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Many firms are allocating increasing parts of their advertising budgets to banner advertising. Yet, for firms that predominantly sell offline, existing research provides little guidance on online advertising decisions. In this study, the authors analyze the impact of banner advertising on consumers' online and offline behavior across multiple distinct campaigns for one focal firm, which predominantly sells through the offline channel. Results suggest that banner and TV advertising increase website visit incidence for consumers who have not visited the focal firm's website in the previous four weeks (nonrecent online consumers). For these consumers, banner and TV advertisements indirectly increase offline sales through website visits. For consumers who have visited the firm's website in the previous four weeks (recent online consumers), the authors find evidence for a cross-campaign, brand-building effect of banner advertising, and TV ads also directly affect offline purchases. Overall, the findings indicate that for firms that predominantly (or even exclusively) sell offline, banner advertising is most suitable to generate awareness for a firm's new products among nonrecent online consumers, and to build their brand(s) among recent online consumers.

Keywords: banner advertising, Bayesian multivariate probit, cross-campaign effects, cross-channel effects, consumer heterogeneity

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What Happens Online Stays Online? Segment-Specific Online and Offline Effects of Banner Advertisements

Today, many firms allocate considerable portions of their advertising budget to the online channel. Global online advertising expenditures are expected to reach US$185 billion in 2016, or 32% of total advertising spending, and to grow further in subsequent years. Approximately 47% of online advertising spending is allocated to banner advertising, particularly with the recent rise of display advertising on social media (ZenithOptimedia 2016). Yet debate continues about whether banner advertising can generate website traffic and online as well as offline sales. Thus, assessing the effectiveness of banner advertising is a top priority for both academics and practitioners (Rutz and Bucklin 2012).

Existing studies on the effects of banner advertising mainly focus on online consumer responses (e.g., Manchanda et al. 2006), whereas research addressing the effects of online marketing tools on offline behavior is limited. This lack of knowledge is surprising, considering that most purchases still take place offline (eMarketer 2014).

Moreover, it is unclear whether the effects of banner advertising hold in a cross-channel context, given the additional decisiveness and effort involved in conducting an offline purchase. Firms that predominantly sell offline thus need more insights into how online advertising campaigns affect offline sales.

A few studies have assessed the impact of online advertising campaigns on offline firm performance (e.g., Danaher and

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Dagger 2013; Dinner, Van Heerde, and Neslin 2014; Lewis and Reiley 2014). However, they leave at least three important questions unanswered.

First, existing studies typically do not allow for heterogeneity in online ad responsiveness (Danaher and Dagger 2013; Lewis and Reiley 2014); thus, for managers it is not clear whom to target online to improve offline sales. In this study, drawing on previous literature, we segment consumers according to the recency of their last touch point with the focal firm (e.g., Blattberg, Kim, and Neslin 2008). We identify consumers' online recency by the recency of their last visit to the firm's website; we define recent (nonrecent) online consumers as those who made (did not make) one or more website visits in any of the past four ad campaigns. In line with prior research, we expect the recency of the consumers' latest touch point with a firm to affect the salience of this firm in consumers' memory and hence their ad responsiveness. A better understanding of the differences in ad responsiveness across consumers in different stages of the purchase funnel is important, given the steady increase in ad spending on retargeted advertising, that is, advertising targeted to consumers who have recently visited the advertising firm's website (Hoban and Bucklin 2015; Lambrecht and Tucker 2013).

Second, prior research does not provide empirical evidence about whether online ad campaigns affect offline sales either directly or indirectly, by first driving consumers to the firm's website or other information source, after which the consumers may conduct offline purchases, in accordance with the research-shopper phenomenon (Verhoef, Neslin, and Vroomen 2007). A deeper understanding of whether online advertising campaigns directly or indirectly affect offline sales is important for website design and sales attribution.

Third, little is known about the within- versus cross-campaign effects of banner advertising on consumers' offline behavior (e.g., Braun and Moe 2013). Existing studies (e.g., Dinner, van Heerde, and Neslin 2014; Lewis and Reiley 2014) do not distinguish between distinct ad campaigns for distinct (sets of) products, making it unclear whether the weekly advertising carry-over is due to a lagged sales response to the information provided in the ads or due to a brand-building cross-campaign effect. For a proper performance evaluation of short-term campaigns, one should focus not only on the within-campaign effects but also on the cross-campaign, long-term impact (Li and Kannan 2014). In summary, we seek to answer three research questions: (1) Does the effect of banner advertising on website visit and offline purchase incidence differ for recent and nonrecent online consumers? (2) Does banner advertising affect offline purchase incidence directly or indirectly (i.e., through website visits), or both directly and indirectly? (3) Does banner advertising in the current campaign affect website visit and offline purchase incidence in subsequent ad campaigns even if the information contained in the banner ad is no longer relevant?

To answer our research questions, we model a consumer's likelihood to (1) visit the advertising firm's website and (2) conduct an offline purchase in a given ad campaign, using a Bayesian multivariate probit model with unique single-source data from GfK Panel Services Germany. Overall, our results show that firms that predominantly sell through the offline channel can benefit from online banner advertising.

In the next section, we review the relevant banner advertising research and formulate our focal expectations. Next, we describe our unique data and develop the model(s) for answering our research questions. Then, we present the empirical results of our analyses and conclude with implications for researchers and managers.

LITERATURE AND BACKGROUND

Link to Prior Research on the Impact of Banner Ads on Offline Sales

Despite its managerial importance, research on the offline impact of banner advertising is scarce. Based on a field experiment, Lewis and Reiley (2014) find exposure to banner advertising increases offline sales for the treatment group. Danaher and Dagger (2013) reveal a positive and significant effect of banner ad exposure on consumers' likeliness to visit the focal firm's website, whereas a direct effect on offline purchase incidence is not supported. Regarding the question of within- versus cross-campaign effects, Lewis and Reiley (2014) examine within- and postcampaign effects on offline sales using a single retail image campaign. They find evidence for a positive and significant within-campaign and a one-week postcampaign effect, whereas the postcampaign effects for the three following weeks are positive but not significant.

Current research thus provides initial evidence that online advertising affects offline sales, both within and across campaigns. However, the question of whether different consumers, particularly recent and nonrecent online consumers of the focal firm, show differential within- and cross-campaign effects, and whether these effects are direct and/or indirect (e.g., mediated by website visits) has been left largely unexplored.

Consumer Online Recency

For marketers, it is of utmost interest to know how the effect of banner advertising varies across different consumer segments. Not accounting for consumer heterogeneity in ad responsiveness can result in biased results on the effectiveness of banner advertising (Rutz and Bucklin 2012). Hoban and Bucklin (2015) reveal that a consumer's online responsiveness to banner ads varies over time as the consumer progresses to different stages of the purchase funnel.[1] Likewise, Ackerberg (2001) finds support for differential effects of advertising for experienced versus inexperienced consumers. For the sake of managerial feasibility, we specifically focus on consumers' prior visit(s) to the focal firm's website—in line with Hoban and Bucklin (2015)—and the time elapsed since the last visit took place. More specifically, we expect ad responsiveness to decline with online recency, the time since the last website visit (cf. Johnson, Lewis, and Reiley 2015).

