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Measuring the Relative Effectiveness of Specific Advertising Channels for a Retailer Predominately Selling Offline

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Abstract

The current marketing environment is characterized by a steady increase in new media and changing media usage patterns. This situation requires firms to understand the interactions between diverse online and offline advertising channels and their impact on multichannel sales. This study investigates the presence, magnitude, and carryover of cross-channel effects for online advertising (emails, online banner ads, and paid search advertising) and offline advertising (TV and aggregated traditional advertising) on multichannel sales. The analysis considers how these advertising expenditures translate directly into sales, and indirectly through mediators (search click-throughs and online banner click-throughs) – thereby enabling offline advertising to be credited for their ability to enhance online advertising's effectiveness.

We apply a vector autoregressive (VAR) model to data from a Norwegian florist predominately selling through the offline channel to study the effects. We find that cross-channel effects and indirect effects are substantial and essential. Indeed, cross-channel elasticities are larger than own-channel elasticities. The result is primarily due to strong cross-channel effects on the offline channel. Online advertising, and in particular, paid search advertising is more effective than offline advertising. In sum, our research suggests that retailers predominately selling offline can benefit from online advertising. Furthermore, ignoring cross-channel effects and endogeneity in advertising channels can lead to a substantial miscalculation of online advertising's effectiveness.

Keywords: advertising elasticity, paid search advertising, online banner advertising, email advertising, offline advertising, cross-channel effects, synergies, vector autoregressive (VAR) model

Disclaimer

The provided data set has been used in a previous master thesis (see Jensen & Bakken, 2019). However, the thesis had a different research question and methodology, resulting in a different outlook on their paper. Ultimately, we believe that using the same dataset causes neither copyright nor plagiarism issues and that our paper is significantly different from the previous thesis.

Introduction

With the explosion of new media and changing media usage patterns, understanding the interactions between diverse advertising channels is an increasingly challenging task for marketers. For instance, consumers do not necessarily passively receive brand information strictly through traditional media (e.g., TV, radio) but actively seek it as needed through search engines and brand websites (Batra & Keller, 2016). The advent of the online channel offers marketers new tools to effectively reach consumers with targeted information, but also requires them to understand the complex interactions between online and offline media. A critical question for marketers is how advertising channels interact and either amplify or diminish the total impact on sales.

The consumer path to purchase is complex, and multiple communication attempts are usually required to propel consumers toward a purchase. An advertising channel's effectiveness is mediated by its historical performance and the concurrent activity of other advertising channels. Therefore, marketers must consider both what the advertising channel can accomplish in isolation – the direct (main) effect – and how it affects the performance of other channels – indirect effects (Batra & Keller, 2016). In a multichannel setting, it is natural to consider the impact of advertising across channels. For instance, an online advertising campaign is likely to have an own-channel effect on online sales, while simultaneously driving offline sales (cross-channel effect) (Dinner, Van Heerde, & Neslin, 2014).

Altogether, there is a pressing need to utilize more media types and understand the specific mechanisms that drive sales, both short- and long-term. Firms' management often neglects long-term and cross-channel effects, and as a result, their budget allocations are usually decided based on gut feeling or how things have been in the past. There is, therefore, an acute need for an accountable solution to properly allocate the advertising budget across online and offline channels (Wiesel, Pauwels, & Arts, 2011). To make progress in this regard, the relative effectiveness of different advertising channels must be assessed and compared.

This study compares the relative effectiveness of advertising channels (traditional advertising excl. TV, TV, paid search, online banner ads, and emails) in driving online and offline sales while incorporating indirect effects (via click-throughs), lagged responses and cross-channel effects. This study, therefore, addresses these research questions:

What advertising channel exerts the most significant total impact (accounting for cross-channel effects and indirect effects) on online and offline sales, respectively?

Is the relative effectiveness of one advertising channel greater for online sales than offline sales (e.g., is the discrepancy between paid search advertising and the less effective advertising channels greater in the online purchase channel than in the offline)?

Is the total impact of the cross-channel effects greater than the total contribution of own-channel effects?

Will offline advertising amplify (induce synergies) or diminish (serve as an information substitute) the total impact of online advertising on sales?

Existing academic research has provided interesting insights into ways to improve the effectiveness of individual forms of online advertising (e.g., Chatterjee, Hoffman, & Novak, 2003; Ghose & Yang, 2009; Hoban & Bucklin, 2015; Manchanda et al., 2006). However, these studies typically omit offline advertising and are of limited use to managers balancing budgets across multiple advertising forms. Studies confirming the existence of within- and cross-channel synergies among offline and online advertising channels have typically looked at measures other than sales (e.g., Joo et al., 2013), or one purchase channel only (e.g., Danaher & Dagger, 2013; Kalyanam et al., 2018; Lewis & Reiley, 2014). To date, Dinner, Van Heerde, and Neslin (2014) is the only study investigating the own-channel and cross-channel effects of online and offline advertising on both purchase channels. However, the research focuses exclusively on a high-end apparel retailer, and results are likely to deviate across industries, making it difficult to generalize results.

Therefore, our research complements their study by looking at a completely different retailer offering perishable products (flowers), where consumer involvement is likely to be lower. In general, the existing literature provides little guidance on online advertising decisions for firms predominately selling through the offline channel (Lobschat, Osinga, & Reinartz, 2017) and the effect of online advertising on offline sales is, in general, still an understudied field (Batra & Keller, 2016; de Haan, Wiesel, & Pauwels, 2016). To the best of our knowledge, this is the first study for this type of product category that incorporates indirect effects, lagged responses, and cross-channel effects, while comparing the effectiveness of multiple specific channels on both purchase channels.

This paper addresses the research questions and complements the study of Dinner, Van Heerde, and Neslin (2014) by analyzing the advertising expenditures and online data of one of Norway's largest florists through a vector autoregressive model (VAR). The focal firm predominately sells through the offline channel but invests in online advertising channels. Thus, we propose that online advertising will have a positive cross-channel effect on offline sales, in line with the research shopper phenomenon in which the consumer uses one channel for search and another for purchase (see Verhoef, Neslin, & Vroomen, 2007). Such behavior would be rational for consumers of this retailer because consumers prefer to buy through channels where the characteristics are accurately portrayed (e.g., the individual quality of the flowers) (Pauwels et al., 2011).

Our research suggests that the cross-channels effects are larger than the own-channel effects, primarily due to strong cross-channel effects of online advertising on offline sales. In contrast to existing evidence, we find that paid search advertising is the most effective channel in driving long-term sales. For instance, the long-term paid search advertising elasticity is more than 80 times higher than the traditional advertising (excl. TV) offline sales elasticity. Interestingly, this discrepancy in effectiveness between paid search advertising and offline advertising channels is even greater for offline sales than online sales. These results have important implications for marketers balancing advertising budget across various channels, and highlight that firms predominately selling through the offline channel can get a higher return on investments by first propelling consumers to the online channel (even if most purchases still are conducted in a physical store).

Overall, our contribution is threefold. First, we contribute by proposing and testing a conceptual framework of how online advertising interacts with offline advertising in driving the consumer towards a purchase. We establish these causal relations with Granger causality tests and quantify the long-term impact on sales of a change to each advertising channel, based on generalized impulse response functions. We show to what extent an advertising channel contributes to driving sales compared to the other advertising channels while accounting for carryover and spillover effects. We thereby demonstrate that firms predominantly selling through the offline channel can benefit from coordinating online and offline advertising.

As our second contribution, we quantify the total sizes of own-channel and cross-channel effects. We show that much of the impact of online advertising arises from a powerful cross-channel effect on offline sales. Thus, ignoring cross-channel effects can lead to a severe undervaluation of online advertising channels. We also demonstrate that the indirect effects on click-throughs have important implications for the magnitude of the total impact. Even for firms offering mid-involvement, perishable products, the research-shopper phenomenon is highly evident. In sum, these findings suggest that firms predominately selling through the offline channel should allocate a substantial proportion of the advertising budget to online channels and use offline channels to enhance their effectiveness.

Third, we contribute to the emerging body of literature on cross-channel effects by analyzing the impact on multichannel sales. The amount of studies investigating the impact of offline advertising on online sales is still sparse. This study contributes to this research area by analyzing offline advertising's direct impact on online sales and the indirect impact through click-throughs. Accounting for the indirect effects enables offline advertising to be credited for their ability to enhance online advertising’s effectiveness. We contribute to research investigating how online advertising drives offline sales by examining within-synergies and applying data from an industry with little academic attention, thereby making generalizable results.

In total, our research offers an important contribution to the literature. We compare each advertising channel's relative effectiveness in driving sales and account for indirect effects through click-throughs and lagged responses. We demonstrate that these aspects have important implications for the size of the elasticities. For instance, while some advertising channels serve as information substitutes (thereby diminishing the total impact on sales), other channels induce searching and increase click-throughs, thereby amplifying the total impact on sales.

Literature Review

Our research falls within the realm of multichannel marketing and integrated marketing communication. Previous research on the two disciplines has focused on own-channel (e.g., Sethuraman, Tellis, & Briesch, 2011; Trusov, Bucklin, & Pauwels, 2009) and only begun to investigate the cross-channel effects (e.g., Danaher & Dagger, 2013; Dinner, Van Heerde, & Neslin, 2014). Even more limited is research that measures both online and offline cross-channel advertising effects at the sales level. Another gap in the literature is an assessment of the advertising channel's relative effectiveness and how this is dependent upon the simultaneous activity of other advertising channels. Thus, indirect effects and endogeneity in advertising channels and each channel's relative effectiveness will be the main focus of this study. In our analysis of the existing evidence, we start with the known own- and cross-channel effects, and in conclusion, outline the gaps in existing knowledge.

Own-Channel Advertising Effects

The body of literature investigating the impact of offline advertising on offline sales is extensive. The research stream has generated two major meta-analyses (Dinner, Van Heerde, & Neslin, 2014). Assmus, Farley, and Lehmann (1984) provide the first empirical generalizations on advertising elasticity. The researchers found an average short-term elasticity of 0.22 and an average carryover effect of 0.46 in the period 1962-1981. Later, Sethuraman, Tellis, and Briesch (2011) expanded upon the work of Assmus, Farley, and Lehmann (1984) and examined the average elasticities from 56 published studies between 1960 and 2008. In the study, the authors focused on advertising in print, television, and "aggregate" media and found that the average advertising elasticities have decreased substantially over the years (they found an average short-term elasticity of 0.12 and a mean long-term elasticity of 0.24).

The recent advent of the online channel means that research into the effects of online advertising is still sparse – and especially its effects on sales. Manchanda et al. (2006) found exposure to an online banner ad to increase the probability of conducting an online purchase for current consumers with a corresponding elasticity of 0.02. Dinner, Van Heerde, and Neslin (2014) studied the effectiveness of advertising for a high-end apparel retailer and found the total elasticity of online banner ads on online sales to be 0.145 and the elasticity of paid search advertising to be 0.158.

Studies that have investigated the effects of online advertising on online metrics other than sales have provided fruitful insights as well. Chatterjee, Hoffman, and Novak (2003) investigated consumer responses to online banner ads and found significant heterogeneity in click proneness across consumers. Drèze and Hussherr (2003) examined online banner ads' performance and assessed the click-through rates' ability to capture their effectiveness. They concluded that online banner ads effectively translated into brand attitudes and proposed that traditional attitudinal metrics capture their effectiveness better than click-through rates. Trusov, Bucklin, and Pauwels (2009) compared the effects of online word-of-mouth marketing with traditional marketing on member growth for a social networking site. The derived results suggested a long-term elasticity of online WOM (0.53) that substantially exceeded the average advertising elasticities reported in the literature. Ghose and Yang (2009) investigated the impact of search rank on search metrics and found that the monetary value of a click-through decreases with rank.

