Personalization in Social Retargeting – A Field Experiment

Completed Research Paper

Thomas W. Frick
Rotterdam School of Management, Erasmus University
Burgemeester Oudlaan 50, 3062 PA Rotterdam, The Netherlands
frick@rsm.nl

Ting Li
Rotterdam School of Management, Erasmus University
Burgemeester Oudlaan 50, 3062 PA Rotterdam, The Netherlands
tli@rsm.nl

Abstract

This study compares the effectiveness of product- and category-specific advertising personalization in Social Retargeting. Social Retargeting combines the features of social advertising, targeting consumers based on social connections, and retargeting, using consumers' browsing behavior to personalize ad content. We conducted a large-scale randomized field experiment in collaboration with a major e-retailer. Contradicting prior empirical findings, our results indicate that product-specific ads outperform less personalized category-specific ads. While theory suggests a positive effect, we find that social targeting decreases the performance of personalized ads. Surprisingly, socially targeted consumers are not more responsive to product-specific ads. We show that our results remain robust and are driven by ad personalization when controlling for temporal targeting and how deep consumers browse the e-retailer's website. Our study contributes to the IS and marketing literature related to personalization in digital advertising and provides valuable suggestions for firms' personalization strategies.

Keywords: Advertising, Business Analytics, Field Experiment, Personalization Specificity, Social Retargeting, Targeting, Temporal Targeting

Introduction

Worldwide digital advertising spending is predicted to hit close to $200 billion in 2016 (Statista 2016). This number indicates that countless advertisers, next to digital content providers, are competing for consumers' attention online. One major way to differentiate from other advertisers competing for consumers' attention is to increase ad relevance through personalization. Advertising personalization refers to firm-initiated adjustment of advertising content towards consumer preferences with the aim of increasing ad relevance (Arora et al., 2008). In a recent study by Adobe, marketers named personalization as the most important marketing capability while being the biggest challenge within their organizations (Adobe Systems Inc. 2014). Although marketers have recognized the potential of personalization, they are still struggling with implementing such a strategy.

While research generally finds that more specific communication with consumers has positive implications for consumer-firm interactions (Bleier and Eisenbeiss 2015a; Ho and Tam 2005; Hoffman and Novak 1996; Komiak and Benbasat 2006), it remains unclear to what extent advertising communication should be personalized. Arora et al. (2008) point out the costs and benefits of different levels of personalization leaving it ambiguous for marketers how specific ad personalization should be. Lower levels of personalization are technically more easily implementable, require less detailed information on consumers, and reduce the risk of preference misclassification leading to negative responses to ads. Higher levels of ad personalization allow marketers to use full information on consumer heterogeneity, match consumer preferences more closely, and allow consumers to decrease their search costs through more specific recommendations. Related work finds that generic brand ads outperform dynamically personalized ads, which only work better for consumers that have narrowly defined preferences (Lambrecht and Tucker 2013). In contrast, when looking at the degree of content personalization, Bleier and Eisenbeiss (2015) claim that highly personalized ads do perform better but decrease in performance faster than less personalized ads. IS research has fostered the discussion of how advertising should be personalized by introducing the concept of the personalization privacy paradox (Awad and Krishnan 2006; Sutanto et al. 2013; Xu et al. 2011). While personalization potentially increases perceived ad relevance, consumers become increasingly concerned about their information being used to personalize offers for them. These contradicting implications of advertising personalization underline the importance of further investigation.

In this study, we will empirically address the question of how specific advertising personalization should be by comparing category-specific with product-specific ad personalization and their implications on advertising performance. Advertising personalization relies on the availability of relevant data to personalize ad content. One online space where consumers make this data, such as demographics and interests, available are social networks. In 2015, the biggest player in the area of social advertising, Facebook, introduced the functionality to dynamically retarget consumers by making use of their external browsing behavior to personalize advertising. Browsing behavior, especially which products a consumer browses, has proven to be a good indicator of consumers' preferences (Bleier and Eisenbeiss 2015a; Lambrecht and Tucker 2013). We call this new form of advertising *Social Retargeting* as it combines the features of social advertising (Bakshy et al. 2012; Tucker 2012) and retargeting (Bleier and Eisenbeiss 2015a; Lambrecht and Tucker 2013).

Social advertising mainly relies on social targeting, making use of consumers' connections to infer preferences (homophily of connected users) (Aral et al. 2009) and increasing relevance through social endorsement (informational social influence) (Burnkrant and Cousineau 1975). Research has shown that both homophily of connected users as well as informational social influence have a positive effect on advertising performance (Bakshy et al. 2012; Tucker 2012). Homophily of connected users describes that consumers that are connected in a social network are more likely to share similar preferences than unconnected users (Tucker 2012). Therefore, friends of users that have shown interest in a certain product are more likely to be intrinsically interested in this product as well. This allows advertisers to more accurately predict consumers' preferences by using information on their friends and therefore to potentially increase the performance of personalized advertising. At the same time, informational social influence increases ad relevance by making the information that a consumer's friends are connected to an advertising brand explicit. Consumers tend to take this information into account when deciding how to react to an ad (Bakshy et al. 2012). Informational social influence increases consumers' trust in advertisers which decreases consumers' reactance and privacy concerns towards personalized recommendations (Komiak and Benbasat 2006).

Personalization and social targeting have proven to be individually effective in increasing advertising performance. However, a combination of personalization and social targeting has not been investigated so far. Earlier research finds that overpersonalizing advertising (i.e., addressing consumers with a too high degree of personalization) leads to negative ad performance (Bleier and Eisenbeiss 2015). The context of social retargeting allows us to look at the combination of these mechanisms and investigate the implications of their combination. While related studies focused on the effectiveness of dynamic retargeting compared to generic brand ads (Lambrecht and Tucker 2013) or to which degree of ad personalization in terms of brand and product category is most effective (Bleier and Eisenbeiss 2015a) we focus on how specific the personalization should be in terms of the recommendation given in the ad. In contrast to former studies that simultaneously displayed a number of products to consumers based on the chosen personalization algorithm, running the risk of confounding their findings with choice set compositions, we solely advertise a single category or product per ad. This way, we aim to isolate the effect originating from category- and product-specific personalization un-confounded of a combination of products that are being displayed to consumers.

We conducted a large-scale randomized field experiment in collaboration with a major European e-retailer on the advertising platform of Facebook. Consumers visiting the e-retailers website were randomly assigned to seeing either category-specific or product-specific personalized ads on Facebook. We examined the extent to which social targeting changes the effect of personalization on ad performance.

We find that product-specific ads generally outperform category-specific ads for both click and conversion probability. This finding contradicts recent empirical findings (Bleier and Eisenbeiss 2015a; Lambrecht and Tucker 2013). Further, the finding stands against the theoretical notions that category preferences are more stable and therefore easier to predict than preferences for specific products (Simonson 2005) and negative implications due to the personalization privacy paradox (Sutanto et al. 2013). Instead this finding is in line with the claim that more specific personalization matches consumer preferences more closely and therefore increases ad relevance (Arora et al. 2008). Second, surprisingly, we find that socially targeted consumers that should be more receptive to personalized advertising are in fact less likely to click on personalized ads. This contrasts prior research in social advertising that points towards a positive effect of both homophily of connected users and informational social influence on advertising effectiveness (Bakshy et al. 2012; Tucker 2012). Additionally, we find that social targeting does not lead to higher consumer acceptance of more personalized product-specific-ads via better preference prediction and higher trust in the advertiser.

In our additional analysis, we check to what extent our findings remain robust and are actually caused by personalization instead of confounding effects. We controlled for the duration between consumers' ad exposures and their last website visits (temporal targeting) and how deep consumers browse the advertiser's website (browsing depth). Consistent with our expectations, we find that the performance of our personalized ads decreases with an increase in time between consumers' website visits and ad impressions. This is the case as consumers continue to develop their preferences making our personalization less accurate. We also show highly personalized advertisements perform better when more closely matching consumers' browsing behavior. We therefore confirm ad personalization to be the main driver of ad performance in our study.

Our study contributes to the IS and marketing literature in several ways, challenges prior findings in the area of personalization in digital advertising, and presents insights into the practice of personalized advertising. First, we contribute to the discussion of adequate levels of advertising personalization by investigating the implications of personalization specificity. While other studies have compared the effectiveness of generic brand with dynamically retargeted ads (Lambrecht and Tucker 2013) or investigated the effectiveness of degrees of content personalization in terms of brands and product categories (Bleier and Eisenbeiss 2015a), we focus on the question of how specific, in terms of category or product, personalization should be. Our findings show that consumers react more positively to more specific advertising personalization, challenging both prior empirical findings (Bleier and Eisenbeiss 2015a; Lambrecht and Tucker 2013) and the notion of the personalization-privacy paradox (Awad and Krishnan 2006; Sutanto et al. 2013; Xu et al. 2011).