Within-Campaign Effects of Banner Advertising

We expect differential within-campaign effects of banner advertising for recent versus nonrecent online consumers. For recent online consumers, the firm and its brand(s) are likely to be more salient (Baumgartner, Sujan, and Padgett 1997), so detecting whether the banner ad to which consumers are exposed is of interest generally requires less effort (Alba and Hutchinson 1987). If they are interested in the offered products, they are more likely to go to the offline store than to first visit the firm's website.

[1]The purchase funnel represents how a consumer's relationship with a firm evolves over time from having little experience and likely being unaware of the firm to being highly experienced and the firm being (more) top-of-mind.

On the other hand, nonrecent online consumers, with lower levels of awareness of the respective firm, may need to be "activated" to enter or move to the next stage of the purchase funnel (e.g., through banner ads; Abhishek, Fader, and Hosanagar 2012) and may require additional information before conducting an offline purchase. In general, consumers often conduct extensive research online and then purchase offline—also referred to as a popular form of the research-shopper phenomenon (Verhoef, Neslin, and Vroomen 2007). Thus, the Internet serves as a transaction channel and as a source of easily accessible product- and brand-related information (Van Bruggen et al. 2010). Thus, we expect nonrecent online consumers to first venture to the focal firm's website before conducting an offline purchase, hinting at an indirect positive effect of online advertising exposure on offline purchase incidence.

Cross-Campaign Effects of Banner Advertising

In a multicampaign setting, where each ad campaign promotes a unique set of products, consumers are confronted with new product information at the beginning of each campaign. However, firms generally also retain certain ad execution elements across ad campaigns, such as the brand name and logo, or the general setup of the ad (e.g., colors, layout). The repetitive exposure to these elements does not provide consumers with new information about the advertising firm but fosters an accumulation of goodwill, with positive effects on brand image and purchase intention—especially for familiar brands (Erdem and Keane 1996). This cross-campaign effect can be described as brand building, given that only the brand elements are still relevant and the products are no longer available.

We expect recent versus nonrecent online consumers to respond differently to banner advertising across different ad campaigns. For recent online consumers, who are in the later stages of the purchase funnel and can draw upon their stored brand schemas from previous experiences, we expect banner advertising from previous campaigns to serve as a powerful reminder—in line with a positive cross-campaign effect on offline purchase incidence, possibly mediated by website visits. For nonrecent online consumers, we expect a relatively weaker cross-campaign effect of banner advertising on offline purchase and website visit incidence, given that nonrecent online consumers may be in a state of disengagement with the advertising firm.

DATA

To adequately answer our research questions, our data need to fulfill four conditions: (1) the data are at the individual consumer level, (2) the data pertain to multiple distinct ad campaigns, (3) the advertised products are available only in the distinct ad campaign, and (4) the data clearly indicate the temporal order of events within a campaign. We are fortunate to have access to unique, single-source data from GfK Panel Services Germany, for which all four conditions are fulfilled.

The data indicate online and offline behavior at the individual household[2] level for 17 "blitz" ad campaigns (cf. Danaher and Dagger 2013) from one focal firm, which predominantly sells its products offline. This allows us to distinguish between recent and nonrecent online consumers, because we observe online behavior, including website visits, for individual households over a relatively long period. We also tested an alternative recency measure, wherein we included consumers' (online and offline) purchase history, and we find our results to be robust. For the sake of managerial feasibility and practicability, we present the results based on consumers' prior visits to the focal firm's website. This type of information is readily available to firms (i.e., through web analytics) and thus allows for an easy, real-time identification of the consumers' relationship with a firm. Moreover, the basis of retargeted advertising, a technique that has received a lot of attention and increased usage in recent years (eMarketer 2013), is consumers' prior visits to a firm's website (Lambrecht and Tucker 2013). In contrast, trying to link consumers' online and offline behavior (e.g., in-store purchases), especially for firms that predominantly sell offline, becomes more difficult and limits the selection of consumers to, for example, loyalty-card holders (Verhoef, Kooge, and Walk 2016). Within each campaign, we have time stamps for all online events, and we observe the day at which offline purchases are conducted at the individual consumer level, which allows us to identify whether the online ad directly and/or indirectly affects offline sales. Finally, we are able to separate the within-campaign banner ad effects from the (brand-building) cross-campaign effects, because the advertised products are available only in stores while the campaign is running. Therefore, the product information in the banner ads is relevant only within that campaign, whereas the brand name is relevant across campaigns, enabling us to answer our third research question.

Our focal firm is a well-known German retailer with a well-established multichannel distribution system, including an online presence[3] and more than 800 shops and franchise stores all over Germany. For reasons of confidentiality, we do not disclose the name of the retailer. Industry experts report that the vast majority of purchases (i.e., about 95% of total sales) from its durable product offering—which exclusively comprises private-label products—are generated in the retailer's offline stores. Its products include a broad variety of durables (e.g., furniture, electronics, clothing), offered on an irregular basis, that appeal to the general public (i.e., there are no niche products).

The firm's product offering is only available for one specific week and is thereafter changed completely (products are removed from the stores and replaced by new products). Moreover, each week's product offering relates to an overarching theme, such as barbecue-related items or sports clothing and equipment. The week's theme is promoted primarily through online banner advertising and sometimes also through TV advertising. Each theme week corresponds to a separate, unique ad campaign designed to inform consumers about the current offering. The respective target group is also general in nature and consistent across the different campaigns. All ads include the brand name. Examples with similar campaign strategies include "fast fashion" apparel retailers like Zara and Mango, as well as hard discounters selling nonfood goods, such as Lidl and Aldi.

At the beginning of each ad campaign, consumers typically have no prior information about the newly introduced durable product offering. The different campaigns with distinct products allow us to obtain insights into the nature of the respective banner ad effects—informative versus brand-building—which has been a topic of discussion for years (Draganska, Hartmann, and Stanglein 2014). According to publicly available information

[2]In the following, we use the terms "household" and "consumer" interchangeably.

[3]According to an industry report, more than 90% of the respondents in a consumer survey stated that they knew of this retailer's website.

about the firm, durable sales account for two-thirds of its total sales. The firm also sells fast-moving consumer goods, mainly through the supermarket channel.[4]

The data combine online advertising exposures and household purchase records. The online and offline purchase data were recorded via a general, retrospective purchase survey, covering a wide range of product categories (e.g., clothing, electronics, kitchen supplies), that households completed on a weekly basis. (For further information, see Web Appendix A.) Furthermore, our data cover households' exposures to banner, contextual, and sponsored search advertising from this firm, as well as their visits to this firm's website, via a browser extension added to the households' computers (GfK 2013).[5] Our data cover 508 unique households over a 17-week observation period (August–November 2009). In addition, we have access to daily TV ad expenditures. For an overview of the different data sources and the overall data structure, see Web Appendix B.