Mayzlin and Shin (2011) investigated message content coupled with consumer search and perceived quality. The research suggested that high-quality firms can benefit from strategically withholding information to encourage search behavior. Li and Kannan (2014) analyzed the effectiveness of online advertising on online consumer behavior, for a franchised firm in the hospitality industry. The researchers found significant spillover effects from firm-initiated channels (emails and online banner ads) to consumer-initiated channels (search, direct, and referral). Moreover, search and email click-throughs had a significantly longer-lasting impact than an online banner ad click-through. Hoban and Bucklin (2015) analyzed the effects of online banner ads for users at different stages of the purchase funnel, on visits to the company's website. The results from the study suggested that online banner ads positively affect visitation to the firm's website for users in most stages of the purchase funnel.

Overall, the existing studies provide interesting insights into ways to improve the effectiveness of individual forms of online advertising. However, few studies have looked at the impact of online advertising on sales. Instead, most of the studies have focused on the many micro-factors that determine the online advertising channels' success (e.g., the impact of search rank). Our dataset unfortunately does not allow us to directly investigate these issues, but we can, however, examine macro-level determinants of the advertising channels' success. Namely, the indirect effects of the advertising channels on click-throughs. Next, we discuss what is known about interactions and cross-channel advertising effects.

Interactions and Cross-Channel Advertising Effects

Understanding the own-channel effects of advertising provides valuable insights for advertising budget allocations. However, to get a holistic picture of the different advertising channels' effectiveness, it is also necessary to understand the interaction effects that may arise. Ignoring interaction and cross-channel effects can lead to a severe undervaluation of the advertising channel. In the upcoming section, we discuss some representative cross-channel studies and highlight findings relevant to our research. We start with studies that have investigated the impact of online advertising on offline sales.

Cross-Channel Effects on Offline Sales

Danaher and Dagger (2013) studied the short-term impact of advertising on offline sales for a large retailer that undertook a short-term promotional sales campaign. The derived results suggested that email and paid search advertising effectively drive offline sales, while online banner ads do not. Lewis and Reiley (2014), however, found positive and sizable effects of online banner advertising on offline sales through a large-scale field experiment on Yahoo!. The same study provided evidence that most of the impact on sales arise from impressions, indicating that consumers can be influenced by an ad without clicking it.

Pauwels et al. (2016) investigated how brand familiarity affects within-online and cross-channel synergies. The results suggested that familiar brands experience significantly higher within-online synergy than cross-channel synergy because consumers have a higher knowledge of familiar brands. For a fast-moving consumer goods retailer, Srinivasan, Rutz, and Pauwels (2016) found positive indirect effects of traditional communication activities (price, distribution, and TV) on sales via online metrics (website visits, paid search click-throughs, and Facebook). The authors emphasized that the findings provided market-level support for the claim that consumers engage online even for everyday products. Kalyanam et al. (2018) conducted several field experiments to investigate the cross-channel effects of paid search advertising on offline sales. The study results suggested that an increase in paid search advertising increased offline retail sales in advertised categories. In sum, the literature has provided evidence of positive cross-channel effects of paid search advertising and online banner ads on offline sales.

Cross-Channel Effects on Online Metrics

The next research stream consists of studies that have investigated the impact of offline advertising on online metrics. Joo et al. (2013) studied how TV advertising affects online consumer behavior. The results indicated that TV ads increased the number of branded and product relevant keyword searches, suggesting that firms can benefit from coordinating TV and search advertising campaigns. A recent study by Du, Xu, and Wilbur (2019) provided similar results, reporting an immediate increase in online searches after the TV ad aired. de Haan, Wiesel, and Pauwels (2016) compared the long-term effectiveness of nine forms of advertising on traffic and conversion. The researchers found content-integrated advertising to be the most effective form, followed by content-separated advertising and firm-initiated advertising.

Cross-Channel Effects on Both Offline and Online Metrics

The final research stream we highlight are studies investigating cross-channel effects on both online and offline behavior. Wiesel, Pauwels, and Arts (2011) investigated the marketing communication effects on offline and online purchase funnel metrics in a B2B-setting. The researchers found evidence of cross-channel effects for offline advertising channels on online funnel metrics and vice versa.

Interestingly, they found that the effect of Google Ads on profits was 17 times higher than the most effective offline activity.

Dinner, Van Heerde, and Neslin (2014) found the cross-channel elasticities of traditional and online advertising to be almost as high as the own-channel elasticities for a high-end apparel retailer. Interestingly, they found paid search advertising to be more effective than traditional advertising, primarily due to a strong cross-channel effect on offline purchases. Another interesting result from the study was that traditional advertising did not enhance the effectiveness of paid search, indicating information-substitution effects.

Lobschat, Osinga, and Reinartz (2017) analyzed the impact of online banner ads and TV on consumers' online and offline behavior. Overall, the study results suggested that firms predominately selling through the offline channel can benefit from online advertising, providing a strong rationale for cross-channel effects in these contexts. More specifically, they found that online banner ads and TV indirectly increase offline sales through website visits and directly through a cross-campaign, brand-building effect.

Overall, the existing academic work on cross-channel effects has provided important insights for managers, but there are still questions left unanswered. For instance, while the literature has made progress in assessing the cross-channel effects of online advertising on offline sales, most studies that investigate the impact of offline advertising on the online channel have focused on other dependent variables than sales.

Another takeaway is the relatively small amount of studies that investigate the impact of online and offline advertising on both purchase channels. To date, Dinner, Van Heerde, and Neslin (2014) is the only study incorporating both advertising channels and both purchase channels. Moreover, the magnitude and relative strength of the different advertising channels are likely to deviate across product categories. Thus, it is plausible that the effects will be different for a florist versus a high-end apparel retailer. Next, we summarize the most important points from this discussion and explain how our study contributes to the existing research.

Gaps in the Literature and the Contribution of our Study

Table 1 represents a comparison of selected prior work. As the table shows, researchers have analyzed the impact of online advertising on different measures. However, few investigate the effects on sales. Also of relevance, is how few studies analyze the impact of online and offline advertising on both purchase channels (to date, there is only one). Thus, the existing studies provide fruitful insights into ways to improve the effectiveness of individual forms of online advertising but are of limited use for strategic decision-making with respect to budget allocation across multiple forms of advertising.

Table 1
Empirical Research on Own-channel and Cross-channel Effects

Authors (Year)	Offline Advertising	Online Advertising	Indirect effects	Offline Sales	Online Sales
Drèze & Hussherr (2003)	-	Online banner ads on CTR and attitudinal metrics	-	-	-
Ghose & Yang (2009)	-	Paid search advertising on search metrics	-	-	-
Trusov, Bucklin & Pauwels (2009)	-	WOM referrals on new sign-ups	-	-	-
Danaher & Dagger (2013)	TV, radio, print	Online banner ads, paid search, social media, email	-	Analyzed	-
Joo et al. (2013)	TV on online search	-	-	-	-
Lewis & Reiley (2014)	-	Online banner ads	-	Analyzed	-
Dinner, Van Heerde & Neslin (2014)	TV, radio, print, billboards	Online banner ads, paid search	Search click-throughs	Analyzed	Analyzed
Lobschat, Osinga & Reinartz (2017)	TV	Online banner ads	Website visits	Analyzed	-
This study	TV, print, in-store, billboards, postal mail	Online banner ads, paid search, email	Search click-throughs, online banner click-throughs	Analyzed	Analyzed

In sum, each of the studies have touched upon some aspects of our research question, but none has fully addressed them. Consequently, marketers still need more guidance on how to derive optimal budget allocations among various advertising channels. Studies investigating the cross-channel effects have predominantly analyzed the effects of online advertising on offline sales, and the effect of offline advertising on online sales has therefore been largely overlooked. Another gap in the literature is the absence of studies emphasizing the advertising channels' spillover effects (Pauwels et al., 2016). Moreover, the aforementioned studies have not provided sufficient evidence about whether the advertising channels affect sales directly or indirectly, by first driving consumers to other information sources.

Our study both complements and contrasts previous research. The Danaher and Dagger (2013) study compares the relative effectiveness of online and offline advertising channels, but are not concerned with the effects on online sales, carryover effects, or long-term effects. Dinner, Van Heerde, and Neslin (2014) fill this gap to a large extent but do not address the indirect effects on online banner click-throughs and attitudinal metrics. We complement their study by investigating more mechanisms that make the cross-channel effect more or less prevalent.

Moreover, we observe that most of the relevant research investigates high-involvement products or services, resulting in a gap in the literature for mid-involvement perishable products (e.g., flowers) that cannot be consumed online. Results are likely to deviate across industries, services, and products, making it difficult to generalize research. Thus, we add to the literature by investigating an industry that has received little academic research. Moreover, for firms predominantly selling offline, existing research provides little guidance on online advertising decisions (Lobschat, Osinga, & Reinartz, 2017).

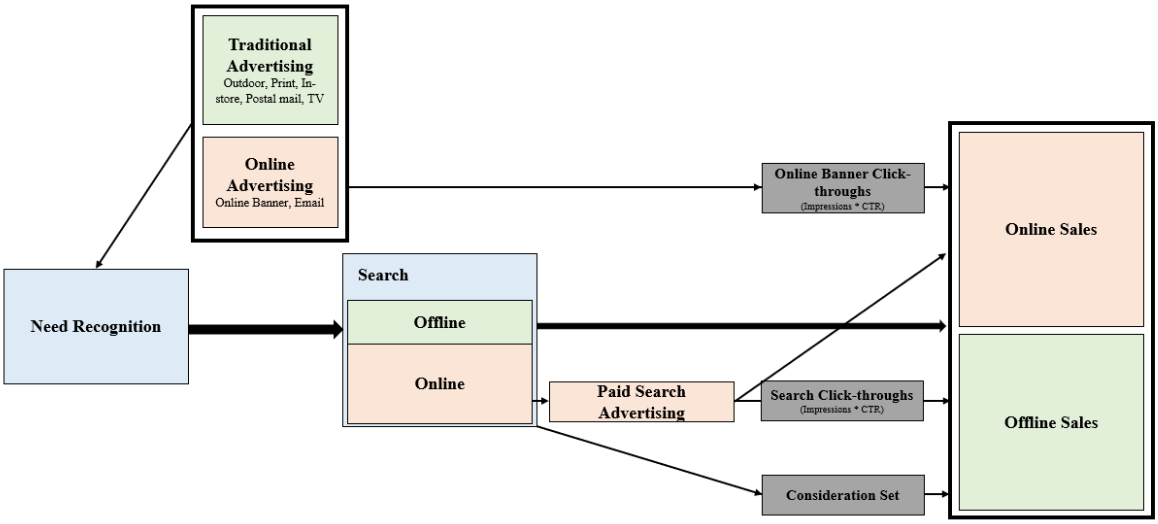
Another aspect to consider is the modeling approach, where current research has tended to omit lagged effects. Current research has therefore not really provided a fully dynamic view of how cross-effects occur across advertising channels (Batra & Keller, 2016). We add to the literature by using a modeling approach that accounts for this. In sum, our study contrasts and complements the aforementioned studies by comparing the effectiveness of online and offline advertising channels on both purchase channels, incorporating carryover effects, spillover effects, cross-channel effects, and indirect effects for the same dataset. Therefore, this paper integrates the diverse research and offers specific contributions to each area. Next, we turn to the conceptual development and the hypotheses.

