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ORIGINAL EMPIRICAL RESEARCH

Synergistic effects of social media and traditional marketing on brand sales: capturing the time-varying effects

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Abstract As social media gains more importance, managers are challenged to quantify its return on sales. The academic understanding in the effectiveness of social media is limited, and in fact the synergistic effects between social media and traditional marketing efforts have rarely been investigated. Despite the dynamics in marketing effectiveness on sales, the time-varying effectiveness of social media has never been studied either. In this study, we capture the time-varying effects of social media and the time-varying synergistic effects of social media and traditional marketing with a time-varying effect model (TVEM) approach. The empirical analyses of a large U.S. ice-cream brand sales reveal that a) the effectiveness of social media and traditional marketing vary over time, b) the synergistic effects vary over time for social media with product sampling and with in-store promotions, c) the proposed TVEM approach has a higher predictive accuracy than the benchmark models, and d) the proposed TVEM approach saves marketing costs by $0.4 million per year, compared to the time-invariant benchmark model. Overall, this study enables managers to not only better understand the synergistic effects of social media marketing and traditional marketing, but also the time-varying effectiveness of their marketing efforts with TVEM approach for better resource allocation.

Keywords Social media · Time-varying effect model · Integrated marketing communications · Marketing effectiveness · Consumer packaged goods

Social media is an interactive platform (e.g., Facebook and Twitter), where firms can share information about their brand and products, and where customers can communicate and share content with people within their network (Rapp et al. 2013). Social media has not only changed the way businesses attract and retain customers, but it has also allowed customers to interact with each other and with the firm. With the advent of social media, media fragmentation has made customers less prone to making decisions based on classic purchase funnel but rather they are more likely to make purchase decisions based on their own opinions, motivated by information from social media rather than from firm initiated marketing (Evans 2010). According to a survey from marketers, the main benefits of social media are the increase in exposure (brand awareness) and increase in the traffic (Colwyn 2014). Since customers are spending more of

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their free time on the internet and social media, marketers focus their marketing budgets towards digital advertising and social media (eMarketer 2014).

Despite the increasing interest in social media, its effectiveness on brand sales is still unknown and unpredictable. Some marketers report increase in sales after using social media, while some report no realized growth in sales (Colwyn 2014). The correct use of social media can dramatically improve the firm's performance through creating value and engaging with the customers; however, negative feeds can tarnish the brand's image and sales (Trainor 2012). Due to social media's rapid dissemination of information and a large number of customers engaged in discussion, the effect of social media on brand sales can change in a shorter period than the traditional marketing does.

Understanding how the effectiveness of social media on sales changes over time in shorter time intervals (e.g., monthly or weekly) is important for marketers in order to promptly react to undesirable outcomes, and to frequently make resource allocation decisions, that can enhance the overall firm performance. The level of customer engagement and interaction among customers on social media can vary over time as changes in product life cycle (PLC) or business performance occur. Not only can customers engage with the brand (e.g., likes on Facebook or share posts), but they can also disengage with the brand (e.g., post negative comments) during the PLC (Srinivasan et al. 2015). Especially the power of microblogging (mWOM) to spread information rapidly can change the effectiveness of social media over time (Hennig-Thurau et al. 2015). The time-varying effectiveness of marketing on firm's performance implies that a specific marketing effort (e.g., television advertising) can have a varying positive and/or negative impact on brand sales over time, depending on external factors such as competition and/or economy (Osinga et al. 2010; Stremersch and Lemmens 2009). Applying this idea of varying marketing effects over time, we aim to investigate the *time-varying effectiveness of social media* on brand sales for short-term resource allocation decisions (Raman et al. 2012; Saboo et al. 2016).

It is important to understand the *synergistic effect* of social media with other traditional marketing. As Srinivasan et al. (2015) mention, the research on media synergy rarely accounts for the synergistic effects of social media. Moreover, media synergy on consumer-packaged goods (CPG) is limited. Specifically, there is less attention on the synergistic effects of social media and traditional marketing of CPG companies despite their heavy investments in all forms of media, including digital media (eMarketer 2014). In this study, we define traditional marketing as an offline form of advertising used to promote sales. We use television advertising, product sampling, and in-store promotion for traditional marketing because CPG companies rely heavily on the aforementioned advertising methods to improve product awareness and encourage product trial (Insignia 2015; Tuttle 2011).

Furthermore, research on media integration does not address the *time-varying* synergistic effects of social media and traditional marketing. The classic purchase funnel assumes that consumers go through a linear decision journey; however, both firm-initiated marketing efforts and consumer generated word-of-mouth (i.e., online WOM and mWOM) can systematically influence the consumer's decision process (King et al. 2014). The synergistic effect between media is inconsistent and unpredictable, possibly due to the waning effects of other media, but also due to the unpredictable time-varying effectiveness of social media. Hence, it is important for firms to capture the time-varying synergistic effects of different media in order to strategically plan resource allocation and to take relevant marketing actions.

Thus, the main objective of this research is to study the time-varying effectiveness of social media and its time-varying synergistic effects with traditional media on brand sales over time. We use the Time-Varying Effects Model (TVEM) to statistically measure the effects over time. We seek to address the following research questions:

1. Does the effectiveness of social media on brand sales vary over time?
2. Do social media and traditional marketing have a time-varying synergistic effect on brand sales?
3. Does the proposed TVEM approach perform better with respect to model fit and prediction accuracy compared to the benchmark models?
4. What is the benefit of using the proposed TVEM approach in resource allocation?

Overall, there are two major contributions of our research. First, we demonstrate how both the main effect and the synergistic effects of social media and traditional marketing vary over time. In doing so, we respond to the unpredictable nature of social media effectiveness and propose using a most current estimate of media effectiveness for better resource allocations.

Secondly, we contribute methodologically by applying a TVEM approach to examine the temporal variations of social media and synergistic effects of social media and traditional media on brand sales. This is the first study to show the usefulness of the TVEM approach to study marketing effectiveness in the marketing literature. The TVEM approach provides a flexible solution to understanding the time-varying effects of marketing inputs by modeling the sales response coefficients as continuous smooth functions of time (Tan et al. 2012). A few recent studies have considered social media and traditional media jointly (e.g., Kumar et al. 2016; Srinivasan et al. 2015); however, exiting studies use static estimation of marketing effectiveness and do not consider the dynamic effectiveness of both social and traditional media together. We also show to what extent TVEM is beneficial to understand the temporal effectiveness of marketing media for a better resource allocation.

We use a weekly brand sales dataset of a large national CPG company. The data set contains detailed sales and marketing information for 6 brands across 5 channels, spanning over an observation period of 3 years. Utilizing the TVEM approach, we are able to find a temporal variation on the effectiveness of social media, measured by social media impressions, and determine whether there are time-varying synergistic effects between social media and traditional marketing (e.g., television advertising, product sampling, and in-store promotion).

The outcomes of our results suggest that (a) the effectiveness of social media has a significant time-varying effect on sales, (b) social media has time-varying synergistic effects with in-store promotion and with product sampling on brand sales, and (c) the proposed TVEM has a better model fit and prediction than the benchmark models, and (d) resource allocation based on TVEM estimation saves marketing spending by $0.4 million per year.

The rest of the paper is organized as follows. First, we discuss the relevant stream of literature and describe our research contribution. Then, we describe the data, key measures, and the methodology for the empirical analysis. Thereafter, we discuss the results and managerial implications of the research. We conclude with limitations and future directions of this research.

Research background

Three research streams are relevant to this study: (1) studies on the effectiveness of social media, (2) offline-online media synergy, and (3) time-varying effectiveness of marketing mix.

Social media effectiveness

Recently, the emergence and the use of social media have been omnipresent. By 2016, Facebook alone has more than 1.55 billion users followed by YouTube, which has 1 billion users, and the total spending on social media has increased 33.5% to $23.68 million, from 2014 to 2015 (Allton 2016; eMarketer 2015). Studies on social media highlight the increase in consumer-power on social media, where consumers can create content, compare competitors' offerings and prices, and communicate with other consumers easily (Labrecque et al. 2013). Such increase in consumer power has challenged marketers to adapt social media and to change their brand management and consumer relationship management (CRM) strategies (e.g., Gensler et al. 2013; Malthouse et al. 2013). Some studies find that microblogging word-of-mouth (mWOM) on social media encourages product adoption and higher customer spending and profitability (e.g., Hennig-Thurau et al. 2015; Stephen and Galak 2012). The customer-brand engagement on social media changes over time and influences the customer's perception of the brand and purchase behavior. Consumers can react positively or negatively about the firm on social media, where both reactions are strongly correlated with time (Pauwels and van Ewijk 2014). Such differential reactions on social media lead to more engaged customer behaviors (i.e., like and share the post, include positive comment) or more disengaged behaviors (i.e., post negative comments and unlike posts), which can benefit or hurt the firm performance over time (Srinivasan et al. 2015). Although prior studies have implied the varying effects of social media on performance, there is no study that empirically examines how the effectiveness of social media vary over time to reflect the firm's dynamic market environment (Morgan 2012).

Media synergy

Next, we review the literature on synergistic effects of media. With the increase in the number of media types, the concept of media synergy has been emphasized in integrated marketing communications (IMC) and marketing budget research (Naik and Peters 2009; Naik and Raman 2003). Marketing actions can have synergistic effects enhancing the effect of one media through the effect of another media (Assael 2011). Naik and Raman (2003) define media synergy as "the combined effect of multiple [media] activities exceeds the sum of the individual effects". Although prior research on media synergies has focused on traditional media integration (i.e., television, sponsorship, and print media), some recent studies have incorporated the integration of traditional media and the new media (i.e., internet and web advertisement). For example, Chang and Thorson (2004) find that compared to the advertisement from the same source (either television or web), television-web advertisements synergy works better. Naik and Peters (2009) capture the synergy effect of offline and online media, with a hierarchical marketing communications model. They find that online advertising (banner and search) amplifies the effectiveness and synergies of offline media (television, print, newspapers, and magazines) in increasing the number of visits on the website.