Online Advertising

The banner ads in our data set are of similar design, with images and brief descriptions of the durable products offered in a given campaign, as well as the retailer's logo. Most of these ads (more than 75%) appeared on websites with journalistic content or websites in the communications category, such as e-mail services, rather than on e-commerce or purchase-related websites. Their appearances did not depend on the consumers' prior browsing behavior, as would be the case with retargeted advertising (Lambrecht and Tucker 2013). Industry experts confirmed that, at the time of data collection, retargeted advertising was not common, either generally (Evans 2009) or by the focal retailer. Moreover, advanced techniques of audience targeting by means of real-time bidding—an automated process by which online advertisers can buy online ad impressions on an individual basis—were also not common in Germany, making up only 3% of total display ad spending in 2010, as confirmed by the International Data Corporation (2012). For each household, where possible, we calculated the average number of banner ad exposures over periods with and without a website visit in the past four campaigns (~30 days). A paired sample t-test shows that the null hypothesis of equal means for the two periods cannot be rejected ($t = .79$, $p = .43$). The correlation coefficient between the total number of purchases and banner ads per household is –.01 ($p = .84$), indicating no significant relationship. The near-zero correlation argues against the use of behavioral targeting practices by the advertising firm. For additional banner advertising endogeneity checks, see Web Appendix C.

We identify contextual ads—online ads on third-party websites targeted on the basis of the website's content, including e-mail—by Google's AdSense network, which uses content analysis algorithms to determine the most relevant ads for a vast variety of websites within their network. These contextual ads are mainly textual, with the possibility to include a small picture or logo. With sponsored search advertising, the firm pays a fee to a search engine operator, such as Google, to display its advertisements as links, alongside organic search results (Ghose and Yang 2009). We focus on nonbranded sponsored search ads to avoid overestimating the effect of sponsored search advertising (Li and Kannan 2014).[6]

We identified 4,454 banner, 243 contextual, and 318 (nonbranded) sponsored search ad exposures.[7] We classified each ad exposure according to whether it happened before or after the website visit on a given day, if any. On a day with multiple website visits for a given household, we used the first website visit as our reference point.

Offline Advertising

We have information on the daily expenditures on TV advertising for all 17 campaigns, of which the focal retailer supported 6 campaigns with nationwide TV ads. Overall, expenditures per campaign are of the same magnitude and fall on the first four days of the campaign week, peaking on either the second or third day of the campaign week.

Website Visits

Our data comprise 1,837 visits to the retailer's website, with an average of 3.62 per household and more than 108 per campaign week. The mean (median) number of households that visit the website across campaigns is 80.60 (82). The campaign with the least (most) website visits attracts 64 (92) households. For each campaign, we observe visits from recent and nonrecent online consumers. On average, about 17% of website visits come from nonrecent online consumers. Nearly 79% of households did not visit the website multiple times in a single campaign week. Slightly less than half did not visit the website in any of the 17 campaigns; that is, the average number of website visits across households that made at least one visit is 6.83. We do not observe which distinct pages consumers visited on the retailer's site. However, given that the main purpose of the website is to inform consumers about the current product offering, we expect consumers to navigate web pages with campaign-related content.

(Offline) Durable Purchases

We observe 509 purchases from the focal retailer, or, on average, approximately one per household. The purchased products were all part of the ad campaigns in a given week, but we do not have access to the exact items for confidentiality reasons. The vast majority of purchases (>93%) took place in one of the retailer's offline stores; 477 (34) purchases were made offline (online), confirming information from industry experts. The low percentage of online purchases might reflect the shipping fees that apply when consumers buy less than a certain amount, or the large number of offline stores. We observe 219 households that did not purchase from the focal retailer in our observation window. Across the 289 households that made at least one purchase, the average number of purchases is 1.76. Meanwhile, the retailer did not run any promotions or special deals. We provide the means and standard deviations of our focal variables for the website visit and

[4]In our observation period, the focal retailer did not advertise its fast-moving consumer goods offering online.

[5]According to a 2009 consumer survey, very few consumers used smartphones for shopping at that time (11%) (TNS Infratest 2009).

[6]We also ran our models including branded sponsored search ads, and we find our results to be robust, except for the effect of contextual ads on website visit incidence, which is no longer significant. Consumers who are exposed to contextual ads likely use branded search to revisit the website.

[7]The data collection system (i.e., web crawler) recorded a data entry every time the web crawler "visited" the website that featured the ad. To avoid double-counting the same banner ad exposure, we considered banner ad exposures only if (1) they were displayed at least five minutes after the earlier occurrence, or (2) the new entry was linked to a different image/ad.

offline purchase model in Web Appendix D. The focal variables are introduced in more detail in the following section.

MODEL DEVELOPMENT

We study the influence of banner ad exposures on the probability that a consumer will (1) visit the firm's website on a given day and/or (2) make a durable purchase in one of its offline stores, using a Bayesian multivariate probit model (Chib and Greenberg 1998; Zenetti et al. 2014).

Website Visit Model

We model the website visits, Website_{it}, for consumer i at day t using a binary probit approach. Website_{it} is a function of latent variable z_{it} through $\text{Website}_{it} = 1$ if $z_{it} > 0$ and 0 otherwise, where z_{it} is specified as follows:

$$
\begin{aligned}
(1)\quad z_{it} = {} & \beta_{0i} + \beta_1\text{Banner}_{it}\text{NR}_{it} + \beta_2\text{Banner}_{it}\text{R}_{it} \\
& + \beta_3\text{BannerStock}_{it}\text{NR}_{it} + \beta_4\text{BannerStock}_{it}\text{R}_{it} \\
& + \beta_5\text{Contextual}_{it} + \beta_6\text{Search}_{it} + \beta_7\text{TV}_t\text{NR}_{it} \\
& + \beta_8\text{TV}_t\text{R}_{it} + \beta_9\text{WebsiteCurr}_{it}\text{NR}_{it} \\
& + \beta_{10}\text{WebsiteCurr}_{it}\text{R}_{it} + \beta_{11}\text{Website}_{it-1} \\
& + \beta_{12}\text{PurchaseCurr}_{it} + \beta_{13}\text{WebsitePrev}_{it} \\
& + \beta_{14}\text{PurchasePrev}_{it} + \beta_{15}\text{R}_{it} \\
& + \beta_{16}\text{Holiday}_t + \sum_{d=1}^{6}\gamma_{\text{Website},d}\text{I}(\text{Day}_t = d + 1) \\
& + \sum_{k=1}^{12}\delta_{\text{Website},k}\text{I}(\text{Campaign}_t = k + 1) + \varepsilon_{\text{Website},it}.
\end{aligned}
$$

In Equation 1, I is an indicator variable; d = 1, ..., 6 indicates the day of the week and k = 1, ..., 12 refers to the number of the campaign (we observe 17 ad campaigns, use the first 4 for initialization, and omit a campaign dummy for identification); and β_{0i} represents a household-specific random intercept that captures a household's overall website visit frequency, which we assume to come from a normal distribution. The error term $\varepsilon_{\text{Website},it}$ also follows a normal distribution. Below, we discuss the explanatory variables in our model.

Banner advertising. We model the effects of both the within- and cross-campaign effects of banner advertising. For within-campaign effects, we consider the log of the cumulative number of banner ad exposures within a campaign up and until day t (Banner_{it}).[8] We use the log transformation to account for diminishing returns (Rutz and Bucklin 2012). We further model the cross-campaign impact by considering a stock variable over the previous four campaigns (BannerStock_{it}), where we use decay parameter λ_1 to capture forgetting. In the Appendix, we give a detailed description of the variable operationalizations.