Conceptual Framework

We develop a framework that gauges how the advertising channels interact with each other and affect sales. The effectiveness of an advertising channel can be amplified or diminished by the simultaneous activity of another channel. If the advertising channels harmonize and jointly enhance the impact on sales, we observe a synergic effect of advertising. These synergic effects can be within channels (e.g., paid search advertising and online banner click-throughs) and across channels (e.g., TV and search click-throughs). However, if the channels are managed in silos and serve as information substitutes, the advertising channels might cancel out each other's effects. Thus, the interaction between the channels is a potentially great source of influence the model must account for.

Figure 1 represents the framework with the five advertising channels, the three mediators, and the two purchase channels. The framework illustrates how consumers move toward a purchase in a series of stages. First, the consumer recognizes the need for the product category. The need can be evoked by the advertising channels to the left in the framework. Second, the consumer searches for information about the product category and encounters paid search advertising (if the search is online). Note that during the search stage, the consumer might discover new brands and include them in the consideration set. Finally, the consumer evaluates the considered brands and conducts a purchase in any of the channels. The advertising effects are direct if the consumer goes directly to a physical store or types in the website’s URL, and indirect (through click-throughs) if the consumer first searches for the product category and then visits the website and/or a physical store.

Figure 1
Conceptual Framework for the Own-channel and Cross-channel Effects of Online and Offline Advertising on Sales



This sequential concept of the consumer road to purchase points to an important aspect of our research – namely, that the advertising channels in the early stages of the decision-making process can have a significant impact on the consumer's responsiveness to subsequent advertising channels. For instance, the repeated exposure to retained ad executive elements across channels can foster synergic effects that enhance the accumulated impact on sales. However, if the information obtained in the first channel serves as an information substitute[1], the total impact might diminish. Therefore, it is important to analyze the indirect effects of the advertising channels to capture the total impact on sales. Next, we discuss and provide theoretical foundations for what effects we anticipate will dominate for each advertising channel based on the existing evidence.

[1] The information provided in one channel serves as a substitute for the information that could have been obtained in another

Offline Advertising

Offline advertising (outdoor, print, in-store, postal mail, and TV) is suited to stimulate need recognition and information gathering in the early stage of the decision-making process. The advertising cues are in turn likely to stimulate the consumer to progress through the early stages of the purchase funnel and obtain more information or conduct a purchase directly. Thus, offline advertising can influence sales in the native channel (own-channel effect) and sales in the online channel (cross-channel effect) by routing the consumer directly to a physical store or the website. The impact on sales can also be *indirect* through the impact on click-throughs.

The research-shopper phenomenon (Verhoef, Neslin, & Vroomen, 2007) provides the rationale for cross-channel effects and the indirect effect via click-throughs. Traditional advertising can stimulate need recognition and more keyword searches, thereby pushing the consumer closer to a purchase. The increased search activity translates into more click-throughs and finally sales. Note that the consumer can first be prompted by offline advertising, then search for the product, and finally purchase it in a physical store. However, offline advertising may serve as a substitute for the information provided in a search and decrease click-throughs (Dinner, Van Heerde, & Neslin, 2014). Thus, we are likely to observe two opposing effects that either amplify or diminish the cross-channel effects of offline advertising on online sales.

TV

Previous research indicates three underlying reasons why TV advertising is likely to have a positive impact on click-throughs and the consideration set: (1) TV strengthens the objective knowledge of products resulting in increased searching for the brand, (2) TV alters the perceived knowledge, increasing the likelihood of entering a branded keyword, and (3) TV influences the consumer through incidental exposure, altering the consumers' consideration sets (Joo et al., 2013). However, in the context of flowers, where consumer involvement is likely to be low compared to more expensive product categories (e.g., cars), the information provided in a TV ad is likely to be sufficient to trigger a purchase. Thus, we believe that TV's ability to transfer feelings and images will evoke the sensory impressions associated with flowers and have a positive direct impact on online and offline sales, and an indirect negative impact on click-throughs. Thus, we hypothesize:

H_1: TV has a positive direct effect on long-term sales, the total positive impact is diminished by a negative indirect effect via click-throughs.

Traditional advertising (excl. TV)

Previous studies (e.g., Lobschat, Osinga, & Reinartz, 2017) suggest that the repeated exposure to brand execution elements (e.g., logo, layout, colors) retained across campaigns can foster goodwill. This process can happen at the preemptive level (the consumer perceives the ads but does not process them, see e.g., Lewis & Reiley, 2014) and manifest in more click-throughs in the long-run and increased consideration for the brand. Given the myriad of advertising impressions, a consumer is exposed to daily, we expect this effect to be highly relevant. Thus, even if the consumer does not consciously process certain advertising cues, some information is stored in memory for later. This goodwill is reflected in an increased likelihood of clicking an online ad. Hence, we hypothesize that:

H_2: Traditional advertising excl. TV has a (marginally) positive direct effect on long-term sales; the total positive impact is amplified by a positive indirect effect via click-throughs.

Emails

Emails are a form of firm-initiated contact reaching consumers that have not yet recognized a need for the product category (i.e., consumers in the first stage of the purchase funnel) (de Haan, Wiesel, & Pauwels, 2016). Consequently, an email can push these consumers closer to an actual purchase by evoking interest in the product category and induce searching (indirect effect) or accelerate the purchase process by stimulating a purchase right away (direct effect). How effectively emails translate directly into sales or positively affect other advertising channels depends on the message's communication-goal. For instance, awareness-focused emails are meant to drive the consumer to another location – offline or online – to get more information (initiate the search process). On the other hand, conversion-oriented emails aim to trigger an immediate purchase (Mullen & Daniels, 2009).

The emails sent by the focal retailer typically contain educational elements (e.g., what fertilizer to use) and encourage the receiver to obtain more information on the website or conduct a purchase directly. Thus, both direct and indirect effects are supported in this context. However, there are also elements of the emails that provide a rationale for the negative effects of emails on sales. In general, firm-initiated contact is increasingly unwanted by consumers, and overuse of emails might annoy the receiver (de Haan, Wiesel, & Pauwels, 2016). Moreover, given the highly informational nature of emails, the content is likely to serve as a substitute for the information that could have been provided by a click-through (reducing spillover effects on e.g., paid search advertising). Another aspect to consider is that some of the emails contain promotions that are only available in physical stores, which makes the cost of purchasing higher when the consumer must switch between channels.

In conclusion, we expect that emails evoke recognition and positively affect online sales (own-channel effect), at least in the short run, and the information-substitution effect to be present given the emails' typical content (negative within-channel synergies). The effect on offline sales (cross-channel effect) is more difficult to anticipate as it involves channel switching. The emails often contain promotions exclusively available in the offline store, which provides a rationale for a positive cross-channel effect. However, it requires that the consumer store the information in memory for later, and it is uncertain whether consumer involvement is high enough in this product category for this to happen. In sum, we expect that the information provided in the emails reduces searching rather than encouraging it. Thus, we expect that the anticipated positive effect of emails will vanish due to the negative indirect effect.

H_3: Emails have a positive direct effect on long-term sales, but the total positive impact vanishes due to a negative indirect effect via click-throughs.

Online Banner Ads

Online banner ads are a form of advertising the consumer encounters in the first stage of the purchase funnel (prospecting), and/or after conducting a search (if the ad is retargeted). Similar to offline advertising and emails, online banner ads are suited to evoke need recognition and accelerate the purchase funnel. Previous research suggests that online banner ads have a positive long-term impact on both online and offline sales (see e.g., Dinner, Van Heerde, & Neslin, 2014; Lobschat, Osinga, & Reinartz, 2017). Evidently, online banner ads work primarily as billboards that can be used to build a positive attitude towards the brand and influence consumers at the beginning of their path to purchase.

The rationale of the direct effect on online sales is that consumers who already progressed to the later stages of the purchase funnel can draw upon their stored brand schemas. Consequently, advertising from previous campaigns can serve as a powerful reminder that triggers a purchase right away (Lobschat, Osinga, & Reinartz, 2017). The cross-channel effect on offline sales is less intuitive. Consumers must first be activated (by an online ad) and visit the website before a purchase is conducted in a physical store. It seems like a roundabout way to create a cross-channel effect. However, such behavior is rational for consumers of the focal retailer because flowers have many non-digital attributes (e.g., individual quality), thereby increasing the perceived risk of an online purchase.

Concerning the indirect effect of online banner ads, we anticipate two effects. Repeated exposure to online banner ads can translate into an accumulation of goodwill, resulting in an increased probability of clicking the ad or conducting a purchase in any channel. When the consumer is exposed to brand information over time, the paid search advertising becomes more relevant, and online banner ads are likely to impact search click-throughs positively.

However, research suggests that the opposite may happen as well. For instance, research has found that repetitive exposure to an online banner ad has a negative impact on click-throughs because consumers become increasingly selective in how they allocate their cognitive resources and time online (Chatterjee, Hoffman, & Novak, 2003). Another aspect to consider is whether click-throughs capture the long-term effects of online banner ads well. Click-throughs and conversion rates can illustrate a direct response to an advertising impression (Braun & Moe, 2013) but do not take into account the possible positive effects on brand attitudes. Drèze and Hussherr (2003) highlighted this issue and demonstrated that even though consumers do not consciously process online ads (and thus do not click on them), these ads still positively affect attitudinal brand measures.

In sum, given the relatively less informative nature of online banner ads, we find it unlikely that they will serve as information substitutes. Instead, we propose that they serve as powerful reminders that encourage website visits and increase searches for the product category. Thus, we hypothesize that:

H_4: Online banner ads have a positive direct effect on long-term sales, the total impact is amplified by a positive indirect effect via click-throughs.

Paid Search Advertising

Paid search advertising represents a form of consumer-initiated contact where the consumer takes control of their purchase decision and seeks information themselves (Court et al., 2009). Thus, the consumer encounters paid search advertising at a more advanced stage in the purchase funnel, when the consumer has already recognized the need for the product category. The purchase can then be conducted in the native channel or in a physical store. In both cases, the impact is served through search click-throughs. Paid search expenditures accrue when the sponsored link is clicked and the potential consumer visits the advertiser's website (IAB, 2019).

The own-channel effect on sales occurs when the consumer clicks on a paid search advertisement and conduct a purchase on the website. The cross-channel effect occurs when the consumer clicks the sponsored link, visits the website to obtain information, and finally conducts a purchase in the offline channel. It is worth noting that the relationship between higher expenditures and click-throughs is not clear. A plausible pattern is an inverted U-shape, where higher expenditures mean more impressions and less-frequently clicked keywords, resulting in lower click-through rates (Dinner, Van Heerde, & Neslin, 2014).

Another aspect to consider is the indirect effect paid search advertising might have on online banner click-throughs. After a search leads the consumer to the website, the consumer is retargeted with relevant online banner ads. The fact that the consumer has previously obtained information about the product category and visited the website makes the online banner ads more relevant and the consumer more click-prone. Thus, we are likely to observe a positive indirect effect on online-banner click-throughs.

In sum, we believe that paid search advertising will have a positive impact on both sales channels. Paid search advertising is a form of consumer-initiated contact implying that the consumer is interested in the product category and intends to conduct a purchase. Moreover, we expect that the indirect effect on online banner click-throughs will amplify the direct effects. Thus, we hypothesize that:

H_5: Paid search advertising has a positive direct effect on long-term sales, the total impact is amplified by a positive indirect effect via click-throughs.

In summary, our framework enables us to investigate the own-channel and cross-channel effects of advertising, while taking into account the complex interplay between the channels. We allow online and offline advertising to exert an indirect effect on multichannel sales through click-throughs. Furthermore, we offer additional depth on how synergic effects and information substitution effects either amplify or diminish the total impact on sales. Next, we turn to the data description and the methodology.