Despite the growing importance of social media, research on synergistic effects of social media with traditional marketing is very nascent. Srinivasan et al. (2015) and Kumar et al. (2016) observe that the consumer activity on social media is affected by traditional communication activities. Nevertheless, prior studies on media synergy assume that the synergistic effects do not vary over time and therefore do not address the time-varying synergistic effects on sales. Our study aims to contribute to this research stream by focusing on the time-varying synergistic effects between social media and traditional marketing.

Time-varying effectiveness of marketing

Substantive insights Prior studies suggest that the effectiveness of marketing varies over time. For example, the classic PLC theory suggests that the advertising effectiveness is higher in the introduction and growth phases, but declines over the PLC (Parsons 1975). Moreover, the effect of marketing-mix on sales can vary over time due to evolving consumer preferences (Du et al. 2015; Sriram et al. 2006) or due to changes in the market environment such as new regulation (Stremersch and Lemmens 2009), increase in competition (Bowman and Gatignon 1996), or introduction of new products (Luan and Sudhir 2010). Similarly, a rise of new marketing media changes the effectiveness of the existing media. Research has found that the internet is as effective in building brands as television advertisements (Draganska et al. 2014), and social media also has dynamic effects on firm performance due to changes in user generated content and consumer reactions over time (Gensler et al. 2013; Srinivasan et al. 2015).

Previous research has acknowledged the time-varying effectiveness of marketing and empirically explained the dynamics in sales with time-varying parameter models. The study by Ataman et al. (2010) applies a multivariate dynamic linear transfer function model and finds that the short-term and long-term elasticity of marketing-mix (i.e., advertising, price promotion, product, and distribution) are different across time. Similarly, the extant literature in optimal resource allocation has highlighted the time-varying effectiveness of marketing actions and empirically validated that resource allocation with time-varying marketing effectiveness improves firm performance (e.g., Osinga et al. 2010; Raman et al. 2012; Saboo et al. 2016).

Modeling insights Leeflang et al. (2009) summarize the empirical papers that incorporate time-varying parameters of marketing effectiveness. The stream of research, which employed the time-varying parameter approach, commonly pre-specifies the shape of variation and assumes discrete times. For example, Kumar et al. (2011) find the time-varying effect of market orientation constructs on business performance by allowing the coefficients to be a linear function of discrete times. Moreover, the state space methodologies such as dynamic linear models (DLM) or Kalman filter (e.g., Osinga et al. 2010; Sriram et al. 2006) make a strong assumption on the underlying states and assume discrete time and discrete state space (Dekimpe et al. 2008; Pauwels 2004). Models that pre-specify the shapes of change or that assume the underlying states can have biased results due to misspecification (Bierens and Pott-Buter 1991) and are sensitive to the number of underlying states (Leeflang et al. 2009). In addition, temporal aggregation of data in discrete times leads to biased parameter estimates and inefficient forecasting (Wei 1978). In this study, we will explore the effectiveness of marketing over time by employing the Time-Varying Effect Model (TVEM) approach. Unlike the class of time-varying parameter models used in prior studies, TVEM does not assume a pre-specified shape or state and estimates the parameters as continuous smooth functions of time. Saboo et al. (2016), while taking an information system perspective, have validated the benefits of TVEM using big data and find that TVEM takes less computational time (i.e., a few seconds compared to hours) and has a better model fit compared to a state-space model like DLM.

Research contribution

Employing the TVEM approach, we contribute to the stream of literature in marketing by examining the time-varying effectiveness of social media, as well as, the time-varying synergistic effects of social media and traditional marketing. Table 1 provides an overview of relevant empirical marketing studies in comparison to this study.

Although several empirical studies (see Table 1) have permitted the parameters to change over time, the previous attempts have constrained the patterns of the parameters and have also not considered the new media, such as the social media. Kumar et al. (2016) find that the social media has synergy with both television advertising and email marketing. We extend the study by Kumar et al. (2016) by modeling the dynamic effects of social media and synergistic effects on brand sales *over time*, using the TVEM approach. Hence, we make a novel substantive contribution to this nascent field.

Conceptualization and hypotheses

In our proposed conceptual framework (see Fig. 1), we hypothesize both the time-varying effectiveness of social media and the time-varying synergistic effects of social media and traditional marketing on brand sales. Furthermore, we control for seasonality, product prices, brands, and the distribution channel. Before we present the conceptual framework, we first describe our key variables: social media and traditional marketing

Key variable description

Social media Social media is online communication platforms (e.g., websites, applications, or microblogs), where users create communities and share information. Prior research on social media operationalized social media with number of firm-generated content (FGC), survey questions, number of likes and comments, number of tweets sent, ratio of positive to negative posts, etc. (e.g., Kumar et al. 2016; de Vries et al. 2012; Hennig-Thurau et al. 2015). Although these measures of social media are valuable and informative, these metrics are not readily available for the managers. We add to the social media research stream by operationalizing with social media impressions (Mª Ángeles et al. 2014). Social media impressions assess the overall exposure of the brand by measuring the total number of times your brand's post is displayed on a consumer's timeline at a given time period (Facebook 2015; Twitter 2015). Unlike other metrics, social media impression captures the extent that brand postings have reached to users who interact with the brand post and the non-

Table 1 Relevant empirical marketing studies analyzing the marketing-mix effectiveness

Most relevant empirical research studies	Time-varying parameter for marketing-mix?	Modeling approach	Marketing-mix variables	Synergy between social media and traditional marketing?
Chang and Thorson (2004)	No	Experiment	Television and web advertisement	No
Sriram et al. (2006)	No	Dynamic Logit (Kalman Filter)	Price and advertising	No
Naik and Peters (2009)	No	Hierarchical Model	Online advertising (banner and search) and offline advertising (television, print, newspapers, and magazines)	No
Osinga et al. (2010)	Yes	DLM (Kalman Filter)	Advertising	No
Ataman et al. (2010)	Yes	DLM (Kalman Filter)	Price, product, promotion, advertising, and distribution	No
Osinga et al. (2011)	No	DLM (Kalman Filter)	Advertising	No
Stephen and Galak (2012)	No	Multivariate autoregressive time-series model	Traditional earned media, social earned media	No
Du et al. (2015)	No	Market response model	Advertising and promotion	No
Srinivasan et al. (2015)	No	VAR model	Price, advertising, distribution, owned/paid/earned media	Yes
Saboo et al. (2016)	Yes	Time-varying effect model	Email and direct mail	No
Kumar et al. (2016)	No	Difference-in-difference model	Television advertising, email, and social media (Firm generated content)	Yes
This study	Yes	Time-varying effect model	Social media (Facebook impressions) and traditional marketing (television advertisement, product sampling, and in-store promotion)	Yes

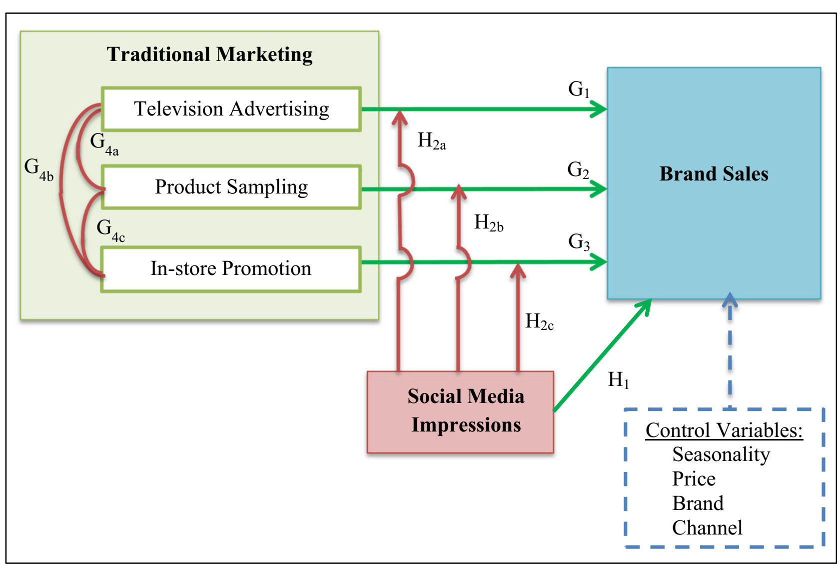
DLM dynamic linear modeling, *VAR* vector autoregressive

interacted users (e.g., my friend who does not know about the focal brand may see the brand post on her Newsfeeds because I have interacted with the post by liking it). Managerially, social media impression is a practical measure because it is readily available to marketers who manage the firm's social media accounts. Thus, operationalizing social media with impressions allows managers to understand the effectiveness of their social media on brand.

Traditional marketing Firms rely on numerous promotional activities, such as advertising, sales promotion, and other forms of persuasions, to reach superior financial performance (Webster and Lusch 2013). Especially, CPG companies of food category invest more on traditional marketing such as television advertising, in-store promotions, and product tasting to improve product awareness and encourage product trial (Insignia 2015; Tuttle 2011). In this study, we capture traditional marketing as television advertising, product sampling, and in-store promotions.

Main effects

Time-varying effectiveness of social media Social media has become an important component of a firm's marketing-mix.



