

Targeted Promotions on an E-Book Platform: Crowding Out, Heterogeneity, and Opportunity Costs

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Abstract

Targeted promotions based on individual purchase history can increase sales. However, the opportunity costs of targeting to optimize promoted product sales are poorly understood. A series of randomized field experiments with a large e-book platform shows that although targeted promotions increase promoted product sales and purchases of similar products, they can crowd out purchases of dissimilar products (i.e., e-books from nontargeted genres) by decreasing search activities of nontargeted goods on the same platform. The effects on total sales are heterogeneous, ranging from net decreases to insignificant drops, motivating a targeting exercise comparing strategies that optimize promoted product sales versus total sales. Targeting for promoted product sales tends to assign promotions to customers who purchased similar products, whereas targeting for total sales assigns promotions on the basis of other user characteristics. Targeting for promoted product sales generated incremental total sales that amounted to approximately 29% of the optimal incremental total sales when targeting for total sales (an opportunity cost of 71%). The optimal targeting exercise highlights how maximizing promotional lift can incur opportunity costs in terms of other forgone sales.

Keywords

field experiments, promotions, search, spillover, targeting

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In a data-rich online marketplace, retailers find it effective to target promotions by drawing on customers' historical behavior. For example, Amazon's homepage offers products "inspired by your shopping trends." A rich literature stream has shown that targeted promotions, such as emails with offerings matching previously revealed preferences, can increase direct promotional response while reducing search effort on the consumer side (e.g., Ansari and Mela 2003). However, the opportunity costs of such targeted promotions remain poorly understood, and marketers risk wasting resources by targeting promotions that generate high promotional response rates but do not increase total purchasing. A targeted promotion offering customers products similar to those they have previously purchased may crowd out sales of dissimilar products. We use a series of field experiments to demonstrate such crowding-out effects and opportunity costs.

Empirically testing the causal effects of targeted promotions presents a nontrivial challenge, owing to the endogeneity induced by targeting strategies that depend on customer preferences. The recommended products are often similar to products in a customer's purchase history, so self-selection may

confound customer preferences and the promotions they receive in observational data. Similar selection biases have proven difficult to resolve using econometric models (e.g., Gordon et al. 2016), highlighting the importance of randomized field experiments when estimating the effects of targeted promotions. We investigated the effects of targeted promotions using a series of field experiments. A cooperating e-book platform simultaneously promoted three different books—each in a different genre—and randomly assigned one book to each customer in the treatment group. Thus, for customers who prefer one of the three promoted book genres over the others, each is assigned to receive either a book in their preferred genre

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(labeled as targeted) or a book in their nonpreferred genre (labeled as treated but untargeted). By simultaneously promoting multiple genres and sampling customers whose historical purchasing matches/mismatches the promoted genres, we induce exogenous variation in targeted/untargeted promotions.

In all studies, we find that targeted promotions reduced cross-genre purchasing behavior, a crowding-out effect exacerbated by the preferred-genre targeting. These negative spillovers are substantial in magnitude and robust to unobservable user characteristics and alternative targeting criteria. Building on this finding, we employ machine learning methods that further exploit the heterogeneity in promotional response to compare targeting strategies that optimize either direct sales or total sales. We find that the former selects customers who have purchased similar products in the past, whereas the latter targets customers on the basis of other historical behaviors such as search, book completion, and genre dispersion behavior. Although targeting to maximize promotional lift carries intuitive appeal, and, in some cases, promoted product sales may be easier to measure, our results show there can be a substantial opportunity cost in terms of total sales lift. In the case of the e-book platform, targeting based on promoted product sales carries opportunity costs in terms of forgone total sales: the incremental total sales achieved are predicted to be approximately 29% of the optimal incremental total sales when targeting based on total sales (or an opportunity cost of 71%). As a proportion of baseline purchasing (as opposed to incremental), this figure translates to 14% fewer purchases, a rather high opportunity cost to incur in exchange for selling four times as many promoted books. “Better” targeting technology that is not carefully deployed will not necessarily improve profits in the end.

These findings have important implications for platform firms. As firms improve their targeting practices, consumers who receive precisely targeted promotions take a less exploratory approach to search, limiting the opportunities for discovery. For retailers with broad product selections, increasing cross-category purchasing is a crucial long-term goal. One estimate suggests that customer lifetime value increases by 5% for each additional category purchased (Kumar, Ramani, and Bohling 2004). Anecdotally, we observe that companies in markets with tendencies toward variety-seeking behavior, such as many content markets, try to promote broadening of consumption: for example, Spotify makes recommendations with the goal of promoting discovery of new artists (Datta, Knox, and Bronnenberg 2017). To maintain long-term customer value, content platforms ought to consider cross-genre effects and optimal targeting objectives when using targeted promotions.

Background

Our work complements research on consumers’ direct response to promotions using various forms of targeting. For example, targeted links in emails based on content categories can increase click-through rates (Ansari and Mela 2003). The

targeting decisions typically make use of customers’ historical behavior, such as clicks in prior emails or prior purchasing. For example, online advertising targeted on the basis of interest categories increases click-through rates (Farahat and Bailey 2012). However, highly specific “retargeted” ads are much less effective when a customer is in the early stages of the search process (Lambrecht and Tucker 2013) and lose effectiveness over time since a customer’s visit (Bleier and Eisenbess 2015). We add to these concerns by noting that, while the promoted product sales are often a first-order concern for a retailer trying to optimize its promotions, it is important to consider whether promotions affect other outcomes, such as purchasing of other products and product categories.

Prior research has found that targeted advertising can generate spillovers by reminding consumers of similar products, but these spillovers decrease as ad exposure increases (Sahni 2016). Positive competitive spillovers may be higher in categories in which consumers face larger information-based switching costs, emphasizing the moderating role of search on advertising spillovers (Anderson and Simester 2013). Furthermore, advertising spillovers vary across settings and outcomes: online display advertising can generate large competitive search spillovers (Lewis and Nguyen 2015), whereas television advertising primarily increases the advertiser’s share of online search (Joo et al. 2014). A field experiment on coupon printing behavior reveals positive spillovers across coupons offered on the same site (McGranaghan et al. 2017). Our study differs from prior research in that we vary the degree of targeting, showing that more targeted offers generate positive spillovers for similar products and negative spillovers for dissimilar products; we also extend this research to a mobile content platform.

Our findings also relate to research on how promotions affect consumer substitution patterns, typically for consumer packaged goods (CPG). For example, across many categories, about a third of the promotional bump in unit sales is due to brand switching (Van Heerde, Gupta, and Wittink 2003). However, even within a CPG setting, positive spillovers can overcome cannibalization: Balachander and Ghose (2003) showed positive advertising effects of within-category brand extensions on the parent brand. A few studies further examine the effect of targeted promotions: for example, Zhang and Wedel (2009) compare the effects of loyalty promotions to competitive promotions that offer competing brands to what a customer previously purchased. They find promotions for previously purchased goods work better online than offline, because customers exhibit more inertia in consumption. Our results relate more to content consumption, such that we expect some degree of variety seeking, as repeat purchase of an identical good is less frequent (i.e., movie, video, music, and book in entertainment markets; Zhao et al. 2013). Furthermore, different pieces of content, whether from the same or different genres, are not direct substitutes in the way that products from a traditional CPG category are, such as different brands of butter or detergent. One study on price promotions for digital movies even finds complementary effects across digital distribution

channels, owing to information spillovers and heightened product awareness (Gong, Smith, and Telang 2015). In comparison, although we find that consumers who receive a targeted promotion also purchase more in the same genre (analogous to intensified repeat purchasing of the same brand), they also purchase less across genres (analogous to promotion-induced substitution).

