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Personalized Online Advertising Effectiveness: The Interplay of What, When, and Where

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Firms track consumers' shopping behaviors in their online stores to provide individually personalized banners through a method called retargeting. We use data from two large-scale field experiments and two lab experiments to show that, although personalization can substantially enhance banner effectiveness, its impact hinges on its interplay with timing and placement factors. First, personalization increases click-through especially at an early information state of the purchase decision process. Here, banners with a high degree of content personalization (DCP) are most effective when a consumer has just visited the advertiser's online store, but quickly lose effectiveness as time passes since that last visit. We call this phenomenon overpersonalization. Medium DCP banners, on the other hand, are initially less effective, but more persistent, so that they outperform high DCP banners over time. Second, personalization increases click-through irrespective of whether banners appear on motive congruent or incongruent display websites. In terms of view-through, however, personalization increases ad effectiveness only on motive congruent websites, but decreases it on incongruent websites. We demonstrate in the lab how perceptions of ad informativeness and intrusiveness drive these results depending on consumers' experiential or goal-directed Web browsing modes.

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1. Introduction

As consumers spend more time and money than ever on the Web (eMarketer 2013, Morris 2013), firms intensify their online advertising efforts (Interactive Advertising Bureau 2013). Display banners represent an especially prominent way to reach consumers with more than five trillion banner ads served every year (Lipsman et al. 2013). The recent surge in online advertising noise, however, also causes many consumers to simply avoid banner ads (Cho and Cheon 2004, Drèze and Hussherr 2003), such that their click-through rates (CTRs) have decreased to as low as 0.1% (MediaMind 2012). In response, an increasing number of firms, including major businesses such as Amazon, Google or Facebook personalize their ads based on individual consumers' recent online shopping behaviors. This method is called retargeting (Helft and Vega 2010, Peterson 2013, Sengupta 2013). Investments in retargeting are steadily growing (Hamman and Plomion 2013) and are expected to soon drive total display ad spending ahead of search advertising again (Hof 2011).

On the one hand, personalization should render a banner more relevant and thus increase its effectiveness (Anand and Shachar 2009, Ansari and Mela 2003, Tucker 2014). On the other hand, consumers might not unanimously favor certain personalized ad content, depending on the timing and placement of its appearance. In particular, with respect to timing, consumers receive personalized banners while being at different positions of the purchase decision process (Howard and Sheth 1969). Prior research suggests that consumers' response to ads featuring the exact products they previously browsed depends on how narrowly their preferences are construed (Lambrecht and Tucker 2013). In addition, even within a given position, consumers may respond differently to personalized ad content depending on how much time has passed between their last online store visit and an ad impression. Personalized banners typically reflect a consumer's previously revealed preferences at her last online store visit. However, such preferences are subject to change over time (Yoon and Simonson 2008).

Moreover, with respect to placement, consumers are exposed to personalized banners on different websites while pursuing different goals or motives. In nonpersonalized settings, prior research suggests that congruence between the motives to which an ad and its display website cater affect consumers' ad response (Goldfarb and Tucker 2011a, Moore et al. 2005, Rodgers and Thorson 2000, Shamdasani et al. 2001, Yaveroglu and Donthu 2008). Yet, it is unclear how motive congruence influences the effects of ad personalization on consumers.

In this research we investigate the effectiveness of personalization in banner advertising by taking into account its interplay with these *timing* and *placement* factors in the course of two large-scale field experiments with a major fashion and sporting goods retailer. In Field Experiment 1, we examine the interplay between ad content personalization and the two nested timing factors of a consumer's current state, defined as the position of the purchase decision process at which she left the retailer's online store, and the elapsed time since that last visit at the moment of an ad impression. Specifically, we study this interplay for banners with different degrees of content personalization (DCP) that reflect consumers' most recent shopping behaviors in the retailer's online store to a greater or lesser degree. The results show that banners with high DCP, featuring products from a consumer's most viewed category and brand combination, generate especially high CTRs in an early information state where consumers did not progress beyond the beginning of the buying process. In more advanced consideration and post-purchase states, however, ad personalization strongly loses effectiveness. Consistent with prior literature (Hoeffler and Ariely 1999, Simonson 2005) we explain these empirical findings through consumers' stabilizing preferences along the buying process that make them less receptive to specific recommendations. Moreover, within the information state, high DCP banners are most effective when a consumer just left the advertiser's online store, but quickly lose effectiveness thereafter over time. After 23 days, they attract even fewer clicks than initially less effective medium DCP banners that feature products from a consumer's most viewed brand. To explain, we draw on previous research (Yoon and Simonson 2008) which suggests that especially in this state preferences change over time. Accordingly, high DCP banners that closely aim at preferences from a consumer's last online store visit are increasingly likely to miss their mark as time since this visit passes and preferences change. We call this phenomenon overpersonalization.

In Field Experiment 2, we examine the interplay between ad content personalization and motive congruence between a banner and its display website as an important placement factor in online advertising (Edwards et al. 2002, Moore et al. 2005). Surprisingly, and contrary to studies on ad targeting that suggest effectiveness increases from context matching (Shamdasani et al. 2001, Yaveroglu and Donthu 2008), we find that the CTR of personalized and nonpersonalized banners is unaffected by motive congruence. In particular, personalized ads are equally more effective than nonpersonalized ads, across motive incongruent and congruent websites. By contrast, for view-through, a lagged measure of ad effectiveness (Hamman and Plomion 2013; Perlich et al. 2012, 2014), we find an influence of motive congruence on consumer response to ad personalization. Specifically, personalization substantially increases view-through response if banners appear on motive-congruent display websites, but slightly decreases it on incongruent websites.

Because these results partially run counter to previous findings on ad targeting, we investigate them in greater detail through two lab experiments. Drawing on the existent ad processing literature (Edwards et al. 2002) we argue and confirm in the lab that personalization determines banners' perceived informativeness and intrusiveness. These, in turn, drive final ad response in terms of click-through and view-through intentions. Moreover, consistent with previous empirical indications (Chatterjee 2005, Cho and Cheon 2004) we show that click-through primarily captures the response of consumers in an experientially browsing mode whereas view-through primarily reflects the response of consumers in a goal-directed browsing mode. For experientially browsing consumers, who do not have a specific goal in mind when seeing a banner on a website (Hoffman and Novak 1996), we find that motive congruence does not influence the effects of personalization on perceived ad informativeness and intrusiveness. In particular, informativeness is always higher for personalized compared to nonpersonalized ads; intrusiveness remains unchanged by personalization. These effects translate into click-through intentions and explain our field results.

Consumers in a goal-directed browsing mode, however, pursue a specific goal at a website where they encounter a banner (Hoffman and Novak 1996). For them, we find that motive congruence influences the effects of ad personalization on perceived ad informativeness and intrusiveness. Specifically, personalization leads banners to appear more informative under congruence, but not under incongruence. Moreover, under incongruence consumers see personalized ads as more intrusive than nonpersonalized ads. These findings explain why, in the field, we find personalization to increase view-through for banners on motive congruent websites, but to decrease it for ads on motive incongruent sites.

Overall, this research shows that, although ad personalization through retargeting can substantially enhance banner effectiveness, its impact hinges on its interplay with timing and placement factors. In §2, we demonstrate how our results contribute to existing research in online advertising. In §§3 and 4, we report the results of two field experiments and provide evidence from the lab for the underlying mechanisms of Field Experiment 2. In §5, we present "back-of-the envelope" calculations that demonstrate the economic relevance of ad personalization. In §6, we conclude with a discussion of our findings and their managerial implications as well as limitations and avenues for future research.

2. Contribution to Related Literature

Our research primarily relates to two literature streams in online advertising: targeting and personalization of online ad communications. The focus of ad targeting is maximizing the effectiveness of given advertisements by managing their recipients (audience targeting), timing, and placement (contextual targeting) (Raeder et al. 2012). First, the literature on audience targeting addresses the segmentation and selection of recipients for given ads based on their online shopping behavior (Perlich et al. 2014, Stitelman et al. 2011), social network (Provost et al. 2009), search and ad response behavior (Bhatnagar and Papatla 2001), cognitive styles (Urban et al. 2014), affiliations (Tucker 2014), and characteristics unknown to the researchers (Goldfarb and Tucker 2011b). Second, a number of studies have examined the effects of ad timing, i.e., when firms should deliver given display banners ads (Braun and Moe 2013, Urban et al. 2014), health promotional emails (Lenert et al. 2004) or mobile ads (Baker et al. 2014). Third, work on contextual targeting has addressed matching display banners to websites based on contextual characteristics of the display website (Goldfarb and Tucker 2011a, Moore et al. 2005, Rodgers and Thorson 2000, Shamdasani et al. 2001, Yaveroglu and Donthu 2008). Moreover, research on real-time bidding, i.e., the auctioning of online advertising space in real time, studies these three aspects combined, for example to derive algorithms that optimize bids for ad impressions (Perlich et al. 2012).

By contrast to ad targeting, where the starting point is a given advertisement, ad personalization begins with a given consumer and seeks to create individualized advertisements that fit her preferences best (Lambrecht and Tucker 2013). Compared with research on ad targeting, work on ad personalization is recently emerging. For example, studies on ad personalization have investigated display banner and email personalization based on consumers' inherent characteristics such as their names and contact information, educational affiliations or celebrity and media preferences (Tucker 2014, White et al. 2008). Others have examined the use of consumers' online behavior such as products viewed on travel or financial services websites (Lambrecht and Tucker 2013, Van Doorn and Hoekstra 2013), response to content links in advertising emails (Ansari and Mela 2003) or combinations of website browsing and ad response (Kazienko and Adamski 2007) as the basis for personalized advertisements.

Our work contributes to the research streams of online ad targeting and ad personalization in four ways. First, previous research on ad personalization has only investigated the effectiveness of a single given personalization intensity. Specifically, Lambrecht and Tucker (2013) investigate retargeting banners with the highest DCP possible, i.e., banners featuring the exact products consumers previously browsed, and compared them with generic advertisements. Yet, firms apply a vast number of algorithms to personalize their ads at certain instances. One way to differentiate approaches is by their personalization intensity, or DCP. To our knowledge, our Field Experiment 1 is the first empirical investigation that focuses on the effectiveness of online ads with varying personalization intensities.

Second, as outlined, prior work in both literature streams has found that certain timing factors influence the effectiveness of targeted and personalized ads. Specifically, a consumer's position in the purchase decision process, at the moment of an ad impression, is a common factor of interest (Lambrecht and Tucker 2013, Urban et al. 2014). We contribute to this literature by studying how the interplay of different DCPs and a consumer's current state determines an ad's effectiveness. By contrast to previous research that distinguishes between different pre-purchase states, we analyze the complete buying process, including a post-purchase state. Moreover, nested within states, we introduce a dynamic perspective that enables us to investigate state-specific changes in effectiveness per DCP over time.

Third, in our second field experiment, we advance the literature with an investigation of placement effects in online ad personalization. Whereas previous research on contextual targeting suggests that motive congruence is highly relevant for nonpersonalized ads (Goldfarb and Tucker 2011a, Moore et al. 2005, Rodgers and Thorson 2000, Shamdasani et al. 2001, Yaveroglu and Donthu 2008), to our knowledge no study so far has examined this aspect in the realm of personalized advertising. In the course of these analyses, we also show how placement effects from motive congruence depend on consumers' current browsing modes, i.e., whether they browse the Web in an experiential or goal-directed mode when receiving an ad.