G: Generalization
H: Hypothesis

Fig. 1 Conceptual framework of the time-varying synergistic effects of social media and traditional marketing on brand sales

Kumar et al. (2016) find a positive effect of FGC on customer spending. However, the effectiveness of social media on brand performance (e.g., sales, customer profitability, and cross-buying) can change, both positively and negatively, depending on customer participation and brand exposure on social media. Especially the interconnected and unpredictable nature of consumer reaction on social media can cause a temporal variation in the effectiveness of social media on the sales. CRM research has found that brand community participation leads to positive brand outcomes, such as increase in customer profitability and stronger brand engagement, loyalty, and purchase intentions (Algesheimer et al. 2010; Kumar 2013). However, according to the motivation theory, customers decide to participate in social media communities if they find perceived usefulness and enjoyment on the brand's social media page (Lin and Lu 2011). Firms create brand posts on social media in order to encourage customer participation (e.g., like and share posts, follow the brand's page) on brand's social media community. Yet, customers can react positively or negatively (e.g., increase or reduce number of likes, comments, and reposts) depending on the vividness and interactivity of FGC on social media (de Vries et al. 2012).

The social connections among consumers affect how brand messages reach customers and how customers react to postings (Van den Bulte and Wuyts 2007). This network effect affects the effectiveness of social media on brand performance because both the positive and negative consumer reaction to brand posts not only impacts those who have participated on the brand's social media page, but also to those non-interacted users who still see the posting on their Newsfeeds. Moreover, users can further participate on social media communities by creating brand stories themselves. The ease of information sharing on social media has allowed consumers to become an author of brand stories by sharing their brand experience on social media (Gensler et al. 2013). Compared to FGC, the user-generated content (UGC) are often unpredictable (i.e., can be either positive or negative about the brand) and inconsistent with the firm's message. Thus, social media participation through UGC can have a varying effect on brand performance.

It is important to recognize that social media (both the increase and decrease in social media impressions) affects firm performance. However, the level of customer participation, customers' reaction to the FGC, and the message of UGC are unpredictable and amplifying the changes in the effectiveness of social media on brand sales over time. Furthermore, the prominent network effect on social media enhances both the positive or negative effect of social media because the message can spread fast to even to those who do not interact with the brand post. This leads to the following hypothesis:

H1: The effect of social media impressions on brand sales varies over time.

Time-varying effectiveness of traditional marketing Studies in marketing-mix hypothesize that the effectiveness of different marketing efforts can vary over time. Thus, we offer generalization (as opposed to hypothesis) about the time-varying effectiveness of traditional marketing.

Television advertising Television is one of the most trustworthy and reliable sources of information to customers (Danaher et al. 2008); thus, marketers have allocated a large portion of their marketing resources to television advertisements. Nonetheless, the effectiveness of television advertising on brand sales can vary across time due to an increase in advertising exposure and the number of competitive advertising. The presence of too much advertising on television can lead to advertisement avoidance and channel switching behaviors (Danaher 1995). Similarly, the increase in the number of competitors' advertising reduces advertisement recall and recognition for the focal brand (Burke and Srull 1988). Since it is well documented, we generalize that:

G1: The effect of television advertising on brand sales varies over time.

Product sampling Distribution of free product samples is a sales promotion technique, where firms provide a trial-sized quantity of the original product to encourage product trial without any risk or obligations (Ailloni-Charas 1984). Product sampling is recognized as a cost-effective strategy to reach the target customers compared to the traditional mass advertising (Tuttle 2011). Even the CEO of Proctor & Gamble has recognized its effectiveness and announced that he will reallocate P&G's marketing budget towards product samples (Neff 2014). Product sampling in the food category, such as ice-cream, means an instantaneous consumption in the store. Hence, consumers get to try the product without any financial burden of risking their grocery budgets (Tuttle 2011). Bawa and Shoemaker (2004) find that the effectiveness of free product samples can vary widely, even between brands in the same product category. Compared to products from a well established brand with a large market share, products with small market shares experience a greater increase in sales from product sampling, by attracting customers who would not have purchased the product without the product sample. However, as the product gains more market share, the effect on sales can decrease over time. Following this rationale, we generalize that:

G2: The effect of product sampling on brand sales varies over time.

In-store promotion In-store promotions have a significant impact on brand choices and brand sales because they encourage consumers to make unplanned purchases and to switch brands (Abratt and Goodey 1990; Deighton et al. 1994; Gupta 1988). Nevertheless, the effectiveness of in-store promotions on brand sales can change over time because of competitive in-store promotions. Consumers are flooded with undifferentiated in-store promotions, such as buy-one-get-one-free (BOGO) or buy two for a lower price from multiple brands, within the same product category (Rapperport 2015). The number of advertisements from the competitors can affect the effectiveness of in-store promotions of the focal firm (Danaher et al. 2008). The increase in exposure of many different in-store promotions not only reduces the probability that consumers recall the differences between the promotions but also induces consumers to become less brand loyal (Burke and Srull 1988). Given the varying effect, we generalize that,

G3: The effect of in-store promotion on brand sales varies over time.

Synergistic effects

Social media and traditional marketing Research on media synergies highlights that the combined effect of two media is greater than the sum of individual effects of each media (Naik and Raman 2003). Kumar et al. (2016) investigate the effect of social media (firm generated content) and traditional marketing (television advertising and email marketing) on customer spending and find positive synergistic effects. Srinivasan et al. (2015) investigate how traditional marketing-mix (distribution and price) and social media (online-owned, (un)earned media, and paid media) explain sales variation. Despite the importance of media synergy with social media and traditional marketing, there is insufficient empirical evidence of media synergy in dynamic markets (Naik and Raman 2003; Naik et al. 2005). As hypothesized and generalized in the main effects section, both social media and traditional marketing have time-varying effectiveness on brand sales. Thus, it is natural to expect the synergistic effects to also vary with time. For example, customers may be exposed to either positive or negative social media content. These brand content and comments on social media may or may not be consistent with the traditional marketing, which the customers are exposed to in offline settings. The consistency (or discrepancy) of the messages and the experience from social media and traditional marketing can strengthen (or weaken) the synergistic effects over time. Hence, we develop hypotheses related to the time-varying synergistic effects of social media and traditional marketing (television advertising, sampling, and in-store promotion) on brand sales.

Social media and television advertising Both television advertising and social media marketing aim to trigger consumer interest and to encourage favorable behavioral outcomes, such as increase in brand awareness and loyalty, and increase in purchase intention. The social media marketing can help or hurt the effectiveness of television advertising on sales over time. Chang and Thorson (2004) find that being exposed to both the television and online advertisements lead to higher customer attention and positive feelings about the brand. Similarly, more exposure on social media (i.e., increase in Facebook book impressions) can improve the effectiveness of television advertising on brand sales by encouraging passive viewers to be more attentive to the focal brand's television advertising and to have positive feelings towards the brand. However, increase in exposure of the brand on social media can also hurt the effectiveness of television advertising on sales if the customers are exposed to negative comments or UGC that is drastically different from the message that the firm intends to say in their television advertisements. Hence, we hypothesize that:

H2a: The synergistic effect of social media impressions and television advertising on brand sales varies over time

Social media and product sampling Both product sampling and social media increase product awareness and encourage product trial that can lead to more favorable outcomes for the firm (Ailloni-Charas 1984; Evans 2010). The synergistic effect of the changes in social media impressions and product trial can have time-varying effectiveness on sales over time. A more positive exposure of the brand on social media (i.e., more sharing and likes from people within the network) can improve the effectiveness of product sample on brand sales by encouraging customers who would not have tried the product sample otherwise. Yet, the increase in social media impressions of negative product reviews or comments can discourage customers from trying the product samples or even lead to a negative product trial experience, due to the initial negative impression of the product. On a similar note, customers who had a good experience from a product trial and have high purchase intention may be discouraged from purchasing the product if they are exposed to negative reviews on social media. Thus, we hypothesize that:

H2b: The synergistic effect of social media impressions and product sampling on brand sales varies over time

Social media and in-store promotion In-store promotions influence customers to make unplanned purchases and to switch brands (Abratt and Goodey 1990; Deighton et al. 1994; Gupta 1988). Firms increasingly rely on social media for promotion campaigns (Evans 2010). The current customers and prospects can be exposed to the brand's in-store promotion from social media content, or in-store promotion may require customers to visit the brand's social media page. However, customers can be exposed to varying messages (positive or negative) on social media and they can also be exposed to competitive in-store promotions occurring at the same time, thereby affecting the synergistic effect of social media and in-store promotion on sales over time.

H2c: The synergistic effect of social media impressions and in-store promotions on brand sales varies over time

Synergy among traditional marketing Prior research on IMC focuses on identifying both the main and synergistic effects of media (Assael 2011; Naik and Raman 2003). The interaction between a firm's marketing activities and the marketing activities of other competitors can influence the trade-offs in marketing planning (Naik et al. 2005). Given the nature of the dynamic competitive market, the synergistic effects between the traditional marketing activities can vary over time. Following this rationale, we generalize that:

G4a: The synergistic effect of television advertising and product sampling on brand sales varies over time

G4b: The synergistic effect of television advertising and in-store promotions on brand sales varies over time

G4c: The synergistic effect of product sampling and in-store promotions on brand sales varies over time

Control variables

We include the following control variables in our model. Consistent with prior research on marketing-mix models, we control for seasonality, price, distribution channel, and brand type, which affect sales in order to estimate the net-effect of traditional marketing and social media on sales (e.g., Ataman et al. 2010; Danaher et al. 2008).