Second, we conduct our study in the context of social media and are the first to jointly investigate the combination of ad personalization and social targeting. We contribute to the discussion on positive and negative implications of social endorsements. While prior research pointed out the positive implications of social endorsements when looking at them in an isolated manner (Bakshy et al. 2012; Tucker 2012), we show that socially targeted consumers react less positive in a personalization context.

Third, we shed light into the conflict of higher levels of specificity in ad personalization and its interaction with social targeting. While previous research might have let to the assumption that socially targeted consumers are more accepting of highly specific personalized ads we find that social targeting decreases the ad effectiveness of more specific ad personalization. We explain this finding with the help of nonconformity theory and the conflict between perceived personalization and social identities in socially endorsed ads.

Last, we overcome limitations of previous studies by investigating the effect of personalization specificity in the context of different types of products. While previous studies focused on experience goods such as travel services (Lambrecht and Tucker 2013) and sports fashion (Bleier and Eisenbeiss 2015a), we investigate the specificity of product personalization for search goods, i.e., consumer electronics. For these goods the consumption uncertainty is lower making it easier for the consumers to assess the quality of the product within an ad. Next to that, we display only a single category or product to consumers in our personalized ads to not confound effects by uncontrolled combinations of several products that are advertised simultaneously to consumers as common in previous studies.

The high popularity of social media and therefore potential for advertisers to reach consumers via this advertising channel underlines the importance of our study. We suggest advertisers to readdress consumers with highly personalized product-specific advertising as soon as possible after their website visit. Our results suggest that using as much data on consumers' browsing behaviors to match their preferences as close as possible pays off. The negative implications of social targeting in our study challenge the current practice of including social endorsements in social advertising by default.

Theory

Advertising Personalization

Advertising personalization is defined as firm-initiated adjustment of advertising content towards the preferences of consumers with the goal to attract consumers and make them purchase a product from the advertiser (Ansari and Mela 2003; Arora et al. 2008). Customized communication with consumers has been found to increase customer loyalty and consumers' attention towards marketing communication (Ansari and Mela 2003; Thirumalai and Sinha 2013). In the IS literature, advertising personalization is categorized as decision personalization, supporting consumers to more easily identify and choose products that match their preferences (Thirumalai et al. 2013).

Matching consumer preferences that change dynamically with advertising content remains challenging for advertisers. Consumers (re)construct their preferences by utilizing accumulated and relevant experiences and gathering additional information (Hoeffler and Ariely 1999). Only after having developed their preferences, consumers eventually establish stable preferences. Hoeffler and Ariely (1999) argue that consumers invest effort, make actual product choices, and gain experience with a product, leading to stabilized preferences.

Consumers' online browsing behavior can give a good indication of preference defining consumer actions (Chen et al. 2009). Online personalization mechanisms leverage consumers' online browsing data and tailor advertising content to consumers' inferred preferences. Prior literature demonstrated positive effects of personalized advertising based on consumers' browsing behavior, commonly named behavioral targeting (Bleier and Eisenbeiss 2015a; Lambrecht and Tucker 2013). Behavioral targeting is mostly employed in remarketing or retargeting advertising campaigns. For this type of advertising advertisers make use of consumers' browsing information on their website and readdress them on external websites.

Although advertising personalization has been shown to positively impact consumers' reactions to advertising, advertisers are struggling with how specific advertising personalization should be. Highly specific personalized advertising recommends specific products to consumers in ads. Less specific personalized advertising recommends a product category. Advertisers need to decide which level of personalization specificity yields the highest returns for them. This decision is difficult as there are advantages for both category-specific and product-specific advertising (Arora et al. 2008).

Advantages of Less Specific Ad Personalization. Prior research in the area of promotional offers using coupons found that the additional benefit from personalizing offers on a specific individual- compared to a segment- and market-level are small and not likely to increase profit (Zhang and Wedel 2009). From a technical perspective, the implementation of less specific advertising personalization requires less information to be transmitted from the advertiser to the advertising platform. This also means that advertisers need to implement less complex tracking systems on their websites. This is especially crucial for big online retailers that sell thousands of products for which specific product-level personalization would require constantly up-to-date information on products, like images, prices, and availability, which needs to be shared with an external advertising platform. In contrast, product information on a less specific category-level is much more stable and can therefore be transmitted to advertising platforms with much less dynamic systems. Other research points out that implementing more specific personalization requires more intensive data processing which may cause delays in displaying content to consumers (Liu et al. 2010).

Not only are the technical requirements lower for less specific personalization but also the data requirements. Recommending specific products to consumers requires sufficient individual level data that accounts for consumer heterogeneity which is mostly derived from consumer histories with the advertiser (Ansari and Mela 2003). To achieve the richest picture on consumer preferences this requires data integration across different sources such as on-site browsing behavior and reactions to externally presented advertising. Although this integration is technically feasible, it often limits the number of consumers that can be reached with personalized ads as this depth of data is only available for a subset of consumers (Arora et al. 2008). In contrast, less specific personalization requires less granular data reducing the required depth of consumer histories. Former research has found that less specific personalization increases the performance of marketing communication also for newer customers with limited transaction history compared to generic offers (Malthouse and Elsner 2006). Highly specific individual-level personalization might make it necessary to profile consumers and collect more data on their preferences before providing personalized recommendations to them (Johar et al. 2014). This contrasts the less specific category-level personalization that allows making preference predictions faster with a smaller amount of consumer data.

Although more specific advertising personalization offers the chance to increase advertising relevance for consumers, its success is highly dependent on the preference prediction accuracy underlying the personalization. Misclassification of consumer preferences, for example, presenting a consumer with a product that she dislikes, can lead to consumer resistance and annoyance (Arora et al. 2008). The loss in content relevance due to preference misclassification might outweigh the loss in specificity of preference prediction, making less specific personalization more favorable than highly specific personalization. Further, theory suggests that category preferences are more likely to be classified accurately as consumer preferences for product categories are more stable than preferences for specific products (Simonson 2005; Tam and Ho 2006). Product-specific preferences are constructed up until the moment of the product purchase, at which consumers then pertain construed preferences. Previous studies found that on average more generic brand ads outperform ads for specific products (Lambrecht and Tucker 2013). Further, research points towards the risk of overpersonalizing advertising resulting in a decrease of ad performance (Bleier and Eisenbeiss 2015a).

Triggered by consumer privacy concerns, consumers might react negatively to ads when they have concerns that too much of their personal information is being used to personalize ads. To reduce possible consumer reactance, Amazon, for example, explains why they recommend certain products to consumers. The dilemma between presenting more relevant ads through personalization and an increase in consumer privacy concerns has been named personalization-privacy paradox in the IS literature (Awad and Krishnan 2006; Lee et al. 2011; Sutanto et al. 2013). Research indicates that consumers are increasingly concerned about personalization when their awareness for personalization is increased through the inclusion of their names in promotional e-Mails (Wattal et al. 2012). Similarly, it is likely that consumers are more aware of personalization when being confronted with highly specific personalization instead of less specific personalization leading to an increased privacy concerns.

Advantages of More Specific Ad Personalization. Although the technical and data processing requirements to implement highly specific personalization are more challenging, firms have the chance to tap into a large amount of consumer data when implementing an infrastructure recording individual-level data. This data allows firms to infer more detailed information about consumer preferences. When not implementing individual-level data tracking systems, firms lose out on a large amount of information on their customers.

Using more details on consumers' browsing behavior and advertising specific products that match consumers' preferences allows advertisers to achieve higher ad relevance (Bleier and Eisenbeiss 2015a; Ho and Tam 2005). More relevant advertising content is processed with more cognitive effort and therefore more likely to influence consumers' preference construction (Ho and Bodoff 2014; Tam and Ho 2006). Advertising content that is in line with consumers' preferences is more likely to be considered via the central route of persuasion (Ho and Tam 2005). Although this does not necessarily mean that the consumer will react positively towards advertising content it points towards a more elaborate consideration leading to a higher likelihood to memorize the ad content. When consumers browse particular products, advertisers can infer that consumers may be interested in these or similar products. Showing ads with a specific product, allows advertisers to be closer to the actual preferences of a consumer. A consumer that has looked at a particular product is more likely to have invested time and effort in product evaluation to narrow down her choice set. In this case, consumers may perceive less specific category ads less relevant, as they refer to a step that they have already taken in their product consideration process.

Moreover, consumers are more likely to recognize advertising relevance for specific products that they have visited than for category-based advertisements. Former research found that perceived personalization increases consumers' intention to adopt recommendations (Komiak and Benbasat 2006). An increase in perceived personalization was also found to decrease consumers' ad avoidance (Baek and Morimoto 2012).

In the context of social networks perceived personalization has been found to increase consumers' perceived ad relevance as well as their intention to click ads (Keyzer et al. 2000).