Fourth, accurately measuring the impact of different advertisements on consumers is a key concern in ad targeting and personalization as well as for online advertising in general. Previous work in targeting and personalization assesses ad effectiveness with various indicators. Some studies rely exclusively on single measures such as online sales (Lambrecht and Tucker 2013), purchase intentions (Goldfarb and Tucker 2011a, Van Doorn and Hoekstra 2013), click-through (Ansari and Mela 2003, Tucker 2014), click-through intentions (White et al. 2008) or view-through (Stitelman et al. 2011). Others combine multiple success measures such as online and offline sales (Lewis and Reiley 2014), click-through, brand consideration, and purchase likelihood (Urban et al. 2014) or click-through, view-through, and online sales (Dalessandro et al. 2012). In our second field experiment, we use click-through as an immediate and the most popular response measure (PricewaterhouseCoopers 2011), and view-through as a measure of lagged ad response that marketers commonly use combined with click-through to evaluate the effectiveness of their retargeting efforts (Hamman and Plomion 2013). We show how these measures complement each other by capturing the response of consumers in experiential or goal-directed browsing modes. In this sense, we also add to the growing literature on attribution modeling (e.g., Abhishek et al. 2013, Li and Kannan 2014).

3. Field Experiment 1: The Interplay of DCP, State, and Time Since Last Online Store Visit

Firms usually engage in retargeting through advertising agencies that create banners on their behalf and deliver them through ad networks which aggregate advertising space across multiple ad displaying websites or publishers. When a consumer first visits the online store of a specific firm, a unique profile is created and linked to a cookie that is placed on the consumer's device. His or her interactions with products in the firm's online store are then tracked and stored in this profile. Afterwards, the cookie allows the ad network to recognize the consumer at any ad displaying website within its reach. On his or her arrival at such a website, the ad network offers the ad agency to deliver a banner to the consumer. To create this banner, the ad agency taps the consumer's profile and determines relevant products from the firm's online store, corresponding to the consumer's previous shopping behavior there.[1] This product selection is often governed by a banner's DCP which determines how closely the ad will relate to the consumer's previously viewed items.

3.1. Design and Implementation

In this first study, we analyze the click-through effectiveness of different DCPs, contingent on two nested timing factors: the consumer's current state, i.e., the position in the purchase decision process at which he or she left the online store at the last visit, and the elapsed time since that visit at the moment of an ad impression. In practice, DCPs are matched to consumers depending on previous or expected response. Because such matching causes endogeneity, we conducted a field experiment with a major fashion and sporting goods retailer[2] which allowed us to randomly assign banners of different DCPs to consumers and analyze their effectiveness. The retailer's assortment contains over 30,000 products, representing more than 180 categories and almost 600 brands. Categories include general fashion products for men, women, and children (shirts, jeans, shoes, etc.), as well as sporting apparel and gear for various sports (ball and racket sports, fitness, etc.).

To manipulate DCP, we defined three personalization rules that reflect, to a greater or lesser extent, a consumer's most recent shopping behavior in terms of product views at the retailer's online store.[3] According to consumer choice theory, each product view requires an implicit category and brand choice (Guadagni and Little 1983, 1998). At the end of each shopping session, a consumer's most viewed category and brand can be calculated, according to the products she viewed during that session. Using these two choices jointly and in isolation results in three treatment conditions representing different and theoretically linked DCPs:

(1) High DCP: A banner features products sampled from a consumer's most viewed category and brand combination during the most recent shopping session.

(2) Medium DCP (category): A banner features products sampled from the consumer's most viewed category during the most recent shopping session.

(3) Medium DCP (brand): A banner features products sampled from the consumer's most viewed brand during the most recent shopping session.

For example, if a consumer primarily viewed Adidas t-shirts during the last shopping session, a banner with high DCP would feature t-shirts (category choice) from Adidas (brand choice). A category-based medium DCP banner would, instead, feature random brand t-shirts. A brand-based medium DCP banner would show random categories of Adidas-brand products. This conceptualization deliberately does not imply whether personalizing based on category choices or brand choices represents a consumer's preferences more closely than the other. It only

[1] We assume here for simplicity that the consumer has only visited the online store of one firm and that only one ad agency advertises to him or her.

[2] The retailer's name and location are protected because of confidentiality agreements.

[3] We focus exclusively on shopping behavior in terms of product views because almost all visitors to an online store perform these activities, whereas only a subset of them pursue subsequent activities in the buying process such as product purchases. Personalizing banners based only on product views thus facilitates a randomized experiment.

implies that combining both choices (high DCP) represents preferences relatively more closely than either of these choices separately. As a control condition we used banners with no personalization. In the above example, such an ad would feature arbitrary products from random categories and brands. All banners also contained the retailer's logo.

The experiment ran for six weeks from October–December 2011. At their first visit to the retailer's online store during the study period, a random 10% sample of individuals who viewed at least one product were randomly assigned to one of the three treatment groups or the control group. Note that the random assignment algorithm allocated proportionally more individuals to the control group. This was explicitly requested by our partner for internal reasons. Yet, the chances of being included in a given group were equal for all consumers and independent from their characteristics or browsing behaviors. After this initial allocation procedure, each time a consumer visited an ad-displaying website within the retailer's ad network she received banners according to her assigned experimental group.

For each ad impression a consumer received, we recorded whether she clicked it, as well as the consumer's current state or position in the purchase decision process at which she left the online store. To proxy for the state, we used clickstream data of each consumer's shopping behavior in the retailer's online store, in line with prior research (Li and Chatterjee 2005). At the moment of a given ad impression, a consumer is defined to be in an information state, i.e., at the beginning of the purchase decision process, if she has merely browsed products but conducted no further purchase-related actions during the most recent online store visit. A consumer who also used the virtual shopping cart but still made no purchase is defined to be in a consideration state, further advanced in the buying process (Li and Chatterjee 2005). A consumer is classified to be in a post-purchase state if she completed a purchase before exiting the online store. Accordingly, in our data we updated a consumer's state after each shopping session. Finally, for each ad impression we recorded the time passed since the consumer left the online store. This indicates how long she was in the current state before receiving a particular banner. Ad impression levels were endogenously defined without frequency caps by consumers' browsing through the ad network. Ads were not targeted to specific websites and no impressions were sold through auctioning systems. Also, the firm did not engage in any promotional activities during the experiment.

3.2. Descriptive Statistics

Forty-four thousand nine hundred ninety-five consumers were randomly selected and assigned to the four experimental groups as shown in Table 1. We report relevant summary statistics in Panel (A).

At the ad impression level, Panel (B) presents the distribution of the total 1,264,885 banners over the experimental groups by states. A mean over all three states is provided at the bottom. Column (1) shows the average time between a consumer's last visit to the retailer's online store and an ad impression. Column (2) reports average CTRs. It appears that personalization, especially with high DCP, strongly increases click-through in the information state, whereas differences between DCPs and nonpersonalized ads become less distinct in later states.

However, these descriptive insights are generally limited in scope. First, they do not account for possible changes in click-through probabilities within states as the time since a consumer's last online store visit increases. Second, they do not acknowledge consumer-specific differences in innate tendencies to click on ads (Chatterjee et al. 2003). Third, they do not control for consumer factors as shown in Panel (A) that might influence CTRs. We therefore proceed with a detailed modeling approach.

3.3. Results and Discussion

Our unit of analysis is the individual banner impression. Empirically, we observe whether consumer i, when exposed to banner impression j, clicks on the banner ($Click_{ij} = 1$) or not ($Click_{ij} = 0$). With the assumption that the click outcome follows a Bernoulli distribution with parameter π_{ij}, we model the click-through probability using the following logistic parameterization:

$$\pi_{ij} = \Pr(Click_{ij} = 1) = \left[1 + \exp(\alpha_i + \beta' X_{ij})\right]^{-1}. \qquad (1)$$

Our model includes a consumer-specific intercept α_i to account for differences in click-proneness among individuals due to unobserved characteristics. In line with prior research (Chatterjee et al. 2003, Jones and Landwehr 1988), we specify α_i as drawn from a random distribution $\alpha_i \sim N(\alpha_i \mid \bar{\alpha}, \sigma_\alpha)$, where $\bar{\alpha}$ is the average click-proneness intercept over all consumers, and its variance σ_α corresponds to heterogeneity in click tendencies between consumers. We specify $\beta' X_{ij}$ as

$$\begin{aligned}\beta' X_{ij} = {} & \beta_1\, HighDCP_i + \beta_2\, MedDCPcategory_i \\ & + \beta_3\, MedDCPbrand_i + \beta_4\, Time_{ij} \\ & + \beta_5\, HighDCP_i \times Time_{ij} \\ & + \beta_6\, MedDCPcategory_i \times Time_{ij} \\ & + \beta_7\, MedDCPbrand_i \times Time_{ij} \\ & + \beta_8\, VisitsTotal_{ij} + \beta_9\, BannerRepetitions_{ij} \\ & + \beta_{10}\, BannersTotal_{ij}, \end{aligned} \qquad (2)$$

Table 1 Summary Statistics for Field Experiment 1

(A) Summary statistics at the consumer level

Treatment	Variable	Mean	Std dev	Min	Max	Obs
High DCP	*VisitsTotal*	1.9586	1.7632	1	51	9,318
	BannerRepetitions	18.0635	36.2231	1	777	9,318
	BannersTotal	28.5324	55.1268	1	1,062	9,318
Medium DCP (category)	*VisitsTotal*	1.9659	1.8574	1	56	9,709
	BannerRepetitions	19.1408	39.3960	1	1,173	9,709
	BannersTotal	29.5754	58.2005	1	1,173	9,709
Medium DCP (brand)	*VisitsTotal*	1.9337	1.7297	1	43	9,551
	BannerRepetitions	18.9830	36.6563	1	734	9,551
	BannersTotal	28.5571	53.0665	1	1,220	9,551
No personalization	*VisitsTotal*	1.8416	1.5839	1	29	16,417
	BannerRepetitions	18.1064	36.6177	1	1,228	16,417
	BannersTotal	26.7481	50.3662	1	1,228	16,417

(B) Summary statistics at the ad impression level

		(1) Time since last online store visit				(2) Click-through rate				
State	Treatment	Mean	Std dev	Min	Max	Mean	Std dev	Min	Max	Obs
Information	High DCP	8.5897	7.5149	0	36	0.0040	0.0630	0	1	217,588
	Medium DCP (category)	8.6435	7.5186	0	31	0.0029	0.0540	0	1	231,582
	Medium DCP (brand)	8.8729	7.6320	0	38	0.0027	0.0519	0	1	222,253
	No personalization	9.2043	8.1260	0	43	0.0013	0.0358	0	1	356,330
Consideration	High DCP	8.6102	7.5822	0	41	0.0025	0.0498	0	1	26,992
	Medium DCP (category)	8.5627	7.4905	0	29	0.0026	0.0512	0	1	28,901
	Medium DCP (brand)	8.9041	7.7109	0	29	0.0021	0.0457	0	1	27,773
	No personalization	9.6136	8.5139	0	41	0.0012	0.0353	0	1	45,675
Post-purchase	High DCP	9.5924	7.9069	0	29	0.0016	0.0393	0	1	21,285
	Medium DCP (category)	9.7340	7.8429	0	29	0.0014	0.0372	0	1	26,665
	Medium DCP (brand)	9.3330	7.9462	0	33	0.0013	0.0363	0	1	22,723
	No personalization	9.6489	8.3502	0	43	0.0008	0.0289	0	1	37,118
All	High DCP	8.6720	7.5587	0	41	0.0036	0.0602	0	1	265,865
	Medium DCP (category)	8.7366	7.5532	0	31	0.0028	0.0524	0	1	287,148
	Medium DCP (brand)	8.9144	7.6677	0	38	0.0025	0.0502	0	1	272,749
	No personalization	9.2845	8.1880	0	43	0.0012	0.0352	0	1	439,123

Notes. DCP, Degree of content personalization. Time measured in days. In total, 1,264,885 banners were delivered that resulted in 2,991 click-throughs.

where $HighDCP_i$, $MedDCPcategory_i$, and $MedDCPbrand_i$ are treatment indicator variables for whether consumer i belongs to an experimental group that receives ads with high ($HighDCP_i = 1$, and 0 otherwise), category-based medium ($MedDCPcategory_i = 1$, and 0 otherwise), or brand-based medium ($MedDCPbrand_i = 1$, and 0 otherwise) DCP. The coefficients β_1, β_2, and β_3 capture therefore the effects of the respective DCP, relative to the effect of a banner with no personalization. We account for the time in days passed between consumer i's last online store visit and ad impression j through $Time_{ij}$. In addition to a direct effect of $Time_{ij}$, the model includes pairwise interactions between this variable and the three treatment indicator variables. It thus captures possible changes in the effect of a particular DCP over time.