Data Description

We apply our model to data (provided by a third-party source) from one of the major florists in Norway, which has asked to remain anonymous. The focal retailer is a well-known brand that operates online and offline stores across the country, typically at shopping malls. While the offline channel accounted for 98% of the sales during the observation period, a modest 2% of the sales was generated through the online channel. Nevertheless, the online store is a channel that is of growing importance to the retailer. We observe the dependent variables, online and offline NOK sales, at the weekly aggregated level (all stores), with 149 weeks of data from January 2015 to November 2017. Table 2 describes the variables used in the analysis, and Table 3 offers descriptive statistics of the endogenous variables.

Table 2
Variable Operationalizations

Variable	**Operationalization**	**Classification**
TV	Weekly cost of television advertising	Offline
Traditional Advertising (excl. TV)	Weekly cost of aggregated offline advertising (in-store promotion, postal mail promotions, print media, and outdoor billboards).	Offline
Online Banner Ads	Weekly cost of online display advertising	Online
Paid Search	Weekly cost of paid search advertising on Google	Online
Emails	Weekly number of delivered emails	Online
Online sales	Weekly online sales revenue in NOK	Performance (Online)
Offline sales	Weekly offline sales revenue in NOK	Performance (Offline)
Search Click-throughs	Weekly number of clicks on sponsored links on Google	Online
Online Banner Click-throughs	Weekly number of clicks on online banner ads	Online
Consideration Set	Weekly percentage of consumers considering the focal retailer when purchasing today	Attitudinal measure
Anniversary dummies	Dummy variables indicating presence of important anniversaries and holidays (Christmas, Mother's Day, Valentine's Day, the Norwegian Constitution Day, Public Summer Vacation)	Control
Seasonality dummies	Dummy variables indicating the general seasons (Summer, Winter, Autumn, and Spring)	Control
Campaign dummy	Dummy variables indicating presence of sales promotions or brand-building campaigns	Control
Price level	Weekly average price level.	Control
Unemployment rate	Weekly unemployment rate in percent at the market level	Control
Weather condition	Weekly mean temperature over the observation period	Control
Competitors' advertising expenditures	Weekly aggregated level of (gross) expenditures for seven of the competitors	Control

Table 3
Descriptive Statistics[2]

Variable	Mean	Median	Std. Dev	Min	Max
TV	941.15	0	2,107.14	0	9,793.98
Traditional Advertising (excl. TV)	357.12	0	1,746.45	0	13,390.66
Online Banner Ads	297.31	84.98	459.11	0	2,420.42
Paid Search Advertising	95.39	85.54	52.03	22.71	450.07
Emails	90.63	0	118.24	0	704.75
Online Sales (NOK)	2,333.72	2,343.45	1,096.92	712.38	10,142.84
Offline Sales (NOK)	117,816.51	109,404.12	41,123.60	60,046.48	412,677.40
Search Click-throughs	5,494.06	5,203.00	2,253.14	1,406.00	14,957.00
Online Banner Click-throughs	6,916.54	1,814.00	20,336.52	0	152,778.00
Consideration Set (%)	22.88	23.08	3.49	16.03	30.13

Advertising Spend

The retailer engages in both online and offline advertising. Their traditional (offline) advertising is a mix of in-store material (e.g., posters), postal mail promotions, print media (newspaper and magazine), outdoor billboards, and television. The offline campaigns are relatively short and unique, making generalizable analysis of any one type difficult. Therefore, we follow Naik and Peters (2009) and aggregate these expenditures across various traditional media. The television expenditures (56% of the total spend) represent an exception as they are relatively consistent across campaigns and are therefore included in the analysis as a separate variable.

On average, the retailer spent 18% of its advertising budget on online banner advertising (Google and Facebook) and 6% on paid search advertising over the observation period. Most of the online banner advertising is general and promotes the retailer’s logo and a specific product, though the exact content cannot be verified. The paid search advertising relates to sponsored links in the search engine when relevant keywords (e.g., flowers, plants) are searched for. Figures 2 and 3 show time-series plots for advertising spend versus offline and online sales over the observation period.

[2] The advertising costs and sales figures reflect a liner a transformation of the data used to disguise the identity of the source

Figure 2
Time-Series Plot for Offline Sales vs. Total Advertising Expenditures[3]

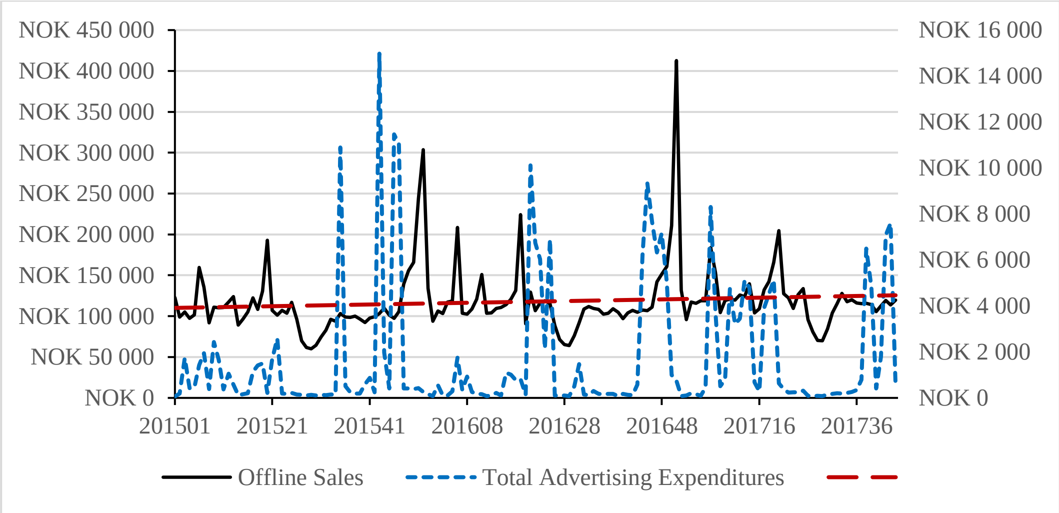
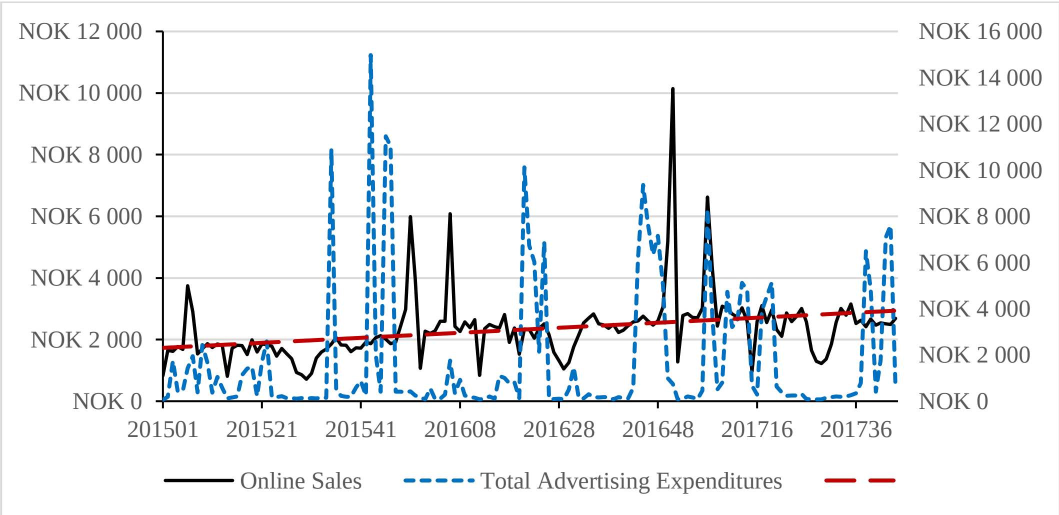


Figure 3
Time-Series Plot for Online Sales vs. Total Advertising Expenditures



[3] The y- and x-axis values reflect a linear transformation of the data used to disguise the identity of the source

Emails, Consideration Set & Click-throughs

The email variable represents the aggregated weekly number of delivered emails sent to both members and non-members. The emails' content is typically inspirational or educational – for instance, how to decorate with the flowers of the season or take care of plants. The consideration set measure is obtained through a weekly survey conducted by Nepa. It reflects the average weekly percentage of the surveyed respondents who would consider buying from the focal retailer the next time they buy flowers. Search click-throughs and online banner click-throughs represent the aggregated weekly number of clicks on sponsored links and online banner ads leading to website visits.

Other Variables Driving the Dependent Variables

Our analysis must control for other factors that drive our dependent variables. The sales variables showed a weekly positive trend (indicated by the red dashed line in Figures 2 and 3) over the observation period with distinctive peaks and dips in specific periods. The observed sales peaks in both channels can (roughly) be explained by the Christmas season (week 51 to 1), Mother's Day, Valentine's Day, and the Norwegian Constitution Day (17th of May). Moreover, the dips can be explained by the Public Summer Vacation in July. Consequently, we include anniversary dummies to account for any natural variation in purchase behavior during these periods. Moreover, the general seasons are likely to impact the demand for flowers, and we include seasonality dummies accounting for this (e.g., Winter, Summer).

The company ran several specific campaigns, which can be classified as sales promotions (e.g., 3 for 2 on flower bouquets) or brand-building (e.g., CSR, inspirational). We implemented dummy variables to account for the effect of sales promotions (which occur every ninth week in the period week 3 2015 to week 31 2016) and brand-building campaigns (91 in total, evenly distributed across the observation period). Another factor likely to have an impact on our dependent variables is the price level. We included the weekly average price level to account for variation in demand driven by this factor.

To account for macroeconomic conditions, we used the unemployment rate at the market level as a proxy. We also accounted for weather conditions by implementing the weekly mean temperature over the observation period since the demand for outdoor flowers and plants is likely to increase when sunny and warm outside. Thus, this variable accounts for variation in weather that cannot be explained by the seasons alone.

We also accounted for the firm's competitors' advertising expenditures by implementing a variable containing the weekly aggregated level of (gross) expenditures for seven competitors (obtained from Nielsen). Advertising by competitors can impact the dependent variables (sales) by either damaging the focal retailer's performance (if the competitors' ads entice potential consumers to switch) or positively affect it if the ads serve as a need recognition reminder (Dinner, Van Heerde, & Neslin, 2014).

Modeling Approach

In this section, we describe our approach to modeling the effects of advertising expenditures (online banner, paid search, traditional advertising excl. TV, and TV) and emails on online and offline sales, and mediators (clicks-throughs and consideration set). Our modeling approach must estimate the relationship between several variables over time, and account for endogeneity and lagged responses to accurately assess the relative effectiveness of different advertising channels and the synergic effects that arise from their complex interplay. Vector autoregressive (VAR) models are commonly used in this field of research and make it possible to estimate the cross-effects of the advertising channels on online and offline sales with aggregated time-series data (de Haan, Wiesel, & Pauwels, 2016; Nijs, Srinivasan, & Pauwels, 2007; Pauwels, Hanssens, & Siddarth, 2002; Pauwels et al., 2011; Srinivasan, Rutz, & Pauwels, 2016). We incorporate the five methodological steps outlined in Table 4.

