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Competitive Price Targeting with Smartphone Coupons

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Abstract. With the cooperation of a large mobile service provider, we conduct a novel field experiment that simultaneously randomizes the prices of two competing movie theaters using mobile coupons. Unlike studies that vary only one firm's prices, our experiment allows us to account for competitor response. We test mobile targeting based on consumers' real-time and historic locations, allowing us to evaluate popular mobile coupon strategies in a competitive market. The experiment reveals substantial profit gains from mobile discounts during an off-peak period. Both firms could create incremental profits by targeting their competitor's location. However, the returns to such "geoconquesting" are reduced when the competitor also launches its own targeting campaign. We combine our experimentally generated data with a demand model to analyze optimal pricing in a static Bertrand–Nash equilibrium. Interestingly, competitive responses raise the profitability of behavioral targeting where symmetric pricing incentives soften price competition. By contrast, competitive responses lower the profitability of geographic targeting, where asymmetric pricing incentives toughen price competition. If we endogenize targeting choice, both firms would choose behavioral targeting in equilibrium, even though more granular geobehavioral targeting combining both real-time and historic locations is possible. These findings demonstrate the importance of considering competitor response when piloting novel price-targeting mechanisms.

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1. Introduction

Mobile coupons are an emerging, frontier platform for implementing richer forms of price discrimination than were previously possible. By 2014, global phone penetration surpassed 3.6 billion users (GSMA 2015). The geopositioning technology built into smartphones enables novel and granular forms of real-time targeting based on location and behavior. According to eMarketer, more than 40% of U.S. firms were predicted to offer mobile coupons in 2015 (eMarketer 2015), and Juniper Research predicts more than 1 billion mobile coupon users by 2019 (Juniper Research 2014). Geoconquesting is a relatively new format of mobile advertising that directs consumers toward a specific firm while they are physically in a competitor's location. According to Local Solutions, "Though geo-conquesting is a relatively new marketing concept, it can be used to great effect. Targeting consumers where they shop (and in areas where they are likely to be using their mobile devices) allows marketers to engage in physical hypertargeting to improve traffic and results" (Hudson-Maggio 2014). According to xAd (2013), one-third of its "geo-precise" campaigns involved geoconquesting. While many prospective firms are in the early stages of piloting such geographically targeted mobile coupon campaigns, most of these test campaigns omit competitive considerations. A recent advertisement for mobile geoconquesting services illustrates this point with a case study of conversions for a campaign by a Honda dealership that targeted competitor dealerships (Figure 1). A major concern is that the lack of competitive considerations could adversely affect the anticipated gains.

The theory of price discrimination offers mixed results on the likely returns to targeting in a competitive environment. A large body of literature dating back to Pigou (1920) has studied the theory of monopoly price discrimination for a firm with market power (see Varian 1989 for a detailed overview). In general, as long as a firm has market power, consumers can

Figure 1. A 2015 Advertisement for Mobile Geoconquesting Services (Case Study of Honda Dealership)

be segmented, and arbitrage through resale is infeasible, a firm will typically have an incentive to price discriminate. Focusing on targeted pricing to a group of consumers, or "third-degree price discrimination," a monopoly firm's ability to target different prices to different consumers based on available consumer information weakly increases its profits. While it is tempting to apply the intuition from monopoly price discrimination to oligopolistic markets, the intuition can be misleading (see Stole 2007 for a comprehensive discussion of oligopoly price discrimination). When oligopoly firms adopt targeted pricing strategies, the impact on industry profits depends on the gains from surplus extraction relative to any potential losses associated with the intensity of competition. Unlike in the monopoly case, oligopoly price discrimination is more nuanced, and the likely gains/losses to firms relative to uniform pricing depend on the characteristics of the market and the nature of price discrimination. Consequently, the determination of the sign and magnitude of returns to targeted pricing in a competitive market is ultimately an empirical, as opposed to theoretical, question. In practice, a firm that runs a pilot study to test the effects of targeted pricing could inadvertently overestimate the return on investment if it ignores its competitors' incentives to adopt similar pricing practices.

We design and implement a mobile field experiment in a large Asian city to study the pricing incentives and likely profitability of targeted mobile coupons in a competitive market. We conduct our experiment with a real-time subject pool of 18,000 mobile subscribers located within "geofences" centered on two shopping malls located 4 kilometers (km) (about 2.4 miles) apart, each with a competing movie theater chain.[1] The experiment is conducted during an "off-peak" hour to avoid exceeding theater capacity. Neither theater had previously used mobile coupons as part of its regular promotional programs, and none of the subjects in our experiments had previously obtained a mobile coupon from either theater. At the time of the experiment, neither theater was using price discounts during off-peak periods of the day. Our mobile coupons capture the potential benefits of an "early-bird" price charged to consumers who are already in one of the shopping malls before noon on Saturday. Our analysis does not alter the regular prices charged by the theaters at their respective box offices. Each subject in our experiment receives an offer via SMS (short message service) from each of the two movie theaters, or receives a single SMS message from one of the two movie theaters. Each SMS message contains an offer to purchase a voucher to see a movie at that theater for a randomly chosen discount off the regular box-office price. A control group receives no offers and, hence, has access only to the regular ticket prices at the theaters' respective box offices. The experiment is designed analogously to the pilot tests run by mobile providers for prospective clients. Typically, a client would use the test to determine the ideal mobile discount to implement in practice.

A novel feature of our current experimental design is that we randomize the mobile discounts offered by each of the two theaters concurrently. Therefore, we can compare a firm's pricing incentives and expected profits when it is the only one engaging in mobile targeting versus when its competitor also engages in mobile targeting. To overcome the challenges of coordinating the price discounts of the two competing firms, we partnered with a major wireless service provider that operates a mobile marketing platform and issues promotions on behalf of its clients. This type of price variation would not be available to a typical movie theater. Theaters rarely change ticket prices for a given time slot over time. For most retailers, obtaining the required price variation to study demand differences across the narrowly defined geographic and behavioral segments we study would also be difficult to obtain. Even if a firm was to randomize its prices, in most markets it would be unlikely to obtain data pertaining to the competitor's demand. Our experimental design resolves these limitations of typical field databases.

Mobile phone technology enables us to analyze several novel targeting opportunities. The ability to locate a consumer geographically in real time using her unique telephone number, GPS, and cell tower triangulation on mobile signal reception allows firms to implement geographic price discrimination. We can measure the returns to a *geofencing* strategy, which the Mobile Marketing Association (MMA) defines as identifying a point of interest on a map and establishing a radius around it for targeting purposes. In our study, we use a foot-traffic radius around a movie theater during a specific time of day (Mobile Marketing Association 2016a). We also measure the returns to a *geoconquesting* strategy, which the MMA defines as using location data to identify a brand's competitors in an effort to promote a competing or competitive offering to their consumers. We use the foot-traffic radius around the location of a competitor movie theater. Finally, we also investigate a *geobehavioral* strategy, which the MMA defines as the ability to target unique audiences and/or users based on the context of a given location, past or present location behaviors, etc. We combine a consumer's current location with a *recency* measure indicating whether an individual consumer had visited one of the theaters during the previous two months.[2] In this case, recency proxies for a customer's historic affinity toward seeing movies.

The experiment shows that a firm would profit from a *geofencing* campaign that targets deep mobile discounts to consumers already inside the geofence during the off-peak period of the day. Conversion increases from a baseline rate of about 0.5% in the control condition to over 4% with a mobile discount of 40% off the regular price. Consistent with Fong et al. (2015), the experiment also reveals substantial incremental sales and profits from a *geoconquesting* campaign that targets deep mobile discounts to consumers inside the competitor's geofence during the off-peak period. Neither theater generates any tickets from control consumers located in the competitor's geofence that do not receive a mobile discount. However, a 60% mobile discount targeted to the competitor's location generates close to a 3% conversion rate and, hence, incremental revenues.

The observed gains from mobile targeting are moderated by competition. When a competitor launches its own "defensive" geofencing campaign, the returns to geoconquesting fall dramatically. Conversion falls below 1%, and the campaign loses almost 80% of the incremental expected revenues. Interestingly, the response rate to defensive promotions in a theater's own location appear to be relatively immune to the incidence and magnitude of the offensive promotions of a competitor, suggesting an asymmetry in cross-promotional effects between the defensive firm and the offensive firm.