Consumers have been found to use a specificity heuristic when assessing the quality of recommendations (Palmeira and Spassova 2012): Experts that provide more specific recommendations are evaluated more favorably. Inline, source certainty, the level to which experts are convinced of the quality of their recommendation has been found to positively influence the persuasiveness of recommendations (Karmarkar and Tormala 2010). Experts with higher source certainty give more specific recommendations. Further, more extreme advertising claims for reputable advertisers have been shown to positively influence ad credibility (Goldberg and Hartwick 1990).

Another advantage for consumers when it comes to more specific personalization is that they receive customized offers that should allow them to more easily make decisions (Xiao and Benbasat 2007). While less specific personalization requires consumers to choose between different product options, product-specific recommendations can reduce choice overload effects and minimize search costs (Ansari and Mela 2003). This allows consumers to make purchase decisions more easily. Assisting consumers in making their choices helps consumers to overcome the confusion originating in large product assortments (Thirumalai et al. 2013).

When weighing the pros and cons of higher levels of advertising personalization we find that the supporting arguments outweigh the counter arguments and therefore hypothesize:

Hypothesis 1 (H1): *Product-Specific Advertising Personalization increases advertising performance compared to Category-Specific Advertising Personalization in Social Retargeting ads.*

Social Targeting

Social network platforms have information about consumers' social networks. Prior research has shown that connected users are likely to share similar preferences (Aral et al. 2009), which is referred to as homophily of connected users and used to infer preferences of consumers' peers. Further, consumers are usually influenced by their peers' actions when forming their preferences (Tucker 2012). Knowing a consumer's connections, advertisers can target and personalize advertising content based on these social connections, which is called social targeting. Prior studies found that social network friends of consumers with high brand affinity are more likely to react positively to a respective brand (Provost et al. 2009).

Social networks monetize on the ability to target consumers based on friend connections by selling social advertising impressions to firms. In social advertising, social connections are made explicit by showing the names of connected users in advertisements. This, so called social endorsement, is supposed to increase ad effectiveness by exploiting a user's social network via social influence even further. Using social endorsement positively influences how individuals perceive advertising on social media (Bakshy et al. 2012). This type of influence resulting from socially endorsed advertising is called informational social influence (Kwahk and Ge 2012). Informational social influence helps individuals to accept externally received information to be true (Deutsch and Gerard 1955). In social advertising this means a socially endorsed ad is viewed as being more credible. Individuals learn from the information that their peers are connected to a brand. This information is perceived as evidence for quality of the presented content. Other studies found evidence of a persuasive effect (informational social influence) of social endorsement in social advertising being present next to a targeting effect as users with similar interests tend to be connected (homophily of users) (Tucker 2012). Other researchers find a positive effect of informational social influence on ad performance, which is moderated by the tie strength between the endorser and the consumer (Bakshy et al. 2012). Thus, we hypothesize:

Hypothesis 2 (H2): *Social Targeting increases advertising performance in Social Retargeting ads.*

As stated earlier, we expect that more specific advertising personalization and social targeting have a positive impact on advertising performance. Via social targeting firms can address consumers that are directly or via a friend connected to their brand. It is interesting to investigate whether the implications of advertising personalization for this consumer segment are different. Based on theoretical notions that explain the effectiveness of social targeting we identify reasons for why social targeting can alleviate concerns of more specific ad personalization. First, homophily of connected users allows advertisers to gain additional information on consumers' preferences and increases the likelihood that preferences are inferred correctly. In addition, firms can leverage the fact that connected consumers are more likely to have preferences that favor their offers (Bakshy et al. 2012; Tucker 2012). This decreases the risk of preference misclassification which especially represents a risk in more specific ad personalization. Second, social endorsements that are included in socially targeted ads allow consumers to understand that their friends are connected to the advertiser leading to an increase in trust in the advertiser. This increase in trust decreases consumers' privacy concerns and reactance arising from the usage of consumers' information to personalize ads (Bleier and Eisenbeiss 2015b). Again, the issue of consumer privacy concerns due to personalization is especially present for more specific ad personalization. We therefore hypothesize that more specific ad personalization is more effective for socially targeted consumers that are connected to the advertiser and for which this connection is made explicit than for non-socially targeted consumers.

Hypothesis 3 (H3): *Social Targeting positively moderates the positive impact of Product-Specific Advertising Personalization on advertising performance in Social Retargeting ads.*

Field Experiment

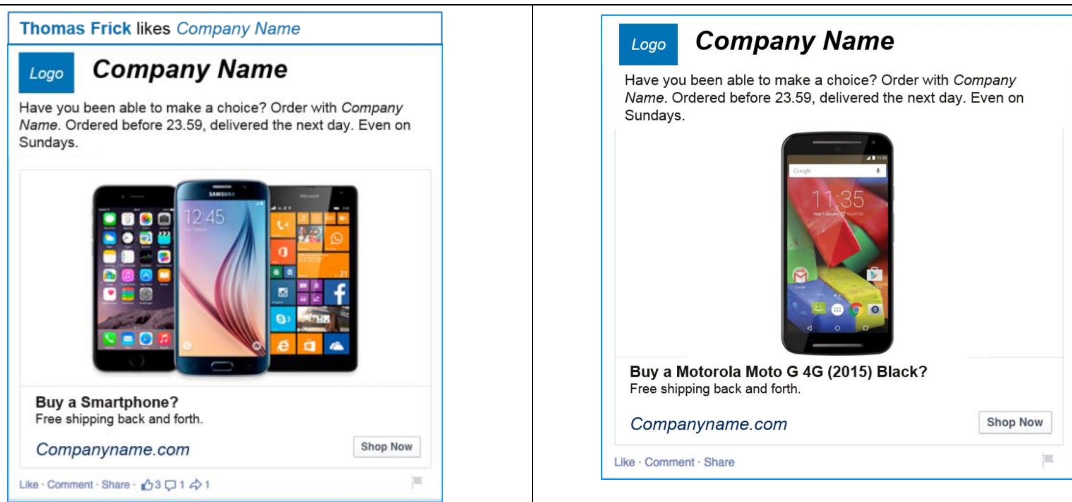
In collaboration with a major European e-Commerce company we conducted a large-scale randomized field experiment to investigate the effectiveness of different levels of personalization specificity in social retargeting. Our partner company sells a wide range of products with a focus on consumer electronics. For our study, we focus on the product categories of laptops, cameras, tablet computers, smartphones, and televisions. Further, we focus on advertising in the newsfeed area of Facebook as the newsfeed is generally the focal area for consumers and captures most of their attention (Wishpond 2014).

Consumers that browsed our partner company's website, viewed at least a category-level page, and were active users of Facebook were eligible to participate in our experiment. Using their browsing behavior, we randomly assigned either product-specific or category-specific personalized social retargeting ads to these consumers. We operationalized the personalization specificity by displaying ads that were related to either the last visited product (product-specific) or the last visited product category (category-specific). We made sure that the two types of ads were exactly the same besides the product and category attributes as shown in Figure 1. This way we rule out alternative explanations originating from the difference in visual appeal or confounding factors originating from the composition of choice sets that are presented to consumers in ads with several products. Category ads displayed the three most popular products (in terms of sales) in a single ad image and were forwarding consumers to the category overview page when being clicked. Consumers were randomly assigned to one of the treatment groups and remained in their respective treatment group for the duration of the experiment. Socially targeted ads displayed a friend's name that likes the company above the ad stating "[Friend Name] likes [Company Name]" (cf. Figure 1, Category-Specific Socially Targeted Ad).

We ran our field experiment for 28 consecutive days in May 2015. Overall, our experiment generated 3,476,626 impressions for 198,234 individual consumers. Consumers were shown a maximum of two ads on a daily basis. The ads generated 25,577 clicks, leading to an overall average click-through rate of 0.736%, and 1,070 purchases, resulting in an average click-to-conversion rate of 4.183%. We measure the ad effectiveness using both clicks and purchases. Clicks measure how many times consumers have actually clicked on a social retargeting ad. Purchases indicate how many times consumers have purchased from our partner company within 28 days after clicking an ad.

Data Structure. We structure our ad campaigns within the Facebook advertising tool in a way that allows us to analyze our data on an ad impression level. After completing our experiment, our dataset consists of 22,400 unique combinations of different ad attributes that allow us to analyze our data with the required granularity. These combinations consist of: Personalization Specificity (2) × Product Category (5) × Country (2) × Visit Depth (2) × Device Type (2) × Temporal Distance (10) × Display Date (28). In appendix A.1 we display the actual levels per variable. Next to that our data allows us to identify the number of socially endorsed impressions as well as the number of social clicks (clicks on an ad with social endorsement). This way we can duplicate our rows introducing a binary indicator variable for social targeting. This variable does not represent a randomized treatment but rather the consumer characteristic of being connected with the advertiser's Facebook page directly or via a friend. Generally, Facebook's advertising algorithm displays friend connections whenever possible. This means that friend connections need to be present and the friend that is supposed to appear as endorser in the ad has not withdrawn Facebook's right to use her name for advertising purposes in her account settings (Tucker 2014). We do not know the number of social conversions, conversions resulting after the click on or from the impression of a socially endorsed ad. Therefore we construct a variable representing the percentage of socially endorsed ads per unique ad attribute combination and operationalize *Social Targeting* using this variable when analyzing conversion probabilities.

