5 a-c shows how this chain of events plays out over time for TV advertising leading to paid search clicks, which in turn lead to new likes, which in turn lead to volume increase.

When the brand increases TV advertising by 1 GRP, paid search clicks increase by 6 clicks in the same week and 3 in the next week (further increases are not statistically significant from zero). We expect this effect of TV ads on online search to be driven by media multitasking, an activity in which consumers divide attention between the television set and a secondary screen, the computer. Anderson and Renault (2006) formally modeled this behavior and found that the rational consumer's willingness to incur a search (paid search in our context) increases when the firm provides partial information about product attributes and price (through TV advertising in our context). In turn, every click increases new likes by 0.25 in the same week and 0.28 in the next week. Finally, each like results in a 1.8 increase in volume in the third week. While the accumulated impulse response function (translating volume change effects into volume effects) indicates that volume stays above its previous baseline, this permanent effect is not significantly different from zero. Both the magnitude and the timing of effects are of interest to the brand manager who can use our results to project the likely effect of increased TV spending. Moreover, the importance of indirect marketing effects through online consumer activity on the P2P highlights the importance of tracking these metrics. A new TV campaign that fails to increase consumer activity on the P2P within the short time period suggested in Fig. 5 is unlikely to move volume beyond the—relatively small—direct effect of TV advertising.

To gauge the practical implications of our results, we conduct counterfactual scenario analyses using the estimated effects. For example, what would the net sales impact be if managers were to increase price while ramping up paid online media or if an unearned media shock hit while managers also increase TV advertising? To answer these questions, we use the long-term unit effects in Fig. 4 to compute the net sales effect, accounting for both direct and indirect effects of such managerial actions.

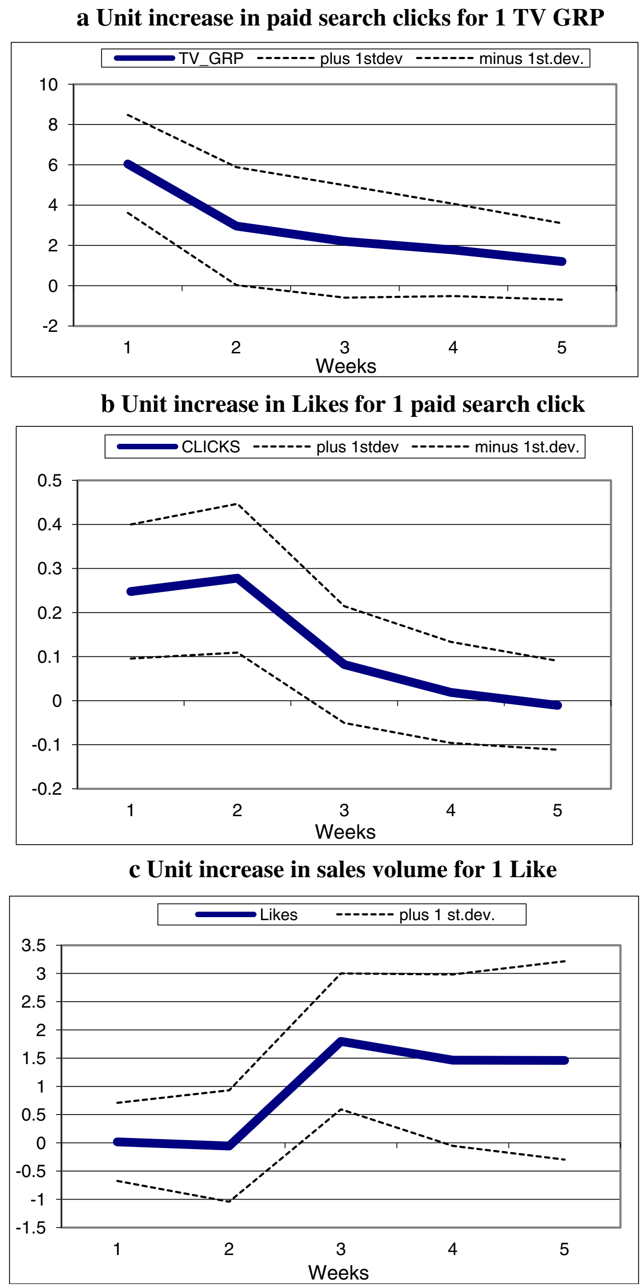


**Fig. 5** **a** Unit increase in paid search clicks for 1 TV GRP **b** Unit increase in likes for 1 paid search click **c** Unit increase in sales volume for 1 like