Table 4
Overview of Methodological Steps[4]

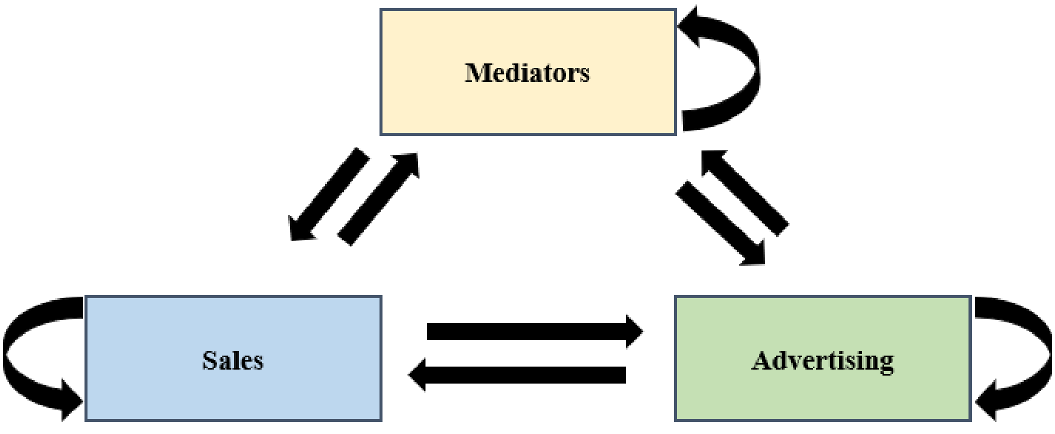
Methodological step	Relevant literature	Research question
1. Granger causality tests	Granger (1969) Trusov, Bucklin, and Pauwels (2009)	Which variables are temporally causing other variables?
2. Unit root and cointegration tests Augmented Dickey-Fuller Test Zivot-Andrews test Cointegration analysis	Enders (2004) Kwiatkowski et al. (1992) Zivot and Andrews (1992) Johansen, Mosconi, and Nielsen (2000)	Are variables stationary or evolving? Are unit root results robust to unknown breaks? Are evolving variables in long-run equilibrium?
3. Model of dynamic interactions Vector autoregressive model VAR in differences	Dekimpe and Hanssens (1999) Bronnenberg, Mahajan, and Vanhonacker (2000) Pauwels, Srinivasan, and Franses (2007)	How do performance and advertising interact in the long and short run, accounting for the unit root and cointegration results?
4. Policy simulation analysis Unrestricted impulse response Cumulative marketing elasticity Restricted policy simulation	Pesaran and Shin (1998) Pauwels, Hanssens, and Siddarth (2002) Pauwels (2004)	What is the net dynamic impact of an advertising change on performance? What is the direct dynamic impact of an advertising change, controlling for its indirect effects?
5. Validation analysis VAR lag specification	Ventzislav and Lutz (2005)	Are the results robust to the lag selection criterion?

[4] Based on Wiesel, Pauwels, and Arts (2011).

The first step in our approach is to test for the presence of endogeneity among the performance variables (sales and mediators), sales and advertising (direct effects), and mediators and advertising (indirect effects). The focal retailer has informed that they follow common practice and allocate advertising budgets relative to performance, which indicates that endogeneity should be present among the variables.

As Figure 4 depicts, we anticipate that advertising expenditures (and click-throughs) lead to more sales and (following the reverse arrow) that sales lead to higher advertising budgets and indirectly to more sales and click-throughs. This effect can unfold in two ways; (1) advertising (e.g., TV) stimulates need recognition and induces the consumer to purchase in any of the channels, or (2) after exposure to the first message, the consumer searches for the product online and then conducts the purchase. Effect (2) on offline sales implies that the consumer is first routed to the online channel via click-throughs before the purchase is conducted in the offline channel, which seems like a roundabout way to create a cross-channel effect.

Figure 4
Modeling Framework[5]



[5] Based on Trusov, Bucklin, and Pauwels (2009).

The rationale of the effect is that the consumer is evoked by the original message (e.g., TV) to find out more about the product category and search for it online. In the online search, the consumer is exposed to paid search advertising and may click on a sponsored link (search click-throughs), which leads the consumer to the website. On the website, the consumer either conducts an online purchase or browses the website and then goes to a physical store. A similar pattern is likely to occur for online banner ads, where we expect that previous messages increase the likelihood of clicking the ad. Thus, we expect advertising (and click-throughs) to stimulate offline sales by first routing the consumer to a different purchase channel. We also include lagged effects of the advertising expenditures and the performance variables (as the curved arrows indicate) to account for the effect previous messages had.

The links represented in Figure 4 can be tested by investigating which variables Granger-cause other variables (Granger, 1969; Hanssens, Parsons, & Schultz, 2001). In essence, Granger causality implies that knowing the historical levels of advertising expenditures significantly adds to the forecast fit of sales – beyond the sales' own history. Thus, the Granger causality test does not consider the immediate effect of advertising on sales and is not relevant when you expect virtually all the effects to be immediate (Trusov, Bucklin, & Pauwels, 2009). In this framework, however, we expect lagged effects to significantly add to the explanatory power of the model.

We adopt the approach of Trusov, Bucklin, and Pauwels (2009) and perform pairwise Granger causality tests on each pair of the variables for a higher number of lags than we intend to include in the model. This is because we investigate the need for modeling a fully dynamic system and are therefore interested in whether we can rule out that, e.g., paid search advertising, Granger-causes sales at any lag (not whether paid search advertising Granger-causes sales at a specific lag). Thus, we test for up to 13 lags (we are unlikely to find new casual relationships beyond this for weekly data) and report the results for the lag that has the highest significance for Granger causality. If any of the performance variables indeed Granger-cause (some of) the advertising variables, we need to capture the complex interactions of Figure 4 in a fully dynamic system (Trusov, Bucklin, & Pauwels, 2009).

Next, we test for the potential of permanent effects of advertising on the performance variables. If any of the advertising channels have a permanent effect on the baseline of the performance variables, sales gains in the current week imply higher sales the next week(s). In this case, the time series for the performance variables would be classified as “evolving” (having a unit root). In essence, an evolving variable has no finite variance, which implies that the standard errors of the estimated effects cannot be trusted (Granger & Newbold, 1974). The opposite classification, that of “stationary”, implies that the performance variables have a fixed mean and that changes do not have a permanent impact (e.g., Dekimpe & Hanssens, 1995, 1999). We perform unit root tests to determine whether each of the variables in our data set is stable versus evolving and use the augmented Dickey-Fuller test procedure that Enders (2004) recommends and Kwiatkowski et al. (1992) test.

Tests for both Granger causality and unit roots enables us to specify the VAR model in Equation 1. In this model, performance variables and advertising are endogenous; that is, they are explained by their own past and the past of the other endogenous variables (Dekimpe & Hanssens, 1999). Specifically, the vector of endogenous variables ($Y_{i,t}$) – search click-throughs, online banner click-throughs, consideration set, emails, offline advertising (excl. TV), TV, online sales, and offline sales – is related to its own past, which allows for complex dynamic interactions among these variables. The vectors of exogenous variables include for each endogenous variable (1) an intercept, C; (2) anniversary dummies (e.g., Valentine’s Day), A; (3) campaign dummy variables, CA; (4) seasonality dummies (e.g., Winter), S; (5) the unemployment rate, U; (6) weekly mean temperature, W; (7) competitor spending, CS; and (6) average price in week t, P. Instantaneous effects are captured by the variance-covariance matrix of the residuals, Σ (Trusov, Bucklin & Pauwels, 2009). The VAR specification is given by:

Equation 1

$$\begin{bmatrix} Y_{1,t} \\ Y_{2,t} \\ \vdots \\ Y_{10,t} \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \\ \vdots \\ C_{10} \end{bmatrix} + A \begin{bmatrix} \delta_{Y1} \\ \delta_{Y2} \\ \vdots \\ \delta_{Y10} \end{bmatrix} + CA \begin{bmatrix} \theta_{Y1} \\ \theta_{Y2} \\ \vdots \\ \theta_{Y10} \end{bmatrix} + S \begin{bmatrix} \gamma_{Y1} \\ \gamma_{Y2} \\ \vdots \\ \gamma_{Y10} \end{bmatrix} + U \begin{bmatrix} \psi_{Y1} \\ \psi_{Y2} \\ \vdots \\ \psi_{Y10} \end{bmatrix} + W \begin{bmatrix} \omega_{Y1} \\ \omega_{Y2} \\ \vdots \\ \omega_{Y10} \end{bmatrix} + CS \begin{bmatrix} \vartheta_{Y1} \\ \vartheta_{Y2} \\ \vdots \\ \vartheta_{Y10} \end{bmatrix} + P \begin{bmatrix} \zeta_{Y1} \\ \zeta_{Y2} \\ \vdots \\ \zeta_{Y10} \end{bmatrix}$$

$$+ \sum_{j=1}^{J} \begin{bmatrix} \phi_{1\,1} & \phi_{1\,2} & \cdots & \phi_{1\,10} \\ \phi_{2\,1} & \phi_{2\,2} & \cdots & \phi_{2\,10} \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{10\,1} & \phi_{10\,2} & \cdots & \phi_{10\,10} \end{bmatrix} \begin{bmatrix} Y_{1,t-j} \\ Y_{2,t-j} \\ \vdots \\ Y_{10,t-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{Y1,t} \\ \varepsilon_{Y2,t} \\ \vdots \\ \varepsilon_{Y10,t} \end{bmatrix}$$

Where t indexes weeks, J equals the number of lags included[6], and ε_t is white-noise disturbances distributed as $N(0, \Sigma)$. The parameters δ, θ, γ, ψ, ω, ϑ, ζ, and φ are to be estimated.

VAR model parameters are not interpretable on their own because of their sheer number and multicollinearity (Ramos, 1997; Sims, 1980). Therefore, to determine significance and compute elasticities, we investigate the net result of all the modeled actions and reactions over time, derived from the impulse-response functions (IRFs). The IRF simulates the over-time impact of a change (over its baseline) to one variable on the full dynamic system and represents the net results of all modeled actions and reactions (see Pauwels, 2004).

We adopt Pauwels (2014) approach to determine significance and compute elasticities. First, we test whether each impulse-response is significantly different from zero. If the estimated impulse-response is larger than its associated standard error, we conclude that it is significant. Second, we translate significant impulse-responses into immediate and cumulative (long-term) elasticities, given by $\frac{\Delta Y_1}{\sigma_X}$ and $\frac{\sum_{t=1}^{26} \Delta Y_t}{\sigma_X}$, respectively. The results derived from the elasticities can be used to draw several managerial implications which will be discussed in the following paragraphs.

[6] To be determined on the basis of the Akaike information criterion and the AR roots table.

Empirical Analysis

Test Results for Evolution and Endogeneity

First, we transform the sales and expenditures variables into natural logarithms to even out the variables distribution and ease the interpretability of the elasticities[7]. Then, we test for stationarity versus evolution in each time series. The unit root tests indicated trend stationarity in all series, except for the attitudinal measure, consideration set. This implies that the consideration set variable should be included in first differences (given that the first differences are stationary), while the rest of the variables can be included in levels. We find that the first difference variables for the consideration set are stationary and include them in the model. However, note that the inclusion of a variable in differences has some implications for the analysis.

The interpretation of the effect of a variable in differences on performance variables is different from the interpretation of the variables in levels. The variable in differences represents the growth (or decline) in that variable from last week and can be interpreted as the "changes in consideration set". Thus, we are now saying that a unit change in the *difference* of the variable yields a certain performance impact. Given the complexity in interpretation, marketers typically transform the variable into a stationary one by subtracting from/dividing with other information (Pauwels, 2014).

Though unfortunate, this is not possible in our case. Consequently, we cannot use the variable to calculate its indirect effects. However, when we investigate the effects of advertising on the consideration set (i.e., treat it as a performance variable), we can to a large extent resolve the difficulties associated with the interpretation by converting the response of the consideration set variable in differences to levels (accumulated responses in Eviews). This allows us to investigate how advertising affects consumer attitudes and examine whether the retailer will gain from a consideration-enhancing focus in advertising activities.