In summary, the extant research suggests that the effectiveness of marketing can vary over time. Additionally, the growing discussion of social media indicates that it is an important medium to consider. Yet, there is no research studying the time-varying effect of social media on brand sales or time-varying the synergistic effectiveness of traditional marketing and social media on brand sales. We seek to address the unanswered questions using the TVEM approach.

Overview of time-varying effect model

With the growth of rich longitudinal data and user-friendly statistical software, TVEM is an excellent method to observe how the relationships between various factors on the outcome change over time. Since our study focuses on identifying the temporal changes and synergistic effects of the marketing actions on sales for a CPG category, applying a semiparametric technique, such as TVEM, is suitable to understand the trajectory of the marketing actions.

Market response models are widely accepted tools for marketing decision making (i.e., setting prices, resource allocation, advertising decisions, etc.). For example, we can consider a simple market response model that measures the effectiveness of advertising (X_{ij}) on sales across different subjects.

$$Sales_{ij} = \beta_0 + \beta_1 \cdot X_{ij} + \varepsilon_{ij} \qquad i = 1, \ldots, \mathrm{N}; \quad j = 1, \ldots, \ \mathrm{M_i} \tag{1}$$

where i is the number of subjects (i.e., customer, stores, brands) and j is the number of repeated measures for subject i. $\mathrm{Sales_{ij}}$ is the outcome variable of subject i at time t_{ij} and the error term is assumed to be normally and independently distributed. Equation (1) assumes a constant effect and does not estimate the changes in slope between sales and advertising over time. In an dynamic market environment, both the intercept (β_0) and the coefficient (β_1) of marketing-mix can vary over time for multiple reasons, such as changes in macro factors (i.e., economy) and customer or product specific factors (i.e., customer preferences and product attractiveness), or growing usage of new media platforms (i.e., internet and social media) (e.g., Du et al. 2015; Gensler et al. 2013). Understanding the true effectiveness of the marketing efforts, at a given time period, is critical to be proactive in making resource allocations decisions.

TVEM was first proposed by Hastie and Tibshirani (1993) as a varying coefficient model, which estimates the coefficients of a covariate as a smooth function of other predictor variables, such as time. Over time, the intercept and the slope coefficient parameters change through an unspecified function, allowing the coefficients to be dependent on time by creating interaction terms between time and the covariates. Compared to existing methods that study the temporal effectiveness of marketing, the key benefit of TVEM is that it does not rely on a prespecified shape (i.e., linear, quadratic, exponential, etc.) to describe the relationship between the covariate and the outcome variable (Tan et al. 2012). Typically, when describing the marketing effectiveness on sales, researchers prespecified the direction and the shape of change (Hanssens et al. 2011). Although prespecifying the shape based on prior knowledge or theory can describe the general relationship between the marketing-mix and sales, it fails to capture the temporal changes in trend. Moreover, prespecifying the shape may cause mis-specification of the functional form (Bierens and Pott-Buter 1991), which can result in inaccurate and misleading results. Rather than assuming the shape of change (i.e., linear or inverted-U shape) of the trajectories, TVEM is a data driven approach that provides a true picture of the time-varying effectiveness of marketing efforts.

Model development

We use a multilevel model, which is an extension of the linear regression models that allows the regression coefficients to be functions of time (Walls and Schafer 2005). Multilevel or hierarchical model is useful in analyzing a longitudinal data where there is a nesting structure with repeated observation across varies time points, allowing the multilevel model to include time as an additional predictor (Raudenbush and Bryk 2002). By including time as a predictor, we can capture both the temporal changes in the dependent variable and the covariates over time.

For example, if we are interested in the relationship between the time-varying marketing action X_{ij} (i.e., advertising) and sales, we can set a simple market response model, as suggested in Eq. (1). However, in order to capture the temporal changes between the marketing effort and sales, we can extend Eq. (1) with multilevel model. We can include time as a predictor in the second level and express the intercept and the slope as functions of time:

$$Sales_{ij} = \left(\beta_{00} + \beta_{01}t_{ij}\right) + \left(\beta_{10} + \beta_{11}t_{ij}\right) \cdot X_{ij} + \varepsilon_{ij} \qquad (2)$$

The intercept ($\beta_0 = \beta_{00} + \beta_{01}t_{ij}$) is the mean trajectory of sales changing linearly over time and the slope parameter ($\beta_1 = \beta_{10} + \beta_{11}t_{ij}$) suggests a linear association between X_{ij} and sales, where the interaction term measures the temporal changes of covariate over time.

Although the multilevel model in Eq. (2) explores the time-varying relationship between the covariate and the outcome variable, the multilevel model assumes the shape of the coefficient function (i.e., linear, quadratic, or cubic) (Tan et al. 2012). The shape of the relationship between the marketing efforts and sales is often unpredictable and force fitting the data into a wrongly presumed shape can lead to a misspecification problem (Bierens and Pott-Buter 1991). TVEM avoids the misspecification problem by uncovering the true shape coefficient from the longitudinal data rather than prespecifying the shapes (Leeflang et al. 2009). We can express TVEM with a single time-varying covariate (i.e., advertising) as below:

$$Sales_{ij} = \beta_0\left(t_{ij}\right) + \beta_1\left(t_{ij}\right) \cdot X_{ij} + \varepsilon_{ij} \qquad (3)$$

where the random error ε_{ij} is assumed to be normally and independently distributed. The intercept function $\beta_0(t_{ij})$ represents the mean trajectory of sales at time t_{ij}, and the slope function, $\beta_1(t_{ij})$, describes the time-varying relationship between the marketing effort and sales. Both the intercept and slope parameters have different estimates at different points in time and revealing the true shape of coefficient over time.

Model estimation

We estimate the unknown coefficient functions of $\beta_0(t_{ij})$ and $\beta_1(t_{ij})$ in Eq. (3) using regression splines, which is a semiparameteric regression model with P-spline smoothing method. A semiparametric model is a partly parametric model that incorporates the flexibility of a nonparametric model (Leeflang et al. 2000; Wand 2003). When there is uncertainty about the functional form and the shape of the relationships between the outcome variable and the covariates, we can estimate the unknown coefficients nonparametrically. The flexibility in semiparametric models prevents misspecification and biased results (Wu and Zhang 2006). The smoothing methods are commonly used to estimate the unknown coefficients nonparametrically. Among the smoothing techniques, such as local polynomial kernels, regression splines, smoothing splines, and penalized splines (see Wu and Zhang 2006, and Ruppert et al. 2003 for details of different smoothing methods), we select the P-spline method (Ruppert et al. 2003) due to its flexibility and efficiency in computation process (Tan et al. 2012). Moreover, the P-spline method has been used in marketing (e.g., Sloot et al. 2006; Stremersch and Lemmens 2009).

The P-spline method is advantageous because it shows no boundary effects and fits the polynomial data well. Moreover, it is computed easily with standard software (Tan et al. 2012). These properties of P-spline allow TVEM to assume that the relationship between the covariate (i.e., marketing actions) and the outcome (i.e., sales) to change in a smooth function without imposing the parametric constraints. The basic idea of P-spline is that the smoothly varying unknown functions are approximated with lower q^{th} order piecewise polynomial functions, referred to as splines. Rather than approximating the whole observation periods ($t = 1$ to J) with a high-order polynomial interpolation and a suffer from Runge's phenomenon,[1] we partition the observation periods to smaller intervals and approximate each spline. The entire observation period is divided into several equally spaced $K + 1$ intervals, where K is the split between intervals commonly referred to as knots or truncated points, τ_k ($k = 1, \ldots, K$) (Stremersch and Lemmens 2009). Each spline has continuous derivatives of orders 1, …, q-1, at the knot. By increasing the number of intervals where each spline is estimated, TVEM can flexibly capture sudden changes in sales (i.e., macroeconomic factors or sudden shift in customer preferences) on sales. We can parametrize the set of splines at given knots (τ_k) using the truncated power basis (Tan et al. 2012; Wand 2003). Hence, a q^{th} order polynomial spline and K knots $\tau_1, \ldots, \tau_K$ can be written as the $q + 1$ power functions of t: $1, t, t^2, t^3, \ldots, t^q$, and the K functions of truncated power functions of order q with K distinct knots at τ_1,

[1] Runge's phenomenon states that when using higher-order polynomials for approximation, the interpolated polynomial will oscillate strongly at the boundaries of an interval and increase in error between the original function and the approximation (De Boor 2001).

.., τ_k : $(t-\tau_1)^q_+$, $(t-\tau_2)^q_+$, $(t-\tau_3)^q_+$, …, $(t-\tau_k)^q_+$. The $(t-\tau_k)^q_+$ denotes that the q[th] degree truncated power function equals to zero if $t \le \tau_k$ and takes on the value $(t-\tau_k)^q$, otherwise.