We also contribute to research on how targeted promotions interact with search behavior. Prior research has found that various forms of product recommendations reduce search activity. For example, a study using personalized rank-ordered product listings found that recommendations change a consumer's focus from the continuation of search to the evaluation of alternatives already inspected (Dellaert and Häubl 2012). Research on web personalization has found that personalized recommendations increase attention to the recommendations even as they decrease other information search (Tam and Ho 2006). Using outbound promotions, as we do in our studies, a field experiment on email promotions found that targeted promotions decreased browsing on a retailer's website (Fong 2017). Reduced search can improve efficiency for consumers (Häubl and Trifts 2000), whereas excess search can be inefficient (Diehl 2005). In extreme cases, a retailer may want to limit customers' ability to search for discounted alternatives, to preserve margins (Ngwe and Teixeira 2017). However, less is known about the potential spillover effects of reduced search on sales. Research in both offline and online environments has shown that increased exposure to the retail environment can increase purchasing, whether operationalized as in-store travel distance (Hui et al. 2013) or online time on site (Moe and Fader 2004). Accordingly, we expect targeted promotions to focus a user's attention on the targeted products or categories and reduce exposure to dissimilar products, generating corresponding effects on sales.

More generally, prior research has documented several drawbacks to targeted promotions and advertising. Because effective targeting requires personal information, consumer privacy is a major concern. Customers may respond negatively when targeting is salient because the advertising is both targeted and obtrusive (Goldfarb and Tucker 2011). Privacy concerns can even arise simply by addressing a customer by name (Wattal et al. 2012). Separately, competition can moderate the effectiveness of targeted promotions. For example, highly personalized offers could intensify price competition (Zhang 2011). If firms do not account for competitive responses to targeted price promotions, it can bias evaluations of targeting profitability (Dubé et al. 2017). We extend this literature by exploring a separate set of consequences of targeting: that is, how it could affect customers' shopping behavior with respect to nonpromoted products. The overall message is that marketers need to be careful with targeting optimized on narrow criteria, even when it performs well on convenient metrics.

Finally, our analysis of optimal targeting relates our main results to nascent research using machine learning to target customers with heterogeneous response to marketing. Ascarza (2018) applied tree-based methods of estimating heterogeneous

treatment effects to evaluate the optimality of a conventional approach to churn management, which targets customers with a high probability of churn. Intuitively, a customer with a high probability of churn provides more opportunity to improve retention. However, Ascarza's (2018) analysis of experimental retention campaigns shows that these customers do not necessarily provide the highest incremental retention. Analogously, we show how targeting customers with high incremental sales of promoted products does not necessarily generate the highest incremental total sales for those customers. Dubé and Misra (2017) use lasso regression to optimize targeted prices, finding that they outperform optimal uniform prices and far outperform the status quo prices. Because prices are continuous and provide more opportunity for fine-tuning, they generate the targeted pricing scheme using the results of a pricing experiment and test the scheme using a follow-up experiment.

We base our findings on two large-scale studies, using targeted promotions through push notifications for a mobile e-book platform in Asia. Study 1 establishes the crowding-out effects by randomly assigning users to receive promotions from one of three genres, effectively randomizing the degree of targeting for customers with a prior preference for one of the promoted genres. Study 2 adds detailed browsing data and longer user histories, allowing us to associate the crowding-out effects with changes in consumer search behavior, check alternative targeting rules, and leverage machine learning methods to compare targeting schemes that optimize promoted product sales versus total overall sales.¹ Table 1 provides an overview of the studies.

Study I: Crowding-Out Effects of Targeted Promotions

Experimental Setting

Our primary studies were field experiments conducted in collaboration with a large e-book mobile app company based in Asia. The mobile reading market in Asia has grown rapidly in recent years, in a market characterized by serialized genre fiction, with most reading occurring on reader's smartphones rather than dedicated hardware. While approximately half the market is controlled by two industry leaders, many smaller platforms continue to compete for readers; the cooperating firm in our studies, backed by a major corporation, is one of the top five platforms and accounts for about a 5% share (<http://www.sootoo.com/content/670385.shtml> [in Chinese]), earning total revenues of \$258.3 million per year. The firm serves a large user base with 130 million visitors to the app per month. It

¹ In the Web Appendix, we report an additional large-scale study that generalizes our main finding to a different setting. This generalization study takes place on an online ticket exchange, a different market with much more expensive products, but as with e-books, consumers may be variety seeking. The study takes place in North America, using targeted email promotions to provide convergent evidence across different markets and communication channels.

Table 1. Overview of Studies.

	Platform	Medium	Average Price	Data	Sample Size	Purpose
Study 1	E-books	Mobile push notification	\$.02 per chapter	Field experiment	20,436	Crowding-out effects of targeting
Study 2	E-books	Mobile push notification	\$.02 per chapter	Field experiment	19,522	Search mechanism, alternative targeting rules, and optimal targeting for promoted product sales versus total sales
Web Appendix C	Event tickets	Email	\$125 per ticket	Field observation	25,164	Generalizability

supplies over 400,000 e-books across various genres such as science fiction, fantasy, romance, biographies, and nonfiction. It sells these books through its dedicated mobile app, where consumers can create an account as well as purchase and read e-books. The firm charges per chapter read, usually at a cost of approximately \$.02.

In each experiment, the firm issued mobile promotions through the app's push notifications. Consumers received an offer to download a promoted book and read several free chapters. In each study, the firm simultaneously offered three different books—each in a different genre—and randomly assigned one book to each customer. Thus, for a sample of consumers who prefer one of the three promoted book genres, each is randomly assigned to receive a book in either their preferred genre (targeted) or their nonpreferred genre (untargeted). We classified promotions as targeted or untargeted on the basis of the proportion of a customer's historical purchasing that was from the same genre as the promoted book.

Study Design

In each study, the firm randomly sent different book promotions providing ten free chapters to read for one of three books, each in a different genre (correspondingly referred to as books A, B, and C and genres A, B, and C for Study 1). The books were chosen by the firm as relatively new books it was interested in promoting. Each user was randomly assigned to one of the books or to a holdout group. The promotions differed only on the book title, and each recipient received only one promotion. In Study 1, the firm provided us with individual-level data consisting of two months of pretreatment purchase activity and one week of posttreatment purchase activity. After the promotion, we recorded all purchase activity.