Contextual and sponsored search advertising. Although our focus is on banner advertising, we control for two other types of online advertising: contextual and sponsored search advertising. We define Contextual_{it} as a dummy variable that indicates whether a consumer has been exposed to a contextual ad in the focal campaign up to and including day t. We operationalize the exposure to nonbranded sponsored search ads (Search_{it}) similar to Contextual_{it}. We acknowledge that exposure to contextual and sponsored search ads may merely indicate a consumer's interest in a particular product. For this reason, we are careful in interpreting the effects from these ads in a causal way, and we note that inclusion of these variables does help to control for consumers' preexisting product interest. Our rationale for using a binary operationalization is that contextual and search ads indicate whether a consumer is interested in a particular product, regardless of the number of search ads. One may, however, argue that the number of ads is related to the level of interest and that the (log of the) number of ads instead of a binary operationalization should be used. The results are robust to this alternative operationalization for our website and purchase model, apart from no longer finding support for a contextual ad effect in the website model. Moreover, our results are robust to excluding Search_{it} and Contextual_{it} altogether. This leads us to conclude that any potential endogeneity is not of the first order in the sense of Rossi (2014). Moreover, we find these types of ads to be uncorrelated with banner ads (also see Web Appendix D), and we note that their occurrence in the data are relatively rare.

TV advertising. We specify the influence of TV advertising (TV_t) as the log of the cumulative daily expenditures, measured in hundreds of thousands of euros, up and until day t. Again, we use a log transformation to account for diminishing returns. Our daily TV variable thus is similar to the daily banner advertising variable, with the distinction that we use aggregate TV ad expenditures and household-level banner ad exposures.

Additional covariates. We include several additional variables that vary across households and time and that may determine a consumer's decision to visit the firm's website at day t. In line with Chen and Hitt (2003), we expect the number of website visits from the previous (WebsitePrev_{it}) and current ad campaign, up to day t (WebsiteCurr_{it}), to influence website visits at day t. WebsitePrev_{it} and WebsiteCurr_{it} capture multiple website visits on a given day, if applicable. Moreover, we consider the influence of durable purchases, both offline and online, conducted in the previous (PurchasePrev_{it}) and current campaign (PurchaseCurr_{it}) periods (Deighton, Henderson, and Neslin 1994). Finally, we allow for the influence of a website visit on the previous day (Website_{it-1}).

Recent versus nonrecent online consumers. As discussed in the conceptual section of the article, we distinguish between recent and nonrecent online consumers (R and NR, respectively). We define recent online consumers as those who have had active online contact with the firm, operationalized by one or more website visits in any of the four campaigns (average cookie lifetime used for retargeting purposes) preceding the current campaign. This variable is not fixed over time per consumer; it evolves from week to week depending on the consumers' behavior in the preceding campaigns. In a robustness check, reported in Web Appendix E, we consider different operationalizations.

We use the resulting NR and R variables to specify differential effects for within- and cross-campaign banner advertising, within-campaign TV advertising, and website visits in the current campaign. To provide a clean test of the differential effects, we also include the main effect of R_{it}. We do not specify differential effects for contextual and sponsored search advertising, because exposure to these types of ads indicates interest in the advertised product, regardless of the consumer type. One could, however, argue that the salience of the focal firm moderates the effect of contextual and sponsored search ads. We explore whether our key results are robust to

[8]Using the cumulative number instead of the daily number of banner ad exposures provides a superior model fit.

the assumption of a homogeneous effect for contextual and sponsored search ads in one of our robustness checks reported in Web Appendix E.

Variables varying over time. Finally, we incorporate several variables that vary over time but not across individuals. We use Holiday_t to capture the effect of potential seasonal sales peaks just before the holidays and/or potential sales dips in the holiday season. We allow for differences in website visit incidence across different days of the week (Day_t), where we leave out the last day of the campaign week for identification. Also, using campaign-level dummy variables, we control for the overall popularity of campaign k, where we omit the final campaign for identification. We provide a detailed overview of all explanatory variables in the Appendix.

Offline Purchase Model

We next model the probability of observing an offline durable purchase[9] in one of the firm's stores by consumer i at day t. Again, we specify a random effects binary probit model; that is, $\text{Purchase}_{it} = 1$ if $x_{it} > 0$ and 0 otherwise, where x_{it} is specified below:

$$
\begin{aligned}
(2)\quad x_{it} = {} & \pi_{0i} + \pi_1 \text{Banner}_{it}\text{NR}_{it} + \pi_2 \text{Banner}_{it}\text{R}_{it} \\
& + \pi_3 \text{BannerStock}_{it}\text{NR}_{it} + \pi_4 \text{BannerStock}_{it}\text{R}_{it} \\
& + \pi_5 \text{Contextual}_{it} + \pi_6 \text{Search}_{it} + \pi_7 \text{TV}_t\text{NR}_{it} \\
& + \pi_8 \text{TV}_t\text{R}_{it} + \pi_9 \text{WebsiteCurr}_{it}\text{NR}_{it} \\
& + \pi_{10} \text{WebsiteCurr}_{it}\text{R}_{it} + \pi_{11} \text{Purchase}_{it-1} \\
& + \pi_{12} \text{PurchaseCurr}_{it} + \pi_{13} \text{WebsitePrev}_{it} \\
& + \pi_{14} \text{PurchasePrev}_{it} + \pi_{15} \text{R}_{it} + \pi_{16} \text{Holiday}_t \\
& + \sum_{d=1}^{6} \gamma_{\text{Purchase},d} I(\text{Day}_t = d + 1) \\
& + \sum_{k=1}^{12} \delta_{\text{Purchase},k} I(\text{Campaign}_t = k + 1) + \varepsilon_{\text{Purchase},it}.
\end{aligned}
$$

In Equation 2, we again account for the influences of within- and cross-campaign banner advertising. As in the website visit equation, we use the first four ad campaigns to initialize the lagged effects for banner advertising. We model the influence of the number of website visits in the current campaign on offline purchase incidence through a variable that differs slightly from that in the website visit model, to account for a same-day effect on offline purchases. The offline purchase model, WebsiteCurr_{it}, therefore also includes website visits on day t. Because the product assortment changes with every campaign, we do not focus on interpurchase time (cf. Manchanda et al. [2006], who focus on a presumably stable assortment of health care and beauty products for which repeat purchases are common). Moreover, our results are robust to including purchase recency in weeks as a control variable, while the effect of purchase recency on offline purchase incidence is not significant.

Additional covariates and variables varying over time. Analogous to the website visit model, we consider the effect of contextual and sponsored search ad exposures (De Haan, Wiesel, and Pauwels 2013), TV ad expenditures (Dinner, Van Heerde, and Neslin 2014), and the number of purchases from the previous campaign (PurchasePrev_{it}) (Danaher and Dagger 2013) on consumers' purchase probability. We also include the number of purchases conducted in the current campaign, before day t, to account for the possibility that consumers' demands might have been fulfilled through previous shopping (Bayus 1992). Again, we include both offline and online purchases in PurchasePrev_{it} and PurchaseCurr_{it}. Analogous to our website visit model, we account for a lagged dependent variable and holiday, day-of-the-week, and campaign-specific effects (Rutz and Bucklin 2012; Toubia, Stephen, and Freud 2011). The Appendix gives a detailed description of our variables.