First, an increase in price of 10% results in a weekly sales decrease of 136,600 units, after accounting for both the direct effect of price on sales and its indirect effect on sales through distribution (see Fig. 4). A simultaneous ramping up of paid search by 10% results in a sales increase of 38,050. Overall, the net sales decreases by 98,550 units due to a combined 10% price increase shock and a paid search shock of 10%. In order to fully offset the sales impact from a 10% price increase, the paid search shock would need to be 36%. Second, we compare the scenario where an unearned customer activity shock of 10% hits while managers also increase TV advertising by 10%. The net effect on weekly sales is an additional 2,520 units using long-term effects in Fig. 4. As it turns out, unlikes can increase by as much as 28% with a 10% positive shock to TV advertising before there is a negative net long-run sales impact. In sum, managers for the analyzed brand can offset the sales harm of a price increase and of more Facebook unlikes by ramping up TV spending and/or inducing more paid search.

Finally, what is the equivalence of TV advertising, owned media (website visits) and earned media (Facebook likes)? We first assess the scenario where a manager increases TV advertising by 10% with a simultaneous earned customer activity shock of 50 new Facebook likes. Using the long-term unit effects in Fig. 4, the combined effect of these two shocks on weekly sales is 1,800 units, after accounting for both direct and indirect effects. Interestingly, this increase can be achieved with the same TV advertising increase of 10% and with a simultaneous owned customer activity shock of only 17.4 additional website visits. In other words, each website visit is equivalent to approximately 3 likes on Facebook in terms of long-term sales impact. Such scenario analyses allow managers to examine the relative interplay between offline marketing and customer activity metrics in driving sales performance.

In sum, our results show that online consumer activity metrics (1) Granger Cause brand sales volume, and are Granger Caused by TV advertising, (2) add to the modeler's power to explain brand sales volume over and above the traditional marketing mix in terms of both adjusted $R^2$ and GFEVD, (3) are important drivers on the path to purchase (P2P) and to off purchase, and (4) have significant and substantial impact on volume and on each other, with the dominant flow of knowledge to feelings to action pathway to purchase.

## Conclusion, implications, limitations, and future research

While many academic papers have focused on social media or search engine marketing alone, little work so far has taken an integrative perspective vis-à-vis the offline and online marketing mix to understand the consumer's path to purchase. Aiming to build this stream of research, we investigate the effects of traditional offline marketing mix instruments and novel online consumer activity metrics in an integrated dynamic framework on the path to purchase in the FMCG space. Our approach allows for interaction and feedback effects among the different marketing mix elements and online consumer activity metrics. Our findings offer new substantive and managerial insights on the important role these new online consumer activity metrics play and how they interact with the traditional marketing mix along the path to purchase.

It is important to note that the online consumer activities on the path to purchase are reflected in paid, owned, and earned media metrics. These online activity metrics differ from traditional media as exposure to (advertising) content is often triggered by an overt (and traceable) user decision. The trace the consumer leaves provides us with a novel opportunity to empirically shed new light on how learning, feeling and doing are related in the consumer's path to purchase journey. The new activity-based consumer metrics are behavior-based data (what consumers actually do) and also offer potentially lower tracking costs and opportunity for earlier warning to help brand managers (in contrast most surveys are monthly at best).