Finally, we include three control variables that influence consumer response to banner ads. First, $VisitsTotal_{ij}$, or the number of consumer i's shopping sessions prior to ad impression j (Chatterjee et al. 2003); this proxies for a consumer's familiarity with the retailer. Second, $BannerRepetitions_{ij}$, i.e., the number of ad impressions since consumer i's last shopping session prior to ad impression j; this controls for banner wear-out due to repetition effects (Braun and Moe 2013, Chatterjee et al. 2003, Yaveroglu and Donthu 2008). Retargeting banners are assembled with products in real time at the moment of an ad impression. A consumer's behavior during the most recent shopping session defines the pool of eligible products. This pool is updated after each shopping session. Ad impressions may therefore be repetitive between two sessions but not across them. Third, $BannersTotal_{ij}$ corresponds to the total number of ad impressions consumer i received before ad impression j (Manchanda et al. 2006).[4] For each state, we estimate a separate

[4] Note that $BannerRepetitions_{ij}$ and $BannersTotal_{ij}$ are unlikely to be completely accurate control variables, for instance if consumers use multiple devices or restrict or delete cookies.

Table 2 Parameter Estimates for Field Experiment 1

	(1) Information state		(2) Consideration state		(3) Post-purchase state	
	Coefficient (std. error)	*p*-value	Coefficient (std. error)	*p*-value	Coefficient (std. error)	*p*-value
Constant	−6.8911*** (0.0865)	<0.01	−7.1445*** (0.3784)	<0.01	−7.4234*** (0.5954)	<0.01
HighDCP	1.3749*** (0.0893)	<0.01	0.8526*** (0.2687)	<0.01	0.6165* (0.3631)	0.0896
MedDCPcategory	1.0081*** (0.0929)	<0.01	0.9237*** (0.2601)	<0.01	0.4812 (0.3572)	0.1780
MedDCPbrand	0.8357*** (0.0953)	<0.01	0.7906*** (0.2738)	<0.01	0.4033 (0.3692)	0.2748
Time	−0.0217*** (0.0073)	<0.01	0.0027 (0.0179)	0.8805	−0.0262 (0.0271)	0.3343
HighDCP × *Time*	−0.0279*** (0.0095)	<0.01	−0.0176 (0.0256)	0.4924	0.0064 (0.0368)	0.8622
MedDCPcategory × *Time*	−0.0167* (0.0098)	0.0878	−0.0254 (0.0254)	0.3171	0.0214 (0.0351)	0.5422
MedDCPbrand × *Time*	−0.0048 (0.0098)	0.6262	−0.0338 (0.0278)	0.2242	0.0119 (0.0377)	0.7525
VisitsTotal	0.0376*** (0.0116)	<0.01	0.1271*** (0.0309)	<0.01	0.2435*** (0.0546)	<0.01
BannerRepetitions	−0.0036*** (0.0012)	<0.01	−0.0076** (0.0038)	0.0436	−0.0031 (0.0068)	0.6506
BannersTotal	−0.0044*** (0.0008)	<0.01	−0.0006 (0.0020)	0.7489	−0.0084* (0.0048)	0.0813
Random Intercept	1.1974*** (0.0939)	<0.01	0.9574 (0.6381)	0.1336	0.8998 (1.0423)	0.3880
Observations	1,027,753		129,341		107,791	
−2 log likelihood	34,591		3,627		1,957	
AIC	34,615		3,651		1,981	
BIC	34,718		3,732		2,059	

Notes. DCP, Degree of content personalization. Time measured in days.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

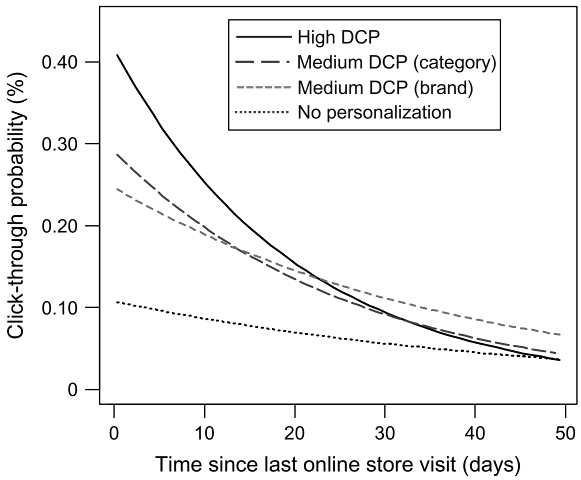
model with a maximum likelihood (ML) estimator and report the results in Table 2.

Information State. The main effects of all treatment indicator variables are positive and significant (*HighDCP* 1.3749, $p < 0.01$; *MedDCPcategory* 1.0081, $p < 0.01$; *MedDCPbrand* 0.8357, $p < 0.01$). This indicates greater click-through effectiveness of personalized compared to nonpersonalized ads. Based on this model, when a consumer has just left the retailer's online store, high DCP, with a click-through probability of 0.41%, is the most effective form of personalization and outperforms nonpersonalized banners (0.11%) by a factor of 3.73. It is also more effective than category-based medium DCP (0.29%) and brand-based medium DCP (0.24%). Yet, whereas all banners lose effectiveness as time since a consumer's last online store visit increases (*Time* −0.0217, $p < 0.01$), this occurs especially for high DCP (*HighDCP* × *Time* −0.0279, $p < 0.01$) and category-based medium DCP (*MedDCPcategory* × *Time* −0.0167, $p < 0.1$). These ads lose effectiveness over time significantly more quickly than nonpersonalized banners. In fact, the decline for high DCP banners is so strong that they become less effective than brand-based medium DCP banners after 23 days. We illustrate these effects in Figure 1.

Consideration State. All main treatment effects are also in this state positive and significant (*HighDCP* 0.8526, $p < 0.01$; *MedDCPcategory* 0.9237, $p < 0.01$; *MedDCPbrand* 0.7906, $p < 0.01$). However, the estimated click-through probabilities of personalized banners are, especially for high DCP, lower than in the information state. Just after a consumer leaves the online store, they are 0.24% (high DCP), 0.25% (category-based medium DCP), 0.22% (brand-based medium DCP), and 0.1% (nonpersonalized). Also, in this state, click-through probabilities do not change significantly over time (*Time* 0.0027, $p > 0.1$; *HighDCP* × *Time* −0.0176, $p > 0.1$; *MedDCPcategory* × *Time* −0.0254, $p > 0.1$; *MedDCPbrand* × *Time* −0.0338, $p > 0.1$).

Post-Purchase State. Finally, only the main effect of high DCP is positive and significant in the post-purchase state (*HighDCP* 0.6165, $p < 0.1$). The respective click-through probabilities when a consumer has just left the online store are 0.18% (high DCP), 0.16% (category-based medium DCP), 0.14% (brand-based medium DCP), and 0.1% (nonpersonalized). Again, there are no significant changes in effectiveness

Figure 1 **Estimated Click-Through Probabilities Over Time in Information State**



Notes. Click-through probabilities are based on the parameter estimates in Table 2, Panel (1), with *BannerRepetitions* and *BannersTotal* held constant at 1, and *VisitsTotal* held at the mean. Predictions start from the moment the consumer leaves the online store and persist until she has not returned for 50 days. These predictions disentangle a time effect from banner wear-out effects because we control for the number of repetitions since a consumer's last shopping session ($BannerRepetitions_{ij}$) and the total number of banners viewed before the focal ad impression ($BannersTotal_{ij}$). By holding these variables constant at 1, we can predict click-through probabilities for the first banner encountered following a shopping session, after a given number of days has passed. Moreover, we set $VisitsTotal_{ij}$ at its mean, to derive click-through probabilities for an average loyal consumer.

over time (*Time* −0.0262, $p > 0.1$; *HighDCP* × *Time* 0.0064, $p > 0.1$; *MedDCPcategory* × *Time* 0.0214, $p > 0.1$; *MedDCPbrand* × *Time* 0.0119, $p > 0.1$).

In summary, personalization can substantially enhance click-through, but the incremental effectiveness of personalized compared with nonpersonalized banners considerably declines across the states of the purchase decision process. Moreover, click-through probabilities significantly change over time, depending on the specific DCP, only in the initial information state, but not in the later consideration and post-purchase states. We tested the robustness of our empirical findings against alternative model specifications. A pooled logit specification as well as a random-intercept probit model and a generalized estimating equation logit model returned similar results. This supports our modeling approach and the insights from Figure 1. Moreover, a marginal effects analysis confirmed our findings for the specific interaction effects between each DCP and *Time* (for details see the Web Appendix (available as supplemental material at http://dx.doi.org/10.1287/mksc.2015.0930)).

3.4. Theoretical Interpretation: Preference Stability

To explain our empirical results, we draw on two key findings from the preference construction literature. First, consumer preferences are constructive and stabilize with increased effort and choices (Bettman et al. 1998, Hoeffler and Ariely 1999). We posit that our first main finding, i.e., that personalized banners lose effectiveness across the states of the purchase decision process, reflects consumers' increasing preference stability which makes them less dependent on recommendations. Second, unstable preferences are more likely than stable preferences to change over time (Yoon and Simonson 2008). We align this explanation with our second main finding that effectiveness decreases over time occur only in the information state, where preferences are unstable, but not in later states where preferences increasingly stabilize.

When consumers first enter a firm's online store, they often have only a broad idea of what they like (Lambrecht and Tucker 2013, Lee and Ariely 2006), without conscious awareness of their category needs or brand preferences (Hoeffler and Ariely 1999, Simonson 2005). By browsing through the assortment they start to develop and construct preferences (Bettman et al. 1998, Payne et al. 1993) which are, however, still fuzzy and unstable. For these consumers, being unaware of their true preferences makes them highly susceptible to influence, very receptive to advice, and easily convinced that a customized offer fits their actual preferences well (Lee and Ariely 2006, Simonson 2005). This explains the noticeable responsiveness of consumers in the information state especially to high DCP banners. By contrast, consumers in the consideration state have actively advanced in the purchase decision process by evaluating different product alternatives (Li and Chatterjee 2005) and using effort to build a consideration set and place items in the virtual shopping cart (Close and Kukar-Kinney 2010). These consumers are therefore more likely to be aware of their more accurately defined and stable preferences (Hoeffler and Ariely 1999). Finally, consumers in a post-purchase state have completed the buying process and thus developed most precise and stable preferences (Hoeffler and Ariely 1999). With greater awareness of their stable preferences, they become less dependent on a firm's recommendations (Simonson 2005). This explains why we observe that consumers respond less strongly to personalized banners in later states of the purchase decision process.

Over time, unstable preferences also tend to change more than stable preferences (Yoon and Simonson 2008) or may simply be forgotten (Petty et al. 1983). Especially in the information state, personalized banners that precisely match a consumer's preferences at the moment she leaves the online store will grow increasingly divergent from her current preferences and therefore lose effectiveness over time. We call this phenomenon *overpersonalization*. Indeed, our results show overpersonalization to be especially acute for high DCP banners that very closely reflect previous preferences. By contrast, the effectiveness of brand-based medium DCP banners, reflecting preferences less closely, stays more persistent over time so that these banners eventually become the most effective form of personalization. This finding aligns with previous research that shows preferences for brand-based attributes to be more stable and less likely to change over time than preferences for nonbrand attributes, such as specific categories (Simonson and Winer 1992). Stable preferences being less likely to change over time finally explains why we do not observe significant declines in banner effectiveness for any DCP in the consideration or post-purchase states.