[7] All 0 values were recoded into 0.00001 to avoid taking the logarithm of zero, in line with (Pauwels et al., 2016)

Second, we investigate if endogeneity is present among the variables and conduct pairwise Granger causality tests. The results are summarized in Table 5. Each cell gives the minimum p-value obtained from the Granger causality tests conducted from 1 to 13 lags. The results show that endogeneity is present among the variables in our data. As we expected, Granger causality is detected for all advertising variables on at least one of the performance variables. Besides, Granger causality is found for many of the other pairings. For instance, sales Granger-causes paid search advertising (indicating management performance feedback; see Dekimpe & Hanssens, 1999). In summary, the Granger causality test results indicate the need to consider the full dynamic system, as in a VAR model, and to account for the lagged effects of advertising (Trusov, Bucklin, & Pauwels, 2009).

Table 5
Results of Granger Causality Tests (Minimum *p*-values Across 13 Lags)

Dependent variable is Granger caused by	Online Banner Click-throughs	Search Click-throughs	Consideration Set	Emails	Online Banner Ads	Paid Search Advertising	Traditional Advertising (excl. TV)	TV	Offline sales	Online sales
Online Banner Click-throughs	----		.02[a]		.00				.01	.05
Search Click-throughs		----		.00		.00	.01	.05	.00	.00
Consideration Set			----	.00			.00			.00
Emails		.02		----	.02	.00	.05	.02	.02	.00
Online Banner Ads	.01	.01	.04		----	.00				.03
Paid Search Advertising		.00		.00		----	.01	.03	.00	.00
Traditional Advertising (excl. TV)	.04		.00	.02		.02	----			.02
TV		.00	.02			.01	.01	----		.01
Offline sales	.00	.00			.00	.00	.03		----	.01
Online sales	.00	.05		.04	.04	.02	.00		.00	----

[a] Consideration set is Granger-caused by Online Banner Click-throughs at the .02 significance level

Model Estimation

We estimate the VAR model of Equation 1 with 8 lags (the optimal lag length selected by the Akaike information criterion and the AR roots table)[8] and find a good model fit (e.g., $R^2 = .94$). We then assess the significance of including interaction terms in the same model. Both models predict well with low root mean square error (RMSE) and mean absolute deviation (MAD). The interaction model provides a better fit-in-sample for offline sales based on both RMSE and MAD, while the deviations for online sales are slightly higher than in the simple model. Overall, interaction terms do not remain significant contributors to model fit, as most of the interaction terms are either non-significant or marginally significant (e.g., 0.001). To illustrate the ability of the VAR system (without interaction terms) to represent the data, we plot predicted versus actual values of weekly sales in Figure 5 and 6. As the figure depicts, the predicted values (labeled VAR) closely track the actual weekly sales.

[8] The Akaike information criterion suggested a number of lags that would imply an unstable solution and potentially invalid standard errors (Grasa, 1989). Thus, the number of lags was reduced until all (inverse) roots had modulus less than one and lied inside the unit circle.

Figure 5[9]

Model Fit: Tracking Plot
Offline Sales

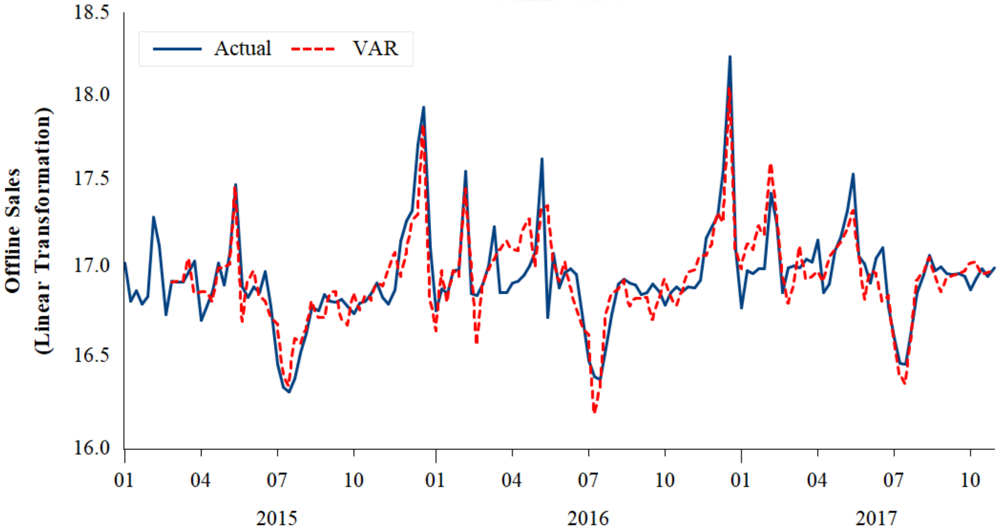
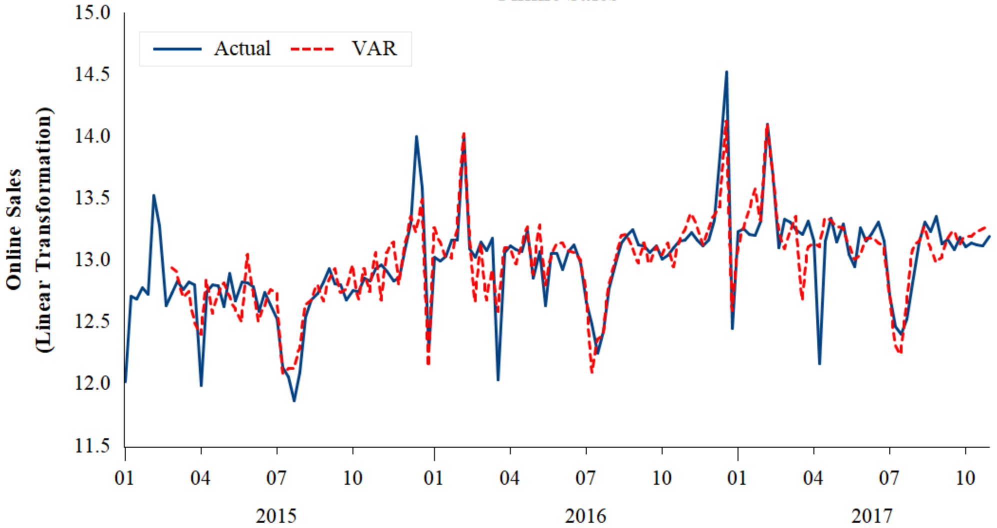


Figure 6

Model Fit: Tracking Plot
Online Sales



[9] The y-axis values reflect a linear transformation used to disguise the identity of the source.

Short-Term and Long-Term Effects for Advertising Channels

To gauge the impact of the advertising channels on mediators and sales over time, we compute IRFs based on the estimated VAR system parameters. The IRFs trace the incremental effect of a one-standard-deviation shock in advertising channels on the future level of each performance variable. These functions enable us to examine the carryover effects of each advertising channel on sales while fully accounting for the indirect effects of these activities in a dynamic system (Trusov, Bucklin, & Pauwels, 2009). We first examine the impact of advertising channels and mediators on sales, then we investigate the effects of advertising on the mediators and indicate the direction and magnitude of the indirect effects, and finally we compute total elasticities based on the analysis.

Direct Effects: Response of Sales to Shock in Advertising

Figures 7 and 8 plot the IRFs for the effects of the advertising channels on online and offline sales over time. The effect of paid search advertising on both sales variables remains significantly different from zero for two to three weeks. In contrast, the effects of offline advertising, online banner ads, and emails remain significant for one week only. This tendency is expected for a familiar brand as the consumers recognize it immediately and react positively to the advertising but quickly become bored, resulting in a quick wear-out (Dahlén, Lange, & Smith, 2010).

Another essential aspect to consider are the negative reactions (e.g., annoyance) consumers tend to get towards advertising over time, especially if the advertisement is encountered on multiple occasions. For this retailer, we observe a marginally negative effect of traditional advertising excl. TV on both sales variables. A possible explanation may be that the consumers do not perceive the ads (consciously process them) or that they find them annoying. The corresponding elasticities reveal that paid search advertising induces both a larger short-term response and a longer carryover effect than the other channels on both sales variables.

Figure 7
IRFs: Response of Online Sales to Shocks in Advertising Channels

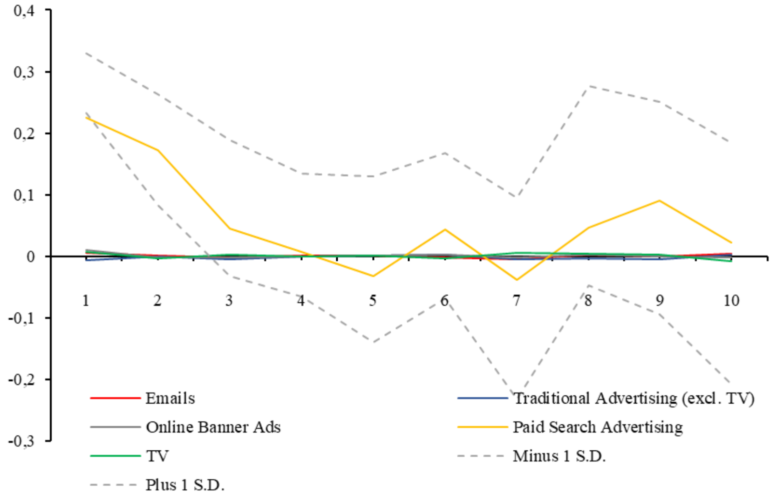
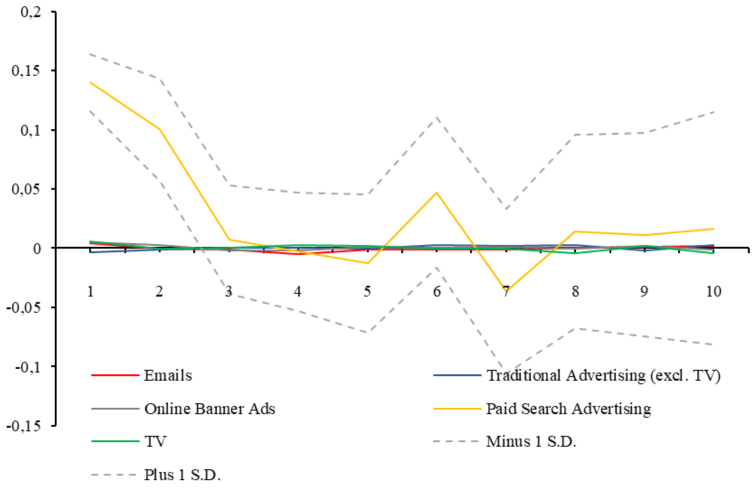


Figure 8
IRFs: Response of Offline Sales to Shocks in Advertising Channels



The paid search advertising elasticities on online sales are remarkably higher than those of the other online advertising channels (see Table 6). In comparison, the immediate (short-term) elasticity of paid search advertising (0.226) is approximately 38 times higher than that of emails (0.006), and 23 times higher than that of online banner ads (0.010) (see Table 7). This discrepancy grows over time, and the cumulative (long-term) elasticity of paid search advertising (0.398) is indeed more than 66 times higher than that of emails (0.006) and 40 times higher than that of online banner ads (0.001). Furthermore, the immediate elasticity of paid search advertising on online sales is 32 times higher than that of traditional advertising excl. TV (-0.007) and TV (0.007). The discrepancy grows over time, and the cumulative elasticity of paid search advertising is more than 56 times higher than that of the two offline advertising channels.