Specifying the order of piecewise polynomial function We can specify the order of piecewise polynomial function as linear, quadratic,[2] or cubic (Tan et al. 2012). A cubic spline (q = 3) is commonly used in functional data analysis because piecewise cubic functions have continuous first and second derivatives allowing the splines around the knot to be smooth (Fox 2000). Moreover, the cubic splines method has been used in the marketing literature for its usefulness to understand the time-varying effect on sales (Sloot et al. 2006; Stremersch and Lemmens 2009). Hence, we select the cubic splines to specify the unknown time-varying coefficient functions, $\beta_0(t)$ and $\beta_1(t)$, from Eq. (3) as:

$$\beta_0(t) = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \alpha_3 t^3 + \sum_{k=1}^{K} \alpha_{3+k} (t-\tau_k)^3_+ \tag{4a}$$

$$\beta_1(t) = b_0 + b_1 t + b_2 t^2 + b_3 t^3 + \sum_{k=1}^{K} b_{3+k} (t-\tau_k)^3_+ \tag{4b}$$

Replacing the unknown coefficient functions Eq. (3) with Eqs. (4a) and (4b), we get:

$$Sales_{ij} = \alpha_0 + \alpha_1 t_{ij} + \alpha_2 t_{ij}^2 + \alpha_3 t_{ij}^3 + \sum_{k=1}^{K} \alpha_{3+k} \left(t_{ij}-\tau_k\right)^3_+ + b_0 X_{ij} + b_1 t_{ij} X_{ij} + b_2 t_{ij}^2 X_{ij} + b_3 t_{ij}^3 X_{ij} + \sum_{k=1}^{K} b_{3+k} \left(t_{ij}-\tau_k\right)^3_+ X_{ij} + \varepsilon_{ij} \tag{5}$$

Selecting the optimal number of knots There is no common guideline for selecting the number and the placement of knots. In fact, the subjectivity in selecting the number of knots is one of the drawbacks of splines (Walls and Schafer 2005). The P-splines approach recommends selecting a sufficiently large K knots to fit the N number of available observations because using a few number of knots may make the model too restrictive and using too many knots may result in estimation problems and show highly nonlinear behavior (Sloot et al. 2006). In our application, we select 12 knots distributed evenly across the observation period of three years. We do not find much merit in increasing the number of knots and find K = 12 as a sufficient number of knots to cover the time range. As recommended by Tan et al. (2012), we select the optimal number of knots based on the smallest Akaike Information Criterion (AIC) values of the fitted model.[3]

Smoothing with penalty parameters The sales equation in Eq. (5) can be estimated with ordinary least squares (OLS). Yet, fitting with OLS makes the curves less smooth and creates fluctuating results, especially when the numbers of knots are large and there are many splines to be fit (Wand 2003). In order to prevent overfitting, P-spline method allows the coefficients of truncated power functions (i.e., $\sum_{k=1}^{K} \alpha_{3+k}$ and $\sum_{k=1}^{K} b_{3+k}$, k = 1,…, K) to act as penalty coefficients.[4] By treating the penalty parameters as random effects, we can estimate Eq. (5) as a linear mixed model (Verbeke and Molenberghs 2000). Linear mixed models are easily computed across multiple platforms (e.g., PROC MIXED in SAS, lme/ nlme in R or S-Plus) making the P-spline estimation approach very appealing.

Research methodology

Data

We obtained data from a nationwide CPG company that produces and distributes ice-cream in the US.[5] The data consists of nationwide sales data of the firm's top six brands during the observation period of three years (2010 to 2013). Our data is at a weekly level, allowing our sales and marketing-mix information to span across 156 weeks. We do not aggregate the data to larger time intervals to preserve the richness of information at a shorter time interval.[6] We obtained the following data from the company corresponding to the 3-year period:

Sales Our weekly sales information is available for six brands across five distribution channels. The firm follows a mixed branding strategy, where both the corporate name and its subsidiary brand names have strong brand value (Rao et al. 2004). The products are distributed in grocery

[2] A quadratic spline (q = 2) has a continuous first derivative and its second derivative is a step function (Walls and Schafer 2005).

[3] We find that our results are highly robust to the selection of number of knots. We have conducted the analysis with different number of knots ranging from 5 to 35 and found that the results are very similar but K = 12 provides the best fit with the lowest AIC.

[4] Wand (2003) recommends treating the coefficients of truncated power functions as random variables with normal distributions, subject to the constraint that these penalty coefficients have finite variance, where $\alpha_{3+k} \sim N(0, \eta_1)$ and $b_{3+k} \sim N(0, \eta_2)$, k = 1,…,K. The finite variance constraint allows the variance parameters, η_1 and η_2, to shrink the penalty coefficients to zero and provide optimal degree of smoothness (Stremersch and Lemmens 2009). We can use the restricted maximum likelihood (REML) estimates of the variance parameters (Wand 2003).

[5] We do not reveal the name of the company due to preserving the confidential agreement.

[6] We find that the weekly level analysis is more robust than at aggregated monthly or yearly level analysis.

chains, convenience stores, and retail stores. Our sales data is specified for five grocery chains. Hence, we have 30 combinations of brand sales across different chain stores.

Social media The company has a big presence in social media such as Facebook, where the firm posts information about its brand and products and engages with its current and potential customers. Social media data contains the total social media impressions values from Facebook. The impressions assess the overall exposure of the brand to Facebook users (Facebook 2015).

Traditional marketing The focal company also relies on traditional marketing to increase awareness and to encourage product trial. For television advertising, we use the weekly Nielsen television rating data for each brand during the observation period measured in gross rating points (GRP). The firm regularly conducts sampling events and in-store promotion to increase sales. The company has product demonstration and taste sampling events usually during the peak seasons. In-store promotion expenses are composed of weekly marketing cost of price promotion coupons (i.e., $1 off any one unit) and cross promotions such as BOGO.[7]

Control variables We included price, brand dummy, and distribution channel dummy as control variables. We control for seasonality by including a seasonal dummy during peak seasons because ice-creams sales exhibit a strong trend of seasonality. We obtained the average price for each brand at a specific distribution channel and used the inflation-adjusted prices in our analysis.[8] Table 2 provides descriptive statistics of the key variables used in our analyses.

Model specification

Similar to prior studies that studied the marketing-mix effectiveness, we adopt a log-log formulation and log-transformed the outcome variable and marketing variables (e.g., Danaher et al. 2008; Hanssens et al. 2011; Du et al. 2015). In order to avoid taking a log a zero, we added a small constant of 1 before taking the log-transformation, for variables that have a minimum value of zero. Expanding from Eq. (3), we include the covariates specific to our research interest and specify the final model as:

$$\begin{aligned}\ln\left(Sale_{ij}\right) &= \beta_0\left(t_{ij}\right) + \beta_1\left(t_{ij}\right)\ln\left(1+Social\ Media_{ij}\right)\\ &+ \beta_2\left(t_{ij}\right)\ln\left(1+TV_{ij}\right) + \beta_3\left(t_{ij}\right)Sampling_{ij}\\ &+ \beta_4\left(t_{ij}\right)\ln\left(1+Instore_{ij}\right)\\ &+ \beta_5\left(t_{ij}\right)\ln(1+(Social\ Media\times TV))_{ij}\\ &+ \beta_6\left(t_{ij}\right)\ln(1+(Social\ Media\times Sampling))_{ij}\\ &+ \beta_7\left(t_{ij}\right)\ln(1+(Social\ Media\times Instore))_{ij}\\ &+ \beta_8\left(t_{ij}\right)\ln(1+(TV\times Sampling))_{ij}\\ &+ \beta_9\left(t_{ij}\right)\ln(1+(TV\times Instore))_{ij}\\ &+ \beta_{10}\left(t_{ij}\right)\ln(1+(Sampling\times Instore))_{ij} + \delta X_{ij} + \varepsilon_{ij} \quad (6)\end{aligned}$$

Where

$\ln(Sales_{ij})$	log of sales for the i^{th} combinations of brand and distribution channel at time j
$\ln(1+Social\ Media_{ij})$	log of social media impression for the i^{th} combinations of brand and distribution channel at time j
$\ln(1+TV_{ij})$	log of television GRP for the i^{th} combinations of brand and distribution channel at time j
$Sampling_{ij}$	Product Sampling indicator for the i^{th} combinations of brand and distribution channel at time j
$\ln(1+Instore_{ij})$	log of in-store promotion expenses for the i^{th} combinations of brand and distribution channel at time j
$\ln(1+(Social\ Media\times TV))_{ij}$	log of interaction variable of social media impression and television GRP for the i^{th} combinations of brand and distribution channel at time j
$\ln(1+(Social\ Media\times Sampling))_{ij}$	log of interaction variable of social media impression and product sampling for the i^{th} combinations of brand and distribution channel at time j
$\ln(1+(Social\ Media\times Instore))_{ij}$	log of interaction variable of social media impression and in-store promotion for the i^{th} combinations of brand and distribution channel at time j
$\ln(1+(TV\times Sampling))_{ij}$	log of interaction variable of television GRP and product

[7] Since in-store promotion does not include the cost of product sampling events and product sampling is conducted only a few weeks in year, we do not find multicollinearity between these two variables.

[8] We find little variation in price across time, brand, and distribution channels; therefore, we do not include price as a main variable in our time-varying effect analysis.

Table 2 Descriptive statistics

	Mean	SD	Correlation				
			1	2	3	4	5
Sales	128,621	140,465	1				
Social media							
Facebook impressions	3,028,254	2,983,436	0.165	1			
Traditional marketing							
Television advertising	1.85	4.06	0.113	0.379	1		
Product sampling	0.164	0.371	0.193	0.383	0.274	1	
In-store promotion	1010	1714	0.377	0.295	0.170	0.245	1

Sales and in-store promotion are in dollars ($); Facebook impression is measured in units; Television advertising indicates the average weekly GRP; product sampling is a dummy variable

	sampling for the ith combinations of brand and distribution channel at time j
$\ln(1 + (TV \times Instore))_{ij}$	log of interaction variable of television GRP and in-store promotion for the ith combinations of brand and distribution channel at time j
$\ln(1 + (Sampling \times Instore))_{ij}$	log of interaction variable of product sampling and in-store promotion for the ith combinations of brand and distribution channel at time j
X_{ij}	vector of control variables such as product price, brand, distribution, and seasonality.
$\beta(.)$	time-varying parameters to be estimated
δ	time-constant parameters to be estimated
ε_{it}	normally and independently distributed random error term

Our proposed model focuses on the time-varying effects of social media and the time-varying synergistic effects between social media and traditional marketing. Equation (6) also includes the time-varying effectiveness of traditional marketing and the synergistic effects among traditional marketing to reflect our conceptualization.[9]

We provide model comparisons in order to validate the benefit of including time-varying parameters in the sales response model. The two benchmark models are: (a) baseline model with no time-varying effects and (b) the monotonic time-varying parameter coefficient model (Kumar et al. 2011), which assumes the coefficients of marketing to be in a linear function of time.