A surprising empirical finding is that high DCP is the most effective form of personalization in the post-purchase state. Consumers in this state are typically well aware of their stable preferences and should thus be particularly resistant to these ads. Yet, comparing the number of products viewed during online store visits that started with or without click-through can help explain this phenomenon. During self-initiated shopping sessions, consumers browsed on average 4.21 products with no major differences across experimental groups. During visits following a click-through, however, consumers in the high DCP group viewed on average only 1.63 products (compared to 2.99 over all groups). In fact, 74% of them viewed only a single item before leaving the online store again. Given that products featured in high DCP banners very closely reflect, or even include, a previously purchased product, the higher click-through effectiveness of these ads might be a result of consumers' curiosity to see these items in an ad.

4. Field Experiment 2: The Interplay of Personalization and Placement

4.1. Design and Implementation

In a second field experiment, we analyze the interplay of banner personalization and placement. Retargeting ads appear on various display websites within the reach of an ad network so that it is critical to know where they are more or less effective. One placement factor that the ad targeting literature suggests to influence the impact of online ads on consumers is whether the motive to which an ad caters is congruent to the motive of its display website (Edwards et al. 2002, Goldfarb and Tucker 2011a, Moore et al. 2005, Rodgers and Thorson 2000, Shamdasani et al. 2001, Yaveroglu and Donthu 2008). To investigate this aspect for personalized advertisements we examine the effectiveness of personalized and nonpersonalized banners appearing on nonshopping- and shopping-related display websites. Retargeting banners refer to consumers' shopping motives so that motive congruence exists only when ads appear on shopping-related websites, but not when shown on nonshopping-related websites. Also, we complete our analyses by introducing view-through as a commonly applied effectiveness measure that captures a form of lagged ad response because banner ads exert effects on consumers even when they are not clicked (Drèze and Hussherr 2003). In particular, view-through captures whether a consumer independently returns to the retailer's online store within a specific time frame in response to a banner she did not click. This measure is commonly applied in academia (Perlich et al. 2012, 2014; Stitelman et al. 2011) and in practice where 78% of firms that use retargeting assess their ad effectiveness with view-through in addition to click-through (Hamman and Plomion 2013).

In cooperation with the same retailer as in Field Experiment 1 we established one general personalization treatment condition: At every ad impression, a banner randomly has high DCP, category-based medium DCP, or brand-based medium DCP, as defined in the first study. The order of DCPs varies randomly to prevent repetition effects. We used the same nonpersonalized control condition as in the first experiment. Again, all banners included the retailer's logo.[5]

The retailer ran the experiment for six weeks, simultaneously with the first study, to ensure comparability. A random 8.5% sample of individuals who viewed at least one product were randomly selected and assigned to the experimental groups at their first visit to the retailer's online store during the study period. After this allocation, they again exclusively saw banners that matched their experimental group for the entire experiment.

For each ad impression, we observed whether it occurred on a motive-incongruent (nonshopping-related) or congruent (shopping-related) display website. Shopping-related websites were those that allow searching for purchase-relevant information, such as price comparison or product testing websites, or to purchase products, such as online auctioning sites (Verhoef et al. 2007).[6] All other websites were defined as nonshopping-related (Rodgers and Thorson 2000).

We recorded consumers' response to each ad impression in terms of click-through and view-through. Following current standards, we attributed a view-through exclusively to the last ad a consumer saw but did not click before returning to the online store. We limited the allowed time frame between an ad impression and an independent return to seven days

[5] In this study, we did not use multiple treatment conditions. This was done to ensure a reasonable number of ad impressions per experimental group, as shopping-related websites form a comparatively small portion of display websites in the reach of our partner's ad network.

[6] Note that this definition of shopping-related display websites excludes retailer or manufacturer websites because they typically do not display advertisements for other retailers.

Table 3 Summary Statistics for Field Experiment 2

(A) Summary statistics at the consumer level

Treatment	Variable	Mean	Std dev	Min	Max	Obs
Personalization	*VisitsTotal*	1.9992	1.8108	1	49	28,474
	BannerRepetitions	19.2010	39.0823	1	1,420	28,474
	BannersTotal	29.3891	53.2950	1	1,422	28,474
	Time	10.4256	9.1547	0	40	28,474
No personalization	*VisitsTotal*	1.8323	1.5376	1	24	10,027
	BannerRepetitions	18.4923	37.3097	1	1,596	10,027
	BannersTotal	26.8324	50.9876	1	1,596	10,027
	Time	11.4396	9.9357	0	42	10,027

(B) Summary statistics at the ad impression level

Measure	Motive congruence	Treatment	Mean	Std dev	Min	Max	Obs
Click-through	Incongruent	Personalization	0.0035	0.0593	0	1	417,270
		No personalization	0.0012	0.0344	0	1	186,620
	Congruent	Personalization	0.0035	0.0587	0	1	26,281
		No personalization	0.0011	0.0331	0	1	10,965
View-through	Incongruent	Personalization	0.0161	0.1260	0	1	417,270
		No personalization	0.0170	0.1291	0	1	186,620
	Congruent	Personalization	0.0455	0.2083	0	1	26,281
		No personalization	0.0363	0.1870	0	1	10,965
Click-through	Incongruent and congruent	Personalization	0.0035	0.0592	0	1	443,551
		No personalization	0.0012	0.0343	0	1	197,585
View-through	Incongruent and congruent	Personalization	0.0190	0.1357	0	1	443,551
		No personalization	0.0190	0.1365	0	1	197,585

Notes. (A) Time measured in days. (B) In total, 641,136 banners were delivered that resulted in 1,795 click-throughs and 11,489 view-throughs.

(Dalessandro et al. 2012; Perlich et al. 2012, 2014). This is a conservative measure compared to current industry standards with time frames of up to 90 days (e.g., Google 2015).

4.2. Descriptive Statistics

We present summary statistics by experimental group for our sample of 38,501 consumers in Panel (A) of Table 3.

Panel (B) reports summary statistics for click-through and view-through at the ad impression level. For click-through, these statistics confirm our previous findings that personalized banners generate more click-through than nonpersonalized ads. In addition, motive congruence appears to have no influence on ad effectiveness. The average CTR for personalized banners is 0.35% under incongruence and congruence. For nonpersonalized ads, the difference is negligible, with a mean of 0.12% under incongruence and 0.11% under congruence.

A completely different picture emerges for view-through. Without accounting for motive congruence, as reported at the bottom of the table, personalized banners (1.90%) do not generate more view-through than nonpersonalized banners (1.90%). However, when we account for motive congruence, personalized banners (1.61%) are less effective than nonpersonalized ads (1.70%) under incongruence, but more effective under congruence (4.55% for personalized, 3.63% for nonpersonalized ads). We illustrate these findings in Figure 2. Again we apply a more detailed modeling approach to account for consumers' differential ad response tendencies and other potential influences on their click-through (view-through) behavior.

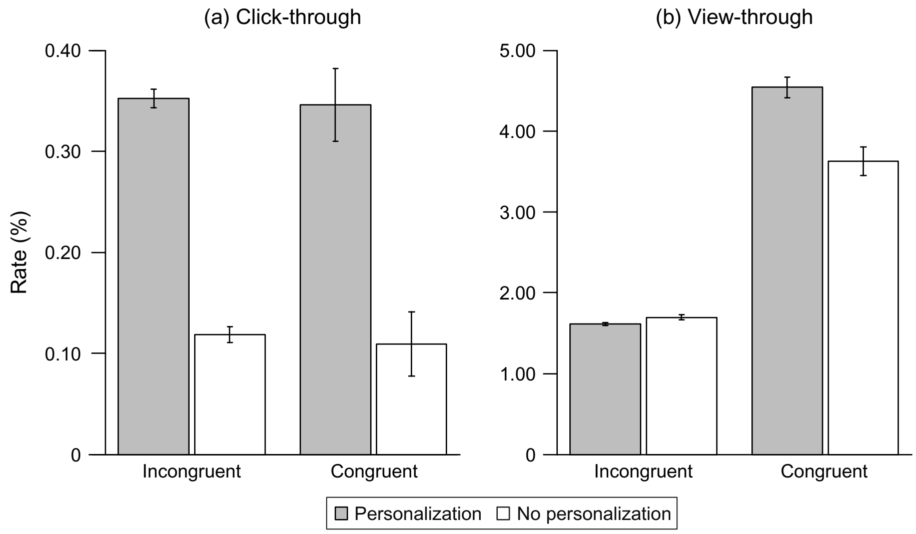
4.3. Results and Discussion

We model the click-through (view-through) probability of consumer i in response to ad impression j analogously to Field Experiment 1, except that we specify $\beta' X_{ij}$ as

$$\begin{aligned}\beta' X_{ij} = {} & \beta_1\, Personalization_i + \beta_2\, Congruence_{ij} \\ & + \beta_3\, Personalization_i \times Congruence_{ij} \\ & + \beta_4\, VisitsTotal_{ij} + \beta_5\, BannerRepetitions_{ij} \\ & + \beta_6\, BannersTotal_{ij} + \beta_7\, Time_{ij}. \end{aligned} \tag{3}$$

If consumer i belongs to the treatment group receiving personalized banners $Personalization_i$ assumes 1 and 0 otherwise. If banner j appears on a motive congruent website, $Congruence_{ij}$ assumes 1 and 0 otherwise. We also include the interaction $Personalization_i \times Congruence_{ij}$ to capture possible differences in the effect of a personalized ad that appears on a motive congruent relative to an incongruent website. Finally,

Figure 2 Observed Effectiveness of Personalized and Nonpersonalized Banners on Motive Incongruent and Congruent Display Websites



Note. Error bars denote standard errors.

we use the same control variables as in the first study as well as $Time_{ij}$ to again capture the time passed between consumer i's last online store visit and ad impression j. In another baseline model we exclude any placement effects. This model shows what advertisers would conclude if they ignored the characteristics of a banner's display website.

We estimate both models separately with click-through and view-through as the respective dependent variables. For click-through, the estimates of our proposed model in Table 4, Column (1), confirm our descriptive findings. Personalized banners are more effective than nonpersonalized ads (*Personalization* 1.0688, $p < 0.01$) and the incremental benefits of personalized over nonpersonalized ads are not influenced by motive congruence (*Personalization* × *Congruence* 0.0755, $p > 0.1$).

The estimates for view-through in Column (3) also match our descriptive findings. In particular, personalized banners generate less view-through than nonpersonalized ads on motive incongruent websites (*Personalization* −0.0511, $p < 0.05$), but more view-through on motive congruent websites (*Personalization* × *Congruence* 0.2384, $p < 0.01$). The need to account for these effects is supported by the increased fit of our proposed model (BIC = 107,056) compared to the baseline model (BIC = 108,101) in Column (4). As the baseline model also shows, not accounting for motive congruence would even disguise any differences between personalized and nonpersonalized ads (*Personalization* −0.0082, $p > 0.1$).

The same alternative model specifications as in Field Experiment 1 confirm the robustness of our empirical findings in this study. Moreover, for view-through, our results are robust under varying time frames from 1 to 30 days for the allowed time between receiving a banner and returning to the online store. Again, we provide details in the Web Appendix.

4.4. Theoretical Interpretation: Motive Congruence and Browsing Mode

Our goal is to theoretically explain the results we find in the field and verify our reasoning in a controlled lab setting. Personalization influences two opposing ad perceptions that determine consumers' response to online ads: perceived informativeness and intrusiveness. Consumers generally perceive personalized messages as more relevant and informative than nonpersonalized communications (Jensen et al. 2012, Skinner et al. 1999). Yet, they also often view them as more intrusive and off-putting (Tucker 2014, Van Doorn and Hoekstra 2013). In particular, intrusiveness refers to the interference of an ad with a consumer's ongoing cognitive processes (Li et al. 2002). Because personalized ads can more easily attract consumers' selective attention (Ha and McCann 2008, Schneider and Shiffrin 1977), they should be more distracting than nonpersonalized ads. This reasoning aligns with the literature on consumer response to persuasive advertising, arguing that ads that stimulate increased processing attention may lead consumers to think about them more thoroughly (Campbell 1995).