Our work builds on the recent work of Srinivasan et al. (2010) who used a sequence in the evaluation of offline brand performance from a consumer's perspective using offline consumer mindset metrics of awareness, consideration and liking for a brand. As in their study, we also investigate the effect of the complete marketing mix in conjunction with online consumer activity metrics. In essence, the path to purchase journey posits that that consumers, in responding to advertising, proceed through a series of stages beginning with awareness and knowledge-building (cognition or learning) to liking and preference (affect or feeling) to conviction and purchase (conation or doing). The contemporary path to purchase model allows for the possibility of multiple pathways for advertising to influence sales and we adopt this perspective in our investigation of the effect of online consumer activity metrics on brand sales. Our modeling approach is well suited to identifying such causal pathways (through Granger Causality tests), as well as estimating the effect sizes involved (through VAR models). We investigate a seemingly low involvement product, believed to draw few, if any, cognitive resources in processing advertising. We next organize our discussion based on the major findings and highlight the managerial implications of the study.

The first major finding is that online consumer activity metrics interact with each other, are affected by traditional communication activities, and convert into sales even for a product that is still mostly bought offline. Our analysis also provides market-level support for Google's managerial claim that consumers engage online even for mundane products: "if consumers will do research online for houses and healthcare, they will do so for Band-Aids and ballpoint pens" (Lecinski 2011, p. 12). In total, online metrics explain about 15% of the variance in sales. While not as impactful as traditional marketing mix activity such as price (20%) or distribution (60%), online metrics drive more sales than TV advertising (5%), and at a lower cost (as communicated to us by the data provider).

We find that online consumer activity metrics of paid, owned, and earned media influence brand performance differentially. In our case, owned media (website visits) is key at 10%, while earned media (3%) and paid media (2%) have smaller, albeit significant, effects.

The second major finding relates to a novel substantive issue: consumer disengagement as measured by unearned media such as Facebook unlikes. Previous work has investigated the effect of negative social media sentiment, e.g., by posting a negative comment or review (e.g., De Matos and Rossi 2008; Sonnier et al. 2011). Posting such negative comments is an effortful way of expressing dissatisfaction – most consumers would exit instead of voicing complaints for low-involvement products (Hirschman 1970; Moe and Schweidel 2012). Facebook with its unlike feature, and similar sites with simple ways of expressing sentiment, allow for a more costless way to express disengagement from a brand. In addition, previous work has investigated the effect of negative WOM on sales without explicitly allowing for feedback effects and the non-linear nature of the path to purchase. We find that consumer disengagement, measured via Facebook unlikes, has a substantial negative effect on sales. Hence, the benefit of obtaining more likes should be accompanied by a careful monitoring of unlikes, and exploring the reasons behind them. Some consumers may unlike the brand because they disagree with the content of a new campaign. Others may have had a bad product or service experience. Still others simply feel overexposed by the number of brand messages. Understanding which is which can help managers take targeted action to prevent harm to the brand.

The third major finding involves the dynamic feedback loops among the studied metrics in our system of equations. For instance, more website visits inform consumers and thus can increase sales, but also increases Facebook unlikes. Additionally, our counterfactuals assess the relative equivalence of these customer activity metrics in terms of sales impact. For the analyzed brand, we show that the sales benefits are similar when TV advertising is increased by 10%, when Facebook likes increase by 50 and when website visits increase by 17. Thus, a website visit is about 3 times more valuable than a Facebook like for the studied brand. This finding suggests caution in the excessive reliance on earned (social) media versus owned media, and we encourage practitioners to consider these tradeoffs in moving the consumers along the path to purchase and beyond.

From a managerial perspective, our results and counterfactuals shed light on the interplay between online and offline activity, which has implications for media spending. We find that a predominant flow exists from TV advertising first to the cognitive consumer metrics (e.g., clicking on a paid search to find out more), then to the affective costumer metrics (e.g., liking the brand on Facebook) and finally to conative (increase brand purchase) metrics. More specific, an impulse response approach reveals how an increase in TV advertising leads to more clicks, which in turn lead to new likes, which in turn lead to volume increase. Evaluating these spillover effects of TV advertising is crucial for brand managers evaluating media spending. A new TV campaign that fails to move the consumers on the path to purchase as reflected in these online activity metrics within a short time period is unlikely to move volume beyond the—relatively small—direct effect of TV advertising. This finding also has practical implications for the ongoing discussion in the advertising industry, which focuses on the potentially detrimental effects of media multitasking: distracting consumer attention away from advertisements. Our findings underscore a potentially positive aspect in this context in a practical sense: the consumer's second screen enables a paid search response to television advertising. It also suggests that advertising managers and brand managers who wants to assess the online effects of their TV advertising budget might consider using additional metrics of success such as paid search clicks as well as other online engagement metrics in addition to the traditional metric of purchases to allow an assessment of how effective TV is in the entire P2P journey.

