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Retargeting Ads for Shopping Cart Recovery: Online Field Experiments

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Abstract

Retargeting ads (RA) aim to convert customers who previously browsed the websites or abandoned shopping-carts. We exploit several randomized field experiments to test how the effects of RA vary depending on ad-copy content and purchase-funnel stages. Results suggest that compared to hold-out without retargeting, RA in lower funnel based on shopping-cart abandonment history significantly enhances purchase responses. The effects are driven by ad content that highlights product return information rather than product reminder or shipping information. Due to lack of touch/feel/trial of online orders, such ad-copy can nudge customers to try the products by reducing shopping risks and, thus, increase purchase rates. Net revenue for RAs with product return information is 49.7% larger than conventional RAs with product information. Also, lower funnel retargeting is 2.25 times as effective as upper funnel retargeting in lifting purchase rates. These findings indicate how to design RAs to recover abandoned carts and boost sales.

Keywords: Shopping-cart abandonment, retargeting, advertising, purchase funnel

Introduction

Online shoppers who have browsed a product or added it in e-shopping carts often leave the website without completing the purchase. The average rate of e-shopping cart abandonment in 2020 reached nearly 70%, implying that online retailers on average only captured around 30% of revenues that they could potentially get. Practitioners have thus started using retargeting ad to remind customers of the products that they previously browsed on the website or abandoned in the digital carts, in order to convert them into purchases. For example, Burberry, Kate Spade and Urban Outfitter are investing significant resources in email campaigns for shopping cart recovery. However, it remains unclear what content of retargeting ad is effective. As discussed in the subsequent section, academic research on retargeting ad, especially for cart abandonment, is sparse. Little is known about how to design a retargeting ad to successfully resolve lingering hesitations of the customers and persuade them to go through checkout without leaving money on the table. Moreover, retailers might oversimplify their retargeting strategy without considering how ad content interacts with online purchase funnel stages, product characteristics, and customer characteristics. Ignorance of such conditional factors may not only waste valuable resources but also be counterproductive for e-commerce performance because of potential negative interaction effects. While practitioners increasingly realize the meaningfulness and feasibility of precision targeting enabled by rich user data tracked by e-commerce platforms, guidance on how to perform "precision retargeting" based on product or customer characteristics is largely absent.

Hence, this research aims to answer two main research questions: (1) To effectively convert abandoned products into purchases, what information should digital retargeting ad include? (2) Under what conditions will the effectiveness of such ad content be attenuated or amplified? To address these two questions, we develop a coherent conceptual framework based on the theory of perceived risk, which is high in online shopping because shoppers cannot touch, feel, or try the product before purchasing. It is thus a key determinant of e-shopping cart abandonment. To answer the first research question, we differ from the very limited literature and focus on relatively "costless" ad content, instead of direct price discount (Luo et al. 2019) which adds significant additional cost and diminishes product profitability. Specifically, we show that a simple reminder in the retargeting ad that the product can be returned significantly boosts the recovery of abandoned carts by alleviating online shoppers' perceived risk. The management information systems literature recognizes that product return is rooted in an information problem in online shopping, namely, product fit uncertainty (Hong and Pavlou 2014; Sahoo et al. 2018; Yang and Xiong 2019). Our research sheds new light on this stream of research by showing that, in the context of abandoned e-shopping cart retargeting, providing product return information is not "a necessary evil" as traditionally considered by the practitioners (Petersen and Kumar 2009). In fact, retargeting ad with a reminder of the retailer's existing product return policy helps increase product sales and profits according to our findings, because it essentially reminds customers of the opportunity for physical trial of the product and thus reduces perceived risk in the online purchase decision making process.

To address the second research question, we identify three moderators, namely, upper- vs lower-funnel stage, product price, and customer tenure with the retailer. They correspond to the key drivers of the prominence of perceived risk in e-shopping according to the literature (Kotler and Armstrong 2011), which implies that the salience of perceived risk in causing customer hesitation in the lower stage of purchase funnel, for low- (vs high) price products, and for customers who are less (vs more) familiar with the retailer. Accordingly, we propose and demonstrate that retargeting ad with product return information is more effective in lower-funnel stage, for high-price products and shorter-tenure customers. By investigating these moderators, our research fills an important gap in the retargeting literature which is largely mute about the potential heterogeneous effects of retargeting ad across products and customers.

Despite the managerial importance, firms struggle to scientifically quantify the impact of shopping cart retargeting campaigns on sales responses with observational data, because estimates from correlational approaches can be confounded by endogeneity and self-section bias. To circumvent this difficulty, we conducted two randomized field experiments sponsored by a large online fashion retailer in Japan. The retailer sent shopping cart recovery emails to its logged-in customers. From the experimental results, we obtain nuanced understanding of both the average treatment effects and the heterogeneity in them. Compared to conventional retargeting ad that simply reminds customers of the product abandoned, retargeting ad with product return information increases incremental sales. This incremental effect is significant among lower-funnel (vs upper-funnel) customers, for whom perceived risk is a more prominent impediment to conversion. In addition, the retargeting message with product return information interacts with product and customer characteristics in such a way that it is even more effective in situations where the perceived risk is higher, i.e., for higher-price products and customers with shorter tenure. Economically, the effect size is nontrivial. After accounting for spillover effect and product return costs, shopping cart retargeting with product return information can generate 50% more total net revenues than the baseline holdout.

Our findings contribute to the digital advertising literature (e.g., Lambrecht and Tucker 2013; Sahni et al. 2019) by identifying an effective yet costless type of retargeting ad message and its boundary conditions. Moreover, adding to the e-commerce literature on the e-shopping cart technology (e.g., Luo et al. 2019), our research advances the understanding on user behavior across different stages of the online purchase funnel and reveals a unique approach to recovering abandoned e-shopping carts by alleviating perceived risk. From a contingency perspective, we demonstrate the heterogeneous effects of retargeting ad conditional on purchase-funnel stages and product-level and customer-level moderators, indicating the potential to enhance e-commerce performance through "precision retargeting" based on product and customer characteristics. Our research also enriches the product return literature (e.g., Hong and Pavlou 2014; Sahoo et al. 2018), which has traditionally focused on how to reduce product return. From a fresh viewpoint, instead of treating product return as a negative outcome of online shopping uncertainty or risk, we show how and when product return information can help alleviate shopping risk and thus positively influence sales and profits by nudging conversions of abandoned carts. Our findings provide actionable managerial implications regarding how to effectively nudge conversions by precisely retargeting on customers along the purchase funnel without sacrificing product profitability.

Relevant Literatures

The information processing theory holds that customers' purchase decision-making consists of various stages (Bettman et al. 1998). There is a long tradition in the literature studying consideration sets and purchase funnel stages (Desai and Hoyer 2000; Hauser and Wernerfelt 1990; Roberts and Lattin 1991). In the online context, purchase funnel is the process of a customer browsing the product webpage, adding it to shopping carts, and purchasing it ultimately (Hoban and Bucklin 2015). At the very beginning, a customer may be unaware of the product and thus has not started any deliberation. If she subsequently becomes interested in the product, e.g., because of exposure to advertising, the customer moves into a consideration stage involving information seeking and preference formation (e.g., browsing web pages and reading product descriptions), i.e., the upper-funnel stage. The process may pause, terminate or proceed to the lower-funnel stage, where the consumer adds the product into her shopping cart and then completes the purchase or abandons the cart. This process is similar to the AIDA (attention, interest, desire and action) framework (Kotler and Armstrong 2011; Lambrecht, Seim, and Tucker 2011).
In traditional offline settings, it is formidable to track a large number of individuals over time and measure how they move across various stages of the purchase funnel.