Modeling challenges

To investigate the relationship between the marketing media and brand sales, we need to address the issues of endogeneity and carryover effects of advertising that can potentially bias the parameter estimates in a demand model. We discuss each issue in the following section:

Endogeneity This may occur from the fact that advertising decisions are likely to be a nonrandom decision of the firm. Since managers can adjust the television advertising, in-store promotion expenses, and the number of FGC on social media of each brand based on the performance of the brand, the endogeneity problem may arise and bias the parameter estimates in Eq. (6). For potentially endogenous variables such as television advertising, in-store promotion, and social media, we use the instrumental variable (IV) approach and attempt to use the relevant IVs that correlate with the media decisions but not respective to the error term of the equation.[10] Similar to Kumar et al. (2015), we use the firm's own brand sales and media variables as instruments, which satisfy the relevance and the exclusion criteria. The managers observe the growth in sales in the previous periods and determine the level of

[9] In our robustness check, we explored the benefit of allowing all parameters to vary over time; however, we only found a slight improvement in the model fit and prediction at the cost of degrees of freedom. In this study, we are more interested in managerially controllable marketing variable that has high financial benefits. Hence, we do not specify the parameters of control variables, denoted as δ, as time varying.

[10] We do not use the IV approach for product sampling and price for the following reasons: Product sampling typically occurs in the beginning of the season, and we capture that effect by including seasonality as a control variable. The focal firm does not change the price of their products much. Due to the lack of variation in price, we do not account for endogeneity issue.

advertising efforts for the current period. We can also include the growth of the endogenous variable to capture the changing trends of the media. Since our data is at the weekly level, we include the change in sales and the focal endogenous media in the previous two months as instruments. With the aforementioned instruments, we adopt the control function methodology in order to account for endogeneity (Petrin and Train 2010). To correct for endogeneity, we include the endogeneity correction residuals in Eq. (6).

Advertising carryover effect The dynamic market response models need to account for the carryover effects of marketing, where the current expenditures on marketing may have lagged effects on future sales. Then the past marketing efforts can be represented as a stock variable rather than as a lagged variable (Hanssens et al. 2011). Hence, similar to Danaher et al. (2008), we use the Adstock variable to model the carryover effects of television advertising on brand sales. The Adstock variable is especially useful for television advertising due to its dynamic and diminishing returns on brand sales (Broadbent 1979). We smooth the television rating data exponentially, by taking a geometric weighted average of the advertising in the current period and the Adstock variable in the previous period: $AdStock_{ij} = \delta AdStock_{ij-1} + (1-\delta)\ln(1 + TV_{ij})$, where the smoothing parameters δ is bounded between 0 and 1. Thus, we replace the TV_{ij} variable in Eq. (6) with the Adstock variable in order to handle the advertising carryover effects.

Unlike television advertising, which has an extended effect on future sales, in-store promotions are most effective during the period when the deal is effective and have much lower carryover effects in the later periods (Cotton and Babb 1978). We expect even lower carryover effects for product sampling because product trial especially in the food category is instantaneous. Consequently, we do not replace the $Sampling_{ij}$ and $In\text{-}store_{ij}$ variables in Eq. (6) with Adstock variables.

Results

In this section, we provide the model fit comparison of our proposed model against the two benchmark models, and analyze the time-varying parameter estimates of our model.

Model fit

We compare the model fit of our proposed TVEM model (Eq. 6) with respect to alternative models: (a) baseline model with no time-varying effects and (b) monotonic time-varying parameter model.[11] For time-varying parameters, (t_{ij}), we select the 12 knots distributed evenly across the observation period of 156 weeks, and estimate the coefficient functions of the intercept and slopes. In Table 3, we evaluate the model fit by comparing the AIC values.

Our results indicate that incorporating the temporal changes in the marketing actions improves the model fit. Compared to the baseline model without time-varying effects (AIC = 6999.24), the monotonic time-varying parameter model has a lower the AIC value and a better model fit (AIC = 6349.70). This result alone provides evidence that just allowing the regression coefficients to be linear functions of discrete times is able to explain the dynamics of sale better. The time-varying coefficients can potentially capture the impact of changes in external factors (e.g., environmental factors or product attractiveness) on sales (Du et al. 2015; Leeflang et al. 2009). Our proposed TVEM model allows the intercept, and the main and synergistic effects of the marketing efforts to vary over time, in a non-monotonic way. Our proposed model provides the best model fit with the lowest AIC of 5821.20 Table 4.

Parameter estimates

Benchmark 1: baseline model without time-varying effects The time-invariant log-log model results suggest that social media has a positive and significant static effect on brand sales (β=0.088, $p < 0.01$). The positive impact of social media on brand sales has been expected based on the results from prior studies (e.g., de Vries et al. 2012).

Similarly, we find that the relative impact of social media is more than four times greater than the effect of television advertising on sales. This finding is consistent with the business reports, which claim that CPG firms find social media and digital marketing to be more effective than mass media marketing (e.g., Neff 2014). The traditional marketing variables have significant and positive effects on brand sales.[12] We find the elasticities of product sampling demonstrations (β=0.697, $p < 0.01$) and in-store promotion deals (β=0.878, $p < 0.01$) to be greater in improving brand sales compared to television advertising which has lower elasticities (β=0.021, $p < 0.10$). This implies that the mass marketing efforts, such as television advertising, are less effective than targeted marketing efforts,

[11] As described in Kumar et al. (2011), we capture the time-varying effect of the marketing variables in a monotonic way. We specify the monotonic time-varying coefficient as: $(t_{ij})_{monotonic} = \beta_0 + \beta_1 * t$, which assumes the coefficients of marketing to be in a linear function of time. We compared the model fit with other functional forms of t and found the linear form of t to provide the best model fit.

[12] We found the interaction variables among different traditional marketing to be insignificant. Consequently, we do not include those in our reporting of results.

Table 3 Model fit comparison

Model	AIC
Baseline model with no time-varying effects	6999.24
Monotonic time-varying parameter model	6349.70
Time-varying effect model (TVEM)	5841.20

Table 4 Parameter estimates of the baseline model without time-varying effects

Independent variables	Estimate	t-value	
Intercept	8.781	29.42	***
Social Media	0.088	4.79	***
TV Advertising	0.021	1.68	*
Product Sampling	0.697	12.52	***
In-store Promotion	0.878	7.47	***
Social Media × TV	0.028	0.40	
Social Media × Sampling	0.172	1.92	*
Social Media × Instore	0.257	3.25	***
Season	0.029	2.05	**
Price	−1.331	−24.21	***
Brand 1	−0.524	−30.53	***
Brand 2	0.298	19.07	***
Brand 3	0.206	13.19	***
Brand 4	−0.224	−10.47	***
Brand 5	0.032	2.18	**
Chanel 1	1.310	34.75	***
Chanel 2	2.907	75.79	***
Chanel 3	2.516	71.23	***
Chanel 4	0.741	19.43	***
Endogeneity correction residual (TV)	0.034	1.78	*
Endogeneity correction residual (In-store Promotion)	−0.024	−3.46	***
Endogeneity correction residual (Social Media)	−0.033	−1.81	*

The interaction variables among traditional marketing were insignificant, and we do not include those in our reporting of results

*$p<0.10$; ** $p<0.05$; *** $p<0.01$

such as product sampling and in-store promotions (Hlavinka and Gomez 2007).

The interaction terms explain the synergistic effect of social media and traditional marketing on brand sales. Our result suggests that the synergy between television advertising and social media is positive but insignificant for brand sales (β=0.028, $p>0.10$). On the other hand, social media has positive and significant synergistic effects with product sampling (β=0.172, $p<0.10$) and in-store promotion (β=0.257, $p<0.01$) on sales, respectively. As for the control variables, we find all of them significant. Finally, the endogeneity correction residuals are all significant.