Limitations of our study mostly pertain to the data. First, our conclusion about the relatively lower importance of online affect as a sales driver may be related to the focus on one social media platform. However, Facebook is by far the dominant platform for this product, and affective responses on other platforms are highly correlated with Facebook likes and unlikes. Second, we only had data for a brand in a product category in one country in a specific time period. Further studies are needed to investigate the extent to which our findings generalize. We specifically call for establishing empirical generalizations and boundary conditions (e.g., by a meta-analysis of the findings in this and previous papers). Third, the data is aggregated over individual consumers because of privacy and reporting ease concerns. Analysis at the individual consumer level, possibly using behavioral approaches, is required for segmentation and targeting insights. Overall, our study should help strengthen marketers' case for building share in consumers' hearts and minds, as measured through consumer online activity and engagement. Additionally, we also show that online consumer activity metrics, which are free or require very little investment, can function as additional leading indicators of sales, building on the work of Srinivasan et al. (2010) on mindset metrics. In the long run, we expect that marketers can effectively design traditional television advertising to influence the related goals of increasing both online consumer engagement and transactions in the P2P. Lastly, online consumer activity metrics captured via paid, owned, and earned media can be input marketing levers as well as outcome metrics that can be tracked to evaluate the path to purchase journey unlike mindset metrics which are not marketing levers. This makes the present context a fascinating topic which we hope future research will build on.

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## References

Achrol, R. S., & Kotler, P. (2011). Frontiers of the marketing paradigm in the third millennium. *Journal of the Academy of Marketing Science, 40*, 35–52.

Ambler, T. (2003). *Marketing and the bottom line*. Harlow: Prentice Hall.

Anderson, S. P., & Renault, R. (2006). Advertising content. *The American Economic Review, 39*(1), 305–326.

Benkwitz, A., Lutkepohl, H., & Wolters, J. (2001). Comparison of bootstrap confidence intervals for impulse responses of German monetary systems. *Macroeconomic Dynamics, 5*, 81–100.

Comscore (2014). http://www.comscore.com/Insights/Press-Releases/2014/3/comScore-Releases-February-2014-U.S.-Search-Engine-Rankings. Accessed Nov 2014.

Court, D., Elzinga, D., Mulder, S., &Vetvik, O.J. (2009). The Consumer Decision Journey. *McKinsey Quarterly*, June.

Danaher, P. J., & Dagger, T. S. (2013). Comparing the relative effectiveness of advertising channels: a case study of a multimedia blitz campaign. *Journal of Marketing Research, 50*(4), 517–534.

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

Dekimpe, M.G., & Hanssens, D.M. (1995). Empirical Generalizations About Market Evolution and Stationarity. *Marketing Science*, *14*-(summer, part 2), 109–121.

Dekimpe, M. G., & Hanssens, D. M. (1999). Sustained spending and persistent response: A new look at long-term marketing profitability. *Journal of Marketing Research*, 36(4), 397-412.

Evans, L., & Wells, G. M. (1983). An alternative approach to simulating VAR models. *Economic Letters, 12*(1), 23–29.

Godes, D., Mayzlin, D., Chen, Y., Das, S., Dellarocas, C., Pfeiffer, B., Libai, B., Sen, S., Shi, M., & Verlegh, P. (2005). Firm's management of social interactions. *Marketing Letters, 16*(3/4), 415–428.

Hanssens, D.M. (2009). Advertising Impact Generalizations in a Marketing Mix Context. *Journal of Advertising Research*, June, 127–129.

Hanssens, D.M., Parsons, L.J., & Schultz, R.L. (2001). *Market Response Models: Econometric and Time Series Analysis.* 2nd Edition, Kluwer Academic Publishers.