We suggest that these personalization effects on perceived ad informativeness and intrusiveness are moderated by whether motive congruence exists between a banner and its display website. Congruence between any banner's motive and its display website enhances the ad's perceived informativeness because it matches the consumer's current goal at that website. Moreover, perceived intrusiveness decreases under motive congruence also because the ad is more related to a consumer's current goal (Edwards et al. 2002).

Table 4 Parameter Estimates for Field Experiment 2

	Click-through				View-through			
	(1)		(2)		(3)		(4)	
	Coefficient (std. error)	*p*-value	Coefficient (std. error)	*p*-value	Coefficient (std. error)	*p*-value	Coefficient (std. error)	*p*-value
Constant	-6.9581^{***} (0.0970)	<0.01	-6.9757^{***} (0.0956)	<0.01	-3.6953^{***} (0.0275)	<0.01	-3.6425^{***} (0.0270)	<0.01
Personalization	1.0688^{***} (0.0777)	<0.01	1.0721^{***} (0.0757)	<0.01	-0.0511^{**} (0.0251)	0.0415	-0.0082 (0.0239)	0.7303
Congruence	-0.2348 (0.3015)	0.4362			0.5627^{***} (0.0589)	<0.01		
Personalization × *Congruence*	0.0755 (0.3214)	0.8142			0.2384^{***} (0.0682)	<0.01		
VisitsTotal	0.0594^{***} (0.0128)	<0.01	0.0588^{***} (0.0128)	<0.01	0.1032^{***} (0.0058)	<0.01	0.1045^{***} (0.0059)	<0.01
BannerRepetitions	-0.0036^{**} (0.0015)	0.0185	-0.0036^{**} (0.0015)	0.0187	-0.0126^{***} (0.0009)	<0.01	-0.0129^{***} (0.0009)	<0.01
BannersTotal	-0.0033^{***} (0.0010)	<0.01	-0.0032^{***} (0.0010)	<0.01	-0.0073^{***} (0.0005)	<0.01	-0.0078^{***} (0.0005)	<0.01
Time	-0.0384^{***} (0.0049)	<0.01	-0.0382^{***} (0.0049)	<0.01	-0.0421^{***} (0.0022)	<0.01	-0.0428^{***} (0.0022)	<0.01
Random Intercept	1.2072^{***} (0.1170)	<0.01	1.2112^{***} (0.1170)	<0.01	0.3967^{***} (0.0314)	<0.01	0.4240^{***} (0.0331)	<0.01
Observations	641,136		641,136		641,136		641,136	
−2 log likelihood	23,662		23,664		107,481		108,027	
AIC	23,680		23,678		107,499		108,041	
BIC	23,757		23,738		107,576		108,101	

Note. Time measured in days.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

To explain our results, we further draw on the widely accepted distinction between two modes of Web browsing, i.e., an experiential and a goal-directed browsing mode. Whereas experiential browsing is guided by the process itself and does not imply the pursuit of a specific goal, goal-directed browsing is based on clearly defined objectives and directed search (Hoffman and Novak 1996). Prior research suggests click-through to mainly capture the response of experientially browsing consumers because those in a goal-directed mode tend not to click on ads because this would interrupt their current goal achievement (Chatterjee 2005, Cho and Cheon 2004, Rodgers and Thorson 2000). View-through, however, captures the response of these consumers because it measures a later return to the advertiser's online store and not an immediate reaction.

We find click-through of personalized and nonpersonalized ads unaffected by whether they appear on motive-congruent websites. Because experientially browsing consumers, who, as argued, primarily account for this outcome, are not deeply engaged with a specific goal on an ad's display website, congruence likely has little or no effect on them. Thus personalization should increase ad informativeness on all websites. For the same reason, it should not increase ad intrusiveness. These two key constructs can therefore explain why the positive effects of personalization on click-through are unaffected by motive congruence.

By contrast, personalization decreases view-through when ads appear on motive-incongruent websites and increases it on congruent websites. Goal-directed consumers, who primarily account for these outcomes, pursue a specific goal on a banner's display website. Thus, under incongruence, where ads do not match this goal, personalization should not render an ad more informative. Rather, since personalized ads more easily attract attention, they are likely to be seen as more intrusive. On motive-congruent websites, however, an ad is more relevant to a consumer's current goal. Thus personalization should increase its perceived informativeness without eliciting intrusiveness.

For our field data we neither observe evaluations of ad informativeness and intrusiveness, nor whether consumers browse in an experiential or goal-directed mode at the moment of an ad impression. Also, consumers who visit shopping websites might be systematically different from those who visit other websites. We therefore seek to replicate our second field experiment in the lab to test our reasoning and obtain behavioral evidence of the suggested mechanisms.

4.5. Lab Experiments

Pre-Test. To verify that click-through primarily reflects the response of experientially browsing consumers whereas view-through mainly captures that of consumers in a goal-directed browsing mode, we conducted a pre-study with 200 participants on Amazon Mechanical Turk. Participants were randomly assigned to two treatment groups. Group 1 was asked to rate under which condition they would be more likely to click on a banner ad using a seven-point rating scale from 1 ("when I see the banner while browsing the Web to pursue a specific goal"), reflecting a goal-directed browsing mode, to 7 ("when I see the banner while browsing the Web without a clear goal in mind"), reflecting an experiential browsing mode. On the same scale Group 2 indicated when they would be more likely to return to the advertised online store at a later point in time. The results show click-through to occur more likely in an experiential browsing mode because the average ratings of Group 1 significantly exceeded the scale midpoint ($M = 5.310$, $t = 7.46$, $p < 0.01$). By contrast, the average ratings of Group 2 were significantly lower than the scale midpoint ($M = 2.910$, $t = -5.93$, $p < 0.01$). This implies that view-through is more likely to occur when consumers browse in a goal-directed mode.

Design and Procedure. Given these results, we designed two lab experiments. In both studies participants were to imagine seeing a specific banner on a specific display website. In Lab Experiment 1, participants browsed the Web in an experiential mode; in Lab Experiment 2 participants browsed in a goal-directed mode. Both studies had 2×2 between subject designs where we varied the motive to which the banner's display website catered (incongruent versus congruent to the banner) and the content of the banner itself (personalized versus nonpersonalized). The final questionnaire included evaluations of perceived ad informativeness and intrusiveness as well as click-through intentions in Lab Experiment 1 and view-through intentions in Lab Experiment 2.

In the first experiment, focusing on consumers in an experiential browsing mode, participants were told to imagine that they went online with no specific purpose, just to browse the Web as a pastime. Roaming different websites, they came across the website of a news network (incongruent to the banner's shopping motive), or a shopping search engine (congruent to the banner's shopping motive). On this website they encountered a banner ad from a fashion retailer whose online store they had recently visited. The banner featured products from the category they had most often examined there (i.e., a personalized banner) or random products from the retailer's assortment (i.e., a nonpersonalized banner). Participants then evaluated the banner's informativeness and intrusiveness with items and scales from Edwards et al. (2002).[7] Participants also indicated their click-through intentions ("I would like to click on the banner") on a seven point scale from 1 ("strongly agree") to 7 ("strongly disagree").

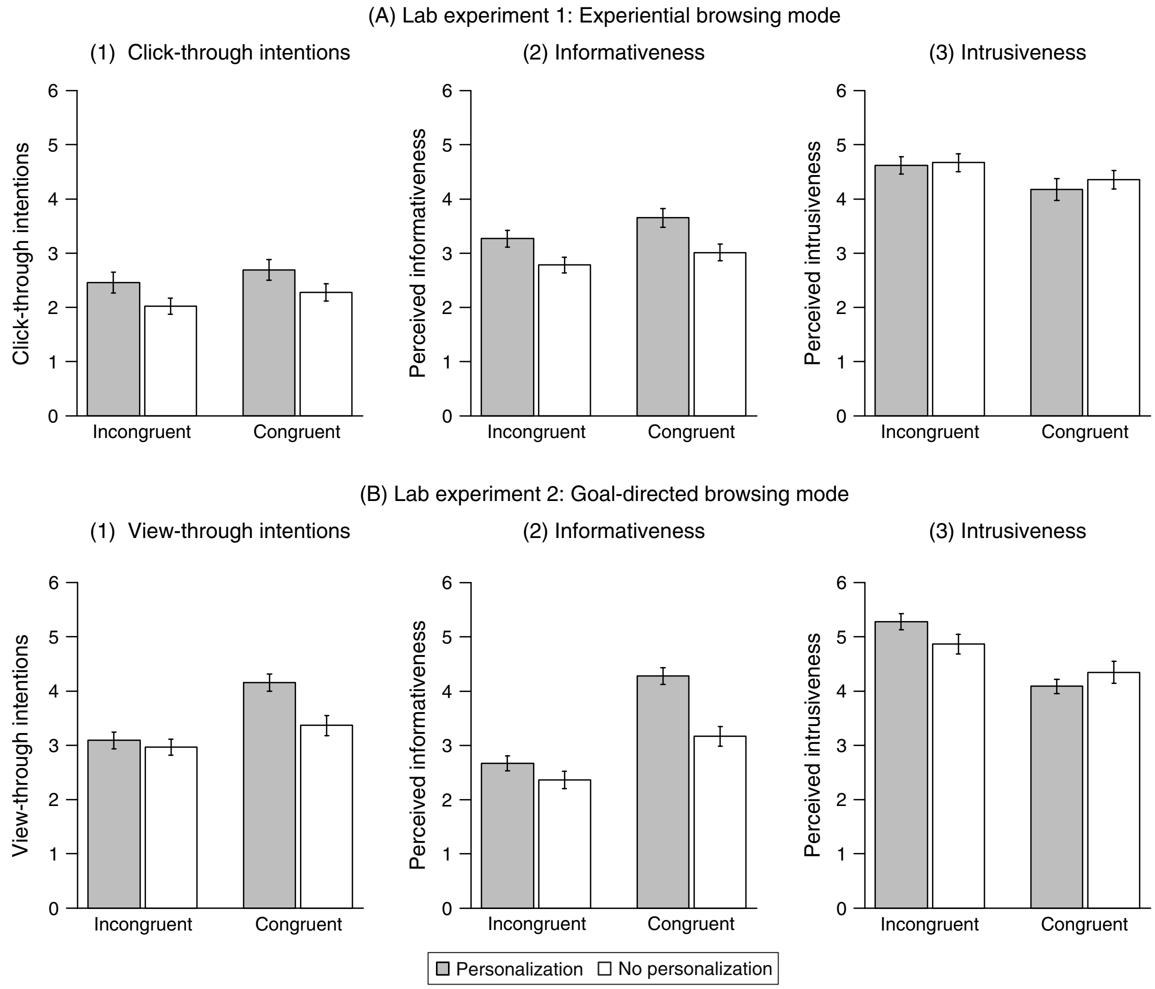
In the second experiment, focusing on consumers in a goal-directed browsing mode, participants were told to imagine that they went online to pursue a specific goal. In the motive incongruent conditions, they visited a news network website specifically to read a certain article. In the motive congruent conditions, they visited a shopping search engine website with the clear goal of looking for clothes to buy. At the respective websites, they also encountered a banner from a fashion retailer whose online store they had recently visited. The banner was either personalized or not as in the first experiment. The final questionnaire was also the same, except that we asked for view-through intentions ("After seeing the banner, I am encouraged to revisit the retailer's online store sometime in the near future" and "after seeing the banner, I am likely to revisit the retailer's online store sometime in the near future") according to Yoo and Donthu (2001). We recruited 355 and 312 participants, respectively, for the two experiments, again through Amazon Mechanical Turk, and assigned them randomly to one of the treatment groups.