Only until recently have researchers leveraged online data to identify the purchase funnel stages and advertising's roles across the stages. Some studies have examined digital ads that retarget on the users who had previously browsed the website and left. Lambrecht and Tucker (2013) examine the effectiveness of retargeting ad with personalized product recommendations based on the user browsing history on that website. Similarly, Bleier and Eisenbeiss (2015) show that banner display ads that are personalized based on browsing history have higher clickthrough rates than non-personalized ads. Hoban and Bucklin (2015) find that banner ads that retarget on previous visitors to the website are mostly effective in increasing future website visits except for those that had never registered an account. Johnson et al. (2017) confirm the positive effect of such retargeting ads on future visits to the website compared to ghost ads which served as control-group counterparts. Luo et al. (2019) compare two types of mobile text ads targeting on registered users of an online retailer, i.e., ad with scarcity message claiming the limited quantity of products available in stock versus ad providing customers with direct monetary incentive. They find that scarcity ad is effective only for upper-funnel users who haven't started e-shopping carts, but ineffective for users with carts. In comparison, while price incentive ad helps encourage purchases among users with carts, it is costly for the retailer and reduces product profitability due to price discount. Sahni et al. (2019) test how the frequency and timing of repeated banner ads retargeted on users who previously visited the website, and showed that the positive ad effect on future website visits reduces as time goes by since the user's first visit. Clearly, customers have different focuses and goals in the upper-funnel stage from those in the lower-funnel stage, and thus the drivers of relevant behaviors will differ across various stages (Kukar-Kinney and Close 2019).

The only existing study that explicitly investigated ads retargeted on lower-funnel customers that remind them of the products abandoned in e-shopping carts is Li et al. (2021), who focus on the timing of the ads. Specifically, they find lower effectiveness of such retargeting ads sent too soon (i.e., with one hour after cart abandonment) than those sent one to three days later.

Extending this line of research, we put forth the notion that the perceived risk of purchasing the product online is the key factor that causes user hesitation, especially in the lower-funnel stage (e.g., Kukar-Kinney and Close 2019). Hence, theoretically, if a retargeting ad can effectively alleviate perceived risk, it should help convert abandoned products into purchases. However, prior research has mostly focused on the commonly used retargeting ad that simply reminds customers of the product that they have abandoned, which does not address perceived risk. As the only exception that examines alternative ad content, Luo et al. (2019) suggest that scarcity message (which does not alleviate perceived risk either) cannot effectively recover abandoned shopping carts, and only direct price discount can. In contrast, our research aims to identify a "costless" ad message without providing monetary incentive. We propose that a reminder of product return information in retargeting ad reduces perceived risk in online shopping and thus encourages conversions, inspired by and adding to the product return literature as summarized in the subsequent section.

Field Experiments and Data

A major online fashion retailer in Japan cooperated with us to conduct a set of field experiments. Like most fashion retailers, this e-tailer sells a large variety of fashion products ranging from clothing, shoes, handbag, to household items. Its core customers are between 20 and 45 years old, males and females. The retailer provided us with access to data on its customers' demographics such as gender, age, residence area, and customer tenure, as well the purchase history, clickstream browsing, and shopping cart data. From the clickstream data records, we can identify the two critical stages of the purchase funnel, namely, browsing a product page (upper-funnel stage) and adding a product in the shopping cart (lower-funnel stage) for each customer. The data time period covers six-month period before the experiments, during the experiments, and three-month period after the experiments.

The retailer conducted several experiments. Experiment 1 aims to test the effects of retargeting ads via two separate parts, Experiment 1a for upper funnel retargeting and Experiment 1b for lower funnel retargeting, both of which were conducted from March 8 to April 20, 2016. Experiment 2 seeks to directly compare the effects of upper versus lower funnel retargeting. It is a longitudinal experimental design conducted among a set of customers as they migrated from the upper funnel to lower funnel. The experiment period was from April 12 to May 22, 2016. The company uses emails to send the retargeting ads to its customers.

The field experiments involved a total of 33,096 customers. Table 1 summarizes their purchase history in the past 6 months before experiments and demographics. In both Experiments 1 and 2, all subjects were existing logged-in users who had registered their names, ages, addresses, and other characteristics on the retailer's website upon registration. The average age is 37.8, which suggests that not just the younger generation purchases online at the retailer's website. About 40 % of customers live in Mega-Tokyo area, while the majority live outside the area. This setting involves shipping and product returns for many users. Around 60 % of customers are females, whereas 40 % are males. This suggests that the product assortment targets both female and male shoppers. The average number of products purchased and average Japanese Yen (JPY) amount spent per customer are 3.36 and 16,933 JPY, respectively. There were some shoppers who spent extremely high amounts of money than general customers in the past 6 months before experiments. We removed these outlies with abnormal amounts of spending (more than two standard deviations above the average). However, including these outliers or not would not change the key results of this research.

Variable	Mean	SD
Age	37.5	9.5
Ratio of male customers (%)	39.8	48.9
Living in Mega-Tokyo area (%)	40.2	49.0
# of products purchased	3.36	6.64
JPY amounts spent	16,933	29,767

Table 1. Customer Characteristics of the Collaborating Online Retailer

There are high variations in terms of the distribution of number of products purchased and amounts spent by products' price range. Around 60% of products purchased are priced less than 5,000 JPY, and 3% of products' prices are equal or over 20,000 JPY. In terms of the amounts spent, products with price over 20,000 JPY constitute nearly 20% of total revenue. These results suggest significant variations of the purchase transactions and product prices in our data.

Per the current policy of the retailer, for general users, the shipping cost is 350 JPY for purchases under 3,000 JPY, and free of charge for purchases of 3,000 JPY or higher. Meanwhile, premium users receive free shipping regardless of the purchase amount. Both general and premium users are allowed to make a return except for only a few products, but only premium members enjoy free return shipping. Experiment 1 includes only general users without premium members, but Experiment 2 includes both general users and premium members. However, there are no overlapped customers in Experiments 1 and 2.

Design and Results of Experiment 1

Experiment 1 consists of two studies, upper purchase funnel retargeting (1a) and lower purchase funnel retargeting (1b). In Experiment 1a, if the customer had browsed more than one products without purchases according to the clickstream data, we retarget the last product browsed. Similarly, in Experiment 1b, if a customers had put multiple products in their shopping carts without purchases, we retarget the last product added into the cart. These rules help account for the heterogeneity of the products browsed and abandoned. Once we identify the upper or lower funnel stages, we randomly assign customers into groups with different retargeting ad messages. The four message types with three retargeted (product info, shipping info, and return info) and the non-retargeted are randomly assigned in Experiments 1a and 1b. The four ad messages are in below.

- Retargeting ads with product information solely. “There is a recommended item you checked previously (insert the retargeted product name and photo)” (hereinafter referred to as “product info” group). In our context of upper funnel retargeting, the company sent this retargeting ad to customers who checked (browsed) the product without purchasing. For the lower funnel retargeting, the company sent the retargeting ad to customers who checked (put in shopping cart) the product without purchasing.
- Retargeting ads with product information and free shipping benefits of premium members. “Shop at ease with free shipping that allows you to not pay any shipping fee regardless the price of the product, on condition of becoming a premium member” (hereinafter as “shipping info”).
- Retargeting ads with product information and free return shipping benefits of premium members. “Shop at ease with free product return shipping that allows you to try the product at home and return it without any fee, on condition of becoming a premium member” (hereinafter as “return info”).
- No retargeting message sent (hereinafter as “holdout” group).