Figure 1. Advertising Examples



Category-Specific Socially Targeted Ad | Product-Specific Ad

Results

Figure 2 presents initial evidence of the average click-through and conversion rates of consumers that are confronted with either personalized product-specific or personalized category-specific ads. We compare average click-through rates and conversion rates from impression to sale. For both measures highly personalized product-specific ads seem to outperform less personalized category-specific ads. Although, these model-free results offer an initial hint on the higher performance of more specific personalization a lot of factors are not controlled for in these model-free results. Especially the effect of social targeting, seasonality factors, and product categories might influence ad performance. We therefore move on to estimate logistic regression models to assess the impact of these factors on advertising performance.

Econometric Analysis

To examine the effects of personalization within social retargeting we analyze the data from our field experiment on an ad impression-level. Our model estimates the probability of a click or a purchase resulting from an ad impression, which we denote as $\Pr(AdPerformance_i = 1)$. We model this latent probability by using a logit function of personalization specificity and social targeting as well as additional control variables, denoted by U_i.

$$\Pr(AdPerformance_i = 1|U_i) = \frac{\exp(U_i)}{1 + \exp(U_i)}$$

$$\begin{aligned} U_i = \alpha_i + \beta_1 ProductSpecificPersonalization_i + \beta_2 SocialTargeting_i \\ + \beta_3 ProductSpecificPersonalization_i \times SocialTargeting_i + \gamma X_i + \varepsilon_i \end{aligned}$$

$ProductSpecificPersonalization_i$ is equal to 1 when an impression features a product-specific ad, 0 when featuring a category-specific ad. $SocialTargeting_i$ is a binary variable equal to 1 when an ad impression includes a social endorsement for which the addressed consumer needs to be either directly or via a peer in her social network connected to the advertiser. X_i represents a vector of ad controls including fixed effects for particular dates, product categories (laptops, cameras, tablet computers, smartphones, and televisions) countries (Belgium and the Netherlands), and devices (Mobile and Desktop). We control for these factors to rule out influences originating in heterogeneity such as seasonality in sales dates, differences in product category attractiveness, cultural differences between consumers in different countries, as well as different responsiveness across devices. ε_i represents the idiosyncratic error term. Table 1 gives the summary statistics for our main variables.

Figure 2. Ad Performance for Category- and Product-Specific Ad Personalization

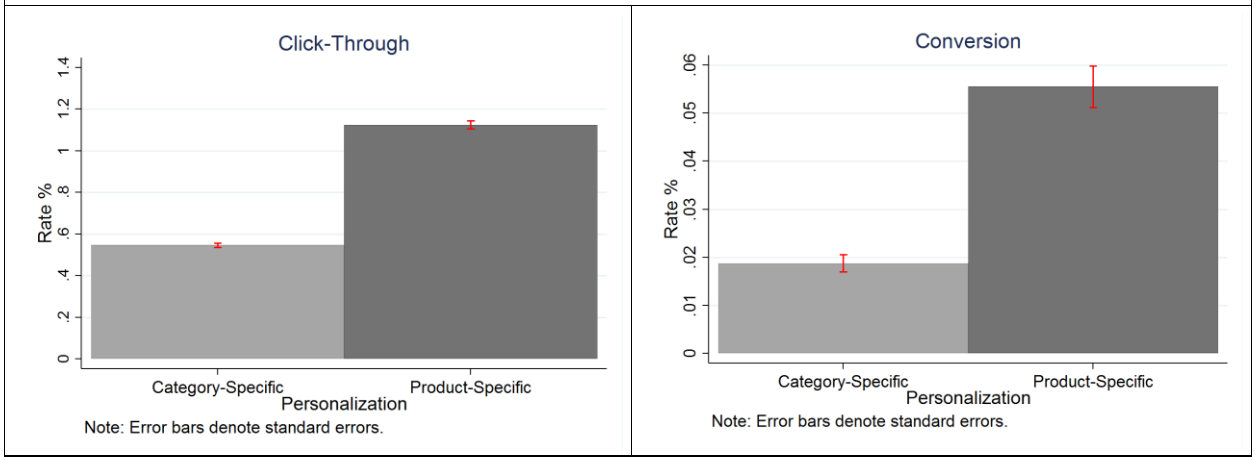


Table 1. Descriptive Statistics on Impression Level (N = 3,476,626)

VARIABLES	mean	sd	min	max
Click	0.00736	0.08546	0	1
Purchase	0.00031	0.01754	0	1
Product Specific Personalization	0.32716	0.46918	0	1
Social Targeting	0.82213	0.38240	0	1

Likelihood to Click. The results of our logistic regressions estimating the click probabilities are summarized in Table 2. Column (1) presents our model with only the control variables for dates, product categories, country, and device. In column (2) we include the binary treatment variable *Product Specific Personalization* to estimate the effect of highly personalized product-specific ads compared to less personalized category-specific ads on click-through probabilities. We find that more specific personalization significantly increases the likelihood of an ad impression leading to a click ($\beta_{ProductSpecificPersonalization} = 0.742, p < 0.001$). This confirms the results that we saw in our model-free comparison between product- and category-specific ads. Further, this result confirms the positive notion of more specific advertising personalization and our hypothesis H1. In column (3) we enter the main effect of *Social Targeting*. This variable essentially estimates whether consumers that are themselves or via a network peer connected to the advertiser and see a social endorsement in an ad react differently to a social retargeting ad. Surprisingly, and contrary to prior findings in the literature, we find that socially endorsed ad impressions lead to lower click-through probabilities ($\beta_{SocialTargeting} = -0.176, p < 0.001$) thus not supporting hypothesis H2. Next, we introduce the interaction between *Product Specific Personalization* and *Social Targeting* into our model to investigate how consumers that are connected to the advertiser react to personalization specificity. Surprisingly, we find that consumers that are connected to the advertiser are less likely to click on highly specific ads ($\beta_{ProductSpecificPersonalization \times SocialTargeting} = -0.070, p < 0.05$). This means that high personalization specificity is in fact less effective for consumers that are connected with the advertiser, therefore more likely to be aware of the advertisers' brand than consumers that are not connected to the advertiser. This stands against the notion that connected consumers are more likely to accept more specific ad personalization. Our hypothesis H3 is not supported.

As the interpretation of interaction coefficients in logistic regression is not straightforward, we calculate the marginal effects of our logit model estimates (Forman 2005; Luo et al. 2013). Further, we conduct a pairwise comparison of the estimated marginal means. Variables in the model were fixed to their mean value. We find, consistent with the coefficients in our logit model, that ads with product-specific personalization that are not socially targeted perform best. The marginal effect for the interaction between *Product Specific Personalization* × *Social Targeting* is -.0005066 (p<.05). Our results remain consistent when estimating probit models with the same model specifications (cf. Appendix A.2, column (1)). Similarly, a linear probability model gives consistent results (cf. Appendix A.2, column (2)).

Table 2. Logistic Regressions for Click Probabilities

VARIABLES	(1) Click Probability	(2) Click Probability	(3) Click Probability	(4) Click Probability
Product Specific Personalization		0.742***	0.741***	0.796***
		(0.013)	(0.013)	(0.028)
Social Targeting			-0.176***	-0.141***
			(0.016)	(0.022)
Product Specific Personalization × Social Targeting				-0.070**
				(0.031)
Date Controls	Yes	Yes	Yes	Yes
Product Category Controls	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes
Device Control	Yes	Yes	Yes	Yes
Constant	-4.052***	-4.320***	-4.177***	-4.205***
	(0.028)	(0.028)	(0.031)	(0.033)
Observations	3,476,626	3,476,626	3,476,626	3,476,626
pseudo R-squared	0.009	0.020	0.020	0.020
AIC	299661.1	296264.1	296142.5	296139.5
Chi2	2935.738	6139.099	6258.353	6302.026

*Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Likelihood to Purchase. We repeat the estimation process while exchanging the dependent variable *clicks* with actual *purchases* (*conversions*). As for clicks, we model the latent probability of a purchase $\Pr(AdPerformance_i = 1)$ by using a logit function of personalization specificity and social targeting. V_i represents a vector of fixed effects including dates, product categories, country, and device. We measure *Social Targeting* as the percentage of socially endorsed impressions for a specific ad attribute combination on a specific day when estimating purchase probabilities as the advertising platform does not provide exact data allowing to link a socially targeted impression with a conversion. τ_i is the idiosyncratic error term.

$$\Pr(AdPerformance_i = 1|V_i) = \frac{\exp(V_i)}{1 + \exp(V_i)}$$

$$V_i = \theta_i + \mu_1 ProductSpecificPersonalization_i + \mu_2 SocialTargeting_i + \mu_3 ProductSpecificPersonalization_i \times SocialTargeting_i + \rho X_i + \tau_i$$

In line with the impact of more specific advertising personalization on click probabilities, we find that product-specific social retargeting ads increase purchase probabilities ($\mu_{ProductSpecificPersonalization} = 1.088, p < 0.001$) (Table 3. column(2)).