Results. We illustrate the descriptive outcomes of both lab experiments in Figure 3.[8] The results of the first experiment replicate our empirical finding that personalized banners have higher click-through than nonpersonalized ads under motive incongruence (2.4574 versus 2.0225; $p < 0.1$) and congruence (2.6923 versus 2.2716; $p < 0.1$) (Panel A.1). Moreover, as suggested, personalization also increases ad informativeness under both conditions (3.2686 versus 2.7809; $p < 0.05$ under incongruence; 3.6511 versus 3.0123; $p < 0.01$ under congruence) (Panel A.2). Yet, in each case personalization does not affect ad intrusiveness (4.1790 versus 4.3563; $p > 0.1$ under incongruence; 4.6231 versus 4.6693; $p > 0.1$ under congruence) (Panel A.3). By contrast and in line with our empirical findings and reasoning, the second experiment shows that for consumers in a goal-directed browsing mode, personalized ads have no higher view-through than nonpersonalized ads on incongruent (3.0886 versus 2.9658; $p > 0.1$), but only on congruent websites

[7] Items for informativeness were "useful," "informative," "important," and "helpful." Items for intrusiveness were "distracting," "disturbing," "forced upon me," "interfering," "intrusive," "invasive," and "obtrusive."

[8] In both lab experiments, validity and reliability measures of all multi-item scales exceeded critical threshold levels (indicator reliabilities > 0.4, composite reliability > 0.6, average variance extracted > 0.5). We averaged all multi-item scales for the following analyses.

Figure 3 **Effects of Personalization and Motive Congruence on Click-Through Intentions, Informativeness, and Intrusiveness**



Note. Error bars denote standard errors.

(4.1533 versus 3.3647; $p < 0.05$) (Panel B.1). Personalization also does not increase informativeness under incongruence (2.6709 versus 2.3596; $p > 0.1$), but only under congruence (4.2800 versus 3.1676; $p < 0.01$) (Panel B.2). Under incongruence, however, personalization leads to higher perceived intrusiveness (5.2803 versus 4.8611; $p < 0.05$), which does not occur under congruence (4.0876 versus 4.3445; $p > 0.1$) (Panel B.3).

Whereas these descriptive statistics provide a first view of the experimental outcomes, our theoretical interpretation requires that we account for certain relationships among the involved constructs. We thus proceed with a simultaneous equation model to analyze each experiment. Following previous research and our argument, personalization potentially affects perceived ad informativeness and intrusiveness. These constructs then influence a consumer's final ad response, i.e., click-through in Lab Experiment 1 and view-through in Lab Experiment 2. Moreover, in line with prior work we allow informativeness to influence intrusiveness (Edwards et al. 2002). This way we account for the possibility that consumers perceive ads as more/less intrusive when they perceive them as less/more informative. We also include a direct effect of personalization on click-through (view-through) to control for the remaining effects of personalization that are not accounted for by our proposed mechanisms.

Let i indicate the participant and $MC = 1$ if the display website is congruent to a banner's motive and 2 if not. The formal system of equations for Lab Experiment 1 is then

$$Informativeness_i^{MC} = \gamma_{11}^{MC} + \gamma_{12}^{MC} Personalization_i^{MC} + \varepsilon_1^{MC}, \quad (4a)$$

$$Intrusiveness_i^{MC} = \gamma_{21}^{MC} + \gamma_{22}^{MC} Personalization_i^{MC} + \gamma_{23}^{MC} Informativeness_i^{MC} + \varepsilon_2^{MC}, \quad (4b)$$

$$ClickIntent_i^{MC} = \beta_{31}^{MC} + \beta_{32}^{MC} Personalization_i^{MC} + \beta_{33}^{MC} Informativeness_i^{MC} \quad (4c)$$
$$+ \beta_{34}^{MC} Intrusiveness_i^{MC} + \varepsilon_3^{MC}, \quad (4d)$$

Table 5 Parameter Estimates for Lab Experiments

	(A) Lab experiment 1: Experiential browsing mode						(B) Lab experiment 2: Goal-directed browsing mode					
	(1) Incongruence			(2) Congruence			(1) Incongruence			(2) Congruence		
Variable	Coefficient (std. error)	*p*-value	R^2 (%)	Coefficient (std. error)	*p*-value	R^2 (%)	Coefficient (std. error)	*p*-value	R^2 (%)	Coefficient (std. error)	*p*-value	R^2 (%)
Informativeness equation			2.8			4.3			1.5			11.8
Intercept	2.781*** (0.145)	<0.01		3.012*** (0.151)	<0.01		2.360*** (0.138)	<0.01		3.168*** (0.160)	<0.01	
Personalization	0.488** (0.214)	0.0220		0.639*** (0.227)	<0.01		0.311 (0.205)	0.1300		1.112*** (0.242)	<0.01	
Intrusiveness equation			37.6			42.0			21.8			39.5
Intercept	6.473*** (0.230)	<0.01		6.607*** (0.238)	<0.01		5.860*** (0.272)	<0.01		6.546*** (0.278)	<0.01	
Personalization	0.270 (0.181)	0.1360		0.300 (0.210)	0.1540		0.551*** (0.172)	<0.01		0.516** (0.211)	0.0140	
Informativeness	−0.648*** (0.066)	<0.01		−0.747*** (0.064)	<0.01		−0.423*** (0.101)	<0.01		−0.695*** (0.072)	<0.01	
Click-/ViewIntent equation			48.8			47.4			35.6			56.0
Intercept	0.829*** (0.419)	<0.01		1.485*** (0.506)	<0.01		2.894*** (0.536)	<0.01		2.986*** (0.707)	<0.01	
Personalization	0.103 (0.180)	0.5670		0.025 (0.178)	0.8870		0.015 (0.193)	0.9360		0.135 (0.182)	0.4570	
Informativeness	0.667*** (0.076)	<0.01		0.561*** (0.076)	<0.01		0.546*** (0.080)	<0.01		0.503*** (0.103)	<0.01	
Intrusiveness	−0.142** (0.059)	0.0160		−0.208*** (0.075)	<0.01		−0.221*** (0.084)	<0.01		−0.250*** (0.089)	<0.01	
Sample size	183			172			152			160		

Note. Results are robust under ML, robust ML, and Generalized Least Squares (GLS) estimators.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

where $Personalization_i^{MC}$ is a treatment indicator variable for whether participant i belongs to an experimental group with a personalized banner stimulus ($Personalization_i^{MC} = 1$, and 0 otherwise). Participant i's respective averaged item responses for informativeness, intrusiveness, and click-through intentions are captured through $Informativeness_i^{MC}$, $Intrusiveness_i^{MC}$, and $ClickIntent_i^{MC}$. The β and γ coefficients are to be estimated and $\varepsilon^{MC} = [\varepsilon_1^{MC}, \varepsilon_2^{MC}, \varepsilon_3^{MC}]' \sim MVN(0, \Psi^{MC})$. The set-up is the same for Lab Experiment 2, except that $ViewIntent_i^{MC}$ replaces $ClickIntent_i^{MC}$. For both experiments, we simultaneously estimate the model equations with ML methods and report the results in Table 5.

The results for Lab Experiment 1 in Panel (A) confirm the descriptive results and our reasoning that, for experientially browsing consumers, personalization increases perceived ad informativeness equally under motive incongruence (0.488, $p < 0.05$) and congruence (0.639, $p < 0.01$) with no significant difference between the estimated coefficients ($TRd = 0.233$, $\Delta df = 1$, $p > 0.1$).[9] Moreover, personalization does not increase perceived intrusiveness under motive incongruence (0.270, $p > 0.1$) or congruence (0.300, $p > 0.1$). As expected, informativeness increases click-through intentions whereas intrusiveness decreases them with these effects, uninfluenced by motive congruence. The same applies to the negative effects of informativeness on intrusiveness. Finally, under neither condition does personalization exert a significant direct effect on click-through intentions (0.103, $p > 0.1$ under incongruence; 0.025, $p > 0.1$ under congruence). This rules out alternative explanations that are not part of the proposed mechanisms. These results support our reasoning and explain why the empirically-found incremental benefits of personalized over nonpersonalized banners are equal on shopping and nonshopping websites.

The results for Lab Experiment 2 (Panel B) show that, for consumers in a goal-directed browsing mode, personalization does not increase perceived ad informativeness under motive incongruence (0.311, $p > 0.1$), whereas it strongly does so under congruence (1.112, $p < 0.01$), with a significant difference between the estimated coefficients ($TRd = 5.909$, $\Delta df = 1$, $p < 0.05$). Also, personalization directly increases perceived intrusiveness to similar extents under incongruence (0.551, $p < 0.01$) and congruence (0.516, $p < 0.05$), with

[9] Difference testing is based on a Satorra-Bentler scaled chi-square difference test that examines whether model fit statistically decreases when the focal coefficients are fixed across motive congruent ($MC = 1$) and incongruent ($MC = 2$) groups.

no significant difference between coefficients ($TRd = 0.016$, $\Delta df = 1$, $p > 0.1$). The negative effect of informativeness on intrusiveness, however, is smaller under incongruence (-0.423, $p < 0.01$) compared with congruence (-0.695, $p < 0.01$), with a significant difference between coefficients ($TRd = 5.177$, $\Delta df = 1$, $p < 0.05$). This finding is especially important because it supports our reasoning that altogether personalization leads to higher perceived intrusiveness under motive incongruence compared to congruence. The relationships between informativeness, intrusiveness, and view-through intentions are, again, as expected. Finally, personalization has no significant direct effect on view-through intentions, neither under incongruence (0.015, $p > 0.1$) nor under congruence (0.135, $p > 0.1$). Again, this rules out alternative explanations of how personalization might affect ad effectiveness other than through informativeness and intrusiveness.

By contrast to consumers in an experiential browsing mode, ad personalization exerts positive and negative effects on consumers in a goal-directed mode. A final assessment requires calculation of the total effect of personalization on view-through intentions. Under motive incongruence, personalization does not increase ad informativeness, but only leads to higher intrusiveness. The total incremental effect on view-through intentions is 0.08.[10] By contrast, under congruence, personalization increases ad informativeness, which in turn reduces intrusiveness. Overall, this leads to a considerably stronger total incremental effect of personalization on view-through (0.624).[11] In these two lab experiments we explain the results from the field. In particular, we confirm that motive congruence does not influence the effectiveness of ad personalization for consumers in an experiential browsing mode, but only for those in a goal-directed browsing mode. Moreover, we provide evidence supporting our theory that informativeness and intrusiveness mediate the effects of personalization on ad response.

5. Economic Implications

Whereas the model results of our field experiments are statistically robust across different specifications, we have not yet demonstrated whether they are economically relevant.[12] This, however, is important for two reasons: First, despite being statistically significant, the absolute differences in click-through and view-through between personalized and nonpersonalized banners are relatively small (see Tables 1(B) and 3(B)). Second, both outcomes are only indirect measures of economic success. The ultimate sales impact of given click-through or view-through occurrences depends on consumers purchasing in the resulting shopping sessions.

To estimate the expected absolute yearly sales revenue after ad costs resulting from personalized versus nonpersonalized advertising, we combine our data with additional information about our partnering retailer. Specifically, we derive (a) the total number of ad impressions shown in one year, and (b) the click-through probabilities for personalized and nonpersonalized banners from Field Experiment 1. Our sample of roughly 1.2 million ad impressions reflects 10% of the total banners the retailer delivered throughout the six-week study period. It thus delivers roughly 1.2 million $\cdot\, 10 \cdot 52/6 = 104$ million banners per year. Estimates for the click-through probabilities of personalized and nonpersonalized banners result from Table 1(B) for high DCP banners (0.0036), overall the most effective form of personalization, and nonpersonalized banners (0.0012). In addition, we obtained estimates about (c) the average conversion probability from click-through to sales (3%), (d) average sales per conversion ($330[13]), and (e) the average costs of banner advertising for our partner retailer. With respect to (e), ad networks apply different pricing schemes for banner ads. Most common are the cost per mille (CPM) scheme, where advertisers pay for the number of banners delivered, and the cost per click (CPC) scheme, where firms pay per click-through, irrespective of the number of ads delivered. We provide respective calculations for both of these schemes. A reasonable CPM estimate for personalized banners is $2.5 per 1,000 impressions or 0.25 cents per impression, according to the ad agency of our partnering retailer. Under CPC, it is $0.68 per click. We begin our calculations under the assumption of equal prices for personalized and nonpersonalized banners. We then relax this assumption in the course of a sensitivity analysis.