The “product info” message is the conventional retargeting practice with a reminder. The “shipping info” and “return info” can serve as a reminder of the product, advertise the information of free shipping or return shipping, and acquire new premium membership. As mentioned before, under the current policy of the retailer, general users can enjoy free shipping fee for purchase of 3,000 JPY or higher, and the “shipping info” message may remind the users of this information. On the other hand, the “return info” message may remind the information about possible product returns to users if they do not like the products after trying it at home. All customers can return the products ordered online. However, only premium members can return the products without return shipping fees, and general users can return the products but would have to pay the fees. As online shoppers tend to perceive high risks because they cannot touch, feel, and try the product before purchasing, the retargeting ad message “return info” can nudge the customers to try the products at home, thus helping reduce risks of online orders. Another objective of these messages is to acquire new premium members. Both “shipping info” and “return info” may remind the benefits of premium accounts to the subjects and thus attain new premium members (thus our subsequent analyses will test the effects on acquiring new premium accounts). Note that these ad messages do not include any fee waivers or price discount incentives, just some reminder information of the benefits if joining the premium members (such information is available on the retailer’s website).

Besides the message variations, we also test two different timings of ad delivery, earlier notification (one day later) or later notification (one week later), for both Experiment 1a and Experiment 1b. Timely ads are generally helpful because consumers’ memory about a product can decay over time (e.g., Burke and Srull 1988; Quester and Farrelly 1998). If the ad is sent too late, there is also an increased chance of purchasing alternative options or substitutions elsewhere (e.g., from competitors). Earlier notifications that address the concerns of product shipping and returns that cause the hesitation may help convert the visitors into buyers.

Before reporting the results, we first conduct randomization tests with the six-month pre-experiment data. The p-values of ANOVA are insignificant for all consumer characteristics across the four treatment groups ("product info" group, "shipping info" group, "return info" group, and holdout group) for all panels. These results indicate that the randomization is successful.

Effects of Retargeting Ads

We first present model-free results. Here we compare the effectiveness of retargeting ads within each of the four scenarios: namely, upper-funnel retargeting with earlier ads, upper-funnel retargeting with later ads, lower-funnel retargeting with earlier ads, and lower-funnel retargeting with later ads. Within each scenario, the difference across groups is only caused by the content of the retargeting ads: "product info," "shipping info," "return info," and holdout group. All purchase rate results of retargeting are computed for the 3 months after the experiment intervention in order to account for the relative long-term effects of advertising. Note that we focus on testing the causal effects of the content of ad messages, instead of the timing of sending the messages, because the latter might be subject to selection bias.

As shown in Table 2, we observe significant differences in purchase rates across the four ad copy groups only in the scenario of lower-funnel retargeting with earlier ads (χ^2=12.368, p=.006). In contrast, various ad contents did not cause significant differences in purchase rates in the other three scenarios (p=.843 for upper-funnel retargeting with earlier ads, p=.609 for upper-funnel retargeting with later ads, and p=.797 for lower-funnel retargeting with later ads).

Funnel stage	Timing	Messege	% of purchasing retargeted item	SE	p-value of χ2 test
upper funnel retargeting	1 day after	product info	1.41	0.27	
		shipping info	1.36	0.27	.843
		return info	1.10	0.24	
		hold out	1.29	0.26	
	1 week after	product info	0.56	0.17	
		shipping info	0.76	0.20	.609
		return info	0.52	0.16	
		hold out	0.45	0.16	
lower funnel targeting	1 day after	product info	12.82	0.88	
		shipping info	14.71	0.92	.006
		return info	16.39	0.97	
		hold out	12.34	0.87	
	1 week after	product info	4.15	0.52	
		shipping info	3.57	0.48	.797
		return info	3.53	0.48	
		hold out	3.74	0.55	

Table 2. Purchase Ratio of Retargeted Item in Experiment 1

Since the hold out group has no retargeting but the other three groups have, we can compare purchase rates of retargeted ads versus not-retargeted. We collapse the three groups of "product info," "shipping info," and "return info" into the retargeted group. Figure 2 pictorially presents the retargeted vs. not-retargeted differences. Again, the data suggest a significant difference only for the scenario of lower-funnel earlier ads, but not for other three scenarios.

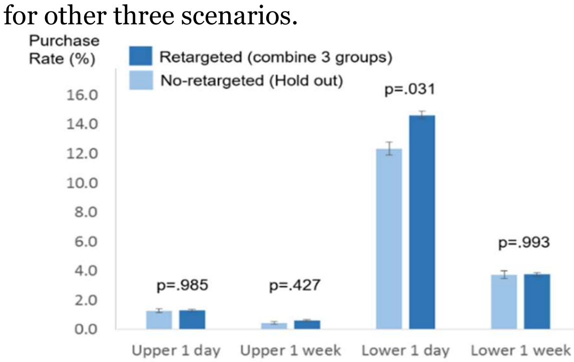


Figure 2 Retargeted vs No-Retargeted in Experiment 1

To carefully examine what ad content is the major force in the retargeting effects, Figure 3 breaks down the purchase rates into "product info," "shipping info," and return info" within the scenario of lower-funnel retargeting with earlier ads. The "return info" group (16.39% vs. 12.34%, *p*<.01) had a significantly higher purchase rate than the holdout group. Also the "return info" has a significantly higher purchase rate than the "product info" (*p*<.01). In contrast, there is no significant difference between the "product info" group and the holdout group (12.82% vs. 12.34%, *p*>.10), and the "shipping info" group had a marginally higher purchase rate than the holdout group (14.71% vs. 12.34%, *p*<.10). In terms of magnitude of the difference, the purchase rate of the "return info" group is 33% larger than that of the holdout group. The ad message of "return info" simply reminds the customers the ease of return shipping and does not provide any price discounts or coupons. Thus, "return info" retargeting ads tend to substantially lift the purchase responses without incurring monetary costs for the company.

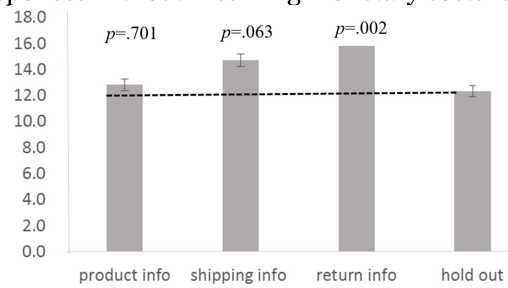


Figure 3. Purchase Ratio of Lower-Funnel Retargeting with Earlier Ad

To account for additional variations with more precise standard errors and estimate the marginal effects of retargeting, we run regression models with covariates at the individual level. Given the binary nature of the dependent variable (whether or not the retargeted product was purchased), we specify a binary probit model. Consistent with the model-free results, we observe significant effects only for lower-funnel earlier ads. Hence, we focus on this scenario in the subsequent analyses. Table 3 reports the estimation results. In Model 1, we compare the impact of each of the three ad messages against the holdout group, and find that "return info" (0.179, *p*<.01) have significant positive effects, whereas "product info" does not have significant effect (0.031, *p*=.61), and "shipping info" has a marginal effect (0.203, *p*=.06). Model 2 focuses on the effect of a dummy variable with 1 indicating customers receiving either "shipping info" or "return info" ad messages (both remind the member benefits) and 0 for customers in the other groups, and shows a significant positive coefficient (0.145, *p*<.01). These findings suggest that compared with the hold out, the retargeting ads with customer services of premium membership information are effective on average. However, it is the ad copy of "return info" rather than "shipping info" that contributes to the effectiveness of retargeting ads with customer service content. Also, Model 3 compares the effect of receiving retargeting ads versus not (dummy variable equals 0 for customers in the holdout group, and 1 for the combined three groups of "product info," "shipping info," and "return info"); the effect is significant and positive (0.109, *p*=.03) consistent with Figure 2. These results suggest that compared with the hold out without retargeting, the retargeting ads in the lower purchase funnel are effective on average. However, there are significant differences among the retargeting ads depending on the ad copy content. It is the ad copy of "return info," rather than "product info" or "shipping info" that can reduce online shopping risk and, thus, contribute to the effectiveness of retargeting ads (as discussed next).