We find that the effect of *Product Specific Personalization* remains positive and significant also when entering the main effect of *Social Targeting* and the interaction effect between *Product Specific Personalization* and *Social Targeting*. Again, we confirm that *Product Specific Personalization* leads to an increase in ad performance compared to category-specific personalization (H1). We do not find significant effects for *Social Targeting* on the probability to purchase. Similarly, we do not see that more personalized ad communication works better for socially targeted advertisements, rejecting H2 and H3. The marginal effect of *Product Specific Personalization* × *Social Targeting* remains negative but non-significant as in our main model. Using both a probit model (cf. Appendix A.2, column (3)) and a linear probability model (cf. Appendix A.2, column (4)) yields consistent results. Further, we in fact find that social targeting negatively moderates the positive impact of product-specific personalization in our linear probability model when estimating purchase probability.
Additionally, we analyze purchase probability by operationalizing a purchase as a buying event within 7 days after seeing an ad instead of clicking on an ad (cf. Appendix A.3). Our results remain consistent.

Table 3. Logistic Regressions for Purchase Probabilities

VARIABLES	(1) Purchase Probability	(2) Purchase Probability	(3) Purchase Probability	(4) Purchase Probability
Product Specific Personalization		1.088***	1.085***	2.377**
		(0.062)	(0.062)	(1.182)
Social Targeting			-0.775	0.366
			(0.618)	(1.284)
Product Specific Personalization × Social Targeting				-1.576
				(1.438)
Date Controls	Yes	Yes	Yes	Yes
Product Category Controls	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes
Device Control	Yes	Yes	Yes	Yes
Constant	-7.231***	-7.677***	-7.037***	-7.977***
	(0.142)	(0.145)	(0.535)	(1.081)
Observations	3,476,626	3,476,626	3,476,626	3,476,626
pseudo R-squared	0.006	0.021	0.022	0.022
AIC	19404.5	19096.1	19096.6	19097.2
Chi2	116.239	422.007	423.474	430.583

*Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Additional Analysis

Our results provide important insights into advertising personalization in social retargeting. To make sure that advertising personalization is driving our results and that we have operationalized our personalization treatment correctly, we run additional analysis to investigate to what extent our results remain stable when controlling for (1) temporal targeting, as well as the (2) browsing depth of consumers.

Temporal Targeting. Temporal targeting aims at addressing consumers at the point in time when they are most receptive towards marketing messages (Luo et al. 2013). Timing is an essential aspect of confronting consumers with advertisements as consumers develop their preferences over time through consideration processes and gathering of further experiences (Hoeffler and Ariely 1999; Simonson 2005). Timing is especially crucial for advertising techniques that base their preference predictions on consumers' browsing behavior. An increase in time between observing consumers' behaviors and readdressing consumers based on previously shown behaviors is likely to be correlated with a change in preferences. The theory of constructive preferences argues that preferences evolve over time with consumers generating more experiences that influence their category and product evaluations (Simonson 2005). Therefore, advertising that is personalized based on consumer behavior loses its effectiveness with a decrease in recency of consumer behavior. Observed consumer behavior then does not represent the current state of consumer preferences anymore and ads based on this past behavior are likely to misclassify consumer preferences. Therefore, our personalized ads, both product-specific and category-specific, should generally decrease in performance over time in case they are being perceived as personalized by consumers.

We introduce *Temporal Targeting* into our model, which is a continuous variable indicating the time between a consumer's website visit and an ad impression in days. A lower value for *Temporal Targeting* indicates a higher degree of temporal targeting – a lower number of days between website visit and ad impression. We run our models including *Temporal Targeting* for all campaigns but focus on the temporal distance between website visit and ad impression from within seven days of the website visit. After the 7th day, the granularity of our data moves from a daily- to a weekly-level. The data for our additional analysis consists of 1,457,527 impressions for 148,588 individual consumers[1]. Reducing the temporal distance window allows us to further assess the robustness of our results when focusing on a smaller time window.

Table 4 shows the results of our models when including *Temporal Targeting*. We first focus on the inclusion of *Temporal Targeting* and its interplay with *Product Specific Personalization* (Column (1)). Then we

[1] When analyzing our data on a weekly level and making use of our complete dataset, results remain consistent at large.

investigate the impact on the whole model including *Social Targeting* (Column (2)). Generally, we find that product-specific personalized social retargeting consistently outperforms less specific category-specific ads in terms of click probability. Further, as expected, we find a decrease in ad performance with an increase in temporal distance between a consumers' website visit and the ad impression. This confirms that personalization seems to be a major driver of ad performance in our experiment.

It is likely that more active consumers who visit Facebook more frequently are more likely to be addressed with higher *Temporal Targeting*. These active consumers are also more likely to click on ads and purchase products online, which has been coined activity bias in previous work (Lewis et al. 2011). This activity bias might amplify the effect of our *Temporal Targeting* coefficient as the variable measures not only the effect originating in the increase in time between a website visit and the confrontation with an ad but also the effect of a decrease in consumers' activeness. To address this issue, we control for *Consumer Activeness*, a variable that measures the average number of reactions to a unique ad attribute combination per impression, similar to the operationalization of *Social Targeting* for conversions. This variable gives a good indication of how actively consumers respond to an ad, which we assume to be highly correlated with consumer activeness. The variable is bound between 0 and 1. Intuitively, a higher rate of actions towards ads indicates more active consumers, which increases click probability. The result shows that the inclusion of *Consumer Activeness* substantially decreases the magnitude of the coefficient for *Product Specific Personalization*. While this indicates that *Consumer Activeness* accounts for a share of our results the coefficients remain significant and consistent in direction. In addition, we find a significant and positive coefficient for the interaction between *Product Specific Personalization* and *Temporal Targeting*. This suggests that highly personalized ads decrease in performance slower, which contradicts earlier findings (Bleier and Eisenbeiss 2015a; Simonson 2005).

In column (2) we enter *Social Targeting*, as well as the interaction with *Product Specific Personalization* into our Model. Our results remain mostly consistent. While *Product Specific Personalization* increases ad performance, *Social Targeting* decreases the likelihood of a click. Again, *Temporal Targeting* shows a significant and negative effect pointing to a decrease in performance of social retargeting ads over time and confirming personalization as a main driver of ad performance. We do not find a significant effect for the interaction between *Product Specific Personalization* and *Social Targeting*.

We replicate our analysis but exchange clicks with purchases as binary dependent variable. We estimate logistic regression to assess the impact of *Temporal Targeting* on purchase probabilities (cf. Table 4, Column (3-4)). In column (3) we see again a positive and significant effect of *Product Specific Personalization*. This effect does not remain significant when including *Social Targeting* in the model (Column (4)). The coefficient for *Temporal Targeting* confirms for both models estimating purchase probabilities that our ads decrease in performance with an increase in temporal distance between website visit and ad confrontation. This once more confirms our operationalization of ad personalization.

Browsing Depth. Consumers' browsing depth, how deep consumers browse a firm's website, gives a good indication about how well consumers have defined their preferences (Bleier and Eisenbeiss 2015b; Lambrecht and Tucker 2013; Moe 2003). To confirm that the higher performance of highly personalized product-specific ads is coming from more specific ad personalization and not from confounding factors like ad attractiveness, we assess to what extent personalization that is closer to consumers' browsing behavior leads to higher performance. We assume that product-specific ads perform better when more closely resembling a consumer's browsing behavior due to more accurate preference predictions.

We include the browsing depth, distinguishing between consumers that have solely browsed category pages and consumers that have browsed specific product pages, in our analysis. We introduce a binary variable indicating whether a consumer browsed product pages (*Product Browsing = 1*) or only category-level pages (*Product Browsing = 0*) before ad exposure. Consumers that browse only category-level pages and are assigned to the *Product Specific Personalization* treatment are presented with one of the top three products within the browsed category. These consumers may perceive the personalization less relevant, compared to the consumers who are confronted with products that they actually viewed during product page browsing. We expect to find a positive and significant effect for the interaction of *Product Specific Personalization* and *Product Browsing*. As consumers are more likely to recognize personalization that happens immediately after their website visit we restrict the time window in our analysis as before to include impressions served 1 to 7 days after a consumer's website visit. We include *Temporal Targeting* in the analysis to control for effects of temporal distance between website visit and ad impression. As before we estimate logistic regressions for both click and purchase probability.