Recent versus nonrecent online consumers. In line with our reasoning for the website visit model, we expect differential within- and cross-campaign responses to banner and TV advertising for recent and nonrecent online consumers. We further allow for potentially different effects of website visits on offline purchase for the two groups of consumers.

Estimation

We simultaneously estimate Equations 1 and 2 on data for all 508 households, 46,288 daily observations, using Markov chain Monte Carlo (MCMC) (Chib and Greenberg 1998). We allow for correlated contemporaneous errors by assuming $\varepsilon_{\text{Website},it}$ and $\varepsilon_{\text{Purchase},it}$ follow a multivariate normal distribution. For identification, we follow Chib and Greenberg (1998) and restrict the diagonal elements of the covariance matrix of this distribution to 1 and estimate the off-diagonal element, that is, the correlation between the two contemporaneous error terms. Moreover, we allow for correlated household random effects, β_{0i} and π_{0i}, by assuming these effects to be multivariate normally distributed. We place a diffuse multivariate normal prior on the set of the β and π parameters. We assume an inverse Wishart distribution for the covariance matrix of the random intercepts, and, finally, we place a [−1, 1] uniform prior on the off-diagonal element of the contemporaneous error covariance matrix. We run 20,000 MCMC iterations, where we use the first 10,000 for burn-in and the final 10,000 iterations for inference. We confirm convergence by inspection of the parameter trace plots for two independent chains of draws with different starting values.

Multicollinearity is not a problem in the data. The maximum variance inflation factor (VIF) values are 2.54 and 2.36, and determinants of the correlation matrices are .07 and .09 for the explanatory variables, including the interactions with consumer type, in the website visit and offline purchase equations, respectively. (For the complete correlation tables for the right-hand-side variables in the website visit and offline purchase equations, including all VIFs, see Tables WA1 and WA2, respectively, in Web Appendix D.) Moreover, the highest correlation among the independent variables, again including interactions with consumer type, in the website visit (offline purchase) model is .59 (.56), which is sufficiently low.

The inclusion of a lagged dependent variable in a random effects model creates a bias that dissipates with the number of observations per cross-sectional unit. We use 91 daily observations (13 campaign weeks) per cross-sectional unit, which we consider sufficient to estimate the model without correction. When we frame our focal models as linear probability models estimated by the Blundell–Bond approach (Blundell and Bond 1998), all our key results are robust. Detailed information about the test and its findings are available upon request from the authors.

[9]Because of the low incidence, we do not explicitly model online purchases. All our results are robust to including online purchases in the dependent variable Purchase_{it}.

RESULTS

We present the results of the website visit and offline purchase equations in Tables 1 and 2, respectively, where we omit the results for the household random intercepts and the campaign and day-of-the-week effects to keep the tables concise. Before discussing our estimation results, we first present an initial test of our expectations.

Model-Free Evidence

We first explore, at the campaign level, the relationship between banner ad exposure and website visit incidence in the current and the previous four campaigns by conducting multiple two-sample t-tests. (For a supporting figure, see Figure WA1 in Web Appendix F.) In line with the proposed within-campaign effect of banner advertising on website visits, we observe higher website visit incidence for consumers who were exposed to banner ads in the current campaign (t = 4.21 and 2.64, $p < .01$ and .01, for recent and nonrecent online consumers, respectively). Also, as predicted, the within-campaign effect is larger for nonrecent online consumers (.12) than for recent online consumers (.07). The expected effect of banner ad exposure in any of the past four campaigns on website visits is not supported: the differences in website visit incidence are not significant.

Next, we examine, at the campaign level, whether banner ad exposures and website visits are associated with offline purchase incidence. (For a supporting figure, see Figure WA2 in Web Appendix F.) We also explore the relationship between banner ad exposure in any of the previous four campaigns and the probability of buying offline. We assess significance by conducting independent-sample t-tests. In line with our expectations, we find a strong effect of website visits on offline purchase incidence for nonrecent online consumers (t = 3.39, $p < .01$, with respect to the baseline condition). We find no evidence for a within-campaign effect of banner ads on offline purchase incidence. For the effect of banner ad exposure in any of the past four campaigns, the results reveal a positive and marginally significant effect for recent online consumers (t = 1.81, $p = .07$). Contrary to our expectations, for nonrecent online consumers, the effect is negative, although nonsignificant (t = −1.55, $p = .12$).

Website Visit Model

In Table 1, we give the estimation results for the website visit equation. We provide the posterior mean and 95% credible intervals (CIs) for the parameters. Our results reveal that, in line with our predictions, banner advertising is effective in increasing website visits within the same campaign for nonrecent online

Table 1
PARAMETER ESTIMATES: WEBSITE VISIT MODEL

Variable	*Description*	*Term*	*Expected Sign*	*Estimate (CI)*
$Banner_{it}NR_{it}$	Log of the cumulative number of within-campaign banner ad exposures for nonrecent online households	β_1	+	.30 (.15, .45)
$Banner_{it}R_{it}$	Log of the cumulative number of within-campaign banner ad exposures for recent online households	β_2	+	−.03 (−.13, .08)
$BannerStock_{it}NR_{it}$	Stock of banner ad exposures from previous campaigns for nonrecent online households	β_3	+	.05 (.00, .10)
$BannerStock_{it}R_{it}$	Stock of banner ad exposures from previous campaigns for recent online households	β_4	+	.04 (.00, .08)
$Contextual_{it}$	Dummy variable for contextual ad exposure within campaign	β_5		.25 (.07, .43)
$Search_{it}$	Dummy variable for sponsored search ad exposure within campaign	β_6		.39 (.20, .58)
TV_tNR_{it}	Log of the cumulative TV expenditures within a campaign for nonrecent online households	β_7		.14 (.05, .23)
TV_tR_{it}	Log of the cumulative TV expenditures within a campaign for recent online households	β_8		.06 (−.02, .15)
$WebsiteCurr_{it}NR_{it}$	Number of within-campaign website visits for nonrecent online households	β_9		.37 (.23, .50)
$WebsiteCurr_{it}R_{it}$	Number of within-campaign website visits for recent online households	β_{10}		−.08 (−.14, −.01)
$Website_{it-1}$	Lagged dependent variable	β_{11}		−.09 (−.21, .02)
$PurchaseCurr_{it}$	Number of within-campaign purchases	β_{12}		.12 (−.06, .29)
$WebsitePrev_{it}$	Total number of website visits in the previous campaign	β_{13}		.08 (.04, .13)
$PurchasePrev_{it}$	Total number of purchases in the previous campaign	β_{14}		−.11 (−.23, .01)
R_{it}	Dummy for recent online households	β_{15}		.50 (.36, .64)
$Holiday_t$	Holiday density in the federal state of household	β_{16}		−.05 (−.11, .00)

Notes: The dependent variable is $Website_{it}$. Numbers in parentheses indicate the 2.5th and 97.5th percentiles of the posterior distribution.

consumers (β_1 = .30; 2.5th and 97.5th posterior percentiles are .15 and .45, respectively). For a nonrecent online consumer with mean household-specific effect and mean campaign popularity, the point elasticity at one banner ad exposure is .25, slightly higher than the website visit-to-advertising elasticity of .10 reported by Hoban and Bucklin (2015). However, Hoban and Bucklin explore consumers' responses to a complex, high-involvement product (i.e., a financial product), whereas we investigate banner ad effectiveness for a promotional blitz campaign for relatively low-priced durable goods. For recent online consumers, the effect is nonsignificant (β_2 = −.03; 2.5th and 97.5th posterior percentiles are −.13 and .08, respectively).