Further, we add consumer demographics (age, gender, and customer tenure) as control variables in Model 4, and find consistent results. The effects of the control variables suggest that younger, male and long-tenured customers are more likely to purchase (-0.010, *p*<.01 for customer age; 0.121, *p*<.01 for gender dummy; 0.112, *p*=.03 for customer tenure) on average. We have included day and category effects, as well as the number of items in the retargeted shopping carts in all models (additional analyses without the day and category effects yield highly similar results). In Model 4b and 4c, we conducted binary logit model and OLS model for robustness check, and the result patterns of these three models are basically the same. Therefore, the findings are robust across these different estimation models.

Variables	Model 1 Probit	Model 2 Probit	Model 3 Probit	Model 4a Probit	Model 4b Logit	Model 4c OLS
Product info	0.031	0.031		0.034	0.066	0.007
	(0.0607)	(0.0607)		(0.0610)	(0.1141)	(0.01295)
Shipping info	0.111 *			0.114 *	0.209 *	0.024 *
	(0.0594)			(0.0596)	(0.1107)	(0.01292)
Return info	0.179 ***			0.187 ***	0.349 ***	0.041 ***
	(0.0588)			(0.0591)	(0.1089)	(0.01295)
(Shipping or return info)		0.145 ***				
		(0.0519)				
(All retargeting ads)			0.109 **			
			(0.0494)			
Age				-0.010 ***	-0.018 ***	-0.002 ***
				(0.00229)	(0.00424)	(0.00049)
Male/Female customer				0.121 ***	0.226 ***	0.028 ***
				(0.0446)	(0.0816)	(0.00991)
Customer tenure				0.112 **	0.213 **	0.024 **
				(0.0513)	(0.0959)	(0.01093)
# of items in the cart	-0.064	-0.065	-0.066	-0.061	-0.107	-0.012
	(0.0535)	(0.0535)	(0.0536)	(0.0538)	(0.1007)	(0.01127)
Day effects	yes	yes	yes	yes	yes	yes
Category effects	yes	yes	yes	yes	yes	yes
Constant	-0.576	-0.590	-0.600	-0.417	-0.694	0.295
	(0.6775)	(0.6760)	(0.6814)	(0.6890)	(1.2001)	(0.17633)
Observations	5,084	5,084	5,084	5,081	5,081	5,081
Log-likelihood	-2,307.5	-2,376.2	-2,310.7	-2,291.1	-2,291.3	
AIC	4,753.0	4,752.4	4,755.5	4,726.2	4,726.6	
R-squared						0.0237

Table 3. Model Based Analysis for Lower-Funnel Retargeting with Earlier Notification

Notes: $***$ p<0.01, $**p$<0.05, $*p$<0.1. Shipping or return info: if ad message is "shipping info" and "return info" then 1, otherwise 0. All retargeting ads: 1 or "product info," "shipping info," and "return info" and 0 for holdout group. Age: customer's actual age. Male/Female customer: if customer is male then 1, otherwise 0. Customer tenure: if customer tenure>=1 year then 1, otherwise 0. Higher price: if price>=19,800 JPY then 1, otherwise 0. # of items in the cart: the number of items in the subject's abandoned shopping cart. Day effects: 42 dummy variables which indicate the particular day when the retargeted email ad is sent. Category effects: 22 dummy variables which indicate particular category of retargeted product. The categories include jacket outerwear, skirt, tops, one piece, pants, underwear, shoes, bag, hat, purse/small goods, accessories, etc.

Results are Driven by Online Shopping Risk

There are various industry reports (e.g., Statista 2015; BI Intelligence 2014) on reasons for shopping cart abandonments. According to consumer surveys, the reasons can include product prices, outside options, technical and security issues with the checkout and payment process. According to Statista (2015), the dominating reasons for shopping cart abandonment was related to price and cost (e.g., unexpected costs during checkout mentioned by 56% of participants, found a lower price elsewhere mentioned by 36%, and overall price too high mentioned by 32%). Other reasons include technical difficulties with the website (complicated website navigation mentioned by 25%, website crash mentioned by 24%, long checkout process mentioned by 21%, and website time out mentioned by 15%) and payment process (concerns about payment security mentioned by 18%, payment declined mentioned by 11%). Also, the BI Intelligence (2014) show that some shoppers complained about the slow delivery (28%) and unavailability of preferred payment options (25%) as the culprit of cart abandonments. However, these reasons cannot account for the variations of purchase rates among the ad message groups here, because our field experiment has randomly assigned the ad messages to the users who would have experienced the same product prices, outside options, technical and security issues.

One alternative reason is that there is a high perceived risk associated with online shopping without seeing the actual product. According to Rajamma et al. (2009) and Kukar-Kinney and Close (2010), online shopping risks due to the lack of touch, feel, and product trial are the major barriers that deter the sales conversions of items added to shopping carts. In other words, there are inherent risks for customers to order online without physically examining and trying the product before purchasing. Indeed, in our study, the "return info" ad copy can remind the customers and give them a reason to purchase the retargeted item, i.e., because if they do not like the previously abandoned product after trying at home, they can simply return it. From this aspect, their shopping risks due to the lack of tactile experience online are reduced by the "return info" ad copy for shopping cart recovery. On the other hand, the "product info" ad copy is conventional retargeting with an emphasis on product information reminder of the product item abandoned in the shopping cart. The "shipping info" is a retargeting with an emphasis on product shipping of the product item abandoned in the shopping cart, but without encouraging product trials to reduce the online shopping risk. Thus, both "product info" and "shipping info" can remind the customers of the retargeted item, but cannot give a reason of product trials to decrease the online purchasing risk. Only the "return info" ad copy nudges customers to order and try the product at home by reminding them customer services of product returns, which can help reduce the inherent online shipping risk.