A limitation of the price experiment is that we are unlikely to observe a firm's true profit-maximizing price (i.e., best response). Instead, we combine our experimentally generated choice data with an empirical model of demand as in Dubé et al. (2017). Besides creating the required data to estimate a choice model, another novel feature of our experiment is that it eliminates all of the usual price endogeneity concerns that have challenged the traditional demand estimation literature using observational field data for consumer goods (e.g., Berry 1994). To ensure the model can accommodate the observed asymmetric cross-price effects of defensive and offensive price promotions, we use a multinomial probit with correlated utility errors. The estimated probit model allows us to supplement the experimental data by predicting the level of demand at untested price points. Accordingly, we can compute each firm's true *best response*: its optimal mobile discount conditional on the competitor's price. We find that each firm would overestimate the returns to targeted mobile coupons if it optimized its respective discount under the assumption that its competitor offers no mobile discount (i.e., charges consumers the full RMB 75 box-office price).

An interesting question is whether targeted mobile couponing during this off-peak period will emerge as an equilibrium strategy and whether the theaters will generate incremental revenues in equilibrium. To analyze the mobile promotions as a noncooperative strategic game, we use the results of the experiment to trace out portions of each firm's best-response function. Assuming firms can only play the prices on our test grid, our results suggest that both firms would offer deep discounts to all consumer segments in equilibrium. We then use our demand estimates to predict the equilibrium discounts under various targeting scenarios in which any positive price is allowed, including those not on the test grid. We start with a baseline case where each firm uses mobile coupons to implement a uniform, early-bird price for consumers located in either mall's geofence during the off-peak period. We then compare this approach with geotargeted pricing based on different real-time locations, behaviorally targeted pricing based on different recency states, and geobehaviorally targeted pricing based on both different real-time locations and recency states. Our analysis abstracts away from some potentially dynamic issues that could arise if our early-bird discounts were to cannibalize demand during peak periods of demand later in the day.

The equilibrium uniform discounts for both firms result in net prices that are about 70% lower than the regular box-office prices. In Section 6.2, we show that these discounts are comparable to the early-bird price discounts offered by the largest movie theater chain in the United States. We then analyze unilateral targeting whereby one firm targets mobile discounts differentially across consumers while the other firm uses a uniform coupon value for all consumers. Both firms unilaterally benefit from targeting on geographic location and/or on past consumer visit behavior, although the unilateral gains from geographic targeting are considerably larger than those from behavioral targeting. There is no theoretical reason for geographic targeting to dominate behavioral targeting per se. This finding is an empirical consequence of the differences in the degree of consumer heterogeneity in geographic space versus purchase recency.

The returns to targeting are found to be quite different in equilibrium when both firms can endogenously choose whether or not to target. Interestingly, targeting on past behavior is more profitable in equilibrium than under unilateral targeting. This is due to the best-response symmetry in the consumer type segments and the fact that competition is more intense in the "high" market (consumers who recently visited a theater) than the "low" market (consumers who did not recently visit a theater). By contrast, the profitability of location targeting falls in equilibrium relative to the unilateral cases. While both firms are still better off than by using a uniform coupon value for all consumers, the gains are mitigated by their asymmetric pricing incentives, leading each firm to target much lower prices in its rival's local market. These results demonstrate how the unilateral manner in which many firms test targeting opportunities in practice could easily misestimate the benefits from targeting if there is competitive response. In our study, firms would overestimate the returns to geotargeting and would underestimate the returns to behavioral targeting. Finally, we find that when firms can endogenously choose the specific targeting format, the coarser form of behavioral targeting emerges as the unique equilibrium even though a more granular geobehavioral targeting was feasible.

2. Background

2.1. Mobile Marketing

Mobile technology has profoundly altered online consumer behavior and created new opportunities for targeted marketing. In particular, users of mobile devices tend to carry them at all times. Compared with PC-based Internet access, a device is more likely to be tied to a single user. Finally, the devices themselves offer location-specific services, and in many cases the service providers will receive location information. These features present an improved opportunity for targeting based on consumers' real-time locations and on behavioral histories tied to a specific person. They also improve managers' ability to evaluate the effectiveness of marketing tactics, by providing improved measurement of individuals' behavior and the ability to run randomized experiments at the individual level.

Mobile coupons are becoming an increasingly popular type of marketing promotion: "47% of mobile consumers want retailers to send coupons to their devices when they are in or near the store" (Lazar 2015). Asia in particular constitutes an ideal setting for mobile couponing. China and India are the top two countries in terms of mobile advertising responsiveness by consumers, with click rates of 78% in China and 58% in India. In China, 33% of mobile consumers rated mobile coupons as their preferred mobile ad format, and 40% considered geographically targeted mobile ads to be acceptable media. By contrast, fewer than 20% considered targeting on a user's name or her keywords used in text or phone calls to be acceptable (PwC 2013).

Industry experts routinely report impressive response rates and incremental returns to firms that geotarget mobile offers. Rocket Fuel (2015), a leading U.S. provider of geotargeted mobile ad placement, reports an average lift rate of 41.23% across geotargeted campaigns. Whole Foods generated a 4.69% conversion rate on mobile coupons targeted to subscribers within driving distance of its stores, a response rate nearly three times the usual industry average (Thinknear 2015). Similar improvements in conversion rates from location-based targeting have been documented for charitable organizations like Goodwill, quick-serve restaurant chains like Quiznos, retailers like Pinkberry, and consumer packaged goods products and automotive service providers (Mobile Marketing Association 2016b). Academics have confirmed the improved response rates on campaigns targeted based on the real-time geographic proximity to a retailer (e.g., Ghose et al. 2013, Luo et al. 2014, Danaher et al. 2015). Danaher et al. (2015, p. 711) explain the appeal of mobile coupons: "They are inexpensive, quick to disseminate, and adaptable; moreover, they can convey a reasonable amount of information; appeal to notoriously difficult-to-reach younger consumers; and be customized on the basis of location, personal information, and prior purchase behavior." They report more than 10 billion mobile coupons redeemed worldwide in 2013.

Practitioners continue to seek increasingly granular forms of *geoprecise* targeting both within a location (e.g., within a store) and across locations (e.g., distinction between "types" of locations). One increasingly popular form of geoprecise targeting is *geoconquesting*, whereby the mobile advertiser targets consumers near a competitor's location. Early practitioner reports suggest that geoconquesting leads to even higher response rates (Walsh 2013). In one of its quarterly Mobile-Location Insights reports, xAd (2013) noted that one-third of their geotargeted campaigns now include such geoconquesting. A recent academic study of mobile promotions for a movie theater finds that real-time targeting of mobile consumers near a competitor's location can increase purchase rates, with higher incremental purchases for very deep discounts off the regular price (Fong et al. 2015).

In addition to location, mobile advertisers can also target consumers based on behavior. The combination of geographic and behavioral targeting should enable firms to triangulate on the most geographically relevant consumers. In our study, we combine geographic location with historic visit behavior. We use the recency measure to proxy for differences in willingness to pay across consumers within a location.

A potential limitation of the existing body of evidence for mobile targeting is the omission of strategic considerations. The evidence typically studies the incentives for a single firm to geotarget offers, holding competitor actions fixed. For instance, YP Marketing Solutions recently ran a hyper geotargeted mobile campaign for Dunkin' Donuts that "targeted competitors' consumers with tailored mobile coupons" (YP Marketing Solutions 2015). They reported a 3.6% redemption rate among mobile users that clicked and took secondary actions. However, this analysis held competitors' actions fixed. In other words, the existing evidence studies targeted marketing through the lens of a monopoly theory. Given the evidence of a strong incentive for a focal firm to poach its competitor's consumers, one might expect the competitor to face symmetric incentives to implement geoconquesting campaigns. Our work contributes to the literature by analyzing the returns to geoconquesting in a competitive environment. We design a large-scale field experiment that allows us to analyze geoconquesting through the lens of oligopoly theory rather than monopoly theory. Our findings indicate that the returns to geoconquesting may be overstated when equilibrium considerations are ignored.