Table 4. Logistic Regressions Including Temporal Targeting

VARIABLES	(1) Click Probability	(2) Click Probability	(3) Purchase Probability	(4) Purchase Probability
Product Specific Personalization	0.136***	0.180***	0.404***	1.799
	(0.032)	(0.046)	(0.145)	(1.285)
Social Targeting		-0.101***		1.194
		(0.030)		(1.368)
Product Specific Personalization × Social Targeting		-0.055		-1.693
		(0.041)		(1.542)
Temporal Targeting	-0.161***	-0.161***	-0.227***	-0.225***
	(0.007)	(0.007)	(0.036)	(0.036)
Product Specific Personalization × Temporal Targeting	0.054***	0.054***	0.065	0.062
	(0.009)	(0.009)	(0.047)	(0.047)
Consumer Activeness	27.161***	27.154***	24.633***	24.755***
	(0.441)	(0.440)	(1.155)	(1.190)
Date Controls	Yes	Yes	Yes	Yes
Product Category Controls	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes
Device Control	Yes	Yes	Yes	Yes
Constant	-4.332***	-4.247***	-7.385***	-8.380***
	(0.044)	(0.050)	(0.207)	(1.191)
Observations	1,457,527	1,457,527	1,457,527	1,457,527
pseudo R-squared	0.063	0.063	0.073	0.073
AIC	161333.9	161296.2	11291.3	11293.9
Chi2	11740.642	11825.311	1047.967	1057.155

*Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Table 5 shows the results of our models including *Product Browsing*. We find a significant and positive effect of *Product Specific Personalization* on click probability. Generally, we find that the interaction between *Product Specific Personalization* and *Product Browsing* is positive and significant for click probabilities confirming that the increase in ad performance is caused by an increase in the level of ad personalization, not other ad characteristics. For click probabilities, we find consistently that with an increase in temporal distance advertising performance decreases; and highly personalized ads improve in performance over time (*Product Specific Personalization* × *Temporal Targeting*). Nevertheless, when focusing on the three-way interaction between *Product Specific Personalization*, *Product Browsing*, and *Temporal Targeting* (Columns (1) & (2)), we find a negative and significant coefficient. This suggests that for consumers that browse the advertiser's page deeper and see highly personalized social retargeting ads the advertising performance decreases faster with an increase in the temporal distance between website visit and ad impression. This is in line with the notion that more specific preferences are less stable and evolve over time (Simonson 2005). When focusing on the influence of *Product Browsing* on purchase probabilities we see that temporal distance has a consistently negative effect on purchase probabilities. *Product Specific Personalization* does improve ad performance consistent with our main results (cf. Table 5 column (3)), although only when not controlling for *Social Targeting*.

Next to that, these models allow us to get some understanding of to what extent personalization or a reminder effect of retargeting is driving our results. While theoretically personalization aims at matching a consumer's preferences as close as possible with an ad a lot of retargeting algorithms simply suggest the consumer's last visited product. As the last visited product is the most recent memory of a consumer's browsing journey there might be a reminder effect of such an ad that encourages the consumer to pick up her browsing journey where she left. In case the reminder effect is driving our results, we would expect that advertising that is matching consumers' browsing behavior more closely does always perform better. In contrast, we find that product-specific personalization does also perform better for consumers that only browse category pages, meaning that category-specific ads would have matched their browsing behavior more closely. This is a good indicator that the specificity of personalization is driving our results.

Table 5. Logistic Regression Including Product Browsing				
VARIABLES	(1) Click Probability	(2) Click Probability	(3) Purchase Probability	(4) Purchase Probability
Product Specific Personalization	0.577***	0.621***	0.774***	1.175
	(0.050)	(0.059)	(0.231)	(1.234)
Product Browsing	-0.062	-0.062	-0.165	-0.164
	(0.045)	(0.045)	(0.223)	(0.223)
Product Specific Personalization × Product Browsing	0.267***	0.270***	0.303	0.327
	(0.064)	(0.064)	(0.302)	(0.302)
Temporal Targeting	-0.219***	-0.219***	-0.270***	-0.269***
	(0.010)	(0.010)	(0.053)	(0.053)
Product Specific Personalization. × Temporal Targeting	0.032**	0.032**	0.076	0.077
	(0.015)	(0.015)	(0.073)	(0.073)
Product Browsing × Temporal Targeting	0.011	0.010	0.022	0.021
	(0.014)	(0.014)	(0.073)	(0.073)
Product Specific Personalization × Product Browsing × Temporal Targeting	-0.063***	-0.063***	-0.100	-0.100
	(0.020)	(0.020)	(0.097)	(0.097)
Social Targeting		-0.102***		-0.575
		(0.030)		(1.293)
Product Specific Personalization × Social Targeting		-0.059		-0.517
		(0.041)		(1.463)
Date Controls	Yes	Yes	Yes	Yes
Product Category Controls	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes
Device Control	Yes	Yes	Yes	Yes
Constant	-3.514***	-3.429***	-6.706***	-6.222***
	(0.048)	(0.053)	(0.237)	(1.132)
Observations	1,457,527	1,457,527	1,457,527	1,457,527
pseudo R-squared	0.034	0.034	0.032	0.032
AIC	166361.6	166320.8	11796.3	11798.3
Chi2	5374.814	5449.317	383.665	387.711

*Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Discussion

With the growing availability of detailed online data on consumers and their online behaviors, opportunities in advertising personalization are constantly increasing. Despite that fact, several areas within advertising personalization remain understudied. In this study, we investigate the impact of personalization specificity in digital advertising and to what extent consumers that are connected to the advertiser on a social network site are more receptive to personalized advertising.

We find that product-specific personalization in social retargeting generally outperforms category-specific personalization. This finding is in line with the general notion that highly personalized digital advertising does match consumer preferences more closely and is therefore more relevant to consumers (Arora et al. 2008). We challenge prior findings that showed that less personalized generic brand ads perform better than more personalized ads unless consumers have narrowed down their preferences (Lambrecht and Tucker 2013).

A potential explanation for our finding is that we are focusing on search goods, i.e., consumer electronics. For search goods consumers focus on specific product attributes to evaluate them. In this case, it might be that consumers are more interested in specific product details, in our case a specific product and its name, than the generic category advertising. When looking at similar studies with contrasting findings we see that the advertised products can be categorized as being rather experience than search goods, namely holiday services (Lambrecht and Tucker 2013) and sports fashion (Bleier and Eisenbeiss 2015a). Further, several products presented in an ad, as in our category-based ads, might induce choice overload with consumers. Consumers that have decided to leave our partner's website without purchasing a product – these are the consumers that we target with our ads – might not know exactly which kind of product they are looking for. When presenting them with several products as we do in the category based ad (the top 3 products) consumers might get the feeling that too much effort from their side is required to find a suitable product.

With respect to social targeting, we find that including social context in ads and using consumers social networks to target them has a negative effect on consumers' likelihood to click and ad. This finding contradicts the notion of informational social influence and homophily of connected user. Social influence should lead to an increase in trust towards the advertiser as well as a higher perceived relevance both positively impacting ad performance. Homophily of connected users allows advertisers to predict consumers' preferences more accurately as their preferences should be similar to the preferences of their friends. Therefore, our results contradict prior findings in the area of social advertising (Bakshy et al. 2012; Tucker 2012). Additionally, we investigate whether social targeting increases consumers' acceptance for higher levels of personalization induced by familiarity with the advertiser (Komiak and Benbasat 2006). We find that consumers that are directly, or via peers, connected to the advertiser are less likely to click on highly personalized ads. This points towards the potential of overpersonalization in social retargeting, comparable to former findings within retargeting (Bleier and Eisenbeiss 2015a).

Although informational social influence has been shown to trigger conformity (Deutsch and Gerard 1955) consumers are simultaneously striving for uniqueness (Chan et al. 2012). Uniqueness describes consumers drive to be different from others where too much similarity leads to negative emotional reactions (Berger and Heath 2008). Uniqueness theory combines both the urge of individuals to identify themselves with others (social identities) as well as the need to differentiate themselves to define their personal identity (Snyder and Fromkin 1980). Individuals tend to adhere to favorable social identities while simultaneously defining their personal identity through differentiation (Brewer 1991). While the personal identity is unique, social identities are related to common characteristics that are popular in a certain social group that is favored by an individual and therefore adopted. Our study context differs significantly from former works in the area of social advertising that presented the positive implications of both homophily of users and social endorsements (Bakshy et al. 2012; Tucker 2012) in that it focusses on personalized advertising instead of advertising in general. Social identities "depersonalize the self-concept" (Brewer 1991, p. 476). This depersonalization by including social endorsements in ads stands in conflict with the personalization of an advertisement. The fact that consumers face ads that recommend products specifically for them does conceptually not match with the endorsement of friends decreasing the feeling of personalization uniquely for their preferences. We empirically find that ads that are more specific and therefore perceived as more unique are harmed more by the inclusion of social endorsements in the ad. This makes sense as the specific recommendation is conflicting more strongly with the friend endorsement. Ad effectiveness decreases through a decrease in the perceived personalization that is hampered by the inclusion of social identities in the marketing communication that was meant for the individual receiver. This might lead to the general decrease in performance for our personalized ads. Related current work shows that consumers tend to not conform in the context of social networks (Sun et al. 2016).