If this explanation of online shopping risk is valid, the risk should be even *greater* for high-price products (e.g., Beatty and Smith 1987), and the effects of "return info" ad copy would be stronger for high-price product items than low-price ones. We test this and report the results in Model 5 in Table 4. In Model 7a, we drop the insignificant interaction terms as shown by Model 5 and 6. Model 7a has the best fit (smallest AIC value) among the models. Model 7b and 7c are binary logit model and OLS model, respectively. We include the price dummy indicator of the retargeted product item (the "higher price" variable), as well as its interactions with retargeting ads. We set 19,800 JPY as the threshold for "higher price" (i.e., 1 for price ≥ 19,800 JPY; 0 otherwise) because the AIC value for the model can be minimized at this threshold. The "higher price" variable has a negative main effect, as expected. However, the interaction effect between "higher price" and ad message with "return info" is positive (p<.05 in Models 7a and 7b and p=.065 in Model 5), indicating that the ad copy highlighting product return information is more effective when the price of retargeted item is high. These findings are consistent with the online shopping risk explanation; by emphasizing "return info" in retargeting ads, online shopping risks could be mitigated, and so their purchase rates are boosted. On the other hand, the interaction between the price dummy and "product info" is not significant (p=.718) and the interaction between price dummy and "shipping info" (p=.459), since both "product info" and "shipping info" are less likely to reduce the online shopping risks in the case of purchasing of expensive product items.

We also test the online shopping risk explanation with another proxy—customer tenure. Relatively, shorter-tenured customers with little prior purchase experience at the focal retailer may perceive higher risks than long-tenured ones. We define shorter-tenured customers as those with a tenure of less than one year and without any shopping experience with the company in the 3 months prior to the experiment. Results in Model 6 in Table 4 include the dummy variable for shorter-tenured customer as well as its interactions with retargeting ads. As the table shows, "shorter-tenured customer" has significant negative effect (-0.258, p=.041) and its interaction with "return info" has significant positive effect (at least p<.05 in Models 7a, 7b, and 7c and p<.1 in Model 5), whereas interaction with "product info" (p=.987) and with "shipping info" (p=.650) are insignificant. These results again indicate only "return info" but not "product info" or "shipping info" is likely to reduce the online shopping risks in the case of promoting the purchases by shorter-tenured customers.

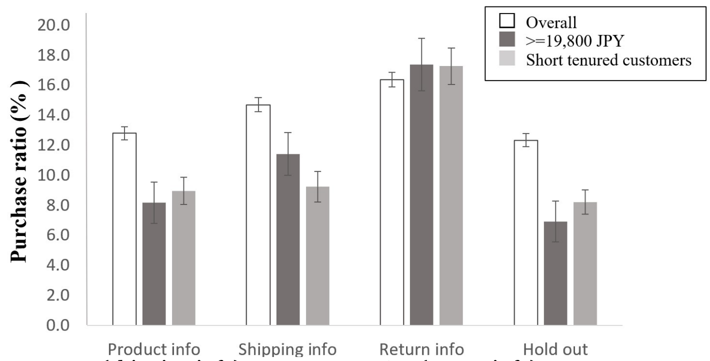
Moreover, following Tucker (2015), we conducted subsample analyses to pinpoint where the effects of lower funnel retargeting with "return info" ad become stronger or weaker. Models 8a and 8b show the results for higher and lower price segments, respectively; and Models 9a and 9b show the results for shorter-tenured customers and the rest, respectively. In model 8a, we estimate the model for the higher-price subsample and find significant effect of "return info" (0.622, p=.021), whereas both "shipping info" and "return info" are insignificant. In addition, we found "return info" is effective (0.473, p<.01) when the subjects are shorter-tenured customers, whereas "shipping info" and "product info" are insignificant. On the other hand, both "shipping info" and "return info" have significant positive effects (.122, p=.058, and 0.142, p=.028, respectively) in Model 9b for the subsample excluding shorter-tenured customers, thus suggesting more evidence for the online shipping risk explanation to the effects of "return info" ad copy.

Variables	Model 5 Probit	Model 6 Probit	Model 7a Probit	Model 7b Logit	Model 7c OLS	Model 8a High price	Model 8b Otherwise	Model 9a Short-tenured customer	Model 9b Otherwise
Product info	0.032	0.031	0.032	0.059	0.006	0.098	0.029	0.109	0.037
	(0.0628)	(0.0655)	(0.0612)	(0.1144)	(0.01294)	(0.2923)	(0.0628)	(0.1831)	(0.0658)
Shipping info	0.105 *	0.121 *	0.112 *	0.206 *	0.024 *	0.297	0.103 *	0.097	0.122 *
	(0.0614)	(0.0642)	(0.0598)	(0.1110)	(0.01290)	(0.2817)	(0.0614)	(0.1772)	(0.0644)
Return info	0.157 **	0.139 **	0.111 *	0.210 *	0.025 *	0.622 **	0.157 **	0.473 ***	0.142 **
	(0.0612)	(0.0644)	(0.0643)	(0.1179)	(0.01413)	(0.2693)	(0.0612)	(0.1651)	(0.0646)
High price	-0.372 *		-0.28 ***	-0.524 **	-0.052 **				
	(0.2009)		(0.1080)	(0.211)	(0.02099)				
High price×product info	0.090								
	(0.2700)								
High price×shipping info	0.174								
	(0.2613)								
High price×return info	0.457 *		0.368 **	0.688 **	0.071 *				
	(0.2476)		(0.1805)	(0.3330)	(0.03941)				
Short-tenured customer		-0.258 **	-0.287 ***	-0.558 ***	-0.055 ***				
		(0.1265)	(0.0730)	(0.1433)	(0.01431)				
S.t. customer×product info		0.003							
		(0.1805)							
S.t. customer×shipping info		-0.080							
		(0.1769)							
S.t. customer×return info		0.300 *	0.332 **	0.623 ***	0.065 **				
		(0.1650)	(0.1287)	(0.2383)	(0.02831)				
Age	-0.009 ***	-0.010 ***	-0.009 ***	-0.017 ***	-0.002 ***	-0.004	-0.009 ***	-0.011 **	-0.009 ***
	(0.00229)	(0.00230)	(0.00230)	(0.00425)	(0.00049)	(0.0102)	(0.00236)	(0.00554)	(0.00258)
Male/Female customer	0.128 ***	0.121 ***	0.127 ***	0.235 ***	0.029 ***	0.266	0.122 ***	0.148	0.128 ***
	(0.0477)	(0.0447)	(0.0448)	(0.0818)	(0.00991)	(0.1943)	(0.0463)	(0.1307)	(0.0484)
# of items in the cart	-0.067	-0.063	-0.067	-0.117	-0.013	-0.028	-0.06	-0.037	-0.067
	(0.0538)	(0.0540)	(0.0541)	(0.1015)	(0.01126)	(0.4200)	(0.0546)	(0.1518)	(0.0592)
Day effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Category effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-0.318	-0.306	-0.312	-0.491	0.318 *	-1.387	-0.327	-1.562 ***	-0.246
	(0.6875)	(0.6863)	(0.6865)	(1.1976)	(0.17584)	(0.6520)	(0.6908)	(0.5368)	(0.6910)
Observations	5,081	5,081	5,081	5,081		430	5,371	947	4,854
Log-likelihood	-2,289.6	-2,285.3	-2,281.6	-2,281.8		-128.4	-2,147.0	-291.6	-1,959.2
AIC	4,729.3	4,720.5	4,713.2	4,713.6		354.7	4,436.0	719.2	4,060.5
R-squared					0.0265				

Table 4. Model-based Analyses Considering High Risk Situations

Notes: *** p<0.01, ** p<0.05, * p<0.1. Age: customer's actual age. Male/Female customer: if customer is male then 1, otherwise 0. # of items in the cart: the number of items in the subject's abandoned shopping cart. Day effects: 42 dummy variables which indicate the particular day when the retargeted email ad is sent. Category effects: 22 dummy variables which indicate particular category of retargeted product.