2.2. Competitive Price Targeting

Besides fleshing out the opportunities to use mobile couponing in a competitive market, our empirical findings contribute to the literature on competitive third-degree price discrimination. For a monopolist, price discrimination will always weakly increase the firm's profits as long as the firm can segment consumers, possesses market power, and can prevent resale. Similarly, under typical conditions, price discrimination will weakly increase an oligopoly firm's profits, holding competitors' actions fixed. Accordingly, Fong et al. (2015) find that a unilateral geoconquesting campaign increases profits significantly. Yet, except under very stylized modeling assumptions, it is difficult to predict whether equilibrium profits rise or fall under competitive price discrimination. This difficulty is nicely demonstrated by Corts (1998), who makes an interesting distinction between two types of models. Suppose there are two consumer markets. A firm characterizes one of the markets as "weak" (and the other market as "strong") if, for any uniform price set by a competitor, the optimal price is lower than in the other market. A pricing model is characterized as exhibiting "best-response symmetry" if firms agree on the strong and weak markets. Otherwise, the model is characterized as exhibiting "best-response asymmetry." Under best-response symmetry, several papers have derived conditions under which the monopoly predictions appear to hold and price discrimination can increase profits under sufficiently intense competition in the "strong" market (Borenstein 1985, Holmes 1989, Armstrong and Vickers 2001). Under best-response asymmetry, several stylized applications of the Hotelling model appear to predict an unambiguous prisoner's dilemma whereby all firms endogenously commit to price discriminating and generate lower equilibrium profits than under uniform pricing (Thisse and Vives 1988, Shaffer and Zhang 1995). However, Corts (1998) shows that this result is not general and that, under best-response asymmetry, the uniform equilibrium prices need not lie between the price discrimination prices. In fact, best-response asymmetry turns out to be a necessary condition for two polar outcomes: "all-out price competition" or "all-out price increases." Under the former, prices and profits fall in all markets. Under the latter, prices and profits increase in all markets. Whether all-out competition or all-out price increases emerge is ultimately an empirical question regarding the relative importance each firm attaches to the strong and weak markets. Based on these findings, our approach to assessing the returns from targeting consists of devising a field experiment to assess the profitability of each consumer market to each of the competing firms.

More recently, Chen et al. (2017) studied the equilibrium incentives of firms to target prices by location, as opposed to by consumer. A novel feature of this setting is that consumers can endogenously move between locations based on their expectations about firms' geotargeting incentives. This *cherry picking* intensifies price competition so that, in equilibrium, a firm does not successfully poach its rival's local consumers.[3] Our corporate partner did not believe that consumers would be likely to change their geographic locations (i.e., make a return trip to the other mall) to obtain the more favorable geoconquesting movie discounts. The return bus fare of RMB 4 between the two malls would offset half the difference between a geofenced price and a geoconquested price, in addition to the 20 minutes of return-trip travel time. In our analysis, we therefore do not consider the ability of consumers to cherry pick. However, this would be an interesting topic for future research on geotargeting and consumers' strategic incentives more generally. In settings with higher-regular-price items, a consumer's incentives to arbitrage on location could be much higher.

A related literature has analyzed the intertemporal incentives for competing firms to target prices based on past consumer behavior (for a survey, see Fudenberg and Villas-Boas 2006). When consumers are also forward looking, firms may find themselves in a prisoner's dilemma with lower profits than if they could credibly commit to not targeting based on past behavior. In our mobile campaigns, we do consider targeting based on past consumer visit behavior, but we do not consider the dynamic incentives of firms or consumers. We cannot rule out that the returns to geobehavioral targeting would become less favorable with forward-looking consumers. However, Shin and Sudhir (2010) have found that even with forward-looking consumers, the prisoner's dilemma may not arise if consumers exhibit a sufficiently strong stochastic preference component like the one in our probit demand model.

Ex ante, our empirical setting appears to exhibit the intuitive properties of best-response asymmetry: the firms are geographically differentiated and can use mobile marketing to target consumers located close to their competitor. Calibrating a model of competitive pricing on our experimental results, we can observe whether the decision to adopt price targeting leads to a prisoner's dilemma. The presence of a prisoner's dilemma would empirically demonstrate how the presence of competition can reverse the profitability of price targeting. The lack of a prisoner's dilemma would not falsify the theory; however, it would suggest that competitive effects need to be quite severe for price targeting to lower profits, and would potentially demonstrate the insufficiency of best-response asymmetry for generating such a result.

Several authors have conducted empirical tests for the incidence of competitive price discrimination (e.g., Shepard 1991, Borenstein and Shepard 1994, Goldberg and Verboven 2005, Busse and Rysman 2005, Borzekowski et al. 2009). Borenstein and Rose (1994) find that the degree of price discrimination in airline fares increases with the degree of competition. However, few papers have analyzed the profit implications of price discrimination and the potential, under best-response asymmetry, for all-out competition. In a study of the U.S. ready-to-eat cereal industry, Nevo and Wolfram (2002) find that shelf prices tend to be lower during periods of coupon availability. Besanko et al. (2003) conduct a structural analysis that calibrates a targeted couponing model with competing firms and manufacturers using ketchup data, finding that competitive price targeting does not lead to all-out war. However, their model also incorporates several other factors including a combination of horizontal and vertical differentiation between products, and horizontal and vertical competition between firms (retailers and manufacturers). Building on these findings, Pancras and Sudhir (2007) study the equilibrium incentives for a consumer data intermediary to sell access to consumer data and provide targeting services to competing firms in a retail distribution channel. They also find that competitive targeting need not lead to all-out war. Our setting provides a convenient context for studying competitive price discrimination as we have two firms selling relatively homogeneous products that are differentiated primarily along a single geographic dimension. We do not consider the incentives of the data intermediary, in this case, the mobile platform, to sell targeting services. The platform offers targeting capabilities that use both real-time location, providing our horizontal dimension, and historical location, used to infer past behavior that comprises our vertical dimension.

3. Field Experiment

3.1. Experimental Design

According to our corporate partners, Chinese movie theaters rarely changed their prices historically. It would therefore be impossible to study theater-level demand across different consumer segments using observational field data. Moreover, a typical theater chain would be unlikely to observe visit behavior to competing chains, rendering the estimation of a theater choice model infeasible. To circumvent this problem, we use data from a unique pricing field experiment that was conducted with the cooperation of a major wireless service provider that provides the platform for targeted mobile promotions. In the experiment, a mobile SMS promotion consisted of an offer to buy one general admission voucher for any 2D movie showing at a given movie theater on the day the SMS message was sent. The SMS message contained a brief description of the offer, and recipients could click on a link to purchase the voucher and take advantage of the price discount for any movie showing in the theater that day. In practice, an advertiser pays RMB 0.08 per message sent. Since this study was coordinated with the wireless provider, all of the messages used in our campaigns were paid for by the wireless provider, not the theaters.[4]

Our subject pool consists of mobile subscribers that were randomly sampled between 11:00 a.m. and 12:00 noon on Saturday November 22, 2014. We used this early Saturday time slot, an off-peak time for movie theaters, to ensure that we would not exceed theater capacities. These types of "early-bird" prices are quite common in the United States.[5] The subjects were sampled from two locations: the 500-meter-radius geofences surrounding two competing theaters (hereafter referred to as firms A and B), respectively located in two large shopping centers. Each subject was classified into one of four segments based on her observed geographic location and type. The geographic location represents the mall in which the subject was located, A or B, at the time of the intervention. Based on the location, a consumer's type was then determined by her historical visits to the theater in the corresponding mall, a measure of recency. A movie theater visit was defined by any dwell time in the theater of at least 90 consecutive minutes, measured using the GPS and cell tower triangulation on mobile signal reception for the individual's phone. A consumer was classified as the "high" type if she visited the movie theater at least once during the preceding two months; otherwise, she was classified as the "low" type. None of our subjects previously received SMS promotions from either theater. Therefore, the "high" versus "low" classification is based on visiting the theater at regular box-office prices. This classification was chosen to capture a consumer's propensity to watch movies. The four consumer segments therefore consist of (A, high), (A, low), (B, high), and (B, low).