We designed our study to manipulate the degree of targeting between the promoted book and the individual while controlling for other differences between customers. Given that we cannot change the preferences of each individual, we manipulate the genre in the promotion. However, solely randomizing the promotion does not guarantee randomization of the degree of targeting, as customers who purchase from a narrower set of genres are more likely to have high fit with one of the promoted genres. Thus, for our primary analysis, we focus our attention on consumers who have a strong preference for one of the three promoted genres, with at least two-thirds of their pretreatment

purchases in the same genre. We then define a promoted genre as *targeted* for a customer when she has previously made over two-thirds of her purchases in that genre (i.e., $\text{fit} > 2/3$). We define a promoted genre as *untargeted* for the other two promoted genres. We highlight that our sample of users is interested in reading books, so even an untargeted offer is not a poor recommendation but, rather, one that does not strongly match the revealed preferences of the consumers (a “more untargeted” promotion would be, say, an ad placed on unrelated apps to attract new users to the reading app). This design ensures that each person in our sample has the same probability of receiving a targeted promotion.

Because the assignments to the three treatment conditions (book A, B, or C) and the holdout group are independent of the cutoff targeting rule, the groups are randomly assigned for the eligible sample in our main analysis. As a result, we can identify targeting effects by framing the group assignments as follows: For an individual who has high fit with genre A, a promotion for book A would result in a targeted promotion, and promotions for book B or C would result in an untargeted promotion. Similarly, for an individual who has high fit with genre B, a promotion for book B would result in a targeted promotion, and promotions for book A or C would result in an untargeted promotion. Finally, for an individual who has high fit with genre C, a promotion for book C would result in a targeted promotion, and promotions for book A or B would result in an untargeted promotion. Thus, in our main analysis, we compare outcomes for users who could have been targeted by one of the promotions, and each user has the same probability of being treated (receiving a promotion), targeted (the subset of treated users whose preferences match the promotion they are assigned), or in the holdout group.

This form of “cutoff” targeting we use for our study is common in industry. For example, direct marketers often score customers on one or more attributes capturing past behavior and target marketing communications on the basis of cutoffs on the relevant dimensions, such as cutoffs on RFM (recency, frequency, monetary) scores or composite scores. Such approaches are widespread enough that Hartmann, Nair, and Narayanan (2011) even suggest that their pervasiveness facilitates the use of regression discontinuity designs to identify the effects of targeted marketing. We also test for robustness by varying the cutoff used to define a genre as targeted and by using fit as a continuous measure of targeting, and we find

Table 2. Summary Statistics by Promoted Genre for Study 1.

Group	N	Paid Chapters	Books Read
Holdout	988	48.6 (158.0)	2.7 (11.5)
Genre A: urban fiction	6,463	58.0 (231.6)	3.0 (11.1)
Genre B: fantasy	6,216	60.8 (237.4)	3.1 (12.5)
Genre C: ancient romance	6,769	58.1 (236.3)	3.1 (10.9)

similar results (reported in the “Robustness Checks” subsection with additional checks reported in Web Appendix A). Several additional extensions show that customers whose historical reading patterns had greater variety showed stronger spillover effects (Web Appendix B). Alternatively, retailers could also specifically target for genre mismatch while selecting on attributes (e.g., volume) that are still predictive of response. In the supplemental ticket exchange study (Web Appendix C), the untargeted group was specifically selected as high-value prospects for cross-genre promotions, and these customers were more likely to make cross-genre purchases relative to similar customers who previously purchased the target genre.²

Our sample for Study 1 included 86,294 customers, of which 58,488 had made prior purchases and 20,436 had a high fit with one of the three promoted genres; 19,448 in the treatment groups received one of the three promotions (classified as targeted and untargeted based on their match with the user’s history), and 988 were assigned to a holdout group that received no promotion. Each customer in the treatment groups received an in-app notification promoting a particular book with a link to read the book with ten free chapters. We pooled the results for customers with high fit with book A with those who have high fit with books B and C, so that our results are averaged across genres, to reflect more systematic and generalizable patterns rather than idiosyncrasies of a specific genre. Table 2 reports the summary statistics for our sample of data (detailed randomization checks reported in Web Appendix A).

Results

We first assess the impact of targeted or untargeted promotion on purchase incidence of the promoted book. The dependent measure for this analysis is an indicator variable for whether the customer read the promoted book during the week following the promotion. We regress the outcome on indicator variables for whether a customer received a promotion and for whether the promotion was targeted. Although we report robustness checks on the model specification subsequently, our basic findings use ordinary least squares regressions taking the following form, where y represents each of several response variables:

$$y_i = \beta_0 + \beta_1 \times \text{Treated}_i + \beta_2 \times \text{Targeted}_i + \varepsilon_i$$

² A prior study by Zhao et al. (2013, p. 157) considered genre and category interchangeably. Thus, cross-genre could mean cross-category in the settings of entertainment goods such as books.

In our basic specification, Treated and Targeted are coded as dummy variables. Thus, the Treated coefficient estimates the promotional lift for untargeted promotions relative to the baseline holdout group, and the Targeted coefficient estimates the differential impact of a targeted promotion relative to an untargeted promotion. The first column of Table 3 presents the results. Consistent with previous research (e.g., Ansari and Mela 2003), precisely targeted promotions are effective for the promoted book; the lift for this group was significantly higher than for the untargeted group. Thus, targeted promotions generate higher incremental promoted product sales compared with untargeted promotions, and our promotions work as expected.

A key goal is to assess the spillover impact of targeted promotions on sales activity for other books. We create two focal dependent measures: the number of same-genre books purchased and the number of cross-genre books purchased. A “same-genre” book is any book that falls under the promoted genre. For example, because book A is a fantasy novel, any fantasy book purchase for an individual who received a promotion for book A will be included in this measure. A “cross-genre” book is defined as a book that is in any genre other than the three promoted genres.³

Similar to purchase incidence, we find that consumers who receive a targeted promotion also purchase more in the same genre. This suggests that targeted promotions could also stimulate additional sales in customers’ preferred genre. We note that the baseline group did not receive any promoted book and thus have no well-defined “same” genre. Instead, we report the number of purchases in their preferred genre, which would be the same genre if they received the high-fit promotion. This resulted in the largest single-genre sales figure for these customers, thus providing the most conservative comparison to the treatment groups.

In contrast, our results also show that consumers who receive a targeted promotion purchase less in other genres compared with the untargeted treatment. Thus, there is a negative cross-genre spillover from targeting. This finding supports the prediction that targeted offers inhibit the diversification of sales at the customer level.

Overall, we find that targeting increases not only purchase incidence for the promoted product but also the number of same-genre sales. However, this positive effect is crowded out by cross-genre sales. Combined, we also find that total sales are negatively affected. The last column of Table 3 reports the total book purchases during the one week after treatment. We find that the positive impact of targeting on same-genre sales does

³ We exclude all promoted genres because otherwise, for an individual in a low-fit condition, his or her high-fit genre would be included in the cross-genre calculations (i.e., if we promote a low-fit book to a customer, by definition, that person’s high-fit genre will be one of the other nonpromoted genres). Because our sample contains individuals who have a high fit with one of the promoted genres, we ensure a fair comparison of cross-selling by excluding all three promoted genres. In addition, our results are robust even if we do not exclude all three promoted genres from the cross-genre definition.

Table 3. Study 1 Regression Results.