Under a CPM pricing scheme, the expected yearly sales revenue after ad costs resulting from personalized banner ads is about (impressions = 104 million) $\cdot$ (click-through rate = 0.0036) $\cdot$ (conversion rate = 0.03) $\cdot$ (sales per conversion = $330) − [(impressions = 104 million) $\cdot$ (CPM/1,000 = 0.25 cents)] = $3,446,560. This estimate exceeds yearly sales revenue after ad costs from nonpersonalized banners ($975,520) by 253%, or $2,471,040. Similar calculations under CPC yield increases of 200% or $2,301,312 for personalized relative to nonpersonalized ads.[14] These calculations clearly demonstrate the substantial economic

[10] $0.08 = 0.311 \cdot 0.546 + (0.311 \cdot (-0.423) + 0.551) \cdot (-0.221)$.

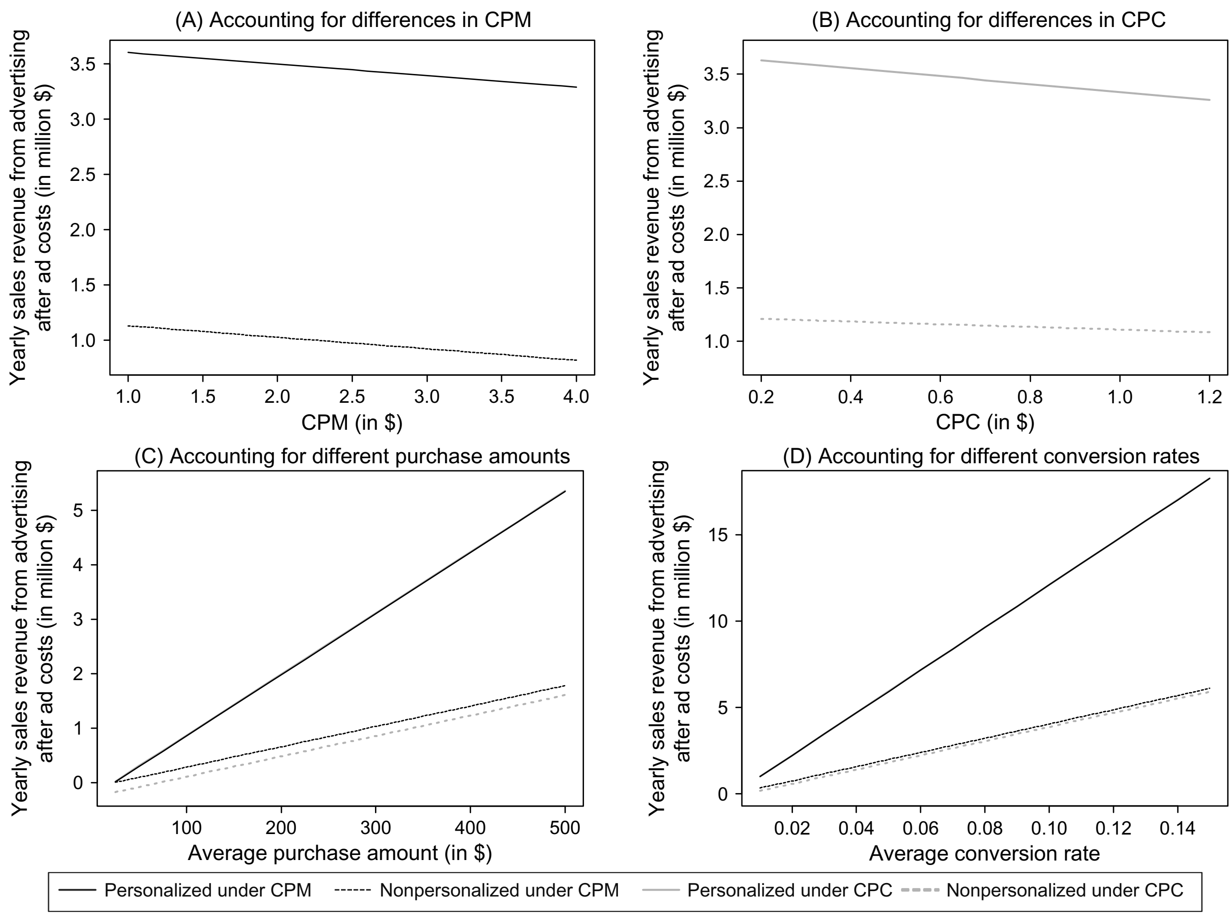
[11] $0.624 = 1.112 \cdot 0.503 + (1.112 \cdot (-0.695) + 0.516) \cdot (-0.250)$.

[12] We thank an anonymous reviewer for suggesting this analysis.

[13] We converted all monetary values from Euros to US dollars.

[14] Total ad costs on a CPC basis are derived as (impressions = 104 million) $\cdot$ (CTR = 0.0036) $\cdot$ (CPC = $0.68).

Figure 4 **Sensitivity Analyses: Yearly Sales Revenue After Ad Costs Resulting from Personalized vs. Nonpersonalized Advertising**



impact of the effectiveness differences between personalized and nonpersonalized banners we find in our field studies.[15]

Next, we test the sensitivity of our calculations to go beyond the case of our specific retailer. First, ad costs might be generally lower for nonpersonalized than for personalized banners. In Figure 4, we therefore plot estimates of yearly sales revenue after ad costs for CPM rates between $1 and $4 (Panel A) and CPC costs between $0.2 and $1.2 (Panel B). Both analyses show that personalized banners yield substantially higher yearly sales revenue after ad costs than nonpersonalized banners even if personalized ads are significantly more expensive than nonpersonalized ads. Second, an average purchase amount of $330 and a conversion probability of 3% apply to our retailer, but may differ across firms. We therefore illustrate the sensitivity of our calculations for different average purchase amounts (ranging from $50 to $500) and conversion probabilities (ranging from 1% to 15%) under CPM and CPC in Panels (C) and (D), respectively. Again, the economic benefits of personalized over nonpersonalized banners remain substantial even under very conservative assumptions.

6. General Discussion and Future Research

As more firms use the Internet to increase their advertising reach, the effectiveness of display banners steadily declines. In response, many firms personalize their ads based on individual consumers' recent online shopping behaviors using a method called retargeting. Whereas personalized banners should be more relevant and thus more effective than nonpersonalized ads, consumers might not unanimously favor certain personalized ad content, depending on the timing and placement of its appearance. In this

[15] Note that nonpersonalized banners in this study feature random products from the retailer's assortment. These ads might be less effective than nonpersonalized banners that feature, for instance, generic pictures, evocative of fashion or sports. To this extent our calculations might overstate the difference between yearly sales generated from personalized compared to nonpersonalized banners. On the other hand, our calculations are conservative in the sense that we only account for revenue increases after immediate response (click-through), because we lack necessary information to also incorporate revenue increases after lagged response (view-through).

research we investigate the effectiveness of ad personalization through retargeting by taking into account its interplay with relevant timing and placement factors. To examine these relationships, we conducted two large-scale field experiments with a major fashion and sporting goods retailer as well as two lab experiments.

For the interplay of content personalization and timing factors, we differentiate three consecutive states. These states describe a consumer's position in the purchase decision process at which she left the advertiser's online store at her most recent visit prior to receiving an ad. Nested within states, we also account for the elapsed time between that last online store visit and the ad impression. Our results show that, on average, personalization strongly increases click-through and that banners of relatively higher personalization intensity achieve the highest CTRs. However, we also find that the click-through effectiveness of personalized banners generally decreases as consumers progress toward the completion of the purchase decision process. We explain these findings through consumers' constructive preferences that stabilize during this progression to make them less dependent on firms' pointed advice. In addition, early in the buying process, highly personalized banners that aim closely at specific preferences are very effective when consumers have just left the online store, but quickly lose effectiveness over time. With consumers' preferences at this point still unstable and subject to change over time, these ads increasingly fail to meet initially revealed preferences, the more time since the last online store visit passes. We call this overpersonalization. Less close personalization, catering to consumers' brand preferences, instead, is more effective over time. For banners that reach consumers more than 23 days after leaving the online store, this form of personalization therefore becomes most effective.

Our finding that retargeting can produce overpersonalization reinforces previous research results. Lambrecht and Tucker (2013) show that personalized banners are less effective than generic brand banners when consumers have abstract, higher-level preferences. Their study focuses on the highest DCP possible and does not control for effectiveness changes over time. Overpersonalization might thus have contributed to the low performance they find for these banners compared with generic ads that appeal beyond a mere product matching.

As to the interplay of content personalization and placement factors, we find that motive congruence has no influence on experientially browsing consumers, but only on consumers in a goal-directed browsing mode. That is, whereas personalization always increases click-through, it increases view-through, i.e., a consumer's probability of returning independently to the advertised online store in response to a banner, only if consumers encounter ads on motive congruent websites. These findings also correlate well with Lambrecht and Tucker (2013) who show that personalization only fuels sales if consumers are actively involved in the advertised category. Moreover, we contribute to the ad targeting literature by showing that the context in which an ad appears does not always influence its effectiveness, but that this influence depends on a consumer's current online browsing mode.

For managers, we highlight three key findings. First, personalizing ads with retargeting methods requires matching personalization intensities to consumers' last observed positions in the purchase decision process and time since those last online store visits. Firms use myriad algorithms to personalize banners to various extents. We recommend that they constantly monitor their customers to determine the optimal time for a specific personalization approach. Second, firms seek to increase the reach of their online ads by delivering them on different display websites within the reach of an ad network. As the heterogeneity of these websites increases, each firm must carefully determine which ad networks and websites offer the most effective outlets. Third, given that placement effects are less likely to occur for consumers in an experiential compared with a goal-directed Web browsing mode, firms should think rigorously about how to recognize and distinguish between consumers' current browsing modes before delivering ads.

Of course, there are limitations to our research. First, our analyses only accounts for consumer response in terms of click-through and view-through. These measures offer insights into a banner's effectiveness, but could also be extended with other directly observable indicators (e.g., duration of shop visit, spending per purchase) or more implicit indicators (e.g., attitudes toward the ad or firm, ad recall). Moreover, a growing research stream investigates different attribution assumptions of specific responses to given ads (e.g., Abhishek et al. 2013, Li and Kannan 2014). These aspects should also be relevant for personalized online advertising. Second, we examine the differential effects of specific personalization intensities. Note however that these only reflect previous browsing behavior in terms of product views. Future research could investigate ad personalization based on further shopping actions, such as products placed in the shopping cart, put on a wish list or purchased. Moreover, we only incorporate consumers' online shopping behaviors, which represent the primary revenue source of our partner firm. Future research might include dependencies between online and offline shopping and personalized online advertising. Also, whereas we proxy for consumers' states through direct observables, future work might implement a richer modeling approach that explicitly treats states as latent, in line with Abhishek et al. (2013). Third, for our dynamic analysis of Field Experiment 1, we investigate the effects of continuously showing banners with the same DCP. Prior work also highlights the beneficial effects of certain pattern strategies for banner advertising (Braun and Moe 2013). To our knowledge, these strategies have not been investigated in retargeting settings. Fourth, whereas we demonstrate the economic relevance of our results and retargeting in general, we do not incorporate competitive pricing aspects into our analyses. Retargeting banners are increasingly marketed through auctioning systems where firms bid for single ad impressions to be delivered to specific consumers at given occasions (Perlich et al. 2012). Whereas our findings may help firms to determine monetary values to bid on specific impressions, future research could explicitly focus on optimal bidding strategies for personalized ads.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2015.0930.

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References

Abhishek V, Fader PS, Hosanagar K (2013) Media exposure through the funnel: A model of multi-stage attribution. Working paper, Heinz College, Carnegie Mellon University, Pittsburgh.