Figure 4 visualizes the purchase ratio of the retargeted item in each treatment group for the situations of relatively higher risks of online shopping (high product price or short customer tenure). The left-most bar within each group represents the overall purchase rate, with the middle bar for higher price items and the right-most bar for shorter-tenured customers. The "return info" group has significantly higher purchase rates than the holdout group under the higher price condition (p =.020). Also, there is a significant difference between "return info" and hold out under the condition of shorter-tenured customers (p<.01). As a comparison, in higher risk situations (higher price and shorter tenure), the purchase rates of "product info" and "shipping info" are not significantly different from the holdout group. Therefore, these results show consistent evidence for the online shopping risk explanation of the effects of retargeting ad with "return info" for shopping cart recovery.



Notes: n(product info) = 1459, 110,223; n(shipping info) =1475, 105, 238; n(return info) =1452, 115, 243; n(holdout) =1418, 101, 243.

Figure 4. Purchase Ratio of Retargeted Products at High Risk Conditions

Effects on Acquiring New Premium Member

Retargeting ads with "shipping info" and "return info" may also acquire new premium members by converting the general users. If customers are locked in as premium members, they may bring in more life-time value to the retailer. Thus, we also check the outcome with the likelihood of becoming a premium member across the lower funnel retargeting message groups. Again, all subjects are general users (non-premium members) at the starting point of experiment 1b, but can be converted into premium members after receiving the ad messages. We find that the hold out group has a conversation rate of 1.8 %, meaning the baseline organic conversion rate is quite low if without any ad message intervention. The conversion rates are 2.4 % for "product info," 2.7 % for "shipping info," and 2.7% for "return info." There are no statistically significant differences across four groups. Also, we calculate the purchase contribution ratio by premium members, which is the total number of purchases divided by the number of purchases by the subjects who are converted into premium members. This ratio is fairly low at 5.9 % (which makes sense due to the costs of becoming premium members), suggesting that 94.1% is not from the new premium accounts, so the "return info" acquires only very limited number of new premium members on average. As such, this ad copy with "return info" is effective not because it can help acquire more new premium members, but because it serves as a reminder that product return is a valid option and thus can reduce the online shopping risks.

Net Revenue of Retargeting Ads

Recall that all the subjects in Experiment 1b are non-premium members, and customers in the "shipping info" and "return info" groups were simply reminded about the possibility of receiving free shipping and return shipping if they become a premium member. While "return info" may reduce online shopping risks, it may add extra costs for the company if the retargeted items are indeed returned. Some of the costs can be defrayed by the membership revenue conditional on becoming a premium member. Hence, we calculate the net sales revenue per retargeted customer and report the results in Table 5. We compare the total sales revenue and find that the revenue of "return info" is the greatest and around 50 % larger than that of holdout group. As mentioned above, purchase ratio of "return info" was 33 % larger than that of holdout group. Also, the average price of retargeted products purchased by subjects of "return info" is around 1.13 times of that by holdout group. These two factors (high purchase rate and high average price) contribute to the higher total sales revenue of "return info." Then, we calculate the additional membership revenues from the newly acquired premium members and subtract the additional shipping and return costs the company needs to bear for the new premium members. According to the company transaction records, the product return rates made by newly acquired premium members of the "product info," "shipping info," "return info", and hold out are 12.50%, 6.67%, 6.67% and 9.09% respectively. Based the calculations, the net revenues per retargeted customer of the "return info" retargeting ad are still 50% greater than the hold out group, after adjusting for the additional costs.

Message	Total sales revenue	Additional membership revenue	Additional shipping/ return costs	Net revenue
Product info	957.3	6.2	11.3	952.3
Shipping info	1138.7	10.2	21.4	1127.5
Return info	1432.9	14.2	17.2	1429.9
Hold out	949.1	9.6	11.3	947.5

Table 5. Total Net Revenue after Adjusting for Shipping and Return Costs

Note: Units are in JPY; average sales revenue per retargeted customers who became premium members after receiving retargeted ads (after cart abandonment for holdout group); Additional membership revenue = total membership revenue (350/month for 3 months).

Spillover Effects of Retargeting Ads for Shopping Carts

Because the clickstream data allow us to identify all product items (retargeted and non-retargeted) in each shopping cart, we can assess the spillover effects on non-retargeted items. That is, we can examine how retargeting ads influence non-retargeted items in the same abandoned shopping cart of each subject. Among all the subjects of lower-funnel retargeting with earlier ads, 10.3% abandoned more than one items in their shopping carts. We calculated the purchase rate of the non-retargeted products. Because we did not send any message to holdout group, this group has only non-retargeted items. In each of the treatment groups receiving retargeting ads, the purchase rate of non-retargeted products is higher than that of the holdout group, and the highest purchase rate occurs in the "return info" group. Yet, the differences are statistically insignificant (e.g., p=.153 between the "return info" group and the holdout group). Also, we compare the economic differences. As indicated in the last column of Table 6, the retailer earned 1502.3 JPY per abandoned shopping cart by using retargeting ads with "return info," compared to 1010.5 JPY per abandoned cart without ads (holdout group). Hence, "return info" can increase the incremental sales revenue by nearly 50% without offering any price discount or coupons. The difference is statistically significant (t= 2.41, p=.016). By computing the difference between the last two columns, one can obtain the average JPY amount spent for non-retargeted items in the abandoned shopping cart. The spillover effect to non-targeted items due to the retargeting ad with "return info" is positive but insignificant compared to the hold out. Thus, the vast majority of the sales lift of "return info" results from the focal effects of retargeted product items, rather than the spillover effects of non-targeted items in shopping cart recovery.

Message	Ave. # of purchased of retargeted products	Ave. # of purchased of all abandoned products	Ave. JPY spent for retargeted products	Ave. JPY spent for all abandoned products
Product info	0.141	0.153	957.3	1003.2
Shipping info	0.155	0.166	1138.7	1196.0
Return info	0.174	0.185	1432.9	1502.3
Hold out	0.135	0.144	949.1	1010.5

Table 6. Effects of Retargeting Ads on All Abandoned Products

Discussion of Experiment 1

Thus far, the results provide causal evidence for the effects of retargeting ads. There is statistically and economically significant impact of lower-funnel retargeting earlier ads with "return info" for shopping cart recovery. Also, despite its effectiveness for immediate lower funnel retargeting, the same ad copy of product return information is insignificant for upper funnel retargeting. This makes sense because consumer shopping risks should be high especially at the lower stage of purchase funnel of online shopping; the "return info" ad copy is critically important for reducing such risks for shopping cart retargeting in the lower stage rather than product browsing retargeting in the upper stage. Regardless of the ad copy message content, retargeting ads for upper funnel retargeting cannot significantly enhance the incremental sales relative to the holdout group. Although consistent with Goldfarb and Tucker (2011) that retargeting may not always be effective, our finding of upper funnel retargeting's insignificant effect is divergent from many prior studies. We posit that this divergence may arise because our outcome variable is sales conversion, while prior studies may use other variables such as store location lookups, traffic visits, and registration sign-ups. Also, most prior studies examine display ads with observation datasets (few with randomized field experiments), while our study examines emailed ads with randomized field experiments. Nevertheless, any retargeting could still serve at least as ad reminders with downstream impact and long-term branding effects, which are difficult to detect with a single field experiment. Although the monetary cost is low for a firm to send emails, flooding customers with emailed ads (especially personalized targeted ads) can cause annoyances and even lead to privacy concerns and customer reactance. Hence, sending email ads may not strictly be "costless"; considering the ineffectiveness of upper funnel retargeting in enhancing sales conversion, firms should be extra cautious when using personalized emails for upper-funnel retargeting.