Each subject was randomly assigned to one of several promotional conditions. Based on a subject's location, the local theater was classified as "defensive," and the more distant theater was classified as "offensive." We use a symmetric design such that we can analyze each theater, A and B, from both offensive and defensive perspectives. In the control condition, a subject did not receive an SMS offer. In our SMS promotion conditions, the discount depths were chosen based on the mobile carrier's experience with previous promotions and based on the pilot study in Fong et al. (2015). In our "defense only" condition, a subject received an SMS message from the defensive theater reading, "To buy a voucher for general admission to any of today's 2D showings at [defensive theater] at a [20%, 40%] discount, follow this link: _." In our "offense only" condition, the subject received an SMS message from the offensive theater reading, "To buy a voucher for general admission to any of today's 2D showings at [offensive theater] at a [40%, 60%] discount, follow this link: _." In our "offense and defense" condition, the subject received two SMS messages, one from each of the offensive and defensive theaters. In the promotion cells, we directly observed whether or not a subject purchased a voucher through the SMS offer. A limitation of our experimental design is that we do not observe the redemption of the voucher. However, our corporate partner did not anticipate that many (if any) respondents would leave the mall and return later that day to see a movie at a peak period.

To construct the sample, we began by sampling mobile subscribers located in the two shopping malls' respective geofences at the time of the study. During the course of the hour when subjects were sampled, approximately 57,000 mobile subscribers were observed across the two locations. The population weights associated with each of the four observed consumer segments are 12% (A, high), 26% (A, low), 18% (B, high), and 44% (B, low). With nine pricing conditions applied to each of the four observed segments, the experimental design involves a total of 36 cells, or nine cells per segment. Approximately 500 subjects were assigned to each cell, with a total sample size of 18,000 subscribers. Within each consumer segment, the randomization of subjects across the nine pricing cells was performed by assigning each sampled mobile subscriber a random uniform integer between 1 and 9. We counterbalanced the order in which the offers from each of the two theaters were received for those subjects receiving an SMS message from each theater. Testing for sequential promotions was outside the scope of this study.

For each subject, we observe whether or not a ticket was purchased from one of the movie theaters. We directly observe when a subject purchased one of the movie vouchers offered in a promotional SMS message. To determine the rate at which our control subjects bought movie tickets in the "no promotion" cells, we use the GPS and cell tower triangulation on mobile signal reception for a subject's mobile device to track whether the subject visited one of our two theaters and dwelled in the theater's premises for at least 90 consecutive minutes. To control for the possible purchase acceleration associated with our time-sensitive SMS offers, we tracked the control subjects for 11 days to assess whether they "ever" went to a movie at one of the two theaters. We used an 11-day period to avoid overlapping with the timing of release of new movies that could change demand.

In total, 553 of our 18,000 subscribers purchased a ticket representing about 3.1% of the sample. Of the 16,000 subjects receiving at least one SMS offer, 535 purchased a voucher, a promotional response rate of 3.3%. This 3.3% conversion rate is comparable to other recent targeted pricing experiments on mobile phones (e.g., Dubé et al. 2017). We never observe a subject visiting a movie theater more than once in the "no promotion" control case, nor do we observe a subject purchasing more than one movie voucher in response to the SMS offer. Therefore, we can treat consumer demand as discrete choice.

In addition to observing the exact prices charged and purchase decisions of each subject, we also observe several measures of each subject's mobile usage behavior. In particular, we observe each subject's average monthly phone bill (average revenue per user), total minutes used, SMS messages sent, and data usage. Summary statistics for the mobile usage variables are reported in Appendix B, Table B.1, by segment.

We report randomization checks in Appendix B, Table B.2. Making all pairwise comparisons for the nine cells (36 comparisons) for our four mobile usage variables (for a total of 144 comparisons) resulted in six differences in means at the 0.05 significance level, and an additional four differences at the 0.10 significance level, which is not a rate greater than chance. Running a Tukey test for each mobile usage variable to correct for multiple comparisons, no significant differences were found between any pair of cells, for any of the four mobile usage variables. In Appendix B, Table B.3, we also provide summary statistics about each of the two malls, finding that both cater to similar demographic profiles of consumers.

A limitation of our experimental design is that mobile coupons not only reduce the net price paid by a consumer but also have a promotional effect that could also shift demand. We partially resolve this concern by testing multiple coupon values, which introduces price variation conditional on the promotion. Yet, our control condition does not have a promotion attached to it. Ideally, we would have a control condition that receives an SMS message with a notification about movie tickets without an actual price discount. However, our corporate partners did not feel comfortable sending consumers promotional SMS messages without some sort of deal included.

4. Experimental Results

An advantage of the design of the experiment is that we can analyze some aspects of the promotional effects model-free. Basic tests for differences in aggregate purchasing across pricing conditions are provided in Appendix B, Tables B.4 to B.7. The analogous tests are reported by consumer segment in Appendix B, Tables B.8 to B.11. For our model-free analysis, we collapse the data across consumer type segments and pool the two firms into "defensive" and "offensive" states. The defensive state indicates a firm's own geofence, whereas the offensive state indicates a competitor's geofence.

4.1. Geotargeted Pricing

We first analyze geotargeted pricing. The corresponding conversion rates (i.e., percentage of subjects that buy a ticket voucher) by promotion condition are reported in Figure 2, and the corresponding average revenues per messaged consumer (using the full ticket price net of the mobile discount) are reported in Figure 3.[6]

The first column of Figure 2 reports the results of geofencing. Defensive promotions raise demand substantially. Increasing the discount from 20% to 40% doubles sales from 1.95% to 4.81% (p-value < 0.01).[7] Therefore, as expected, a theater faces a downward-sloping demand curve in its local market. The corresponding first column of Figure 3 indicates that a geofenced discount of 40% off the regular price increases expected revenue per messaged consumer to RMB 2.17.

The first row of Figure 2 reports the results of geoconquesting. To a lesser extent, these offensive promotions also increase sales. None of the sample consumers purchase a ticket from the offensive firm at the regular price. A 40% discount does generate offensive ticket sales of 0.21%. Increasing the offensive discount from 40% to 60% increases offensive ticket sales substantially from 0.21% to 2.37% (p-value < 0.01).[8] Interestingly, these results confirm that a theater faces a downward-sloping demand curve in its competitor's local market

Figure 2. Purchase Rates

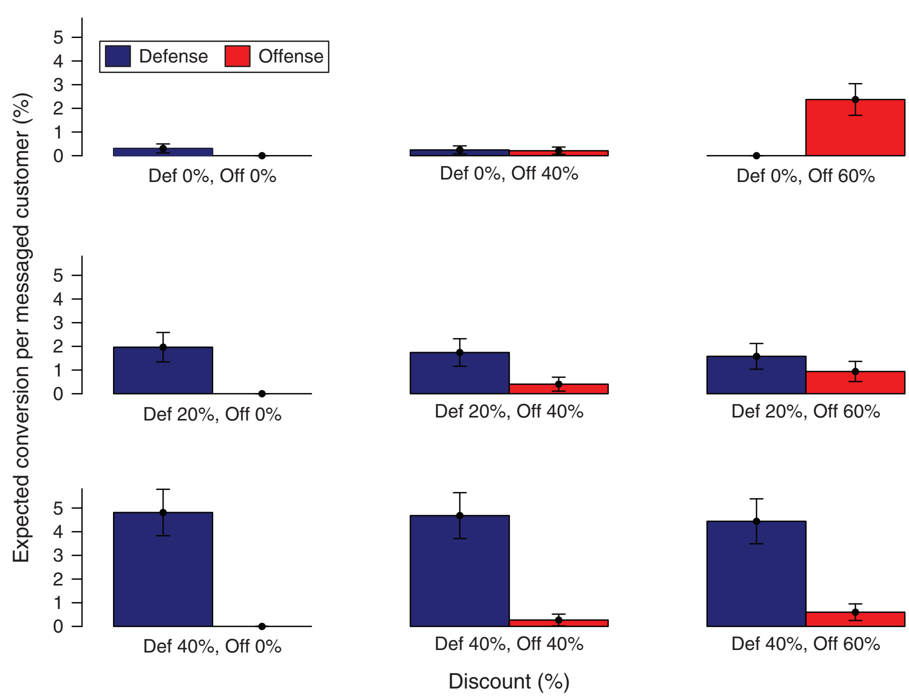
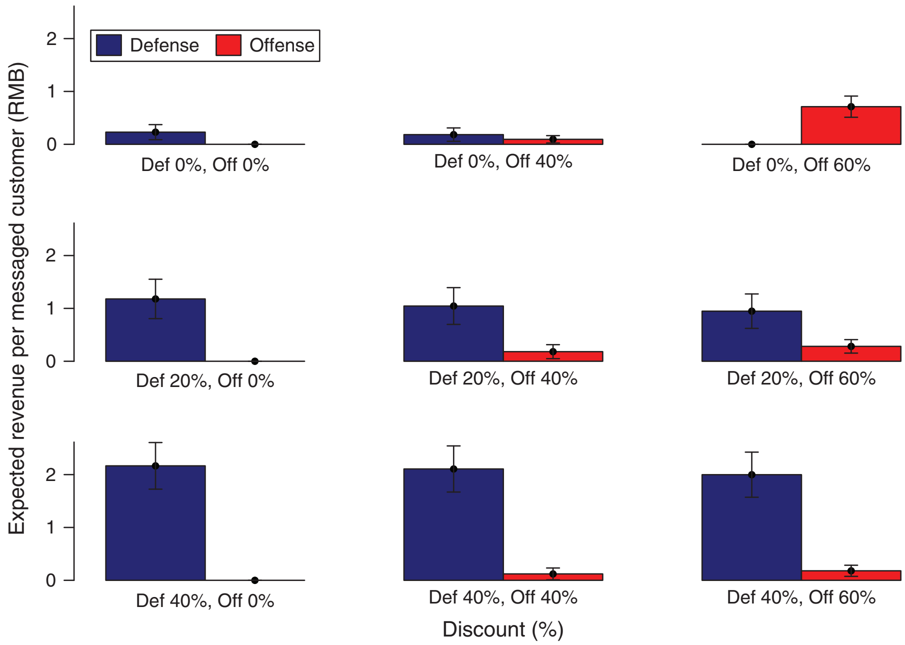