Anand BN, Shachar R (2009) Targeted advertising as a signal. *Quant. Marketing Econom.* 7(3):237–266.

Ansari A, Mela CF (2003) E-customization. *J. Marketing Res.* 40(2):131–145.

Baker BJ, Fang Z, Luo X (2014) Hour-by-hour sales impact of mobile advertising. Working paper, Fox School of Business and Management, Temple University, Philadelphia.

Bettman JR, Luce MF, Payne JW (1998) Constructive consumer choice processes. *J. Consumer Res.* 25(3):187–217.

Bhatnagar A, Papatla P (2001) Identifying locations for targeted advertising on the Internet. *Internat. J. Electronic Commerce* 5(3):23–44.

Braun M, Moe W (2013) Online display advertising: Modeling the effects of multiple creatives and individual impression histories. *Marketing Sci.* 32(5):753–767.

Campbell MC (1995) When attention-getting advertising tactics elicit consumer inferences of manipulative intent: The importance of balancing benefits and investments. *J. Consumer Psych.* 4(3):225–254.

Chatterjee P (2005) Changing banner ad executions on the Web: Impact on clickthroughs and communications outcomes. *Adv. Consumer Res.* 32(1):51–57.

Chatterjee P, Hoffman DL, Novak TP (2003) Modeling the clickstream: Implications for web-based advertising efforts. *Marketing Sci.* 22(4):520–541.

Cho C-H, Cheon HJ (2004) Why do people avoid advertising on the Internet? *J. Advertising* 33(4):89–97.

Close AG, Kukar-Kinney M (2010) Beyond buying: Motivations behind consumers' online shopping cart use. *J. Bus. Res.* 63(9):986–992.

Dalessandro B, Hook R, Perlich C, Provost F (2012) Evaluating and optimizing online advertising: Forget the click, but there are good proxies. Working paper, Stern School of Business, New York University, New York.

Drèze X, Hussherr F-X (2003) Internet advertising: Is anybody watching? *J. Interactive Marketing* 17(4):8–23.

Edwards SM, Li H, Lee J-H (2002) Forced exposure and psychological reactance: Antecedents and consequences of the perceived intrusiveness of pop-up ads. *J. Advertising* 31(3):83–95.

eMarketer (2013) Social, digital video drive further growth in time spent online. (May 8). Accessed June 23, 2015, http://www.emarketer.com/Article/Social-Digital-Video-Drive-Further-Growth-Time-Spent-Online/Article/1009872.

Goldfarb A, Tucker CE (2011a) Online display advertising: Targeting and obtrusiveness. *Marketing Sci.* 30(3):389–404.

Goldfarb A, Tucker CE (2011b) Privacy regulation and online advertising. *Management Sci.* 57(1):57–71.

Google (2015) Attribution reports and conversion data. Accessed June 23, 2015, https://support.google.com/adwords/answer/1722023?hl=en.

Guadagni PM, Little JDC (1983) A logit model of brand choice calibrated on scanner data. *Marketing Sci.* 2(3):203–238.

Guadagni PM, Little JDC (1998) When and what to buy: A nested logit model of coffee purchase. *J. Forecasting* 17(3/4):303–326.

Ha L, McCann K (2008) An integrated model of advertising clutter in offline and online media. *Internat. J. Advertising* 27(4):569–592.

Hamman D, Plomion B (2013) Chango retargeting barometer. Report, Chango, Toronto. Accessed June 23, 2015, http://www.iab.net/media/file/Chango_Retargeting_Barometer_April_2013.pdf.

Helft M, Vega T (2010) Retargeting ads follow surfers to other sites. *New York Times* (August 29). Accessed June 23, 2015, http://www.nytimes.com/2010/08/30/technology/30adstalk.html?_r=0.

Hoeffler S, Ariely D (1999) Constructing stable preferences: A look into dimensions of experience and their impact on preference stability. *J. Consumer Psych.* 8(2):113–139.

Hof R (2011) Can behavioral targeting survive privacy worries? *Forbes* (July 20). Accessed June 23, 2015, http://www.forbes.com/sites/roberthof/2011/07/20/can-behavioral-targeting-survive-privacy-worries.

Hoffman DL, Novak TP (1996) Marketing in hypermedia computer-mediated environments: Conceptual foundations. *J. Marketing* 60(3):50–68.

Howard J, Sheth JN (1969) *A Theory of Buyer Behavior* (John Wiley & Sons, New York).

Interactive Advertising Bureau (2013) First quarter 2013 Internet ad revenues set new high, at $9.6 billion. Press release (June 3). Accessed June 23, 2015, http://www.iab.net/about_the_iab/ecent_press_releases/press_release_archive/press_release/pr-060313.

Jensen JD, King A, Carcioppolo N, Davis L (2012) Why are tailored messages more effective? A multiple mediation analysis of a breast cancer screening intervention. *J. Comm.* 62(5):851–868.

Jones JM, Landwehr JT (1988) Removing heterogeneity bias from logit model estimation. *Marketing Sci.* 7(1):41–59.

Kazienko P, Adamski M (2007) AdROSA—Adaptive personalization of Web advertising. *Inform. Sci.* 177(11):2269–2295.

Lambrecht A, Tucker C (2013) When does retargeting work? Information specificity in online advertising. *J. Marketing Res.* 50(5):561–576.

Lee L, Ariely D (2006) Shopping goals, goal concreteness, and conditional promotions. *J. Consumer Res.* 33(1):60–70.

Lenert L, Muñoz RF, Perez JE, Bansod A (2004) Automated e-mail messaging as a tool for improving quit rates in an Internet smoking cessation intervention. *J. Amer. Medical Informatics Assoc.* 11(4):235–240.

Lewis RA, Reiley DH (2014) Online ads and offline sales: Measuring the effects of retail advertising via a controlled experiment on Yahoo. *Quant. Marketing Econom.* 12(3):235–266.

Li H, Kannan PK (2014) Attributing conversions in a multichannel online marketing environment: An empirical model and a field experiment. *J. Marketing Res.* 51(1):40–56.

Li H, Edwards SM, Lee J-H (2002) Measuring the intrusiveness of advertisements: Scale development and validation. *J. Advertising* 31(2):37–47.

Li S, Chatterjee P (2005) Shopping cart abandonment at retail websites—A multi-stage model of online shopping behavior. Paper presented at the 2005 Marketing Science Conference, Emory University, Atlanta, June 16–18.

Lipsman A, Aquino C, Flosi S (2013) 2013 U.S. digital future in focus. Report, ComScore, Reston, VA. Accessed June 23, 2015, http://www.comscore.com/Insights/Presentations-and-Whitepapers/2013/2013-US-Digital-Future-in-Focus.

Manchanda P, Dubé J-P, Goh KY, Chintagunta PK (2006) The effect of banner advertising on Internet purchasing. *J. Marketing Res.* 43(1):98–108.

MediaMind (2012) Global benchmarks report—H1 2012. Report, MediaMind, New York. Accessed June 23, 2015, http://www.iab.net/media/file/MediaMind_Benchmark_H1_2012.pdf.

Moore RS, Stammerjohan CA, Coulter RA (2005) Banner advertiser-Web site context congruity and color effects on attention and attitudes. *J. Advertising* 34(2):71–84.

Morris B (2013) More consumers prefer online shopping. *Wall Street Journal* (June 3). Accessed June 23, 2015, http://online.wsj.com/article/SB10001424127887324063304578523112193480212.html.

Payne JW, Bettman JR, Johnson EJ (1993) *The Adaptive Decision Maker* (Cambridge University Press, Cambridge, UK).

Perlich C, Dalessandro B, Raeder T, Stitelman O, Provost F (2014) Machine learning for targeted display advertising: Transfer learning in action. *Machine Learn.* 95(1):103–127.

Perlich C, Dalessandro B, Hook R, Stitelman O, Raeder T, Provost F (2012) Bid optimizing and inventory scoring in targeted online advertising. *Proc. 18th Internat. Conf. Knowledge Discovery Data Mining* (*SIGKDD*) (ACM, New York), 804–812.

Peterson T (2013) eBay opens up its data for ad targeting—Follows lead of Amazon, Google and Facebook. *Adweek* (April 8). Accessed June 23, 2015, http://www.adweek.com/news/technology/ebay-opens-its-data-ad-targeting-148469.

Petty RE, Cacioppo JT, Schumann D (1983) Central and peripheral routes to advertising effectiveness: The moderating role of involvement. *J. Consumer Res.* 10(2):135–146.

PricewaterhouseCoopers (2011) Measuring the effectiveness of online advertising. Report, PricewaterhouseCoopers, London, Accessed June 23, 2015, http://download.pwc.com/ie/pubs/2011_measuring_the_effectiveness_of_online_advertising.pdf.

Provost F, Dalessandro B, Hook R, Zhang X, Murray A (2009) Audience selection for on-line brand advertising: Privacy-friendly social network targeting. *Proc. 15th Internat. Conf. Knowledge Discovery Data Mining* (*SIGKDD*) (ACM, New York), 707–716.

Raeder T, Stitelman O, Dalessandro B, Perlich C, Provost F (2012) Design principles of massive, robust prediction systems. *Proc. 18th Internat. Conf. Knowledge Discovery Data Mining* (*SIGKDD*) (ACM, New York), 1357–1365.

Rodgers S, Thorson E (2000) The interactive advertising model: How users perceive and process online ads. *J. Interactive Advertising* 1(1):42–61.

Schneider W, Shiffrin RM (1977) Controlled and automatic human information processing: I. Detection, search, and attention. *Psych. Rev.* 84(1):1–66.

Sengupta S (2013) What you didn't post, Facebook may still know. *New York Times* (March 25). Accessed June 23, 2015, http://www.nytimes.com/2013/03/26/technology/facebook-expands-targeted-advertising-through-outside-data-sources.html?pagewanted=all.

Shamdasani PN, Stanaland AJS, Tan J (2001) Location location location: Insights for advertising placement on the Web. *J. Advertising Res.* 41(4):7–32.

Simonson I (2005) Determinants of customers' responses to customized offers: Conceptual framework and research propositions. *J. Marketing* 69(1):32–45.

Simonson I, Winer RS (1992) The influence of purchase quantity and display format on consumer preference for variety. *J. Consumer Res.* 19(1):133–138.

Skinner CS, Campbell MK, Rimer BK, Curry S, Prochaska JO (1999) How effective is tailored print communication? *Ann. Behavioral Medicine* 21(4):290–298.

Stitelman O, Dalessandro B, Perlich C, Provost F (2011) Estimating the effect of online display advertising on browser conversion. *Proc. 5th Internat. Workshop Data Mining Audience Intelligence Advertising* (*ADKDD*) (ACM, New York), 8–16.

Tucker CE (2014) Social networks, personalized advertising, and privacy controls. *J. Marketing Res.* 51(5):546–562.

Urban GL, Liberali G, MacDonald E, Bordley R, Hauser JR (2014) Morphing banner advertising. *Marketing Sci.* 33(1):27–46.

Van Doorn J, Hoekstra JC (2013) Customization of online advertising: The role of intrusiveness. *Marketing Lett.* 24(4):339–351.

Verhoef PC, Neslin SA, Vroomen B (2007) Multichannel customer management: Understanding the research-shopper phenomenon. *Internat. J. Res. Marketing* 24(2):129–148.

White TB, Zahay DL, Thorbjørnsen H, Shavitt S (2008) Getting too personal: Reactance to highly personalized email solicitations. *Marketing Lett.* 19(1):39–50.

Yaveroglu I, Donthu N (2008) Advertising repetition and placement issues in on-line environments. *J. Advertising* 37(2):31–44.

Yoo B, Donthu N (2001) Developing a scale to measure the perceived quality of an Internet shopping site (SITEQUAL). *Quart. J. Electronic Commerce* 2(1):31–45.

Yoon SO, Simonson I (2008) Choice set configuration as a determinant of preference attribution and strength. *J. Consumer Res.* 35(2):324–336.