However, experiments 1a and 1b cannot directly test the effectiveness of upper vis-à-vis lower funnel targeting due to a selection bias. That is, customers who added items in shopping carts are likely to have stronger interests in the focal items than those who only browsed the products. Hence, it may be the different types of customers rather than the upper or lower funnel retargeting ads that cause the effects. To correct this selection bias, we conduct Experiment 2.

Design and Results of Experiment 2

Experiment 2 has two key purposes. First, it is intended to replicate the effects of low funnel retargeting for shopping cart recovery in order to generalize the findings of our study. Second, it seeks to create an experimental design to make a causal comparison on the effects of lower vis-à-vis upper funnel retargeting. To achieve the dual purposes, Experiment 2 is a longitudinal design. We track a set of customers over time as they migrate from upper funnel to lower funnel so that the customers are directly comparable at both funnel stages. See Figure 5 for a schematic presentation of this experiment procedure. First, we randomly divided the customers who had browsed a product page without further actions into two groups. We sent the first group upper funnel retargeting ads, but did not send such ads to the second group. We then tracked both groups of customers over time for one month. For those in each group that subsequently added product items into their shopping carts and abandoned them, we further divided them into two randomized groups. Subsequently, we sent one (but not the other) group the lower funnel retargeting ads. This longitudinal experiment procedure led to four treatment groups: 1) retargeted on upper funnel and retargeted on lower funnel, i.e., both retargeting, 2) retargeted on upper funnel but not retargeted on lower funnel, i.e., upper funnel retargeting, 3) not retargeted on upper funnel but retargeted on lower funnel, i.e., lower funnel retargeting, and 4) not retargeted on upper funnel and not retargeted on lower funnel, i.e., no retargeting.

This design in Experiment 2 can directly compare the effectiveness of upper versus lower funnel retargeting, as all customers are comparable and randomized in these groups across both funnel stages. The only difference across these groups is the retargeting ad message treatments they received. In other words, the subjects are randomly assigned at "time zero," i.e., when they are browsing the product page at the top of the purchase funnel. So all subjects here have completed the migration from upper to lower funnel and are comparable across the funnels. Without this random assignment at time zero, the early stage upper funnel treatment has a causal effect, but the later stage lower funnel treatment will be confounded by self-selection bias, which would have made the comparison across the two purchase stages not valid (similar to the cases of Experiment 1a and 1b). Therefore, we were able to test the causal effects of upper vis-à-vis lower funnel retargeting. This longitudinal tracking design of Experiment 2 provides a method extension to Experiment 1.

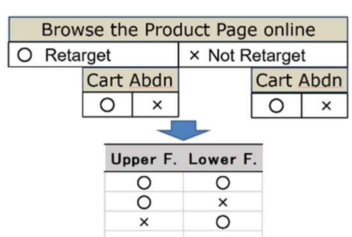


Figure 5. Experiment 2 Longitudinal Design Implementation Scheme

The subjects in Experiment 2 included both general users and premium members. Because premium members are well aware of the benefits of free shipping and return, "shipping info" and "return info" messages would not fit them (or waste the ad impression from the retailer's standpoint). As such, the retailer decided to send all retargeting ads with "product info" ad message at both upper and lower funnels in Experiment 2. Hence, the results may be more conservative than using "return info" as in Experiment 1b.

Table 7 shows the randomization checks. The ANOVA results suggest that there are no significant differences across four groups in terms of consumer demographics and purchase history. Hence, the randomization is successful. We note that the total JPY amount spent and number of products purchased in the past six months before the Experiment 2 are significantly higher than those in Experiment 1. This difference may be attributed to the fact that all the subjects in Experiment 1 are general (not premium) users at the starting point of the experiment, whereas those in Experiment 2 included both general and premium customers (which may also explain why the same "product info" in lower funnel retargeting is significant in Experiment 2 but not in Experiment 1b: since premium, loyal customers purchase more and pay more attention to targeted ads).

Group	N	Age	Gender: % of male customers	Area: % of customers living in Mega Tokyo	Total JPY: spent in the past 6 months	# of products: purchased in the past 6 months	Average price: paid per item in the past 6 months
Both retargeting	1,564	38.1	35.1	42.4	39,045.0	8.25	6,056.6
Upper funnel retargeting	1,587	38.1	36.2	39.8	36,258.0	7.46	6,080.4
Lower funnel retargeting	1,593	38.1	37.7	41.4	37,661.6	7.82	6,120.2
No retargeting	1,564	38.3	36.1	41.8	37,042.7	7.79	6,137.4
p value of ANOVA or $\chi 2$ test	–	0.971	0.135	0.585	0.399	0.230	0.976

Table 7: Randomization Check for Experiment 2

The initial numbers of subjects assigned to the four groups in Experiment 2 are 1564, 1587, 1593 and 1564, respectively. Because of the longitudinal nature of the experiment, we track each group of customers over time. For example, for "both upper and lower funnel retargeting" group, a qualified subject has to first browse a product's web page without purchasing, and then receive a retargeted ad the next day. After that, when this subject puts the same product in a shopping cart but abandons it without purchasing, we send another retargeted ad the next day. Following this stringent procedure, a customer would qualify as a final subject of this group only if (1) she had previously browsed the product's webpage and put the product in shopping carts without purchasing and (2) the retargeted product item is the same at both upper and lower funnel stages. As a result, only 30 out of the initial 1564 customers qualified as final subjects of "both retargeting" group. Similarly, we ended up with 35 subjects for the "upper-funnel retargeting" group, 33 subjects for the "lower-funnel" retargeting group and 37 subjects for the no retargeting group. Thus, although this longitudinal experiment design is the valid method to directly compare upper versus lower funnel retargeting, it can dramatically reduce the sample size.

The results suggest that the purchase rates of "both retargeting" group (30.0 %) and that of "lower funnel retargeting" group (27.3 %) are higher than those in "upper funnel retargeting" group (14.3 %) and "no retargeting" group (18.9%). To account for additional variations with more precise standard errors and estimate the marginal effects of retargeting, we run regression models with covariates at the individual level. Again, as the dependent variable is binary (whether or not the retargeted product was purchased), we estimate binary probit models. Given the key focus of Experiment 2 in comparing the causal effects between upper and lower funnel retargeting, Model 1a in Table 8 sets the upper funnel retargeting group as the baseline and exclude the both-retargeting and no-retargeting groups. The results in Model 1a show that, compared to the baseline of upper funnel retargeting, the lower funnel retargeting indeed has significant positive effect (0.988, p=.025). This finding is highly consistent with that in Model 1b (binary logit) and Model 1c (OLS). Thus, these result robustly suggest that lower funnel retargeting has significant stronger effects on purchase rates than upper funnel retargeting.

We also run other models with the hold out group as the baseline. Model 2a results suggest that compared to the hold out without any retargeting, upper funnel retargeting does not significantly increase the purchase rate (-0.224, *p*=.386). Also, the lower funnel retargeting has a marginally significant positive effect (0.483, *p*=.058) relative to the hold out group. There is a significant category effect of the accessory categories dummy in Model 1a (1.826, *p*<.01) and in Model 2a (1.017, *p*=.039). We also introduce consumer living area, which is marginally significant in Model 2a (-0.490, *p*=.060). Here, we could not introduce day and category fixed effects due to the small sample size of Experiment 2.