	Promo Purchase Incidence	# of Same-Genre Purchases	# of Cross-Genre Purchases	Total # of Purchases
Targeted	.0039** (.0009)	.0900** (.0338)	-.3093** (.0898)	-.2390* (.1054)
Treated	.0026 (.0020)	.1527* (.0732)	1.6726** (.1946)	1.8278** (.2283)
Constant	.0000 (.0019)	.0931 (.0706)	.3128 [†] (.1876)	.4059 [†] (.2201)
R-squared	.0005	.0005	.0030	.0025
N	20,436	20,436	20,436	20,435

[†] $p < .10$.

* $p < .05$.

** $p < .01$.

Notes: "Targeted" indicates the group that received a promotion for a high-fit genre. "Treated" indicates that a user received one of the promotions. The baseline group did not receive any promotion. Robust standard errors are in parentheses.

not overcome the negative impact on cross-genre sales, leading to less total purchasing. Thus, the targeting of promotions may, in some cases, result in an adverse overall sales impact, although we do not find this to be the case in all our analyses, and all promotions outperform the baseline condition.

Study 2: Search Mechanism and Optimal Targeting

Study 1 provides evidence that targeted promotions may have negative spillovers on cross-genre sales. We hypothesize that this effect, driven by a targeted promotion, is due to lower levels of search activity and exposure to new products. In Study 2, we conduct another randomized field experiment with the e-book app retailer to investigate whether search activity can explain these results. We were able to collect more detailed "tapstream" data that allowed us to examine the relationship between search activity and targeting spillovers. We were also able to collect longer user histories, with a five-month pretreatment period and a three-week posttreatment period. This helps us reduce noise in targeting measures, enabling us to explore the observed heterogeneity in promotional response. The longer posttreatment period helps account for demand shifting in the outcome measures (for example, someone who is already reading a book may have a delayed response). The design of Study 2 followed that of Study 1, using a new set of promoted books from three different genres.⁴

A sample of 77,731 customers, 50,349 of whom had made prior purchases, were included in Study 2. A total of 19,522 customers had a high fit with one of the promotions, of whom 14,687 received one of the three promotions. We also had a random holdout sample of 4,835 individuals that received no promotion. Again, each customer in the treatment groups

Table 4. Summary Statistics by Condition for Study 2.

Group	N	Paid Chapters	Books Read	Unique Search
Holdout	4,835	1,483.3 (2,525.9)	27.9 (48.6)	16.1 (34.6)
Genre D: fantasy	4,948	1,519.7 (2,412.1)	29.5 (57.7)	17.7 (44.0)
Genre E: romance	4,879	1,434.6 (2,368.7)	28.9 (61.5)	17.5 (47.8)
Genre F: horror	4,860	1,470.9 (2,455.9)	29.4 (62.1)	17.6 (46.7)

received an in-app notification that promotes a particular book with a link to read the book with ten free chapters.

Randomization checks comparing the pretreatment activity for each group are reported in Web Appendix A. We detected a few significant differences in pretreatment activity between the holdout group and the genre-framing group. These differences did not affect our analysis, as our primary comparisons are between groups of users receiving the promotion. In addition, we test specifications that control for pretreatment activity and a differences-in-differences specification that controls for unobserved factors (Web Appendix B). Table 4 reports the summary statistics for our sample of data.

Replication of Crowding-Out Effects

We first report the effects of the treatment on the same dependent measures in Study 1: purchase incidence for the promoted book, the number of same-genre sales, and the number of cross-genre sales. Table 5 shows that Study 2 replicates the findings of Study 1. Specifically, we find that targeted promotions are effective for both the promoted book and purchases in the same genre. However, cross-genre sales are adversely affected. The total sales impact for the targeted and untargeted groups did not have a significant difference.

Robustness Checks

Our initial targeting rule defined a targeted user as one who purchased at least two-thirds of total purchases in the promoted genre. We also consider alternative targeting cutoffs and report how the main effects and spillover effects vary with the targeting precision. This includes varying the cutoffs employed and varying the product categorization used to characterize past

⁴ The experiment for Study 2 included an additional factor, which varied the creative used in the push notification to test whether making the promoted title versus the promoted genre more salient would moderate the spillover effects from targeting. The genre and framing factors were assigned independently, in a $(3 \times 3) + 1$ design. We did not observe strong spillovers from framing, so we report results that pool across framing conditions here and report the framing effects and their tactical implications in Web Appendix A.

Table 5. Study 2 Regression Results.

	Promo Purchase Incidence	# Same-Genre Purchases	# Cross-Genre Purchases	Total # of Purchases
Targeted	.0087** (.0018)	3.2190** (.1325)	-3.3985** (.1111)	-.1708 [†] (.0948)
Treated	.0023* (.0010)	-1.6109** (.0584)	1.6597** (.0681)	.0511 (.0998)
Constant	.0027** (.0007)	1.9272** (.0561)	1.1129** (.0395)	3.0428** (.0814)
R-squared	.0027	.0638	.0654	.0002
N	19,522	19,522	19,522	19,522

[†] $p < .10$.

* $p < .05$.

** $p < .01$.

Notes: "Targeted" indicates the group that received a promotion for a high-fit genre. "Treated" indicates that a user received one of the promotions. The baseline group did not receive any promotion. Robust standard errors in parentheses.

Table 6. Cutoff Sensitivity Analysis, Targeting Coefficient.

Fit	Promo Purchase Incidence	# Same- Genre Purchases	# Cross- Genre Purchases	Total # of Purchases	N
$\geq 2/3$.0087**	3.2190**	-3.3985**	-.1708 [†]	19,522
= 1	.0095**	1.3517**	-1.4918**	-.1307	4,539
$\geq .9$.0103**	2.8558**	-3.0218**	-.1557	12,978
$\geq .8$.0088**	2.9813**	-3.1743**	-.1842*	15,881
$\geq .7$.0085**	3.1523**	-3.3516**	-.1908*	18,384
$\geq .6$.0092**	3.2861**	-3.4360**	-.1407	21,116
$\geq .5$.0088**	3.2607**	-3.3883**	-.1188	24,145
$\geq .3$.0095**	3.3293**	-3.2587**	.0800	29,364
$\geq .1$.0079**	3.1472**	-2.7035**	.4516**	35,518
> 0 (Any Purchase)	.0064**	2.1308**	-.6633**	1.4739**	50,349
= Most Purchased Genre	.0047**	2.1595**	-2.2502**	-.0906	50,349
Finished Book in Genre	.0083**	4.0539**	-3.9133**	.1489	10,514
Broader Categories	.0031**	2.6947**	-2.6996**	-.0018	37,219
$\geq 2/3$ Multi Pretest Purch.	.0088**	3.3500**	-3.5547**	-.1959*	18,480
$\geq 2/3$ Excluding Top 1%	.0087**	3.0500**	-3.2026**	-.1438	19,487
$\geq .5$ Multi Pretest Purch.	.0089**	3.3667**	-3.5141**	-.1385	23,103
$\geq .5$ Excluding Top 1%	.0083**	2.9831**	-3.1393**	-.1479 [†]	24,064
Continuous Fit	.0102**	4.1819**	-9.2773**	-1.4363**	77,731

[†] $p < .10$.

* $p < .05$.