To formally test the differential effects for recent versus nonrecent online consumers, β_1 and β_2, we compare the posterior distributions for the two parameters. The 2.5th and 97.5th percentiles of the differences between β_1 and β_2 are .03 and .17, respectively, confirming that the effect of banner advertising for nonrecent online consumers (β_1) is significantly larger than that for recent online consumers (β_2). In line with a cross-campaign, brand-building effect, we find both recent (β_3 = .05; 2.5th and 97.5th posterior percentiles are .00 and .10, respectively) and nonrecent consumers (β_4 = .04; 2.5th and 97.5th posterior percentiles are .00 and .08, respectively) to be more likely to visit the firm's website after exposure to banner ads in (the) previous campaign(s).

Our results further reveal that nonrecent online consumers' propensity to visit the website is positively affected by TV ads (β_7 = .14; 2.5th and 97.5th posterior percentiles are .50 and .23, respectively). Exposure to contextual and search ads is associated with higher levels of website visit incidence (β_5 = .25; 2.5th and 97.5th posterior percentiles are .07 and .43, respectively; β_6 = .39; 2.5th and 97.5th posterior percentiles are .20 and .58, respectively), in line with our expectations. Notably, a prior website visit in the current campaign increases the visit probability for nonrecent online consumers (β_9 = .37; 2.5th and 97.5th posterior percentiles are .23 and .50, respectively), whereas the effect is negative for recent online consumers (β_{10} = −.08; 2.5th and 97.5th posterior percentiles are −.14 and −.01, respectively). Additional visits in the current campaign thus provide little additional information for recent online consumers. Also, the reason for the initial website visit may have been curiosity; once recent online consumers learn about the new product assortment, their need for information may be fulfilled. Nonrecent online consumers, in contrast, may feel that they can learn more and/or further reduce risk by visiting the website again. Finally, we find that neither the random intercepts nor the residuals are significantly correlated across equations. For the correlation of the random intercepts, we obtain a posterior mean of −.13 (2.5th and 97.5th posterior percentiles are −.38 and .13, respectively). The correlation of the residual terms of the website visit and offline purchase equations is estimated at .01 (2.5th and 97.5th posterior percentiles are −.13 and .11, respectively). Interestingly, under the assumption that the residuals of the two equations follow a bivariate normal distribution, the insignificant residual correlation provides evidence for the exogeneity of the website visit variable in the offline purchase equation (Knapp and Seaks 1998).

Offline Purchase Model

Table 2 contains the estimation results for the offline purchase equation. Partly in support of our expectations, we find a positive significant cross-campaign effect for recent online consumers (π_4 = .09; 2.5th and 97.5th posterior percentiles are .02 and .15, respectively). With mean household-specific effect and mean campaign popularity, the point elasticity at exposure to three banner ads in the previous campaign is .08, which is lower than previous findings by Dinner, Van Heerde, and Neslin (2014), who report a long-term display ad elasticity of .15. For nonrecent online consumers, the cross-campaign effect is negative and marginally significant (π_3 = −.08; 2.5th and 97.5th posterior percentiles are −.18 and .00, respectively). A possible explanation for this result is that nonrecent consumers are disappointed that the products from previous week's ads are no longer offered. In line with Danaher and Dagger (2013), we find no evidence for a direct within-campaign effect of banner ads on offline purchases; however, for nonrecent online consumers, we do find a strong positive effect of website visits on offline purchases (π_9 = .31; 2.5th and 97.5th posterior percentiles are .13 and .48, respectively). Assuming a mean household-specific effect and mean campaign popularity, a single website visit gives a 133% increase in offline purchase probability. In combination with the finding that banner ads positively affect website visit incidence for nonrecent online consumers, we thus find support for an indirect effect on offline sales. We assess the significance of this indirect effect by inspecting the posterior distributions of the two effects that make up the indirect effect, that is, the effect of within-campaign banner ads on website visit incidence and the effect of website visits on offline purchase incidence. We find that both posterior distributions are made up of strictly positive effects, thus providing evidence for a significant positive indirect effect.

TV ad expenditures have a positive impact on the probability that recent online consumers purchase offline (π_8 = .12; 2.5th and 97.5th posterior percentiles are .02 and .22, respectively). Thus, whereas TV ads drive nonrecent online consumers to the website, perhaps because they have a remaining need for information and do not feel ready to venture to the store, recent online consumers may skip this step and feel comfortable enough to directly visit the store. We find no support for a direct impact of contextual and search ads on the probability to buy offline. A likely explanation for this is that consumers who actively search for a product online prefer to buy online. Because our focal firm charges a shipping fee for its online orders and only sells private-label products, consumers might turn to other online firms to obtain the sought-after product.

Model Comparison

To better appreciate the impact of banner advertising on website visit and offline purchase incidence, we compare the fit of our focal model with that of a model in which we omit within- and cross-campaign banner effects. The log-marginal densities for the model with and without banner ad variables are −6,780.78 and −6,804.78, respectively. We conclude that banner effects are important in predicting website visit incidence.

We further compare the hit rates for our focal model with those of the alternative model without banner effects. We separate the results for the website visit and offline purchase equation to understand the importance of banner ads for explaining these two key variables. We follow previous work (e.g., Kopalle et al. 2012) in setting the classification cutoff value to the empirical mean, where we use the segment mean, nonrecent versus recent online consumers, to account for the

Table 2
PARAMETER ESTIMATES: OFFLINE PURCHASE MODEL

Variable	*Description*	*Term*	*Expected Sign*	*Estimate (CI)*
$Banner_{it}NR_{it}$	Log of the cumulative number of within-campaign banner ad exposures for nonrecent online households	π_1	+	–.14 (–.40, .12)
$Banner_{it}R_{it}$	Log of the cumulative number of within-campaign banner ad exposures for recent online households	π_2	+	–.23 (–.49, .01)
$BannerStock_{it}NR_{it}$	Stock of banner ad exposures from previous campaigns for nonrecent online households	π_3	+	–.08 (–.18, .00)
$BannerStock_{it}R_{it}$	Stock of banner ad exposures from previous campaigns for recent online households	π_4	+	.09 (.02, .15)
$Contextual_{it}$	Dummy variable for contextual ad exposure within campaign	π_5		–.10 (–.59, .29)
$Search_{it}$	Dummy variable for sponsored search ad exposure within campaign	π_6		.00 (–.46, .39)
TV_tNR_{it}	Log of the cumulative TV expenditures within a campaign for nonrecent online households	π_7		.06 (–.05, .14)
TV_tR_{it}	Log of the cumulative TV expenditures within a campaign for recent online households	π_8		.12 (.02, .22)
$WebsiteCurr_{it}NR_{it}$	Number of within-campaign website visits for nonrecent online households	π_9	+	.31 (.13, .48)
$WebsiteCurr_{it}R_{it}$	Number of within-campaign website visits for recent online households	π_{10}	+	.07 (–.06, .19)
$Purchase_{it-1}$	Lagged dependent variable	π_{11}		–.02 (–.37, .31)
$PurchaseCurr_{it}$	Number of within-campaign purchases	π_{12}		.04 (–.20, .27)
$WebsitePrev_{it}$	Total number of website visits in the previous campaign	π_{13}		.05 (–.06, .16)
$PurchasePrev_{it}$	Total number of purchases in the previous campaign	π_{14}		.07 (–.05, .19)
R_{it}	Dummy for recent online households	π_{15}		–.21 (–.37, –.04)
$Holiday_t$	Holiday density in the federal state of household	π_{16}		.00 (–.10, .09)