Figure 3. Expected Revenues per Messaged Consumer



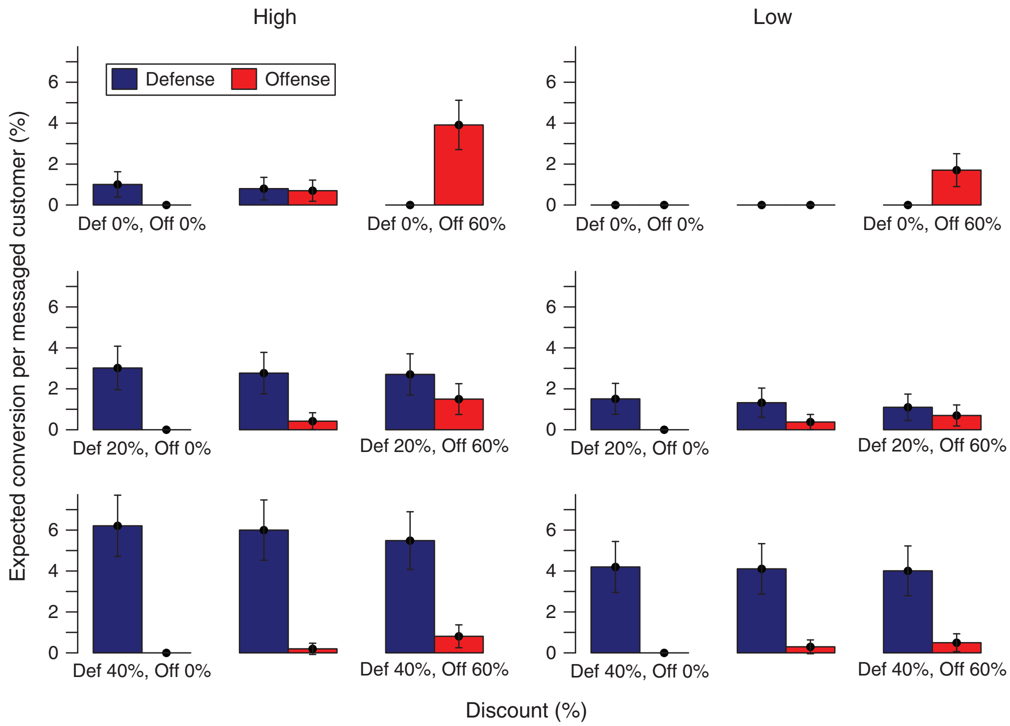
and that the "other mall" represents a potential market for a theater. The corresponding first row of Figure 3 indicates that a geoconquested discount of 60% off the regular price increases the expected revenue per messaged consumer to RMB 0.71. These are incremental revenues given that the control cell generates no ticket sales from the competitor location. Suppose a theater had already implemented a geofencing campaign with a 40% mobile coupon for consumers in its own location. Implementing the geoconquesting campaign with a 60% mobile coupon for consumers in the competitor location increases total revenues by 32.7%.[9] Moreover, the differences in defensive and offensive price sensitivities suggest an opportunity for geographic price targeting based on own versus competitor location.

The remaining four cells of Figure 2 capture the cross-promotional effects when both the offensive and defensive firms implement a campaign concurrently. Interestingly, defensive promotions appear to be immune to an offensive promotion. As we move along the columns of the second and third row, we fail to reject that the level of sales for the defensive firm remains unchanged and the cross-effects of offensive promotions on defensive demand are all statistically insignificant. If we focus on the high segment in location A only (see Figure 4), then we do see a slight cross-effect from the offensive promotion. The demand for defensive tickets at a 40% discount falls from 5.95% to 4.92% when the offensive promotion is increased from 40% to 60%, although this difference is not significant (p-value = 0.73). Therefore, demand for the "offensive" theater comes primarily from the outside good—i.e., the conversion of nonpurchasers conditional on the defensive firm's prices. This role for category expansion indicates that the full market coverage assumption in Shaffer and Zhang (1995) does not apply in our study of movie theaters and that a prisoner's dilemma is therefore not a foregone conclusion when both firms engage in geoconquesting in this market.

The effects of the offensive promotions do appear to be mitigated by a defensive promotion. As we move down the rows of the third column, we observe a large and statistically significant decline in the level of offensive ticket sales compared to the response when there is no defensive promotion. For instance, increasing the offensive discount from 40% to 60% increases offensive ticket sales by 2.2 percentage points (p-value < 0.01) when there is no defensive discount, but by only 0.54 percentage points when there is a defensive discount of 20% (p-value = 0.05, with a difference in differences of 1.63 percentage points, p-value < 0.01). Therefore, the defensive theater not only draws its demand from converting local nonpurchasers; it also draws demand away from the offensive theater. Substitution patterns between the two firms are therefore asymmetric, with the offensive firm facing more competition from the defensive firm than vice versa. The corresponding cells of Figure 3 indicate that the expected revenues per consumer in the geoconquesting campaign with a 60% mobile coupon are only RMB 0.18 when the defensive firm issues a 40% discount.

We now turn to each firm's pricing incentives. Based on Figures 2 and 3, the incremental purchases from the promotions generate incremental revenues per consumer for both the offensive and defensive firm. Furthermore, the cross-promotional effects on revenues

Figure 4. Purchase Rate by Segment



are asymmetric. Both firms have a clear incentive to implement the deep discount, although the "optimal" discount level for each firm likely lies somewhere off the price test grid.

4.2. Geobehaviorally Targeted Pricing

Now we analyze the opportunity for geobehaviorally targeted pricing, distinguishing between the "defensive" and "offensive" locations, as well as high versus low consumer recency types. The corresponding purchase rates by promotion condition are reported for each segment in Figure 4. Most of our intuition about the sales lift from discounts in the geotargeted pricing case above carry over to each of the consumer type segments. There is an asymmetric cross-promotional effect in each segment whereby the offensive firm's geoconquesting coupons are offset by the defensive firm's geofencing coupons, but not vice versa. The magnitudes of the effects differ by segment. The sales levels are smaller in the low segment than in the high segment, as expected. Therefore, both firms compete in the two consumer type markets, although competition appears to be more intense in the high market than in the low market.

An interesting feature of the experimental data is that none of the low consumer types purchases a ticket at the regular price. However, aggressive discounts are capable of drawing a substantial number of these consumers to buy tickets. A defensive discount of 40% attracts over 4% of the low consumer segment to purchase.