** $p < .01$.

Notes: Each estimate reflects the coefficient on the Targeted variable, which indicates the group that received a promotion for a high-fit genre (defined by the first column). Coefficients on Treatment variable are reported in the Web Appendix.

purchasing. The Study 2 sample includes longer pretreatment histories, rendering a wide variety of alternative criteria feasible. In Table 6, we report the estimated coefficients for Targeted (i.e., the first row of Table 5) under a variety of targeting rules. The coefficients for Treated (i.e., the second regressor in Table 5) are reported in Web Appendix A.

The first row provides the results from the two-thirds cutoff as a benchmark. The section presents a range of cutoffs, beginning with users who have only purchased in the promoted genre ("= 1") down to selecting all users who have ever purchased in the promoted genre (">0"). We also consider a targeting rule where the user's highest historical share of purchases is from the promoted genre. The latter approach provides targeting rules with cutoffs below half such that the targeted book remains their preferred genre and the other two treated books are in a nonpreferred genre. The results of this sensitivity analysis are consistent with our main results. We find that a targeted

promotion increases both the promoted book's purchase incidence and the number of same-genre purchases. However, a targeted promotion also decreases the number of cross-genre purchases. Interestingly, the effect on total purchasing turns positive when the targeting rule becomes relatively imprecise (e.g., " $\geq .1$ "), even though promoted product sales are lower for this group.

As we further lower the cutoff to zero, we essentially use a targeting rule where a promotion is categorized as targeted if the user has purchased at least one book in the same genre. Under this specification, we would not have "balanced" (by construction) treatment groups, and we would have users in more than one targeted group (a user can have multiple preferred genres and, thus, fit the criteria to be selected into the sample for more than one promoted book). However, this rule would be more in line with the current common practice of targeting many firms use, in which targeting is usually defined

in a binary fashion of whether the consumer has purchased from the genre or not. The results are presented in the row labeled “>0 (Any Purchase).” Again, the lower cross-genre sales are consistent with the main results, but the total sales are higher for targeted users. An alternative approach that defines targeting as the highest share genre of the three promoted genres (“= Most Purchased Genre”) suggests that the increase is driven by mostly positive spillovers for customers who have purchased from the promoted genre but do not necessarily purchase from it more than from other genres. Yet another approach would be to target on the basis of books a user finished rather than books started. Drawing on a sample of users who read at least one book to the end, we considered them targeted if they finished at least one book from the promoted genre (“Finished Book in Genre”). Finishing a book could be perceived as a better measure of satisfaction with prior purchases and thus worth considering as an alternative targeting criterion.

For narrow categories, we might expect to see negative correlation between past and future purchasing. One way to ensure this is not affecting our results is to use broader genre definitions. The books are categorized using a genre hierarchy, with 239 narrow genres, 3 of which we use in our main analysis. Alternatively, we can use the platform’s ten broader categories to define same-genre and cross-genre spillovers. Under this definition, the promoted books still come from different categories. The spillover effects replicated using the broader genre definitions (“Broader Categories” in Table 6). The results are similar to our previous analysis, though the magnitude of the effects appears to attenuate owing to the less precise targeting.

We also investigate other targeting rules that both restrict and relax how the sample is created. First, some users might have only purchased one book in the pretreatment period and were categorized as “high fit” for that specific book’s genre. Thus, we eliminate users who have purchased only one book in the pretreatment period (“ $\geq 2/3$ Multi Pretest Purch”). The critical cross-genre and total purchase results do not change. In addition, the positive impact on the purchase incidence of the promoted book indicates that the promotion does work as expected. Second, the results could be driven by extremely heavy readers, because the data, similar to many measures of online activity, are skewed (the top 1% of users account for over 20% of books purchased). Thus, we eliminate the top 1% of users determined by the number of purchases (“ $\geq 2/3$ Excluding Top 1%” and “ $\geq .50$ Excluding Top 1%”). The results are consistent with the main results.

Finally, we consider our entire sample of users. In the main results, our users were selected if their preferred genre is one out of the three promoted genres. This allows us to create a randomized targeting design. However, we do eliminate users who may have a wide taste in different genres. To account for these users, we estimate a regression on the entire sample and, instead of using a dummy variable indicating targeted status, we use “fit” (the share of historical reading from the promoted genre) as the focal variable (we retain a dummy variable for

treated status). Fit is calculated as the number of historical book purchases in the promoted genre divided by the total number of historical book purchases (e.g., the level of precision of targeting). Note that users with higher fit with the promoted books may be different from users with lower fit. However, it does allow us to assess the correlation between fit and the various outcome variables for all users. The results (“Continuous Fit” in Table 6) also support our theory: a higher fit in targeting is positively associated with purchasing both the promoted book and books in the same genre. However, there is a consistently negative association with purchasing both cross-genre and total number of books.

Explanation for the Findings: Shifts in Search Activities

We can rule out several possible explanations for the findings. First, customers may decide to curtail their activity with a given retailer as a result of reactance to obtrusive targeting (Goldfarb and Tucker 2011). While this may be a contributing factor (and customer response can be heterogeneous), it cannot account for the overall positive promoted product sales and positive same-genre spillovers. Another possibility is that targeted promotions could simply cause pure substitution effects between products by drawing attention to certain genres. In Study 1, we find differences in total purchasing across conditions, so for at least a subset of customers, the promotions affect not only what customers buy, but also how much.

The results of Study 2 allow us to explore whether changes in search activity could drive the spillovers. We track measures of search activity that provide some insights into the mechanisms for the crowding-out effects. The depth of search activity is measured as the unique books inspected by a user, including books that the user reads. Other research linking search and consumption has used unique items inspected, either including or excluding the chosen option (e.g., Bronnenberg, Kim, and Mela 2016); our results are qualitatively similar measured either way. The breadth of search activity is measured as the number of unique genres searched (or search incidence beyond the promoted book, for the same genre). Because search activity is an observed intermediate outcome, we also include controls for pretreatment activity. Without these controls, the estimated indirect effects of targeting through changes in search activity are inflated, as users with a high propensity to search in the pretest period were likely to search more in the posttest period and were shown to have purchased more in the analysis of user characteristics. In particular, including the controls reduced the role of cross-genre search volume but not of search breadth, even though the controls include pretest measures of both search breadth and reading dispersion.⁵ Figure 1 summarizes the results regarding the underlying mechanism with search activity.

⁵ We specify genre dispersion as an entropy measure: $-\sum_{i=1}^N [p(g_i) \times \log p(g_i)]$, where $p(g_i)$ is the proportion of books categorized as the i th genre. A larger value indicates greater dispersion in genres purchased from.

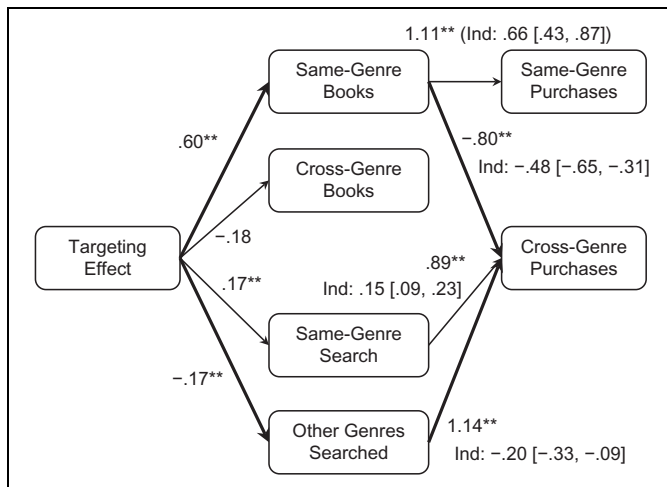


Figure 1. Search mediates cross-genre spillovers.