To make sure that our results are driven by advertising personalization we additionally control for the impact of temporal targeting and consumers' browsing depth in our models. Consistent with our expectations and underlining that advertising personalization is driving our results, we find that in general higher temporal targeting yields higher ad performance for both more and less specific ad personalization. This is the case as with an increase in time between a consumer's visit to the advertiser's webpage and the confrontation with an ad the consumer's preferences are likely to change (Simonson 2005) making the personalization less relevant for the consumer. We find this effect to be consistent for click and purchase probabilities. To confirm that more specific personalization is driving the superior performance of product-specific ads, we investigate whether more specific personalization works better for consumers that have browsed the advertisers' site deeper. We find that more specific personalization works better for consumers that browse actual product pages indicating personalization that matches consumer preferences more closely to perform better. This confirms the presence of a positive effect of more specific personalization on ad performance. Nevertheless, for consumers that browse the firm's website deeper, the performance of highly personalized ads is decreasing faster as they are likely to not remember the specific product that they viewed or changed their preferences to another product because of less stable product specific preferences (Simonson 2005).

Practical Implications

Advertising personalization is enjoying an increasing popularity in the digital advertising industry with most marketers praising its higher response and engagement rates (EMarketer 2015). Still, marketers are struggling with finding the most performant specifications for their personalized ads. Our results shed light on the question of how specific advertising personalization should be. We advise advertisers to generally use highly specific advertising personalization. We found that recommending specific products to consumers increases ad effectiveness.

In the context of personalized advertising, we find that including friends' names in the ad and making use of preference similarities due to homophily of connected users does not increase but decrease advertising performance. This result challenges the current perspective on social advertising that propagates the by default inclusion of social endorsements in ads and does not allow advertisers to make a choice whether to include social endorsements or not. Potentially, platform providers should reevaluate their guidelines and assess whether socially endorsed ads do underperform unendorsed ads in personalized contexts. Consumers are not becoming more accepting of more specific personalization when they are connected with the advertiser.

Further, consumers should be readdressed with ads as soon as possible after their website visit. We find across all specifications that advertising performance for both click and purchase probabilities decreases with an increase in the temporal distance between a consumer's website visit and the ad impression.

Limitations and Future Research

In our study, we are comparing different levels personalization specificity but do not conduct a so-called uplift test to generally evaluate the contribution of social retargeting to a firm's success. We operationalize advertising performance by both clicks on the ad as well as purchases within 28 days after a consumer has clicked an ad. We are aware of this limitation and see potential for future research to combine personalization characteristics with an investigation of how these ads increase consumers' purchase probabilities compared to consumers that do not see ads. Although we are not able to control for the influence of other marketing channels, we are confident that our experimental randomization splits influences of neglected marketing channels evenly across treatment groups.

Social targeting does not represent a randomized treatment variable in our field experiment. To alleviate potential issues we make sure that the percentage of social impressions compared to non-social impressions in our experiment remains stable over time. The randomization of social targeting is mostly important when having the aim to distinguish between effects induced by homophily of connected users and informational social influence. Theory suggests that both effects have a positive influence on advertising performance. In our case we find that social targeting negatively influences ad performance, therefore questioning former theory and pointing towards a potential overpersonalization issue.

We investigate the effectiveness of social retargeting ads for consumer electronics. The focus on this rather search good related product domain might limit how generalizable our study results are. At the same time, we see our contribution in investigating this type of product domain that differs from previous studies that investigated the effectiveness of retargeting ads for sports fashion (Bleier and Eisenbeiss 2015a) and holiday services (Lambrecht and Tucker 2013) which can be classified as being rather experience than search goods. Future research could investigate to what extent the type of advertised product influences the effectiveness of personalized ads.

References

Adobe Systems Inc. 2014. "Real-Time Marketing Insights Study,". [online] Available at: https://offers.adobe.com/en/na/marketing/landings/_46316_real_time_marketing_insights_study.html [Accessed: 02 May 2015].

Ansari, A., and Mela, C. 2003. "E-Customization," *Journal of Marketing Research* (40:2), pp. 131–145.

Aral, S., Muchnika, L., and Sundararajan, A. 2009. "Distinguishing Influence-Based Contagion from Homophily-Driven Diffusion in Dynamic Networks," in *Proceedings of the National Academy of Sciences* (106:51), pp. 21544–21549.

Arora, N., Dreze, X., Ghose, A., Hess, J. D., Iyengar, R., Jing, B., Joshi, Y., Kumar, V., Lurie, N., Neslin, S., Sajeesh, S., Su, M., Syam, N., Thomas, J., and Zhang, Z. J. 2008. "Putting One-to-One Marketing to Work: Personalization, Customization, and Choice," *Marketing Letters* (19:3-4), pp. 305–321.

Awad, N. F., and Krishnan, M. S. 2006. "The Personalization Privacy Paradox: An Empirical Evaluation of Information Transparency and the Willingness To Be Profiled Online for Personalization," *MIS Quarterly* (30:1), pp. 13–28.

Baek, T. H., and Morimoto, M. 2012. "Stay Away From Me," *Journal of Advertising* (41:1), pp. 59–76.

Bakshy, E., Eckles, D., Yan, R., and Rosenn, I. 2012. "Social Influence in Social Advertising: Evidence from Field Experiments," in *Proceedings of the 13th ACM Conference on Electronic Commerce* (1:212), pp. 146–161.

Berger, J., and Heath, C. 2008. "Who Drives Divergence? Identity Signaling, Outgroup Dissimilarity, and the Abandonment of Cultural Tastes," *Journal of Personality and Social Psychology* (95:3), pp. 593–607.

Bleier, A., and Eisenbeiss, M. 2015a. "Personalized Online Advertising Effectiveness : The Interplay of What, When, and Where," *Marketing Science* (34:5), pp. 669–688.

Bleier, A., and Eisenbeiss, M. 2015b. "The Importance of Trust for Personalized Online Advertising," *Journal of Retailing* (91:3), pp. 390–409.

Brewer, M. B. 1991. "The Social Self: On Being the Same and Different at the Same Time," *Personality and Social Psychology Bulletin* (17:5), pp. 475–482.

Burnkrant, R., and Cousineau, A. 1975. "Informational and Normative Social Influence in Buying Behavior," *Journal of Consumer Research* (2:3), pp. 206–215.

Chan, C., Berger, J., and Van Boven, L. 2012. "Identifiable but Not Identical: Combining Social Identity and Uniqueness Motives in Choice," *Journal of Consumer Research* (39:3), pp. 561–573.

Chen, Y., Pavlov, D., Canny, J. F., and Ave, H. 2009. "Large-Scale Behavioral Targeting Categories and Subject Descriptors," in *Proceedings of the 15th ACM International Conference on Knowledge Discovery and Data Mining* (39:5), pp. 209–217.

Deutsch, M., and Gerard, H. B. 1955. "A Study of Normative and Informational Social Influences Upon Individual Judgement," *Journal of Abnormal Psychology* (51:3), pp. 629–636.

EMarketer. 2015. "Personalization Drives Engagement, Conversions – eMarketer," [online] Available at: http://www.emarketer.com/Article/Personalization-Drives-Engagement-Conversions/1012914 [Accessed: 08 February 2016].

Forman, C. 2005. "The Corporate Digital Divide: Determinants of Internet Adoption," *Management Science* (51:4), pp. 641–654.

Goldberg, M., and Hartwick, J. 1990. "The Effects of Advertiser Reputation and Extremity of Advertising Claim on Advertising Effectiveness," *Journal of Consumer Research* (17:2), pp. 172–179.

Ho, S. Y., and Bodoff, D. 2014. "The Effects of Web Personalization on User Attitude and Behavior: An Integration of the Elaboration Likelihood Model and Consumer Search Theory," *MIS Quarterly* (38:2), pp. 497–520.

Ho, S. Y., and Tam, K. Y. 2005. "Web Personalization as a Persuasion Strategy: An Elaboration Likelihood Model Perspective," *Information Systems Research* (16:3), pp. 271–291.

Hoeffler, S., and Ariely, D. 1999. "Constructing Stable Preferences: A Look Into Dimensions of Experience and Their Impact on Preference Stability," *Journal of Consumer Psychology* (8:2), pp. 113–139.