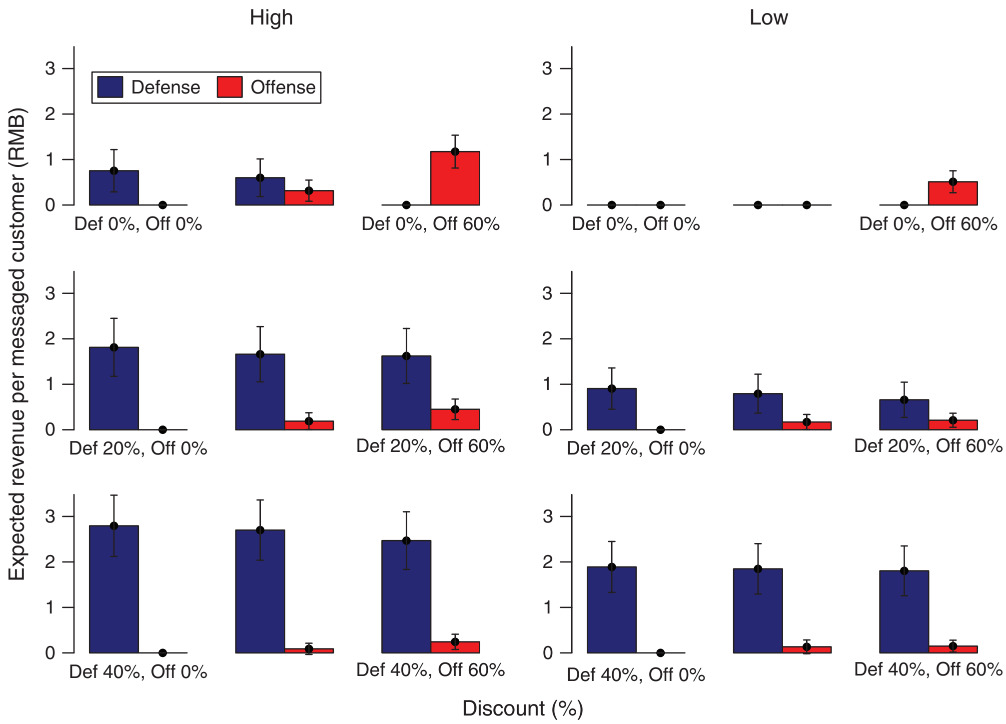
Looking again at pricing incentives, we report the average revenues per potential consumer by segment in Figure 5. As in the uniform geotargeted case, both firms appear to have a strong incentive to offer deep discounts in each of the consumer segments. We therefore have strong evidence that firms will want to implement discounts. However, it is unlikely that the experimental price test grid contains the exact optimal price in each market.

In sum, our model-free analysis indicates that each firm appears to have an incentive to use "early-bird"-type mobile discounts during the off-peak period of demand. The potential gains appear to vary by both geographic location and consumer type segment. However, the returns to a targeted mobile coupon campaign are clearly mitigated by the targeting efforts of a competitor. We also observe a stark geographic asymmetry whereby the offensive firm's targeting efforts are more vulnerable to those of a defensive firm than vice versa. A clear limitation of the analysis of the raw experiment is that the coarseness of the price grid prevents us from observing each firm's optimal price (i.e., best response) and, hence, from observing the equilibrium prices that would likely prevail in this market. We overcome this limitation in Section 5 by combining our experimental data with a model of demand.

5. Probit Demand

We need a model to impute the conversion rates at price points off the experimental price test grid. In this section, we describe the trinomial probit model of demand

Figure 5. Expected Revenues per Messaged Consumer by Segment



that we use to estimate demand along the entire support of prices. By allowing for correlated errors, the model should be flexible enough to fit the observed patterns of asymmetric cross-promotional effects for the defensive versus the offensive firm in a market described in Section 4. Another popular specification is the random coefficients logit, which is easier to estimate. The flexibility of this model would come from measuring within-subject, unobserved heterogeneity in tastes for theaters. Since we have cross-sectional data in this application, we prefer the probit, which allows for flexible substitution patterns without the need for explicitly modeling within-subject unobserved heterogeneity.

5.1. Consumer Demand

Let $h=1,\ldots,H$ denote the consumers, and let $j=A,B$ denote the theater alternatives, where $j=C$ is the no-purchase alternative. Each consumer belongs to one of the $k=1,\ldots,K$ observable segments (based on geography and historic purchase intensity). At the population level, the segment proportions are denoted by $\{\lambda^k\}_{k=1}^K$. Each theater has attributes $X_j=(\mathbb{1}_{1j},\mathbb{1}_{2j},p_j)$, where $\mathbb{1}_{1j}=1$ if j is theater 1 and 0 otherwise. We denote the ticket price at theater j as p_j.

Assume a consumer h in segment k obtains the following indirect utility from her choice:

$$u_{hA}=\theta_A^k-\alpha^k p_A+\tilde{\varepsilon}_{hA},$$
$$u_{hB}=\theta_B^k-\alpha^k p_B+\tilde{\varepsilon}_{hB},$$
$$u_{hC}=\tilde{\varepsilon}_{hC},$$

where $\tilde{\varepsilon}$ are random utility shocks. Let

$$\eta_h\equiv\begin{bmatrix}\tilde{\varepsilon}_{hA}-\tilde{\varepsilon}_{hC}\\ \tilde{\varepsilon}_{hB}-\tilde{\varepsilon}_{hC}\end{bmatrix}\sim N(0,\Psi^k)$$

if consumer h is in segment k. We can write the vector of theater-specific indirect utilities as

$$U_h\equiv\begin{bmatrix}u_{hA}\\ u_{hB}\end{bmatrix}=B^kX+\eta_h,\quad \text{where } X=\begin{bmatrix}X'_A\\ X'_B\end{bmatrix}$$

is a 6×1 vector of product attributes and $B^k=I_2\otimes\beta^{k^T}$ is a 2×6 matrix of parameters with $\beta^k=(\theta_A^k,\theta_B^k,\alpha^k)$. Finally, index consumer choices by $y_h\in\{A,B,C\}$.

The expected probability that a consumer h in segment k chooses alternative j is

$$\Pr(y_h=j\mid B^k,X,\Psi)=\Pr(u_{hj}-u_{hi}>0,\forall\, i\neq j).$$

We can simplify our analysis by using the following transformations for consumer h in segment k:

$$Z^{k,(A)}=\begin{bmatrix}u_{hA}-u_{hB}\\ u_{hA}\end{bmatrix},\quad Z^{k,(B)}=\begin{bmatrix}u_{hB}-u_{hA}\\ u_{hB}\end{bmatrix},$$

or, in matrix form

$$Z^{k,(j)}=\Delta^{(j)}U_h,\quad j\in\{A,B\},$$

where

$$\Delta^{(A)}=\begin{bmatrix}1&-1\\1&0\end{bmatrix},\quad \Delta^{(B)}=\begin{bmatrix}-1&1\\0&1\end{bmatrix},$$

and $E(Z^{k,(j)}) \equiv \mu_Z^{k,(j)} = \Delta X B^k$, $\mathrm{Var}(Z^{k,(j)}) \equiv \Sigma_Z^{(j)} = \Delta^{(j)} \Psi^k \Delta^{(j)T}$, and $\mathrm{corr}(Z^{k,(j)}) \equiv \rho_Z^{(j)} = \Sigma_{Z(A,B)}^{(j)} / \sqrt{\Sigma_{Z(A,A)} \Sigma_{Z(B,B)}}$.

If we standardize $Z^{k,(j)}$, we obtain $z^{k,(j)} = [D^{(j)}]^{-1/2} \cdot Z_h^{k,(j)}$, where $D^{(j)} = \mathrm{diag}(\Sigma_Z^{(j)})$ and $E(z^{k,(j)}) \equiv \mu_z^{k,(j)} = [D^{(j)}]^{-1/2} \Delta X B^k$. We can now write the choice probabilities as follows:

$$\begin{aligned} &\Pr(y = j \mid B^k, X, \Psi^k) \\ &\quad = \Pr(z^{k,(j)} > 0 \mid \mu_z^{k,(j)}, \rho_Z^{(j)}) \\ &\quad = \int_{-\infty}^{\mu_{zA}^{(j)}} \int_{-\infty}^{\mu_{zB}^{(j)}} \phi(x, y; \rho_Z^{(j)})\, dy\, dx, \quad j \in \{A, B\} \\ &\quad = \Phi(\mu_{zA}^{(j)}, \mu_{zB}^{(j)}; \rho_Z^{(j)}), \end{aligned} \tag{1}$$

where $\phi(x,y;\rho) = (1/(2\pi\sqrt{1-\rho^2}))\exp[-(x^2 - 2xy\rho + y^2)/(2(1-\rho^2))]$, $\Phi(x,y;\rho) = \int_{-\infty}^{x}\int_{-\infty}^{y} \phi(u,v;\rho)\, dv\, du$, and $\Pr(y = C \mid B^k, X, \Psi^k) = 1 - \sum_{j \in \{A,B\}} \Pr(y = j \mid B^k, X, \Psi^k)$.