** $p < .01$.

Notes: Ind = indirect effects. This figure illustrates the underlying mechanism with search activity. Detailed regression results reported in the Web Appendix. Each model also includes controls for all four pre-treatment search variables and dispersion. Bootstrapped 95% confidence intervals for significant indirect effects (product of targeting coefficient on search and search coefficient on purchase) are reported in square brackets.

Figure 1 illustrates how search provides a potential mechanism for the spillover effects of targeted promotions. For example, the first path shows that targeting increases the number of same-genre books searched by .60, and each unit of increased search increases same-genre books purchases by 1.11, generating a positive indirect effect of $.60 \times 1.11 = .66$ (which has a 95% bootstrapped confidence interval of [.43, .87]). An intuitive interpretation is that targeted promotions increase search depth in the targeted genre, generating positive same-genre spillovers.⁶

There are two main paths by which targeted promotions affect cross-genre spillovers (Figure 1; arrows in bold): search depth and search breadth. Same-genre search *depth* (the top path) appears to reduce cross-genre sales, which we conjecture is due to increasing the share of the user's preferred genre in his or her consideration set, crowding out books from other genres. This may be compounded by the nature of search on mobile devices, as interface constraints may result in more sequential, path-dependent search. Thus, targeted promotions crowd out cross-genre purchasing in part by increasing search depth in the targeted genre.

Targeted promotions also affect the *breadth* of search activity, which in turn affects purchasing from other genres. Both the incidence of search within the targeted genre and the

number of other genres searched have a positive effect on cross-genre purchases. Notably, this results in opposing effects: the increase in same-genre search incidence has a positive effect (though this is offset by the negative effect of same-genre search depth), and the decrease in other genres searched (the bottom path) has a negative effect. Thus, targeted promotions crowd out cross-genre purchasing in part by reducing search breadth.

Together, the increased depth within genre and decreased breadth across genres indicate that a narrower allocation of search contributes to the negative cross-genre spillovers. These search results support the intuition that a shift in search activity drives the negative cross-selling effects of targeted promotions.

Heterogeneous Effects of Targeting by Genre-Specific Results

The importance of user heterogeneity is reflected by the effect of historical behavior covariates in the mediation model (which uses data from the experiment but should be considered an observational study with respect to intermediate outcomes). We might also expect that readers of different genres may respond differently to targeted promotions, and the effects may interact with other user characteristics. As a first step, this section reports heterogeneous effects for each genre-specific promotion. We follow this in the next section with an analysis of targeting that takes into account that the behavioral covariates can affect the response to each promotion differently, and that a sophisticated firm can use this to target more precisely.

As an alternative to the analyses in which we pool across three promoted genres, we ran regressions with the three promotions as separate treatments, interacted with consumer preferences with those treatments. The regression equation is as follows:

$$y_i = \beta_0 + \beta_1 \times \text{Genre D Promo}_i \times \text{Genre D Pref}_i + \beta_2 \times \text{Genre D Promo}_i + \beta_3 \times \text{Genre D Pref}_i + \beta_4 \times \text{Genre E Promo}_i \times \text{Genre E Pref}_i + \beta_5 \times \text{Genre E Promo}_i + \beta_6 \times \text{Genre E Pref}_i + \beta_7 \times \text{Genre F Promo}_i \times \text{Genre F Pref}_i + \beta_8 \times \text{Genre F Promo}_i + \beta_9 \times \text{Genre F Pref}_i + \varepsilon_i.$$

The "Pref" covariates control for differences between users with different pretreatment genre preferences, while the "Promo" variables are dummy-coded indicators for whether a user received the promotion for that genre. The results are reported in Table 7. While the point estimates of the treatment and targeting effects naturally vary across promotions, the relative coefficients are similar for each genre and consistent with the average effects in our main analysis. All of the interactions ($\text{Genre D Promo}_i \times \text{Genre D Pref}_i$, $\text{Genre E Promo}_i \times \text{Genre E Pref}_i$, and $\text{Genre F Promo}_i \times \text{Genre F Pref}_i$) between genre preferences and the matching promotions have positive promoted product effects and same-genre effects and consistently negative effects on cross-genre purchasing.

⁶ For regression model results on the effects of targeting on search, as well as the effects of search on purchasing, see the Web Appendix. For example, targeted promotions reduce the breadth of customer search by an average of .28 genres outside the targeted genre, or by about 5% in total number of genres explored.

Table 7. Study 2 Regression with Genre-Specific Effects.

	Promo Purchase Incidence	# Same-Genre Purchases	# Cross-Genre Purchases	Total # of Purchases
Genre D Promo × Genre D Pref	.0134** (.0036)	2.8857** (.1888)	−2.7837** (.1817)	.1154 (.1866)
Genre D Promo	.0018 (.0015)	−1.5626** (.0737)	1.4627** (.0998)	−.0981 (.1363)
Genre D Pref	.0026* (.0011)	1.7557** (.0501)	1.0381** (.0739)	2.7965** (.1000)
Genre E Promo × Genre E Pref	.0053† (.0028)	2.9657** (.2053)	−3.3631** (.2034)	−.3922* (.1931)
Genre E Promo	.002 (.0019)	−1.0717** (.0760)	1.2489** (.1372)	.1792 (.1543)
Genre E Pref	.0025** (.0009)	2.0759** (.0680)	1.1947** (.0503)	3.2731** (.0988)
Genre F Promo × Genre F Pref	.0258† (.0146)	1.8838** (.3491)	−1.9280** (.2562)	−.0184 (.4054)
Genre F Promo	.0028* (.0013)	−1.8723** (.0568)	1.9664** (.0956)	.0969 (.1204)
Genre F Pref	.0065† (.0039)	1.2049** (.0689)	.5289** (.1453)	1.7402** (.1722)
R-squared	.0040	.0691	.0689	.0031
N	19,522	19,522	19,522	19,522

† $p < .10$.* $p < .05$.** $p < .01$.

Notes: Robust standard errors in parentheses.

Thus far, our results suggest that while there are robust crowding-out effects of targeting, the net total sales effects are heterogeneous. In Study 1, there is a statistically significant decrease of total sales as a result of targeting promotions, while in Study 2 the decrease is only marginally significant. In addition, we find that targeting effects can differ depending on historical behavior and genre preference. Such heterogeneity in promotional response represents an opportunity for the firm to target more precisely; we explore how they might do so leveraging recursive partitioning machine learning methods for optimal targeting.