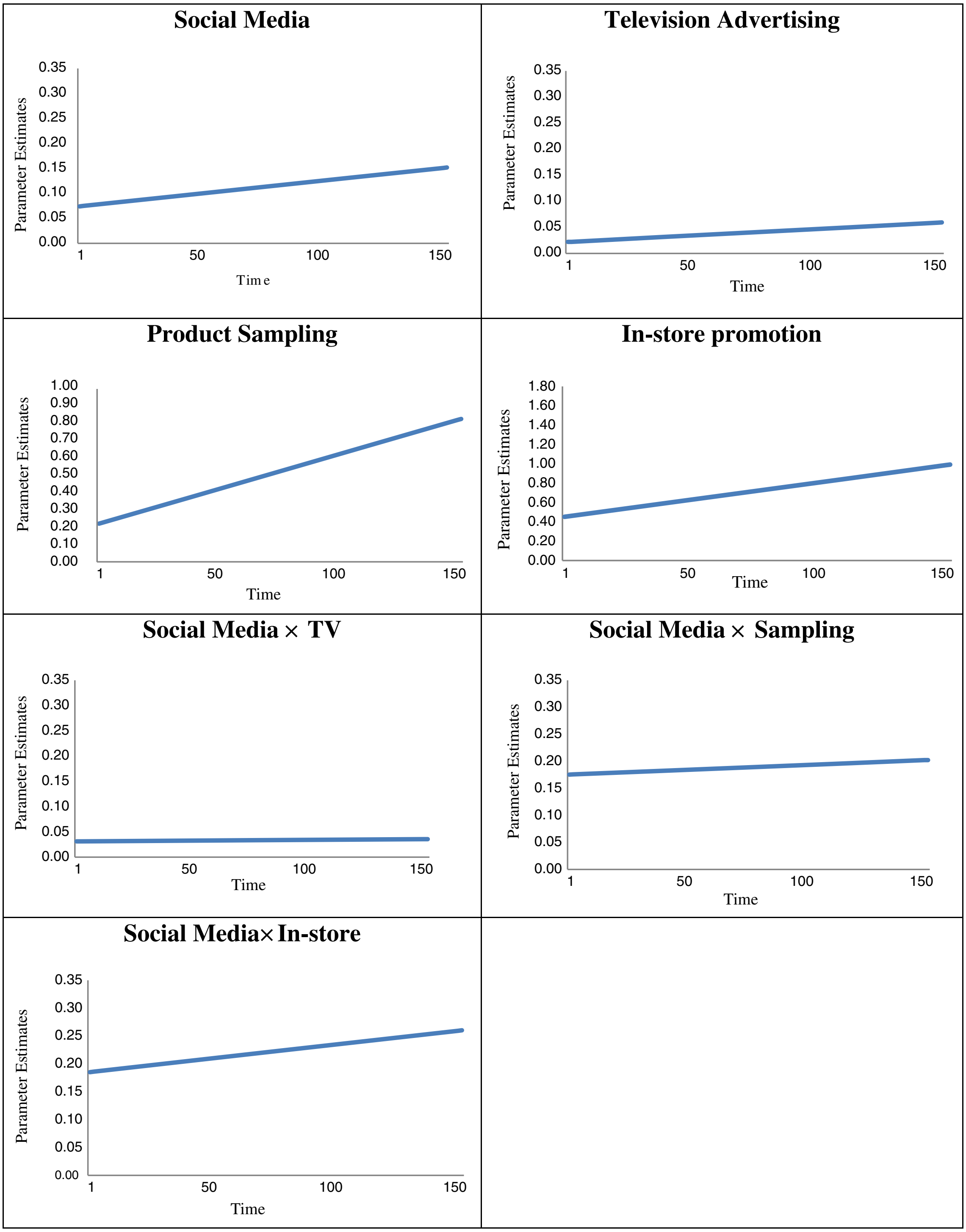
Benchmark 2: monotonic time-varying parameter model We find that the marketing effects (both main and synergistic) on sales change over time, in a linear form (see Fig. 2). Although the insights from these plots are valuable, the effect of marketing cannot increase over time eternally. Moreover, the monotonic time-varying parameter model imposes a strong parametric assumption of a linear change in the relationship between two covariates over time. Therefore, capturing the temporal change of the effectiveness in a flexible functional form is beneficial to understand the true relationship between the marketing actions and brand sales.

Proposed model: time-varying effect model We indeed find that the effects of social media, traditional marketing, and the synergy vary over time in a nonlinear pattern, where we see the increases as well as the decreases in the effect sizes over time (see Fig. 3). For example, compared to the linear effect of the horizontal synergy between social media and product sampling in monotonic model, TVEM approach finds that the relationship is in fact U-shaped.

H1 proposes that the effectiveness of social media on brand sales to vary over time. As illustrated in Fig. 3, we find that the effect of social media varies at an increasing rate in a nonlinear pattern. Compared to the coefficient of social media from the baseline model without the time-varying effect (β=0.088, $p<0.01$), the TVEM suggests that the parameter estimates of social media increases to β=0.20 at the end of the time horizon.

We present the time-varying synergistic effects of social media and traditional marketing in Fig. 3. The synergy between social media and television advertising is mostly flat and does not vary with time. Thus, H2a is not supported. However, we observe the time-varying synergistic effects of social media and product sampling, and effect of social media and in-store promotions. Therefore, H2b and H2c are supported. These results suggest that the synergistic effects of social media on the relationship between more timely marketing efforts (i.e., product sampling and in-store promotions) on brand sales vary over time while there is no synergistic effect of social media and mass marketing communications (i.e., television advertising) on brand sales. Since social media increases brand exposures and allows firms to engage more with its target customers (Evans 2010), the social media users are probably more responsive to a more timely marketing efforts, such as free samples and promotions.

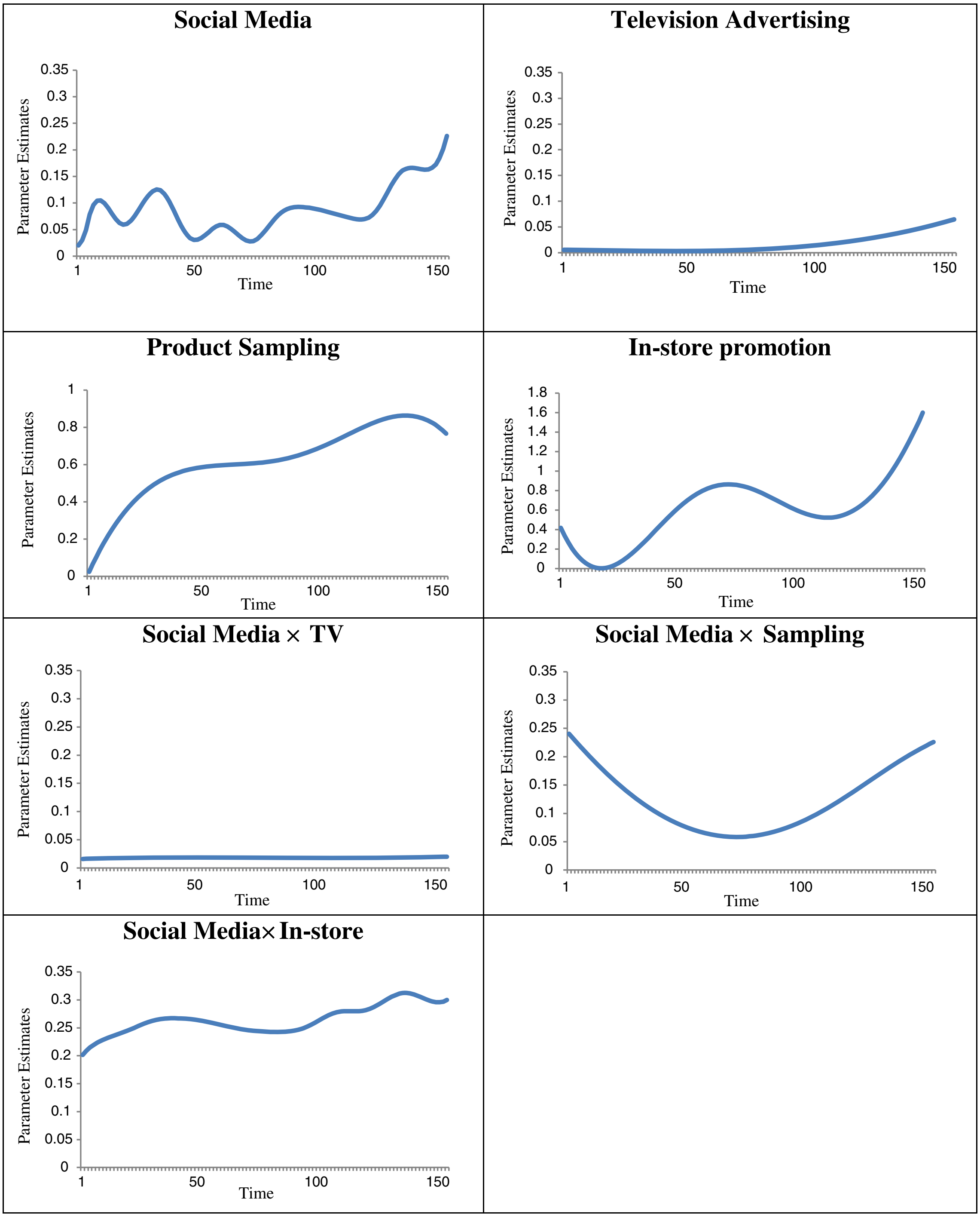
Consistent with the findings from Srinivasan et al. (2015), we also find that television advertising has a positive effect on sales. The effectiveness of television is increasing at an increasing rate in the observation period rather than staying constant over time or increasing in a linear pattern. Thus, a time-varying effect of television advertising on sales supports G1. We also find support



Note: The interaction variables among traditional marketing were insignificant, and we do not include those in our reporting of results.

Fig. 2 Parameter estimates of monotonic time-varying parameter model

for G2 and G3, where the effectiveness of product sampling and in-store promotion vary over time. For product sampling, the parameter estimates are positive, but the rate of increases in the effectiveness changes over time. This finding is consistent with prior literature that studied the positive effects of product sampling on brand sales (Bawa and Shoemaker 2004), although, we extend the findings by validating the time-varying effectiveness of



Note: The interaction variables among traditional marketing were insignificant, and we do not include those in our reporting of results.

Fig. 3 Parameter estimates of time-varying effect model (TVEM)

product sampling. Similarly, the effectiveness of in-store promotion on sales is consistently positive, consistent with the findings from the baseline time-invariant model. Yet, we find that the parameter exhibits a non-linear pattern of both increasing and decreasing trends. This can result from an increase in the number of competitive brands' promotions occurring simultaneously with the focal brand (Burke and Srull 1988; Rapperport 2015).