Hoffman, D. L., and Novak, T. P. 1996. "Marketing in Hypermedia Computer-Mediated Environments: Conceptual Foundations," *Journal of Marketing* (60:3), pp. 50–68.

Johar, M., Mookerjee, V., and Sarkar, S. 2014. "Selling vs. Profiling: Optimizing the Offer Set in Web-Based Personalization," *Information Systems Research* (25:2), pp. 285–306.

Karmarkar, U. R., and Tormala, Z. L. 2010. "Believe Me, I Have No Idea What I'm Talking About: The Effects of Source Certainty on Consumer Involvement and Persuasion," *Journal of Consumer Research* (36:6), pp. 1033–1049.

Keyzer, F. De, Dens, N., and Pelsmacker, P. De. 2000. "Is this for me? How Consumers Respond to Personalized Advertising on Social Networking Sites," *Journal of Interactive Advertising* (15:2), pp. 124–134.

Komiak, S., and Benbasat, I. 2006. "The Effects of Personalization and Familiarity on Trust and Adoption of Recommendation Agents," *MIS Quarterly* (30:4), pp. 941–960.

Kwahk, K., and Ge, X. 2012. "The Effects of Social Media on E-Commerce: A Perspective of Social Impact Theory. System Science," in *45th Hawaii International Conference on System Sciences*, pp. 1814–1823.

Lambrecht, A., and Tucker, C. 2013. "When Does Retargeting Work? Information Specificity in Online Advertising," *Journal of Marketing Research* (50:5), pp. 561–576.

Lee, D., Ahn, J.-H., and Bang, Y. 2011. "Managing Consumer Privacy Concerns in Personalization: A Strategic Analysis of Privacy Protection," *MIS Quarterly* (35:2), pp. 423–444.

Lewis, R., Rao, J., and Reiley, D. 2011. "Here, There, and Everywhere: Correlated Online Behaviors Can Lead to Overestimates of the Effects of Advertising," *Proceedings of the 20th International Conference on World Wide Web*, pp. 157–166.

Liu, D., Sarkar, S., and Sriskandarajah, C. 2010. "Resource Allocation Policies for Personalization in Content Delivery Sites," *Information Systems Research* (21:2), pp. 227–248.

Luo, X., Andrews, M., Fang, Z., and Phang, C. W. 2013. "Mobile Targeting," *Management Science* (60:7), pp. 1738–1756.

Luo, X., Andrews, M., Fang, Z., and Phang, C. W. 2013. "Mobile Targeting," *Management Science* (60:7), pp. 1738–1756.

Malthouse, E. C., and Elsner, R. 2006. "Customisation with Crossed-Basis Sub-Segmentation," *Journal of Database Marketing & Customer Strategy Management* (14:1), pp. 40–50.

Moe, W. 2003. "Buying, Searching, or Browsing: Differentiating Between Online Shoppers Using In-Store Navigational Clickstream," *Journal of Consumer Psychology* (13:1), pp. 29–39.

Palmeira, M., and Spassova, G. 2012. "The Specificity Heuristic: Consumer Evaluation of Expert Recommendation," *Advances in Consumer Research* (40), pp. 653–654.

Provost, F., Dalessandro, B., Hook, R., Zhang, X., and Murray, A. 2009. "Audience Selection for On-line Brand Advertising: Privacy-friendly Social Network Targeting," in *Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 707–716.

Simonson, I. 2005. "Determinants of Customers' Responses to Customized Offers: Conceptual Framework and Research Propositions," *Journal of Marketing* (69:1), pp. 32–45.

Snyder, C., and Fromkin, H. 1980. "Uniqueness: The Pursuit of Difference", *Plenum*, New York.

Statista. 2016. "Digital ad spend worldwide 2015 | Statistic," [online] Available at: http://www.statista.com/statistics/237974/online-advertising-spending-worldwide/ [Accessed: 29 February 2016].

Sun, M., Zhang, X., and Zhu, F. 2016. "Nonconformity in Online Social Networks: Experimental Evidence," *Working Paper*.

Sutanto, J., Palme, E., Tan, C., and Phang, C. W. 2013. "Addressing the Personalization-Privacy Paradox: An Empirical Assessment from a Field Experiment on Smartphone Users," *MIS Quarterly* (37:4), pp. 1141–1164.

Tam, K., and Ho, S. 2006. "Understanding the Impact of Web Personalization on User Information Processing and Decision Outcomes," *MIS Quarterly* (30:4), pp. 865–890.

Thirumalai, S., and Sinha, K. K. 2013. "To Personalize or Not to Personalize Online Purchase Interactions: Implications of Self-Selection by Retailers," *Information Systems Research* (24:3), pp. 683–708.

Tucker, C. 2012. "Social Advertising," *Working Paper - SSRN eLibrary*, pp. 1–28.

Tucker, C. 2014. "Social Networks, Personalized Advertising and Privacy Controls," *Journal of Marketing Research* (51:5), pp. 546–562.

Wattal, S., Telang, R., Mukhopadhyay, T., and Boatwright, P. 2012. "What's in a "Name"? Impact of Use of Customer Information in E-Mail Advertisements," *Information Systems Research* (23:3), pp. 679–697.

Wishpond. 2014. How to Track Referrals Using Google Analytics. [online] Available at: http://corp.wishpond.com/facebook-marketing-resources-for-business/best-practices-to-performance-marketing-on-facebook/ [Accessed: 02 May 2016].

Xiao, B., and Benbasat, I. 2007. "E-Commerce Product Recommendation Agents: Use, Characteristics, and Impact," *MIS Quarterly* (31:1), pp. 137–209.

Xu, H., Luo, X., Carroll, J., and Rosson, M. 2011. "The Personalization Privacy Paradox: An Exploratory Study of Decision Making Process for Location-Aware Marketing," *Decision Support Systems* (51:1), pp. 42–52.

Zhang, J., and Wedel, M. 2009. "The Effectiveness of Customized Promotions in Online and Offline Stores," *Journal of Marketing Research* (46:4), pp. 190–206.

Appendix

A.1 Data Structure and Variable Levels of Facebook Campaigns[2]

Personalization Specificity (2)	Product Category (5)	Country (2)	Visit Depth (2)	Device Type (2)	Temporal Distance (10)[3]
(1) Category-Specific	(1) Cameras	(1) Belgium	(1) Category Page	(1) Desktop	1
(2) Product-Specific	(2) Laptops	(2) Netherlands	(2) Product Page	(2) Mobile	2
	(3) Smartphones				3
	(4) Tablet Computers				4
	(5) TVs				5
					6
					7
					14
					21
					28

A.2 Alternative Estimators for Click and Purchase Probabilities

VARIABLES	(1) Probit Click Probability	(2) Linear Click Probability	(3) Probit Purchase Probability	(4) Linear Purchase Probability
Product Specific Personalization	0.293***	0.007***	0.685**	0.001***
	(0.010)	(0.000)	(0.316)	(0.000)
Social Targeting	-0.049***	-0.0008***	0.115	0.0001
	(0.008)	(0.000)	(0.334)	(0.000)
Product Specific Personalization × Social Targeting	-0.032***	-0.002***	-0.473	-0.001**
	(0.011)	(0.000)	(0.384)	(0.000)
Date Controls	Yes	Yes	Yes	Yes
Product Category Controls	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes
Device Control	Yes	Yes	Yes	Yes
Constant	-2.175***	0.016***	-3.400***	0.0005**
	(0.013)	(0.000)	(0.282)	(0.000)
Observations	3,476,626	3,476,626	3,476,626	3,476,626
pseudo R-squared	0.020		0.022	
R-squared		0.002		0.018

*Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

A.3 Estimates for View-Through Conversions (within 7 days after seeing an ad)

VARIABLES	(1) Purchase Probability	(2) Purchase Probability	(3) Purchase Probability	(4) Purchase Probability
Product Specific Personalization		0.251***	0.251***	0.908*
		(0.029)	(0.029)	(0.491)
Social Targeting			-0.157	0.262
			(0.309)	(0.439)
Product Specific Personalization × Social Targeting				-0.801
				(0.597)
Date Controls	Yes	Yes	Yes	Yes
Product Category Controls	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes
Device Control	Yes	Yes	Yes	Yes
Constant	-6.411***	-6.490***	-6.359***	-6.706***
	(0.081)	(0.081)	(0.270)	(0.374)
Observations	3,476,626	3,476,626	3,476,626	3,476,626
pseudo R-squared	0.008	0.009	0.009	0.009
AIC	76710.0	76637.1	76638.8	76638.9
Chi2	695.492	781.149	781.304	786.128

*Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

[2] All combinations are unique for the 28 days during which the experiment ran in May 2015.

[3] Measured as within the t^{th} day after the website visit