Machine Learning with Optimal Targeting for Promoted Book Sales Versus Total Sales

In this section, we combine the results of the experiment with machine learning techniques to investigate the consequences of more sophisticated approaches to targeting. We base our previous results on the observation that firms tend to target promotions for promoted product sales, and doing so prescribes offering products that are similar to what a customer has purchased in the past. Alternatively, firms may run randomized experiments as we have and optimize for different outcomes (e.g., promoted books sales, total sales) by targeting on various measures of historical activity. As such methods become more widely available in data-rich markets, it will be increasingly important for firms to understand the trade-offs they may incur.

We simulate this optimization process by applying widely available machine learning methods to fully exploit the heterogeneity of the responses across different dimensions. The dimensions used were identified in our analyses of search behavior and genre-specific effects. Thus, we include prior purchase share from the focal genres, along with several dimensions of customer histories that potentially moderate promotional response. The historical behaviors used as targeting variables include search behavior (books inspected), books read to completion (book finished), books downloaded (total sales), and

genre dispersion in prior purchasing (the aforementioned entropy measure). We generate optimal targeting schemes using these dimensions, assuming that the platform will send each customer a promotion for one of the three titles promoted in our experiment (or send nothing).

An overview of the procedure is as follows. We apply causal trees with honest estimation to nonparametrically estimate the heterogeneous treatment effects of each promotion (Athey and Imbens 2016). This method adapts regression trees for the estimation of treatment effects to partition the covariate space into a “tree” that minimizes prediction error (while estimating constant treatment effects within each leaf of the tree). We select this method because it generates very flexible targeting rules, as the partitions can occur at any value of any dimension, while the rules also remain relatively interpretable, as they address one dimension at a time. The overall structure can be made arbitrarily complex, accommodating high-order interactions between dimensions through sequential splits. The approach avoids overfitting by using cross-validation in the partitioning process and a holdout sample for treatment effect estimation after the partition is set. The trees were partitioned and treatment effects estimated for each outcome variable separately (promoted books sales and total sales).

The tree, consisting of partitioning of the targeting dimensions along with estimated treatment effects, was then used to predict the effect of each promotion for each user. We then assigned the promotions to users to maximize the estimated treatment effects (assigning no promotion when all three promotions had a negative effect). We run the procedure to maximize sales of the promoted book or the total sales and report each scheme’s performance on each of the response variables.

We use the causal tree method developed by Athey and Imbens (2016), implemented in the causalTree package in R, to partition our sample into groups on the basis of their responsiveness to our experimental promotions. The partitions are drawn to minimize mean squared error (MSE) of the estimated treatment effects, assuming constant treatment effects within

Table 8. Optimized Targeting on Promoted Product Sales Versus Total Sales.

A: Allocation of Promotions by Targeting Scheme									
Genre to Optimize	Genre to Optimize Total Sales								
	Promoted Product Sales	No Promo	Genre D	Genre E	Genre F	Total			
No Promo	68	383	1,857	459	2,767				
Genre D	550	6,816	21,595	12,187	41,148				
Genre E	764	462	24,727	4,108	30,061				
Genre F	0	188	2,892	460	3,540				
Total	1,382	7,849	51,071	17,214	77,516				

B: Targeting Based on Promoted Product Sales									
	Pretreatment Characteristics							Predicted Incremental Sales	
	Genre D Share	Genre E Share	Genre F Share	Total Sales	Books Finished	Books Inspected	Genre Dispersion	Promoted Product	Total Sales
No Promo	13.7%	12.3%	.2%	69.6	2.3	51.1	2.0	.0000	.0000
Genre D	18.2%	14.8%	.9%	83.3	3.9	66.7	1.4	.0031	.3664
Genre E	6.2%	26.2%	1.7%	22.9	.7	16.0	1.1	.0011	.2018
Genre F	5.4%	11.9%	18.5%	27.6	1.9	16.7	2.0	.0019	-.0650
Total	12.8%	19.0%	2.0%	56.9	2.5	44.2	1.3	.0022	.2698

C: Targeting Based on Total Sales									
	Pretreatment Characteristics							Pred. Incremental Sales	
	Genre D Share	Genre E Share	Genre F Share	Total Sales	Books Finished	Books Inspected	Genre Dispersion	Promoted Product	Total Sales
No Promo	7.7%	53.6%	.4%	341.8	5.4	329.7	2.0	.0000	.0000
Genre D	8.6%	8.5%	1.4%	185.4	7.1	159.1	1.8	.0024	4.0787
Genre E	14.8%	19.9%	2.2%	25.3	.7	17.6	1.2	.0003	.3935
Genre F	9.1%	18.1%	1.6%	69.1	5.4	47.7	1.5	.0001	1.1019
Total	12.8%	19.0%	2.0%	56.9	2.5	44.2	1.3	.0005	.9170

partitions. Since treatment effects are not observed directly, an unbiased estimate of MSE is used to evaluate potential partitions. Each dimension is evaluated at every value as a potential split point, to select the partition that reduces MSE the most. The resulting “leaves” of the tree are split using the same procedure in a recursive manner.

The targeting exercise involves estimating the effects of multiple treatments for each user. Our approach is to fit a separate causal tree for each of the three experimental promotions. While the same holdout group is used, the sample is split for cross-validation and “honest estimation” independently for each promotion. We use tenfold cross-validation to avoid overfitting in the tree splitting process; otherwise, a more complex tree would invariably reduce MSE. The honest estimation sample is used to estimate treatment effects on the tree once the partition is drawn. In this way, if a covariate affects outcome levels but not the treatment effects, a cluster of treated or control observations near a partition boundary could affect the estimated treatment effects.

For each promotion g and outcome o , this procedure predicts the promotional lift $\delta_{g,i}^o$ for each user i , where we fix the lift from no promotion $\delta_{no\ promo,i}^o = 0$. We combine these values for

each promotion, for a given outcome, as inputs to the targeting procedure where we select the promotion that maximizes promotional lift for the targeted outcome. For each user i and outcome o , the targeted treatment is denoted by $t_i^o = \arg \max_g \{\delta_{g,i}^o\}$. For example, when targeting on promo-

tional response, a user is assigned the Genre D promotion if the predicted lift from the Genre D promotion is greater than the predicted lift from the Genre E or Genre F promotion (and greater than zero). This assignment is then used to compute the average targeting dimension values in Table 8 and promotional lift in Figure 4. The “opportunity cost” of optimizing one outcome o in terms of suboptimal result for another outcome p can be expressed as

$$\sum_i (\delta_{t_i^p,i}^p - \delta_{t_i^o,i}^p).$$

The results of the targeting procedures are characterized in Table 8. Each row depicts counts or averages for users who would be assigned the promotion from the respective genre to maximize the respective outcome variable (promoted product sales or total sales). “No Promo” represents the small group of