Variables	Model 1a Probit	Model 1b Logit	Model 1c OLS	Model 2a Probit	Model 2b Logit	Model 2c OLS
Upper funnel retargeting	Baseline	Baseline	Baseline	-0.224	-0.372	-0.062
				(0.2582)	(0.4508)	(0.07234)
Lower funnel retargeting	0.988 **	1.766 **	0.210 **	0.483 *	0.787 *	0.126 *
	(0.4418)	(0.8451)	(0.09261)	(0.2547)	(0.4467)	(0.07073)
Mega Tokyo	-0.616	-1.053	-0.134	-0.490 *	-0.858 *	-0.135 *
	(0.4252)	(0.7605)	(0.09425)	(0.2607)	(0.4660)	(0.07224)
Accessory	1.826 ***	3.121 ***	0.547 ***	1.017 **	1.688 **	0.331 **
	(0.6543)	(1.1447)	(0.16304)	(0.4937)	(0.7967)	(0.15036)
Constant	-1.389 ***	-2.427 ***	0.107 ***	-0.781 ***	-1.225 ***	0.235 ***
	(0.3677)	(0.7478)	(0.07427)	(0.2520)	(0.4528)	(0.07320)
Observations	68	68	68	135	135	135
Log-likelihood	-27.7	-27.8		-66.1	-66.2	
AIC	63.5	63.6		142.2	142.3	
R-squared			0.206			0.081

Table 8. Model Based Analysis for Experiment 2

Note: *** *p*<0.01, ***p*<0.05, **p*<0.1. Experiment design here is longitudinal. We track a set of customers over time as they migrate from upper funnel to lower funnel so that the customers are directly comparable at both funnels. The retargeted product is the same for the same customer across both funnels in the design. Mega Tokyo: if customers live in Mega Tokyo area then 1, otherwise 0. Accessory: If the retargeted product category is accessory or small articles then 1, otherwise 0.

In terms of the economic significance, we calculate that the upper funnel retargeting generates an average of 3,979.5 JPY in sales revenue on the basis of product webpage browsing history. In contrast, the lower funnel retargeting generates an average of 8,933.3 JPY in sales revenue on the basis of shopping cart abandonment history. Thus, these findings provide causal evidence that lower funnel retargeting is more effective (about 2.25 times) than upper funnel retargeting once the retargeted users are comparable across the purchase funnel stages.

Discussion of Experiment 2

Overall, the results indicate that the lower funnel retargeting has significantly stronger effect than upper funnel retargeting. A limitation in Experiment 2 is that the retargeting ad copy was "product info" only. This limitation arises because the longitudinal tracking design of Experiment 2 requires a large sample size. A lot of customers may leave the website after browsing the product page and would not reach the lower funnel, i.e., no cart abandonment. Thus, although there may be many customers for retargeting at the upper funnel, very few of them are left for retargeting at the lower funnel. In addition, because Experiment 2 includes existing premium members who are well aware of the membership benefits already, the retailer did not want to test other ad copies of "shipping info" and "return info." Interestingly, the findings suggest that even with the same "product info" ad copy, it is effective for immediate lower funnel retargeting in Experiment 2, but not in Experiment 1b. The difference may be due to the sample composition. While Experiment 1 sampled only general users, Experiment 2 sampled both general users and premium members (who are active, loyal buyers and thus can be more responsive to ads than general users). Nevertheless, based on Experiment 1b (where "product info" is less effective than "shipping info" and "return info" ad copy messages), it seems that our findings in Experiment 2 with the "product info" ad message may be conservative in replicating the effects of retargeting for shopping cart recovery and supporting the higher sales effectiveness of lower vis-à-vis upper funnel retargeting.

Conclusion

Our research enriches the literature on e-commerce systems by demonstrating how to improve the performance of the e-shopping cart technology, by increasing conversions of abandoned carts and thus sales and profits. As summarized by Luo et al. (2019), the e-commerce literature has mostly focused on webpage design (e.g., Mandel and Johnson 2002 and Ansari and Mela 2003) and online display banner or search ads (e.g., Rutz and Trusov 2011 and Sahni 2015) and largely ignored the final yet vital step right before purchase in the lower-funnel stage, i.e., e-shopping cart usage and abandonment. We answer their call for future research on user behaviors with e-shopping cart and how to optimize e-shopping cart performance, which are also of prime interest to practitioners because of the astonishingly high rate of cart abandonment. Our findings advance the understanding of how to effectively mitigate perceived risk across online purchase funnel and convert abandoned e-shopping cart into purchases, without substantially sacrificing product profitability.

Moreover, we add novel insights to the literature on digital advertising. An emerging stream of studies have recognized the importance of retargeting ad and explored its effectiveness (summarized in Table 1). We differ from prior research by focusing on how to design the content of retargeting ad to enhance conversion and reveal the effectiveness of a unique type of ad message. Given the different goals and focuses of users as they move down the purchase funnel, it is unlikely that the same ad can be effective for both upper and lower funnels. However, prior studies have rarely compared the effectiveness of an ad design across funnel stages, and the empirical challenge in doing so is non-trivial to conduct longitudinal field experiments that track users migrating from upper funnel to lower funnel. Our research fills this gap by investigating how the effectiveness of an ad design varies as a user migrates through the online purchase funnel from upper to lower stages. Our research indicates that, when designing an ad to retarget on lower-funnel customers, online retailers should attempt to alleviate their perceived risk with the online purchase. We empirically demonstrate the possibility to do so using a proper retargeting ad message without hiking promotional cost, and identify the boundary conditions. Finally, the potential heterogeneous effects of retargeting ad across products or customers remain under-studied. Adding to the literature, we unveil the significant moderating roles of product-level and customer-level conditional factors, suggesting the potential to enhance retargeting ad effectiveness via more precise targeting based on product and customer characteristics.

This research also sheds new light on the product return literature. The majority of prior studies focus on identifying the factors that can help reduce product returns (e.g., Hong and Pavlou 2014; Sahoo et al. 2018), from a common standpoint viewing product return as an undesirable *outcome* for online retailers. In contrast, from a fresh perspective, we show that product return information is not a necessary evil, and that reminders of product return information can in fact cause favorable effects on sales and profits if targeted on the right group of online shoppers (i.e., those who have abandoned the e-shopping cart). By examining product return information as a component in ad design, this research bridges literatures on digital advertising and product return, two longstanding essential topics in e-commerce that have been investigated by separate streams of research. The risk and uncertainty associated with online product purchase has been of constant interest to e-commerce researchers (e.g., Hong and Pavlou 2014; Sahoo et al. 2018; Yang and Xiong 2019). Our research contributes to the literature on perceived risk by developing a theoretical framework that highlights the key role of perceived risk in the mechanism behind e-shopping cart abandonment which impedes lower-funnel conversions, how a proper retargeting message can alleviate perceived risk, and the moderating roles of product price and customer tenure due to their associations with perceived risk. Our findings imply that the risk premium for shopping online (vs offline) does not necessarily have to be compensated by monetary incentives such as price discount (Blattberg and Neslin 1990). Instead, non-monetary information such as a simple reminder of the retailer's existing product return policy can effectively reduce or offset the risk premium for lower-funnel customers.

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