Notes: The dependent variable is $Purchase_{it}$. Numbers in parentheses indicate the 2.5th and 97.5th percentiles of the posterior distribution.

panel structure of our data. The hit rate for the focal website visit equation is .77. The hit rate decreases by 1.49% when we leave out banner ad variables. This decrease in fit may seem small; however, since the majority of website visits are made by recent online consumers, the positive significant effect of banner ad exposure on website visits for nonrecent online consumers has relatively little influence on overall fit. Zooming in on nonrecent online consumers, we observe a 2.16% drop in the hit rate for the website visit model when omitting banner ad variables. With regard to the offline purchase equation, we find a hit rate of .68, which drops 3.55% if we omit banner ad variables.

To assess the impact of banner advertising on out-of-sample performance, we re-estimate our focal and alternative model without banner ad variables, while leaving out the final four campaigns. We again find a significant and positive within-campaign (cross-campaign) banner effect for nonrecent (recent) online consumers on website visit (purchase) incidence. We use the parameter estimates to predict website visits and offline purchase for the omitted campaigns. Again, we find that banner ads are important in predicting website visit incidence and offline purchase incidence: for the omitted final four campaigns, the log-marginal densities for the model with and without banner ad variables are 2,642.15 and 2,693.58, respectively.

Robustness Checks

Apart from the previously mentioned robustness checks, we test whether consumers use alternative sources of information, whether results are drive by consumers' online intensity or preexisting interest in the offered products, and whether our results are robust to cross-lags, and a different operationalization of $WebsiteCurr_{it}$ in the offline purchase model. For further details on these robustness checks, see Web Appendix E. In addition, we estimate a bivariate probit model with a latent campaign interest variable to rule out the explanation that website visit and offline purchase incidence are both driven by unobserved interest in the offered product(s) (see Web Appendix G).

DISCUSSION AND IMPLICATIONS

In this article, we use unique, single-source data to model the impact of banner advertising on consumers' decisions to visit the firm's website and purchase offline. We address three important research questions: (1) Does the effect of banner advertising on website visit and offline purchase incidence differ for recent versus nonrecent online consumers? (2) Does banner advertising affect offline purchase incidence directly, indirectly (i.e., through website visits), or both directly and indirectly? (3) Does banner advertising in the current campaign affect website visit and offline purchase incidence in subsequent ad campaigns even if the information contained in the banner ad is no longer relevant? We summarize our key findings in Table 3. Overall, we provide evidence that firms that (predominantly) sell through the offline channel can benefit from online banner advertising for their products. Our results are of great interest to firms that promote changing assortments with blitz campaigns, such as "fast fashion" retailers or hard discounters. Banner advertising allows these firms to elicit a within-campaign response as well as to build the brand across campaigns.

Our findings point to a different consumer decision-making process and a different role for banner and TV ads, for recent versus nonrecent online consumers; thus, they call for an adapted communication approach for these types of consumers. We also extend knowledge on which advertising activity is most successful for consumers in different stages of the purchase funnel. In the following section, we discuss our findings and the resulting implications for targeting purposes and the attribution of advertising efforts.

Targeting

Nonrecent online consumers (i.e., consumers in earlier stages of the purchase funnel) seem to become activated by the firm's banner advertising both from the current campaign as well as from the previous campaign(s) and are likely to visit the firm's website to search for more information. Thus, these consumers should be targeted with banner ads that provide concrete information about the firm's current product offering. Given that TV advertising serves the same role of motivating these consumers to visit the firm's website, TV ads aired at time slots when mostly nonrecent consumers are watching should explicitly mention the website and highlight the information that can be obtained there. Moreover, these consumers are likely to revisit the firm's website within the same campaign. Importantly, those who have visited the firm's website are also more likely to make an offline purchase, in line with the research-shopper phenomenon.

For recent online consumers, who have already moved to later stages of the purchase funnel, the information contained in banner ads is likely to fulfill their information needs, which may explain why we find no evidence for a within-campaign effect of banner ads on website visits. Also, once these consumers visit the website, they are less likely to revisit it during the remaining campaign days, possibly because they are more experienced in directly finding the required information. Interestingly, for these consumers, TV ads directly increase offline purchases. TV advertising, with its ability to transfer feelings and images in combination with external pacing, seems to stimulate these consumers beyond just providing information about the firm and its brand(s). Managers may thus want to highlight the proximity of their offline stores in TV ads targeted at recent online consumers. Finally, our results show a positive cross-campaign effect of banner advertising on offline purchase incidence for recent online consumers. Thus, banner advertising positively alters consumers' preferences through reminding them of the advertising firm and its brand(s)—in line with a brand-building effect. Hereby, we extend prior findings from Dinner, Van Heerde, and Neslin (2014) by ruling out the explanation that the cross-campaign effect of banner advertising is due to a lagged sales response to information provided in the ads. Lewis and Reiley (2014) show that the effect of display ads persists several weeks after the last exposure. We build on their findings by showing that consumers who differ in online recency show differential ad responses, both within- and cross-campaigns. Draganska, Hartmann, and Stanglein (2014) provide evidence for a brand-building effect of banner advertising; however, they do not investigate consumers' actual purchase behavior as an outcome variable. Thus, we believe we are the first to provide evidence for a cross-campaign, brand-building effect of banner advertising on offline purchase incidence while allowing for consumer heterogeneity.

Attribution

Our findings illustrate that the attribution of offline sales to online banner ads is not straightforward, as one cannot solely rely on intermediate online performance measures—such as click-through rates as indicators of consumers' subsequent

Table 3
OVERVIEW OF KEY FINDINGS

Research Question	*Supported Relationship*	*Within- vs. Across-Campaign*	*Recent (R) vs. Nonrecent (NR) Online Consumers*	*Finding*
1	Banner advertising → website visit(s)	Within-campaign	NR	Nonrecent online consumers are more likely to visit the advertising firm's website after being exposed to banner advertising during the current ad campaign.
2	Banner advertising → website visit(s) → offline purchase(s)	Within-campaign	NR	Nonrecent online consumers are more likely to conduct an offline purchase after visiting the firm's website during the current ad campaign. Combined with the finding that banner advertising increases nonrecent online consumers' likelihood to visit the firm's website, we infer an indirect effect of banner advertising on offline purchase incidence. We find no support for a direct effect.
3	Banner advertising → website visit(s)	Cross-campaign	R/NR	Recent and nonrecent online consumers are more likely to visit the advertising firm's website after being exposed to banner advertising during the previous ad campaign(s).
	Banner advertising → offline purchase(s)	Cross-campaign	R	Recent online consumers are more likely to conduct an offline purchase after being exposed to banner advertising during the previous ad campaign(s).