Table 6
Online Sales Elasticities of Advertising Actions

Online Sales Classification	Variables	Immediate	Cumulative
Mediator	Online Banner Click-throughs	0.019	0.019
Mediator	Search Click-throughs	0.281	0.454
Mediator	Consideration Set (D)	-0.424	-1.067
Online Advertising	Emails	0.006	0.006
Offline Advertising	Traditional Advertising (excl. TV)	-0.007	-0.007
Online Advertising	Online Banner Ads	0.010	0.010
Online Advertising	Paid Search Advertising	0.226	0.398
Offline Advertising	TV	0.007	0.007
Lagged DV	Offline Sales	0.486	0.486
Lagged DV	Online Sales	0.598	0.598

Table 7
Paid Search Advertising Online Sales Elasticity Relative to the Other Channels

Online Sales Paid Search Advertising Elasticity Relative to:	Immediate	Cumulative
Emails	38	66
Traditional Advertising (excl. TV)	-32	-57
Online Banner Ads	23	40
TV	32	57

The estimated immediate (0.140) and cumulative (0.240) paid search advertising elasticities on offline sales (see Table 8) are smaller than those of online sales, indicating that the own-channel effect of paid search advertising is greater than the cross-over effect. However, the relative superiority of paid search advertising is just as evident for offline sales. Paid search advertising outperforms both the online advertising channels and the offline advertising channels in every aspect. The immediate impact of paid search advertising on offline sales is 47 times higher than that of traditional advertising excl. TV (-0.003), and 28 times higher than that of online banner ads (0.005) (see Table 9). Notably, the cumulative effect of paid search advertising on offline sales is 240 times higher than that of emails (-0.001), 80 times higher than that of traditional advertising excl. TV (-0.003), and 48 times higher than that of online banner ads (0.005).

Table 8
Offline Sales Elasticities of Advertising Actions

Offline Sales Classification	Variables	Immediate	Cumulative
Mediator	Online Banner Click-throughs	0.010	0.007
Mediator	Search Click-throughs	0.193	0.388
Mediator	Consideration Set (D)	-0.262	0.091
Online Advertising	Emails	0.004	-0.001
Offline Advertising	Traditional Advertising (excl. TV)	-0.003	-0.003
Online Advertising	Online Banner Ads	0.005	0.005
Online Advertising	Paid Search Advertising	0.140	0.240
Offline Advertising	TV	0.006	0.009
Lagged DV	Offline Sales	0.479	0.479
Lagged DV	Online Sales	0.194	-0.052

Table 9
Paid Search Advertising Offline Sales Elasticity Relative to the Other Channels

Offline Sales Paid Search Advertising Elasticity Relative to:	Immediate	Cumulative
Emails	35	-240
Traditional Advertising (excl. TV)	-47	-80
Online Banner Ads	28	48
TV	23	27

Indirect Effects: Response of Sales to Shock in Mediators

Given the differential interpretation of variables in levels (click-throughs) and variables in differences (consideration set) we examine their impact on sales separately in the two upcoming sections. First, we examine the effect of a one-standard-deviation shock in click-throughs on the future level of weekly sales and indicate the direction of the indirect effects. The search click-through elasticities exert the highest positive impact on both sales variables. For online sales, the immediate search click-through elasticity (0.281) is more than 14 times higher than that of online banner click-throughs (0.019) and the cumulative elasticity is 24 times higher (see Table 6).

For offline sales, the immediate search click-through elasticity (0.193) is more than 19 times higher than the online banner click-throughs elasticity (0.010), and the cumulative impact is 55 times higher (see Table 8). The higher elasticity of search click-throughs is in line with our previous findings and is somewhat intuitive. Online banners function as recognition reminders (first stage of the purchase funnel) while consumers encounter search advertising in the search stage of the purchase funnel (second stage). At this point, the consumer has recognized the need for the product category (stimulated by e.g., online banner ads) and initiated an information search where the consumer is more likely to visit the website and gather information about the alternatives. Indicating that we will find the strongest (positive) indirect effects via search click-throughs.

The consideration set elasticities on both sales variables indicate that growth in the variable exerts a negative impact on short-term sales. The result is somewhat surprising; conventional wisdom suggests that being a part of the consumer's consideration set is a necessary precondition for choice (see e.g., Nedungadi, 1990) and we would expect consideration set and click-throughs to move in the same direction. For instance, click-throughs do not simply reflect underlying attitudes (e.g., a well-known brand obtains higher click-throughs), they also shape them. When consumers search for flowers or plants, they may begin with a few brands in mind but then discover new ones through interaction with online advertising, which increases their thoughts about those new brands (Hanssens & Pauwels, 2016)

Indirect Effects: Response of Mediators to Shock in Advertising

Tables 10-12 display the calculated immediate and cumulative elasticities for each mediator and provide some indications for the magnitude of the indirect effects of each advertising channel. The effects of the advertising channels on search click-throughs are relatively small, indicating that these forms of advertising do not enhance the effectiveness of search click-throughs. However, for online banner click-throughs, we observe stronger effects. Paid search advertising has the largest impact on online banner click-throughs (1.478), suggesting that consumers more frequently click on online banner ads after they have searched for relevant keywords. The strong effect is probably related to retargeting (the consumer gets targeted ads based on search engine searches and website visits). However, the effect is immediate, suggesting that it does not retain for long periods of time.

Table 10
Search Click-throughs Elasticities of Advertising Actions

Search Click-throughs Classification	Variables	Immediate	Cumulative
Mediator	Online Banner Click-throughs	0.010	0.010
Mediator	Search Click-throughs	0.480	0.896
Online Advertising	Emails	0.003	n.s.
Offline Advertising	Traditional Advertising (excl. TV)	-0.002	-0.002
Online Advertising	Online Banner Ads	0.006	0.001
Online Advertising	Paid Search Advertising	0.372	0.493
Offline Advertising	TV	n.s.	-0.004
Lagged DV	Offline Sales	0.361	0.232
Lagged DV	Online Sales	0.209	0.209

Table 11
Online Banner Click-throughs Elasticities of Advertising Actions

Online Banner Click-throughs Classification	Variables	Immediate	Cumulative
Mediator	Online Banner Click-throughs	0.534	0.633
Mediator	Search Click-throughs	2.295	-0.983
Online Advertising	Emails	0.073	-0.074
Offline Advertising	Traditional Advertising (excl. TV)	n.s.	0.315
Online Advertising	Online Banner Ads	0.366	0.456
Online Advertising	Paid Search Advertising	1.478	1.478
Offline Advertising	TV	0.042	-0.021
Lagged DV	Offline Sales	4.385	0.634
Lagged DV	Online Sales	3.154	-2.913

Traditional advertising (excl. TV) has a positive long-term impact on online banner click-throughs (0.315), suggesting that these forms of advertising serve as powerful reminders. The short-term elasticities of emails (0.073) and TV (0.042) are positive, however, in the long run, emails (-0.074) and TV (-0.021) have a negative impact. A possible interpretation is that these forms of advertising evoke need recognition and make the brand salient immediately. Consequently, the consumer is more likely to notice the banner ads and progress in the purchase funnel to the information search stage and enter the website (i.e., click on the ad). However, in the long run, these forms of advertising serve as a substitute for the information provided by a click-through.

Next, we examine the accumulated responses of an evolving variable (consideration set) to shock in advertising. First, we observe that sales exert a negative impact on the consideration set, indicating dissatisfaction. For instance, after the consumer conducts a purchase, the consumer "updates" the consideration set. If the consumer is not happy with the purchase from the retailer, the retailer is deemed less attractive. However, the effects are small and make sense since the consideration set has a negative impact on both sales variables. Second, the impact of the advertising channels on the consideration set are either insignificant, relatively small or negative. This indicates that the advertising actions of the retailer do not have a large impact on the consideration set, or that advertising has a spillover effect on competing brands. For instance, advertising cues that help the consumer retrieve and consider a target brand could simultaneously increase the likelihood of considering similar competitors (Nedungadi, 1990).

Table 12
Consideration Set Elasticities of Advertising Actions

Consideration Set Classification	Variables	Immediate	Cumulative
Mediator	Online Banner Click-throughs	0.001	0.001
Mediator	Search Click-throughs	-0.037	-0.073
Mediator	Consideration Set (D)	0.992	6.716
Online Advertising	Emails	n.s.	n.s.
Offline Advertising	Traditional Advertising (excl. TV)	0.001	0.001
Online Advertising	Online Banner Ads	0.002	-0.006
Online Advertising	Paid Search Advertising	-0.030	-0.068
Offline Advertising	TV	n.s.	n.s.
Lagged DV	Offline Sales	-0.036	-0.101
Lagged DV	Online Sales	-0.023	-0.023

Total Effects

Finally, we summarize the findings by calculating total elasticities based on the Dinner, Van Heerde, and Neslin (2014) approach, and answer the hypotheses. Table 13 shows how the total long-term advertising elasticities can be decomposed. First, we focus on offline advertising channels. We find support for the hypothesis that TV has a positive direct effect on long-term sales, partially offset by a negative indirect effect on search click-throughs (H_1). The size of the indirect effects is smaller than the positive direct effects, resulting in positive own-channel and cross-channel effects.

Table 13
Total Long-term Advertising Elasticities and Their Decomposition (Boldfaced Numbers are Cross-Channel Effects)

	Online Sales			Offline Sales			Total Sales Elasticity[a]	
	Direct Effect (a)	*Indirect Effect (b)*	*Total Effect (a)+(b)*	*Direct Effect (c)*	*Indirect Effect (d)*	*Total Effect (c)+(d)*	*Absolute*	*In % of Revenues*
Emails	0.006	−0.001	0.005	**−0.001**	**−0.001**	**−0.002**	0.003	−0.001
Online Banner Ads	0.010	0.009	0.019	**0.005**	**0.004**	**0.009**	0.028	0.009
Paid Search Advertising	0.398	0.252	0.650	**0.240**	**0.202**	**0.442**	1.092	0.446
Traditional Adv. (excl. TV)	**−0.007**	**0.005**	**−0.002**	−0.003	0.001	−0.002	−0.003	−0.002
TV	**0.007**	**−0.002**	**0.005**	0.009	−0.002	0.007	0.012	0.007

[a]In % of Revenues = $\%Revenues_{Online} \times (a+b) + \%Revenues_{Offline} \times (c+d)$. In this application, $\%Revenues_{Offline} = 0.98$, because 98% of sales goes through the offline channel.

Traditional advertising (excl. TV) has a direct negative impact on both sales variables. However, there is a positive indirect effect via online banner-click throughs on both sales variables. The indirect effect via search click-throughs is negative but small (-0.001), and the positive direct effect dominates, indicating that this form of advertising does not effectively drive sales on its own but does stimulate brand retrieval, translating into more online banner click-throughs. Thus, the hypothesized positive indirect effect through click-throughs is supported (in sum, H_2 is partially supported).

Second, we investigate the impact of online advertising channels on sales. Emails have a positive direct own-channel effect and a negative direct cross-channel effect, as we indicated previously. Thus, although the emails contain offers exclusively available in the offline store, emails do not effectively overcome the channel-switching barrier. The positive own-channel effect is partially offset by a negative association with online banner-click throughs, indicating that the emails do not increase the likelihood of clicking online banner ads but drive online sales on their own. The effect on search click-throughs is insignificant. In sum, we find support for H_3.