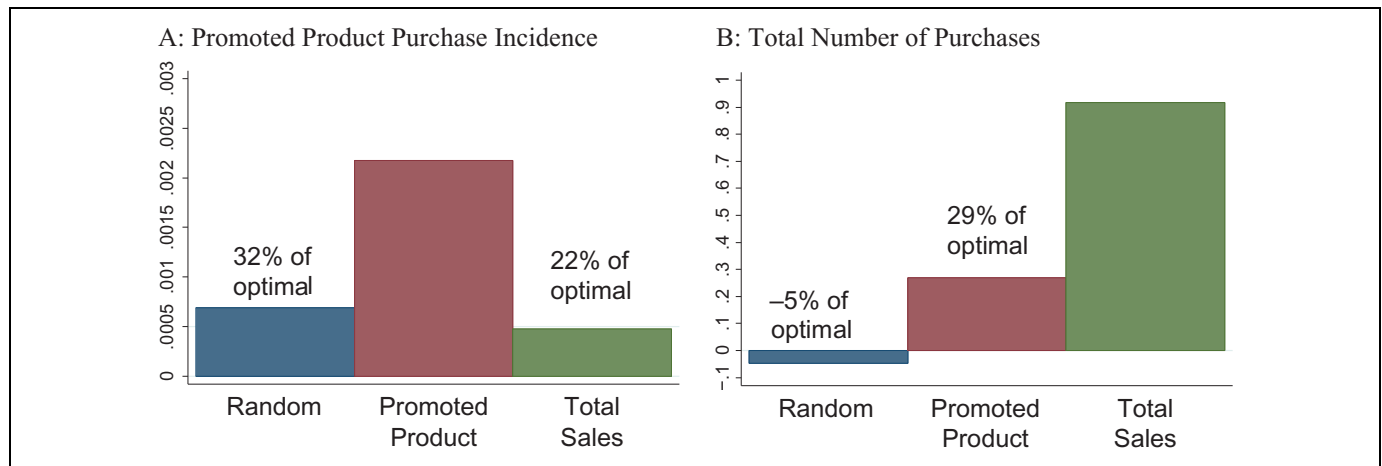


Figure 2. Predicted incremental sales by targeting scheme.

users who have a negative predicted treatment effect for all three promotions. Panel A of Table 8 compares counts of promotion assignments when optimizing promoted product sales versus total sales, cross-tabulating each individual user's assigned promotion genre under each of the two targeting schemes. If the two schemes were identical, the counts would all fall along the diagonal, but this is not the case. Relative to targeting for promoted product sales, targeting for total sales shifts promotions between Genres E and F, and from Genre D to both Genres E and F. Thus, while there are some similarities in the targeting schemes, there are also clear differences.

Panels B and C of Table 8 compare averages for the tree-splitting dimensions used to generate the targeting schemes, for targeting of promoted product sales and total sales, respectively. Notably, optimal targeting based on promoted product sales tends to assign promotions to customers with higher genre shares for each of the promoted books. In comparison, optimal targeting based on total sales assigns promotions based on other metrics, as shown by the larger differences in the average values in terms of search behavior, books completed and downloaded, and genre dispersion. There are also differences in genre shares, but the average shares shift away from the intuitive pattern that emerges when targeting for promoted product sales.

The resulting average sales for each scheme are reported in Figure 2. We compare the average sales under the two optimized targeting schemes with random targeting, which is computed by averaging the predicted treatment effects for each of the three promotions for each user. When targeting to optimize promoted book sales, the average lift in purchase incidence is .22%, increasing response by a factor of 4 compared with targeting for total sales, which performs roughly the same as random targeting. In contrast, targeting for total sales results in an average treatment effect of .92 books, increasing total sales by over a factor of 3 compared with targeting based on promoted product sales, confirming that targeting based on promoted product sales carries opportunity costs in terms of forgone total sales. The incremental total sales achieved are

predicted to be roughly 29% of the optimal incremental total sales when targeting based on total sales (or an opportunity cost of 71%). As a proportion of baseline purchasing (as opposed to incremental), this figure translates to 14% fewer purchases, a rather high opportunity cost to incur in exchange for selling four times as many promoted books.

Our optimal targeting exercise relates our main results to recent findings on how conventional targeting schemes may be suboptimal. Ascarza (2018) showed that an intuitive and conventional approach to churn management, targeting customers with a high probability of churn, does not necessarily provide the highest incremental retention. In our analysis, we compare optimized targeting using two different incremental outcomes, finding that targeting for promoted product sales targets different customers than targeting for total sales. Furthermore, targeting for promoted product sales tends to select customers who have purchased similar products in the past, an intuitive approach to improving promotional response, whereas targeting for total sales selects more on other historical behaviors. While targeting to maximize promotional lift carries intuitive appeal, and in many cases may be easier to measure, there may be a substantial opportunity cost in terms of total sales lift.

Conclusions

Combining randomized field experiments and machine learning methods, we evaluate targeted promotions' opportunity costs, heterogeneous effects, and optimal targeting schemes in the context of a large e-book platform. We find that targeted offers cause a reduction in cross-genre sales. We also uncover a potential mechanism: the negative effects are primarily due to a reallocation of search activity. The heterogeneity in treatment effects allows us to leverage recursive partitioning algorithms to contrast two optimized targeting strategies: maximizing total promoted sales vs. maximizing total overall sales. We demonstrate that targeting to maximize direct promotional response (vs. total sales) has substantial opportunity costs in terms of forgone revenue for the e-book platform as a whole. Similar

trade-offs arise in the context of optimized promotions, in which an optimized targeting scheme based on promoted books sales would underperform on total sales. Our results suggest that firms that use highly targeted promotions should attend to changes in search patterns and diversity of sales at the customer level. Conversely, broader search patterns can generate cross-selling opportunities and increase sales diversity, potentially improving customer retention and lifetime value. Thus, the cross-genre spillovers from targeted promotions have important tactical implications. Furthermore, we show how firms using more sophisticated targeting schemes can still incur substantial opportunity costs, depending on how the firm sets its objective. While artificial intelligence and machine learning may seem trendy, they should be deployed with care.

The implications of these effects could depend on channel structure. Consumer-facing retailers, such as the e-book app publisher, benefit more directly from cross-genre search and purchasing. Retailers that sell a wider variety of products would also benefit more from untargeted promotions. Upstream suppliers, whether they are manufacturers and distributors or the ticket sellers and e-book authors in our examples, may prefer targeting that maximizes conversion in their strongest segment. However, they should prefer untargeted promotions to targeted promotions that favor another supplier; as an overall promotional policy, they may do better if downstream sellers use more untargeted promotions. Thus, the pattern of spillovers and opportunity costs of targeted promotions could have important competitive implications for platform firms and their upstream sellers.

Our results are surprising in light of the observation that similar types of targeted promotions are widely used. If it were the case that targeted promotions increase sales for promoted items but do so consistently at the cost of sales for other products, one would expect firms to rely less heavily on such targeting. However, the targeted promotions improve over baseline, which is how firms are likely to evaluate them rather than to compare them with untargeted promotions. Furthermore, it is possible that competition puts pressure on firms to target more precisely, to attract and retain customers' attention. In our empirical settings, we examine digital platforms that face limited competition, especially within the pool of customers who have already adopted their respective platforms. A key limitation of our study is that we do not observe user behavior across competing apps. A related limitation is that we study the effects of one-shot promotions, involving a small number of book titles. Other titles and genres likely vary in the magnitude of trade-offs from different targeting rules. Furthermore, for sustained promotional policies, a mix of targeted and untargeted promotions may perform best to maintain interest and compete for attention. Studying the long-term effects of policies that blend promotions that encourage or limit customer search is an important topic for future research.

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