purchase behavior—and should take consumer heterogeneity into account. For nonrecent online consumers, the success of a banner ad campaign can be gauged by the number of website visits generated by banner ads, as they are strongly linked to offline sales. Importantly, managers should not only attribute an offline purchase to a preceding website visit but also value the banner ads that have led to the website visit (cf. Xu, Duan, and Whinston 2014). In determining whether banner ads contributed to a website visit, it is important to account for banner ad targeting, for example, through programmatic buying. For recent online consumers, a lack of online response should not be interpreted as an indication of low banner ad effectiveness because these consumers do show a positive (cross-campaign) offline sales response. To appreciate the value of banner ads for driving offline sales, one should look beyond intermediate online performance measures and allow for dynamics. A focus on within-campaign online performance measures is too narrow for firms that also sell offline; it would lead to the conclusion that banner ads should be solely targeted to nonrecent online consumers, whereas an analysis of both online and offline performance measures that accounts for cross-campaign effects shows that banner ads are effective for both types of consumers, albeit through different routes.

LIMITATIONS AND FURTHER RESEARCH

We acknowledge some limitations of our study, which, at the same time, give rise to interesting future research avenues. Although we find our results to be robust to consumers' general online intensity as captured by household random effects, and we rule out the explanation that the within-campaign banner ad effect reflects a consumer's online presence that day, we do not observe consumers' browsing behavior across the different campaign weeks. Similarly, we control for overall campaign popularity using campaign fixed effects and account for the overall impact of holidays but do not account for these factors at the individual consumer level. We acknowledge that not accounting for consumer-specific and time-varying influences may lead to an overestimation of the relationships between the variables. Future research should ideally account for the influence of consumer-specific and time-varying influences, such as time-varying browsing behavior, campaign liking, and holidays, at the individual consumer level.

The banner ads that we study were not retargeted or purchased through programmatic buying. However, we acknowledge that in today's online advertising world, the majority of banner ads are targeted at previous visitors and/or purchased in real time. Therefore, future research needs to consider the potentially endogenous nature of current advertising data when analyzing online advertising effectiveness with observational data.

We study the effects of banner advertising on website visit and offline purchase incidence and do not discuss the financial impact. Future research should use revenues and cost data to calculate the return on investment of banner ads targeted at recent and nonrecent consumers.

Finally, future research should investigate possible synergy effects between banner and TV advertising. We explored synergy effects using our data and found no support; all the effects reported in this article are robust to including the interaction effects between banner and TV advertising. We note that, unfortunately, we do not observe consumer- or segment-level TV ad exposures. Future research may uncover synergy effects using consumer-level banner and TV ad exposures. Doing so could open an interesting avenue by which to explore differential advertising decay parameters depending on a consumer's recency level.

Appendix

OPERATIONALIZATION OF FOCAL VARIABLES

Variable	*Description*
Website_{it}	Binary variable that indicates whether consumer i makes a website visit on day t; 1 = yes, 0 = no.
Purchase_{it}	Binary variable that indicates whether consumer i conducts an offline purchase at day t; 1 = yes, 0 = no.
Banner_{it}	Log of the cumulative number of banner ad exposures plus 1 within a campaign up to and including day t. In the offline purchase model, we exclude banner ad exposures that take place after 5 P.M. on day t, because these banners are unlikely to lead to a same-day offline purchase, given that many shops close at 6 P.M. We do take these banners into account at day t + 1, if still in the same campaign.
BannerStock_{it}	Stock variable over the previous four campaigns.[a] More specifically, for each of the previous four campaigns, we first determine the log of the total number of banner ad exposures plus 1 within a campaign and introduce decay parameter λ to capture forgetting from one campaign week to the next (cf. Dinner, Van Heerde, and Neslin 2014). We sum the discounted stock components to obtain our banner ad stock variable (BannerStock_{it}): $\text{BannerStock}_{it} = \sum_{k=1}^{4}\lambda_1^k \text{Banner}_{i,t-\text{Day}_t-7k}$. The time subscript on the right-hand side shows that we subtract Day_t from t. This subtraction ensures that BannerStock_{it} is based on previous campaigns and not the current campaign. Drawing on Dinner, Van Heerde, and Neslin (2014), we set λ to .84.[b] We use the first four ad campaigns for initialization, which leaves us with 13 ad campaigns for estimation.
Contextual_{it}	Binary variable that indicates whether a consumer has been exposed to a contextual ad in a campaign up to and including day t; 1 = yes, 0 = no.
Search_{it}	Binary variable that indicates whether a consumer has been exposed to a search ad in a campaign up to and including day t; 1 = yes, 0 = no. We focus on nonbranded sponsored searches. Findings from a field experiment conducted by Blake, Nosko, and Tadelis (2015) reveal that sponsored search ads and organic search results (for the same firm) are close to perfect substitutes, supporting the notion that consumers who enter the firm's name into a search engine simply use sponsored search ads to navigate to the firm's website.
TV_t	Log of the cumulative TV ad expenditures, measured in hundreds of thousands of euros, up to and including day t. In the offline purchase model, TV_t does not include TV ad expenditures at day t because ads are shown in the evening when shops are closed. Thus, the influence of these ads can only materialize the next day.

Appendix
CONTINUED

Variable	*Description*
$WebsiteCurr_{it}$	Number of website visits by consumer i in the current ad campaign. In the website (purchase) model, $WebsiteCurr_{it}$ does not (does) include website visits at day t (if they occur before 5 P.M.).[c]
$PurchasePrev_{it}$	Number of purchases by consumer i in the previous campaign.
$PurchaseCurr_{it}$	Number of purchases by consumer i in the current ad campaign.
$Website_{it-1}$	Binary variable: 1 = website visit, 0 = no website visit by consumer i at day t − 1.
$Purchase_{it-1}$	Binary variable: 1 = offline purchase, 0 = no offline purchase by consumer i at day t − 1.
NR_{it}	Binary variable: 1 = no website visit in the previous four campaigns, 0 = at least one website visit in the previous four campaigns.
R_{it}	Binary variable: 1 = at least one website visit in the previous four campaigns, 0 = no website visit in the previous four campaigns, that is, 1 − NR_{it}.
$Holiday_t$	Holiday density: number of federal states, relative to total number (16), in which day t is a holiday. Numbers range from 1 to 6: 1 = 0 federal states, 2 = 1–3 federal state(s), 3 = 4–6 federal states, 4 = 7–10 federal states, 5 = 11–14 federal states, 6 = 15–16 federal states.
Day_t	Day of the campaign week at day t; that is, 1 = first day of the campaign, 7 = final day of the campaign.
$Campaign_t$	Campaign number at day t: $Campaign_t$ = 1, 2, ..., 13.

[a]We also tested for longer and shorter operationalizations of three and five weeks to operationalize the BannerStock variable, and we find our results to be robust.
[b]Our results are robust to setting λ to .7 or .9, although model fit decreases slightly.
[c]A robustness check confirms that our results hold if we exclude same-day website visits from $WebsiteCurr_{it}$ in the offline purchase model. We provide additional details in Web Appendix E.

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