Similar to the static baseline model, the time-varying parameter of television advertising is less than the product sampling and in-store promotion. Product sampling and in-store promotions resonate better with the target audience, compared to a mass-marketing effort, like television advertising and have great effects on sales (Hlavinka and Gomez 2007). We also find support for G4a-G4c. However, the interaction variables among traditional marketing vary over time enveloping the zero value, suggesting that these variables are not significantly different from zero (similar to the benchmark model results).

Predictive accuracy

We compare the predictive accuracy of our proposed TVEM against the two alternatives (time-invariant baseline model and monotonic time-varying parameter model) by evaluating both the in-sample and out-of-sample fits. We assess the predictive performance of the models by measuring the relative absolute error (RAE). RAE is a ratio between the absolute error from the proposed model over the absolute error of the naïve model, which is the baseline model without the time-varying effect (Kumar et al. 1995).[13] For in-sample prediction, we forecast the weekly sales of all 3 years. For the out-of-sample prediction, we use the first 140 weeks of data as our estimation period in order to determine the coefficients of the covariates. We then use this information to predict the sales of for the holdout period of 16 weeks (i.e., 141 through 156 weeks). We present the RAE of the monotonic time-varying parameter model and our proposed TVEM approach for both the in-sample and out-of-sample fit in Table 5.

We observe that both monotonic time-varying parameter and TVEM models produce RAE less than 1, suggesting that both models are superior to the time-invariant baseline model. The monotonic time-varying parameter model has both in-sample and out-of-sample RAE of 0.90 and 0.73, respectively. This reduction in error suggests that a large portion of dynamics in sales is not explained by the time-invariant parameters. We observe that our proposed TVEM method, which allows the social media, traditional marketing, and synergistic effects to vary over time, exhibits the best model fit with the lowest RAE (with in-sample 0.59 and out-of-sample 0.65). These results suggest that TVEM predicts 41% and 35% better than the naïve model, for in-sample and out-of-sample respectively. Such a remarkable improvement in fit indicates that allowing marketing efforts to vary over non-linear continuous functions of time predicts sales better. Hence, the strong predictive power of TVEM provides support for the importance of incorporating the time-varying effects of marketing to explain the dynamics in sales.

[13] RAE ranges from 0 to 1 if the proposed model performed same or better than the naïve approach. If RAE closer to 1 suggests that the focal model performed very similar to the naïve prediction. While, RAE farther from 1 indicates that the focal model predicted much better than the naïve model (Kumar et al. 1995).

Table 5 Model comparison on predictive accuracy

Goodness-of-Fit (RAE)	Monotonic time-varying parameter	Time-varying effect model (TVEM)
In-sample	0.90	0.59
Out-of-sample	0.73	0.65

RAE is calculated by dividing the absolute deviation for the given model by the corresponding effect for the naïve model; we use the time-invariant baseline model as the naïve model

RAE relative absolute error

Discussion and implications

Implications for academics

While most research has focused on social media or the marketing-mix effectiveness, little work has taken a holistic perspective of the time-varying effectiveness of social media along with traditional marketing. In order to build on this research stream, we empirically investigate the time-varying effects of social media, traditional marketing, and their synergistic effects on brand performance. It is important to frequently reallocate resources in response to a dynamic external environment (Fruk et al. 2013; Saboo et al. 2016). Employing the TVEM approach, our findings show that the effectiveness of social media and traditional marketing on brand sales vary over time. Moreover, we find that the synergistic effects between social media and traditional marketing (except for television advertising) indeed vary over time in a curvelinear pattern. Empirical applications of measuring the effect of social media on brand performance are still very limited let alone the time-varying efforts.

Implications for marketing practices

Managers are under pressure to improve the accountability of their resources spent on marketing media. We propose using the TVEM approach to not only better understand the changing effectiveness but also to obtain guidance in resource allocation decisions. In other words, the TVEM approach accounts for the changing environment and consumer behaviors and constantly updates the change in the effectiveness of marketing on brand performance.

Table 6 Relative marketing elasticity

Marketing	Social Media			Television Advertisement			Product Sampling			In-store Promotion			Social media ×TV			Social media ×Sampling			Social media ×In-store		
	50[a]	100	150	50	100	150	50	100	150	50	100	150	50	100	150	50	100	150	50	100	150
Social media	N/A	N/A	N/A	28.5	11.0	3.99	0.94	1.33	1.74	0.15	0.24	0.17	4.89	8.39	12.03	1.16	1.76	1.08	0.34	0.58	0.79
Television advertisement	0.03	0.09	0.25	N/A	N/A	N/A	0.03	0.12	0.44	0.01	0.02	0.04	0.17	0.76	3.01	0.04	0.16	0.27	0.01	0.05	0.20
Product sampling	1.06[b]	0.75	0.57	30.4	8.25	2.29	N/A	N/A	N/A	0.16	0.18	0.10	5.20	6.29	6.91	1.24	1.32	0.62	0.36	0.43	0.45
In-store promotion	6.46	4.17	5.84	185	45.9	23.3	6.07	5.56	10.1	N/A	N/A	N/A	31.6	35.0	70.2	7.51	7.34	6.29	2.21	2.41	4.59
Social media × TV	0.20	0.12	0.08	5.84	1.31	0.33	0.19	0.16	0.14	0.03	0.03	0.01	N/A	N/A	N/A	0.24	0.21	0.09	0.07	0.07	0.07
Social media × sampling	0.86	0.57	0.93	24.6	6.25	3.70	0.81	0.76	1.61	0.13	0.14	0.16	4.21	4.76	11.16	N/A	N/A	N/A	0.29	0.33	0.73
Social media × in-store	2.92	1.73	1.27	83.4	19.0	5.07	2.75	2.30	2.21	0.45	0.41	0.22	14.3	14.5	15.3	3.39	3.04	1.37	N/A	N/A	N/A

[a] In weeks

[b] Ratio of elasticity of product sampling over social media

Relative marketing elasticity[14] Do managers really need to actively reallocate their resources on multiple marketing media? We motivate the need to frequently update the resource allocation decisions (Fruk et al. 2013), by comparing the relative marketing elasticities of the time-varying marketing variables across three time points in our observation periods. Based on the results from our TVEM analysis, we present a mixture of relative marketing elasticities, at week 50, 100, and 150. Each value represents the ratio of elasticities of two marketing variables. For example, we find that in week 50, the elasticity of product sampling is 1.06 times greater than that of the social media. Yet, we find that the relative elasticity changes to 0.75 in week 100, and 0.57 in week 150. Stated differently, the effectiveness of social media relative to product sampling increases over time, while the elasticity of free samples relative to social media decreases. As illustrated in Table 6, the relative marketing elasticity between time-varying marketing variables are not constant across the three time periods. In fact, the relative elasticity changes (both increase and decrease), in response to the time-varying effectiveness of each marketing efforts. Managers should acknowledge that the marketing effectiveness varies over time and use the proposed TVEM approach in order to better allocate their marketing resources to the most effective media.

Optimal resource allocation In this study, we find a higher prediction accuracy for our proposed TVEM approach, which demonstrates the importance of the most recent impact of marketing on brand performance. Thus, allocating marketing resources in a dynamic manner based on the most recent observed effect of marketing is necessary for managers. We quantify the savings in marketing costs, by comparing the most recent elasticities from the proposed TVEM approach to the static model elasticities from the baseline model. Specific to our research context, we find that the focal firm can save more than $0.4 million dollars a year in television advertising and in-store promotions yet maximize sales, ceteris paribus.[15] Moreover, we compare the impact of increase in social media impressions between the baseline and the proposed models. We also quantify the impact of more exposure and reach of the firm generated content in social media on brand sales.[16] Compared to using the parameter estimate (β =0.088) from the baseline model, the last parameter estimate from TVEM approach (β =0.286) represents the most recent impact of social media on sales. We find that on

[14] We thank the area editor for recommending the relative marketing elasticity analysis.

[15] We obtained an estimated cost for increasing television GRP from the company representative. In our hypothetical analysis, we have used the average price of $20,000 for 1 GRP per week for three exposures of 20 weeks of television advertisements per year.

[16] We present the benefit on sales instead because we do not know the cost of social media impressions to compute cost savings.

average, the 10% increase in social media impressions increases sales by \$133 per week with the baseline model and by \$498 each week with the TVEM approach. These results highlight the importance of gaining insights on the updated effectiveness of marketing actions in order to better understand the implications on sales and to efficiently allocate marketing resources accordingly.

Conclusion and future directions

In summary, to the best of our knowledge, this is the first study that demonstrates the time-varying effects of the new media (i.e., social media), traditional media, and the time-varying synergistic effects of both using the TVEM approach. The TVEM approach can not only easily be estimated with standard statistical packages but also uncover the true underlying relationship between the marketing actions and brand performance. We hope this research encourages both the managers and the researchers to apply TVEM in their business and research scenarios to better understand and capture the time-varying effectiveness of marketing investments.

Although our study contributes to the marketing literature and practice, it has a few limitations. While we use a unique comprehensive data set with social media impression values and sales data at the weekly level, we are limited to using only one source of social media platform. Future research can explore the impact of social media impressions on brand performance for different platforms such as Instagram and Twitter. Although it is difficult to obtain weekly level competitor marketing information, as well as information about other external factors, future research can capture the time-varying marketing, effects after accounting for competitors' activities. Another opportunity for future research lies in understanding the time-varying effectiveness of mobile marketing.

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