The probabilities in Equation (1) give rise to the usual trinomial probit model of choice. We estimate these choice probabilities using the Markov Chain Monte Carlo (MCMC) algorithm proposed by McCulloch and Rossi (1994). The following priors are assigned:

$$B^k \sim N(\bar{B}, A^{-1}),$$
$$\Psi^k \sim IW(\nu, V),$$

where $A = \mathrm{diag}(0.01)$, $\nu = 6$, and $V = \mathrm{diag}(\nu)$. The estimation algorithm is defined over the unidentified parameter space. In our results, we report posterior distributions for the identified quantities. We conduct all of our analysis in R, using the rmnpGibbs function from the bayesm package. Since we expect the taste coefficients and random utility covariances to differ across segments, we estimate the model separately for each segment. For each run of the estimation algorithm, we simulate a chain with 200,000 posterior draws and retain the last 100,000 draws for inference. The algorithm produces a set of draws, $\{\Theta^r\}_{r=1}^R$, from the posterior distribution $F_\Theta(\Theta \mid \mathbf{D})$, where $\mathbf{D}$ is our data and $\Theta^r = \{(B^{1,r}, \Psi^{1,r}), \ldots, (B^{K,r}, \Psi^{K,r})\}$ are our demand parameters. We can compute the posterior choice probabilities for each of our k segments, $\Pr(y = j \mid X, \Theta^k)$, where $j \in \{A, B, C\}$.

5.2. Aggregate Demand and Substitution Patterns

To derive the demand system for each theater, we integrate over all of the consumers in the population. The posterior total market share for theater j is

$$S_j(p) = \sum_k \lambda^k \int \Pr(y = j \mid B^k, p, \Psi^k)\, dF(\Theta \mid \mathbf{D}), \tag{2}$$

where we focus on the price vector $p = (p_A, p_B)$ and drop the theater dummy variables to simplify the notation hereafter.

The posterior own- and cross-price elasticities of the total market share for theater j are

$$\varepsilon_{jj} = \frac{p_j}{S_j(p)} \sum_k \int \lambda^k \frac{\partial \Pr(y = j \mid B^k, p, \Psi)}{\partial p_j}\, dF(\Theta \mid \mathbf{D})$$

and

$$\varepsilon_{ji} = \frac{p_i}{S_j(p)} \sum \int_k \lambda^k \frac{\partial \Pr(y = j \mid B^k, X, \Psi)}{\partial p_i} F(\Theta \mid \mathbf{D}),$$

respectively. Exact expressions for the derivatives, $\partial \Pr(y = j \mid B^k, X, \Psi)/\partial p_i$, are derived in Appendix A.

5.3. Demand Estimates

A unique feature of the demand estimation exercise is that the prices consumers face at each theater were generated through randomization, eliminating the usual endogeneity concerns associated with observational marketing data.[10] Recall that the pool of consumer subjects come from four distinct segments based on their geographic location and historic movie theater visit behavior: (i) high consumers in location A, (ii) low consumers in location A, (iii) high consumers in location B, and (iv) low consumers in location B. We estimate a separate choice model in each of the four segments. As we explain below, we want the theater-specific intercepts and the covariance terms to be segment specific. The intercepts will help us fit differences in response rate levels across segments. The covariance terms will help us fit the non-IIA substitution behavior differences across cells. We use both a multinomial logit model and a multinomial probit model to verify whether the IIA problem from the former leads to inferior fit. Recall that we do not need to estimate the segment weights, λ^k, as these are observed by matching mobile subscribers with their location at the time of the study and their historic theater visit behavior.

Table 1 summarizes the posterior fit of each specification, by segment, using the posterior log marginal likelihood computed with the method of Newton and Raftery (1994). In each case, we trimmed the lower and upper 1% of draws to avoid underflow problems.[11] The results indicate that the additional flexibility of the multinomial probit, which allows for correlated and heteroskedastic random utility shocks, improves fit in the high consumer segments in both locations. However, the probit fares only marginally better than the

Table 1. Posterior Model Fit by Segment

Segment	Multinomial logit	Multinomial probit
High consumers in location A	−778.5684	−774.7321
Low consumers in location A	−456.5403	−456.4356
High consumers in location B	−784.3276	−768.8367
Low consumers in location B	−489.8145	−488.7583

logit in the low consumer segments in both locations. The improved fit of the probit stems largely from its ability to fit the cross-promotional effects, especially in the high consumer segments. In Appendix B, Figure B.1 reports the offensive purchase rates in each of our experimental cells. Focusing on the high consumer segment, the probit fits the purchase rates better as the offensive firm increases its discount from 40% to 60% off the regular price. The probit allows for more flexible substitution between the two theaters relative to the outside good. As a result, offensive promotions can increase offensive ticket sales without stealing "too much" business from the defensive firm.

To assess the differences in fit of the logit and probit specifications, we report the predicted purchase probabilities along with the observed purchase rates in Appendix B, Figures B.1 and B.2. In the figures we can see that the probit does a better job predicting the cross-promotional effects noted in Section 4. Recall that for both theater locations, the offensive purchase rate in the high consumer segments is sensitive to the defensive price. The probit predictions better capture this sensitivity. Thus, we conclude that the added flexibility of the probit is better suited for modeling demand in this market.

Hereafter, we focus our results on the multinomial probit specification. We report the estimated coefficients from the multinomial probit in Table 2. For each coefficient, we report the posterior mean and the 90% posterior credibility interval. We observe quite a bit of heterogeneity across the consumer segments, as one would expect. Most important, we find a lot of heterogeneity in the distribution of the utility shocks, especially with regard to the covariance in the shocks. Our point estimates are consistent with substantial heteroskedasticity, although we cannot rule out that the variance of theater B shocks is one. At the bottom of Table 2, we report the correlations, $\rho_{A,B}$. We find that the theater-specific utility shocks are highly positively correlated for the high consumer types in both locations. The strong evidence for correlation explains why we select the multinomial probit in favor of the multinomial logit in each segment. The intuition can be seen in the raw data. All offensive discounts in the high segment draw some demand away from the defensive firm. However, only the large discount of 60% off draws new buyers into the category. For the low segment, the theater-specific shocks are highly negatively correlated in location A. In our data, we observe almost no substitution between the theaters in this segment, consistent with strong idiosyncratic preference for a specific theater. Accordingly, any increases in demand from a discount appear to derive from category expansion. The correlation is small and positive in segment B, and, once we account for parameter uncertainty, we cannot rule out that the correlation is zero. The relatively high correlations in the strong segments will also intensify demand in these segments.

Next, we turn to our estimated price elasticities. In Table 3, we report the posterior mean own and cross-price elasticities in each consumer segment, computed at the regular prices (both charge RMB 75) and also at the largest discount of 60% (both charge RMB 30). As expected, the low consumer segment has higher own elasticities than the high consumer segment at both price levels. In all four segments, we find that both firms' regular prices of RMB 75 are at very elastic regions of their respective demand curves. Given that both theaters are far from capacity at regular prices during the off-peak time slot,[12] we would expect the effective marginal cost per ticket to be close to zero. In our analysis, we ignore the potential role of concession revenues. Hence, optimized uniform pricing should be at the unit-elastic region of total demand, which is the weighted average of the segment demands. If firms are optimizing their profits and setting uniform prices, they should be operating in the inelastic region of at least one of the segments. This evidence suggests an

Table 2. Posterior Means of Multinomial Probit by Segment

Coefficient	High A	Low A	High B	Low B
θ_A	−0.344	0.25	−1.066	−1.413
	(−0.651, −0.028)	(−0.178, 0.695)	(−1.344, −0.79)	(−1.737, −0.964)
θ_B	−1.043	−0.628	−0.376	0
	(−2.002, −0.425)	(−1.499, −0.023)	(−0.741, −0.035)	(−0.311, 0.349)
α	−0.027	−0.044	−0.027	−0.028
	(−0.033, −0.021)	(−0.053, −0.035)	(−0.036, −0.019)	(−0.043, −0.017)
$\Psi_{A,A}$	1	1	1	1
	—	—	—	—
$\Psi_{B,B}$	1.006	0.738	1.152	0.577
	(0.437, 2.105)	(0.323, 1.393)	(0.692, 1.651)	(0.287, 1.237)
$\Psi_{A,B}$	0.787	−0.795	1.025	0.152
	(0.341, 1.259)	(−1.125, −0.542)	(0.801, 1.234)	(−1.019, 0.663)
$\rho_{A,B}$	0.796	−0.951	0.962	0.348
	(0.443, 0.931)	(−0.99, −0.826)	(0.926, 0.985)	(−0.953, 0.955)

Note. 90% posterior credibility intervals are in parentheses.