Online banner ads have a positive direct own-channel and cross-channel effect. The positive direct effects are further amplified by positive indirect effects on both purchase channels, resulting in the second-highest total elasticity of all the channels (0.009), H_4 is supported. Paid search advertising has the most significant positive direct effects on both purchase channels. Thus, the channel-switching barrier is not evident in these two forms of advertising. The positive impact of paid search advertising is further amplified by strong and sizable indirect effects, in support of H_5. Interestingly, paid search advertising is the channel that most effectively drives online banner click-throughs.

An overview of the hypothesis results can be found in Table 14. Overall, we observe that the sum of each advertising channel's cross-effects is larger than the own-channel effects (see Table 15). This provides support for the Dinner, Van Heerde, and Neslin (2014) claim that cross-channel effects are important. Moreover, even though the total sales elasticity of paid search advertising on online sales is greater than the total sales elasticity on offline sales, the discrepancy between paid search advertising and the less effective channels is even greater in the offline channel.

Table 14
Summary of Hypotheses and Empirical Support

Hypotheses		**Support?**
H_1	TV has a positive direct effect on long-term sales, the total positive impact is diminished by a negative indirect effect via click-throughs.	Yes
H_2	Traditional advertising excl. TV has a (marginally) positive direct effect on long-term sales; the total positive impact is amplified by a positive indirect effect via click-throughs.	Partially
H_3	Emails have a positive direct effect on long-term sales, but the total positive impact vanishes due to a negative indirect effect via click-throughs.	Yes
H_4	Online banner ads have a positive direct effect on long-term sales, the total impact is amplified by a positive indirect effect via click-throughs.	Yes
H_5	Paid search advertising has a positive direct effect on long-term sales, the total impact is amplified by a positive indirect effect via click-throughs.	Yes

Table 15
Total Own-Channel and Cross-Channel Effects (in % of Revenue)

	Cross-Channel Effect	Own-Channel Effect
Emails	−0.001	0.000
Online Banner Ads	0.008	0.000
Paid Search Advertising	0.433	0.013
Traditional Advertising (excl. TV)	0.000	−0.002
TV	0.000	0.007
Total	**0.440**	**0.019**

Notes: The elasticities are displayed in % of revenues. Thus, online sales elasticities are multiplied with 2% and offline sales elasticities with 98%.

Another interesting finding is that traditional advertising (excl. TV) has a positive indirect effect on sales via click-throughs, while the opposite is true for TV. The result indicates that TV and other traditional advertising channels should be analyzed separately. Furthermore, online advertising – in particular paid search advertising – accounts for a large chunk of the cross-channel effects. Which provides support for the notion (e.g., Lobschat, Osinga, & Reinartz, 2017) that even retailers predominately selling through the offline channel can benefit from online advertising and that the research-shopper phenomenon is highly relevant in this context.

Discussion

In sum, we have demonstrated the relative superiority of paid search advertising relative to the other advertising channels. The size of the paid search advertising short-term elasticity corresponds well with previous findings in the literature (e.g., Dinner, Van Heerde & Neslin, 2014). Paid search advertising is a form of advertising the consumer encounter when the consumer himself has initiated the contact. The other form of advertising, firm-initiated contact (traditional advertising excl. TV, TV, emails), can reach consumers that have not yet recognized a need for the product category and can push the consumer closer to a purchase. However, firm-initiated contacts are increasingly unwanted by the consumer and can be considered annoying (Blattberg, Kim, & Neslin, 2008). Conversely, are customer-initiated contact (e.g., paid search advertising) response rates found to be more directly sales effective (e.g., Li & Kannan, 2014; Shankar and Malthouse, 2007; Wiesel, Pauwels, & Arts, 2011).

Furthermore, the analysis has detected that even though the own-channel effect of paid search advertising is stronger than the cross-over effect, the relative long-term impact is even greater on offline sales. Thus, for managers to allocate budgets efficiently should this relative impact be emphasized. The relatively greater impact (than the other channels) and the size of the long-term paid search elasticity substantially exceed the range of values reported in the literature (e.g., Dinner, Van Heerde & Neslin, 2014). Paid search advertising is typically expected to have a high immediate impact that quickly diminishes over time, while traditional advertising and online banner ads are expected to increase consumer awareness and knowledge for long periods (Dinner, Van Heerde & Neslin, 2014). Our analysis, however, suggests otherwise: the impact of traditional advertising excl. TV and online banner ads are immediate, while paid search advertising has a significantly longer carryover than any other advertising channel.

A plausible explanation for the relatively strong long-term impact of paid search advertising is how customers process advertising messages. Customers are typically exposed to thousands of advertising impressions every day, which they ignore or process as the preemptive level. The message can still evoke need recognition, but it is unlikely that the customer processes the details (such as the sender). However, when the customer actively seeks the information (as in a search), the customer consciously processes the information and pays more attention. Thus, when the customer has invested time learning about the product category, it is more likely that the consumer remembers the advertiser and have that exact retailer top of mind (even if a purchase is conducted weeks later). These results highlight the need for researchers to employ a model that can also account for the carryover effects of advertising channels.

Another interesting and somewhat surprising result is the consideration set's negative sales elasticities. A possible explanation is that the consideration set has reached its potential. Conventional wisdom suggests that managers should invest in increasing the attitudinal metric with the most remaining potential (Hanssens et al., 2014), and the focal retailer has already achieved high levels of consideration. Thus, advertising spending aimed at building consideration would insert greater impact if the level was 20% instead of, e.g., 70%. Moreover, it may be the case that consumers report increased consideration for the brand but fail to purchase it for several reasons, including geographical distance or habit inertia for the previously purchased brand (Hanssens et al., 2014). Thus, an enhancement in retrieval probability will translate into a positive choice effect only if preferred competitors are not concurrently included in the consideration set (Nedungadi, 1990).

Finally, advertising effects can still occur without changes in attitudinal metrics, i.e., consumers react to an advertising cue without changing their mind (e.g., the brand was in the consideration set to begin with and it remains there after the stimuli-induced purchase). Indeed, Hanssens et al. (2014) found that consideration has lower sales conversions than other metrics (e.g., liking) and that purchases of low involvement products are not preceded by significant attitude change. Thus, even when advertising successfully lifts consideration, it does not imply that the attitude metric converts into sales. Hence, focusing on lifting consideration can be interpreted as an ineffective advertising focus that does not increase this particular retailer's top line.

Implications

Our investigation of the relative effectiveness of different advertising channels in a setting where the retailer predominately sells through the offline channel offers several potential contributions for advancing the field's knowledge and understanding of how to derive optimal budget allocations across online and offline advertising channels.

First, we have demonstrated that cross-channel effects are essential, and ignoring them can lead to a severe undervaluation of online advertising channels' effectiveness. Specifically, paid search advertising has the most significant impact on both short-term and long-term sales in both purchase channels. The findings contrast previous research that has not detected the long-term impact of paid search advertising and highlights the importance of accounting for the dynamic performance of advertising channels. Accounting for dynamic performance and carryover by the VAR system model produces a long-term elasticity that is several times higher than that reported by, e.g., Dinner, Van Heerde, and Neslin (2014).

Second, there has been a lack of studies investigating the impact of offline advertising on online sales. The study contributes to this emerging body of literature by distinguishing between TV and other traditional advertising channels. For instance, Dinner, Van Heerde, and Neslin (2014) found a negative indirect effect of traditional advertising via click-throughs. Our study nuances this finding by demonstrating that TV has a negative impact on click-throughs, while traditional advertising (excl. TV) has a positive impact. However, we emphasize that the industry investigated has implications for the findings, and it is likely that the results and magnitude of the different advertising channels deviate across industries (e.g., florist vs. high-end apparel retailer).

Third, the assessment of synergic effects enables us to provide concrete evidence of the importance of coordinating advertising channels and managing them in tandem. Our framework and model also enable traditional advertising channels to be credited for their ability to enhance online advertising (through increased online searching translating into clicks), which can affect both online and offline sales. Our research contributes to this emerging body of literature by quantifying the effectiveness of different advertising channels and comparing their contributions to performance.

Fourth, analyzing the impact of advertising channels on the consideration set allows us to detect what can be interpreted as an ineffective advertising focus for this retailer. The consideration set sales elasticities are negative. In other words, the retailer is unlikely to benefit from a consideration enhancing focus in advertising campaigns, as the consideration set likely has reached its potential (or that a purchase is not preceded by significant attitude change). Instead, the retailer should focus on lifting other attitudinal metrics, such as loyalty.

A practical benefit from applying the proposed model is likely to come from better measures of the effects of both online and offline advertising channels. As we noted previously, the VAR model incorporates the potential endogeneity likely to be present within advertising channels and click-throughs, incorporates indirect effects among marketing variables and sales, and allows each variable to have different and potentially long-lasting carryover effects. The general results are a potentially different estimate of the return on the firm's online advertising investments relative to offline advertising. While the focal retailer predominately sells through the offline channel, online advertising is especially effective in driving offline sales, supporting the research-shopper phenomenon.

Conclusion

This study aimed to increase the understanding of how to derive optimal advertising budget allocations and how this depends on cross-channel effects, indirect effects, and lagged responses. We calculated and compared advertising elasticities by applying data from a florist predominately selling through the offline channel. Specifically, we investigated cross-channel effects and synergic effects from multiple advertising channels' contemporaneous activity on the implications for long-term elasticity calculations.

We developed a vector autoregressive model that accounts for the endogeneity in advertising, dynamic advertising effects, and multiple dependent variables. The ability to handle endogeneity among advertising channels and performance variables is an essential feature of the proposed modeling approach. It permits us to assess the relative effectiveness of different advertising channels in the short and long term while accounting for dynamic mechanisms.

For this retailer, we find that cross-channel advertising effects are larger than own-channel effects, particularly from online advertising to offline sales. The results suggest that firms should consider cross-channel effects in evaluating advertising return on investment (especially since online advertising often is cheaper) and manage online and offline advertising in tandem to exploit synergic effects.

Overall, our findings suggest that online advertising effectively drives long-term offline sales and is not a strictly online tool suited to drive short-term sales. In contrast to Dinner, Van Heerde, and Neslin's (2014) study, we find that the effect of paid search advertising has a substantial carryover. The results indicate that consumers looking for flowers can learn from a single click-through, and the effect carries over to future sales. In sum, our work has several important implications for practicing managers, offering them a tool to improve the metrics they use for assessing the effectiveness of offline and online advertising on sales when synergic effects are present.

Limitations

Our study has several limitations that can provide avenues for future research. Our data come from one large florist. Thus, data limitations prevent us from analyzing the effects of advertising for competing retailers. Though unfortunate, this is common to this type of company-specific data set. The data are also at the aggregate level. Therefore, we do not address segmentation in response to search advertising vs. traditional advertising at the individual level. Future research utilizing individual data should investigate the heterogeneity in consumer responses to advertising (e.g., where the consumer is in the purchase funnel likely has consequences for the responsiveness to paid search advertising vs. TV).

Another limitation of our research is the high familiarity of the focal retailer. Future research should further investigate the usefulness of memory-based metrics in assessing the effectiveness of different advertising channels. Moreover, we cannot account for the number of stores relative to the competition. Although flowers are hedonic products, the purchase is typically not planned a long time, and where the purchases are conducted is characterized by convenience (i.e., closest shop). However, advertising can have an essential function in evoking the need for the product category and the pleasure associated with flowers and plants.

In summary, our goal was to shed new light on the actual effectiveness of different advertising channels while accounting for endogeneity and complex mechanisms enhancing their performance (synergies, cross-over effects). We do this by quantifying the dynamic performance effects of advertising in the setting of a florist – a setting that allows us to investigate how advertising affects sales indirectly and directly in the native channel and through cross-channel effects for a firm predominantly selling through the offline channel. Thus, we are among the first to quantify and compare elasticities while accounting for these complex mechanisms.

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