Hanssens, D., Pauwels, K., Srinivasan, S., Vanhuele, M., & Yildirim, G. (2014). Consumer attitude metrics for guiding marketing Mix decisions. *Marketing Science, 33*(4), 534–550.

Hirschman, A. O. (1970). *Organizations, and States*. Harvard: University press. Exit, Voice, and Loyalty: Responses to Decline in Firms.

Horváth, C. (2003). Dynamic Analysis of Marketing Systems. Doctoral Thesis, University of Groningen, Alblasserdam: Labyrinth Publication.

Internet Live Stats (2014). http://www.internetlivestats.com/google-search-statistics/. Accessed Nov 2014.

Keller, K., & Lehmann, D. (2006). Brands and Branding: Research Findings and Future Priorities. *Marketing Science*, *25*(November-December), 740–759.

Kotler, P., & Keller, K. (2012). *Marketing management* (14th ed.). Upper Saddle: Pearson Prentice-Hall.

Lautman, M. R., & Pauwels, K. (2009). What is important? identifying metrics that matter. *Journal of Advertising Research, 49*(3), 339–359.

Lecinski, J. (2011). *Zero Moment of Truth.* http://www.zeromomentoftruth.com. Accessed 2014.

Li, H., & Kannan, P. K. (2014). Attributing conversions in a multichannel online marketing environment: an empirical model and a field experiment. *Journal of Marketing Research, 51*(1), 40–56.

Moe, W., & Schweidel, D. (2012). Online product opinions: Incidence, evaluation, and evolution. *Marketing Science, 31*(3), 372–386.

Naik, P., & Peters, K. (2009). A hierarchical marketing communications model of online and offline media synergies. *Journal of Interactive Marketing, 23*(4), 288–299.

Nielsen (2012). State of the Media: Advertising and Audience Part 2. http://nielsen.com/content/dam/corporate/us/en/reports-downloads/2012-Reports/nielsen-advertising-audiences-report-spring-2012.pdf. Accessed April 2014.

Ofcom (2013). Communications Market Report 2013. White paper.

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

Pauwels, K., & Hanssens, D. M. (2007). Performance regimes and marketing policy shifts. *Marketing Science, 26*(3), 293–311.

Pauwels, K., & van Ewijk, B. (2014). Do Online Behavior Tracking or Attitude Survey Metrics Drive Brand Sales? An Integrative Model of Attitudes and Actions on the Consumer Boulevard. *Marketing Science Institute*, Working Paper #13-118.

Pauwels, K., & Weiss, A. M. (2008). Moving from free to Fee: How marketing can stimulate gains and stem losses for an online content provider. *Journal of Marketing, 72*(3), 14–31.

Pesaran, M. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters, 58*, 17–29.

Sonnier, G. P., McAlister, L., & Rutz, O. J. (2011). A dynamic model of the effect of online communications on firm sales. *Marketing Science, 30*(4), 702–716.

Srinivasan, S., Vanhuele, M., & Pauwels, K. (2010). Mind-set metrics in market response models: an integrative approach. *Journal of Marketing Research, 47*(4), 672–684.

Stephen, A. T., & Galak, J. (2012). The effect of traditional and social earned media on sales: an application to a microlending marketplace. *Journal of Marketing Research, 49*(5), 624–639.

Tellis, G. (2004). *Effective advertising: How, when, and Why advertising works*. Thousand Oaks: Sage Publications.

Trusov, M., Bucklin, R. E., & Pauwels, K. (2009). Effects of word-of-mouth versus traditional marketing: findings from an internet social networking site. *Journal of Marketing, 73*(September), 90–102.

Vakratsas, D., & Ambler, T. (1999). How advertising works: what Do We really know? *Journal of Marketing, 63*(January), 26–43.

Wiesel, T., Pauwels, K., & Arts, J. (2011). Marketing's profit impact: quantifying online and Off-line funnel progression. *Marketing Science, 30*(4), 604–611.

Zephoria (2014). https://zephoria.com/social-media/top-15-valuable-facebook-statistics/. Accessed Nov 2014.

Zigmond, D., & Stipp, H. (2011). Multitaskers may be advertisers' best audience. *Harvard Business Review, 12*(1/2), 32–33.