Table 3. Multinomial Probit Elasticities by Segment

	High, A		Low, A		High, B		Low, B	
	Firm A price	Firm B price	Firm A price	Firm B price	Firm A price	Firm B price	Firm A price	Firm B price
				Both set regular prices of RMB 75				
Firm A	−5.33	0.15	−10.17	1.07E−16	−16.99	13.17	−7.88	3.72
Firm B	3.44	−8.35	1.77E−14	−11.82	0.02	−4.84	0.42	−8.96
				Both set prices of RMB 30 (60% off)				
Firm A	−1.40	0.10	−2.07	0.00	−7.97	5.95	−3.10	0.77
Firm B	1.52	−3.44	0.00	−4.33	0.01	−1.25	0.03	−1.91

Note. Evaluated at regular prices of RMB 75.

opportunity for firms to generate substantial demand during off-peak hours through large discounts off their box-office prices, which are uniform across all time slots (peak and off-peak). This result is consistent with the substantial returns to large discounts we observed in each segment in our raw experimental data, as discussed in Section 4 and in Figures 3 and 5.

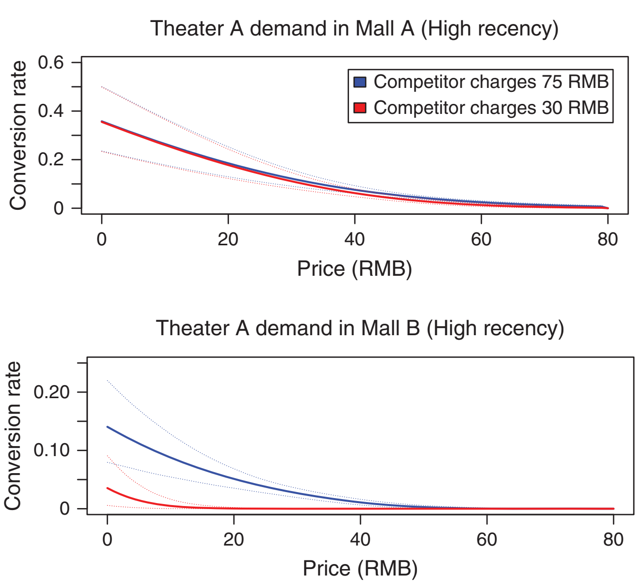
We can see these patterns by looking at the estimated demand functions plotted in Figures 6 and 7. Each plot reports the posterior expected demand function along with the 90% posterior credibility interval. In Figure 6, we can see the asymmetric substitution patterns. When theater B lowers its price, the shift in demand for theater A in mall A is minimal. However, the shift in demand for theater A in mall B is quite large. Figure 6 illustrates the much higher intensity of competition in the high segment than in the low segment. In mall B, a decrease in the price for theater B has a much larger effect on high demand for theater A than low demand for theater A.

The cross elasticities are also as expected. In the high consumer segments, we observe highly asymmetric cross elasticities, with the offensive firm's demand much more vulnerable to the defensive firm's price. In the low consumer segments, we observe relatively little substitution between the two theaters, meaning that discounts mostly draw new consumers into the category.

6. Decision-Theoretic Pricing

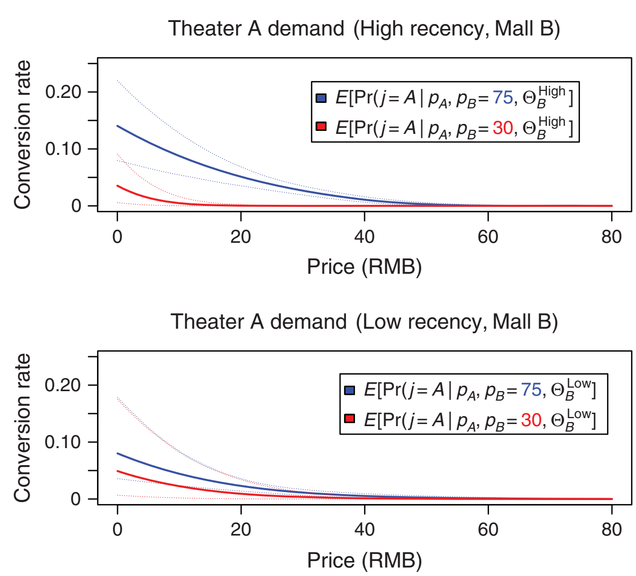
We now describe how a theater would likely use the demand data to implement a mobile couponing strategy during the off-peak period of demand. We propose a decision-theoretic approach that accounts for the uncertainty in demand and profitability. We use the posterior expected profits as each firm's reward function. Posterior profits are computed based on the posterior distribution of demand, which we simulate using the R posterior draws from the chain used to estimate the demand function via our MCMC algorithm. We

Figure 6. Shift in Posterior Expected Demand for Theater A When Theater B Cuts Its Price



Note. Dotted lines represent the 90% posterior credibility intervals.

Figure 7. Shift in Posterior Expected Demand for Theater A When Theater B Cuts Its Price



Note. Dotted lines represent the 90% posterior credibility intervals.

assume the firms use the data, $\mathbf{D}$, and the demand estimation procedure in Section 5.1 to form the following posterior beliefs about demand parameters, $F_{\Theta}(\Theta \mid \mathbf{D})$. We also implicitly assume firms are risk neutral.

In our analysis, we assume that consumer demand is fully captured by the probit specification. We do not allow for strategic consumers to arbitrage the targeting through their expectations about differential pricing across locations. As we explained in Section 2.2, our corporate partners did not believe that consumers would switch locations to try and obtain these coupons. Even if consumers were aware of the existence and timing of the coupons, the differences in targeted prices between locations turns out to be small relative to the additional time and expense of the trip.[13] We also do not allow for consumers to purchase tickets for use during peak periods later in the day.

On the supply side, we do not account for potential costs charged by the mobile platform for each targeted SMS message. According to our corporate partners, in practice, firms pay between RMB 0.025 and RMB 0.06 per SMS message sent. The cost is per message and not per response. This cost would not affect our results for the full-price scenarios in which a theater does not issue mobile coupons and, hence, charges only the full box-office price of RMB 75. For each of the mobile coupon campaigns we study, the SMS cost would be identical since each campaign requires sending a coupon to all mobile subscribers. Therefore, SMS costs would not affect our substantive conclusions about the relative performance of different mobile campaigns. Moreover, given the high incremental profits associated with using even a uniform mobile coupon campaign relative to charging the full box-office prices, the SMS costs will not change our theaters' incentives to use mobile coupons in general.

6.1. Targeted Pricing Structures

The base case consists of a *uniform pricing strategy* whereby a theater targets the same mobile discount to all consumers across the two locations and type segments during the off-peak period of demand. Firm j's optimal uniform pricing problem consists of picking the price p_j^{uniform} as follows:

$$p_j^{\text{uniform}} = \arg\max_{p_j} \left\{ p_j \sum_{k=1}^{K} \lambda^k \mathbb{E}[\Pr(j \mid p, \Theta^k) \mid \mathbf{D^k}] \right\}$$
$$\approx \arg\max_{p_j} \left\{ p_j \left[\sum_{k=1}^{K} \lambda^k \frac{1}{R} \sum_{r=1}^{R} \Pr(j \mid p, \Theta^{r,k}) \right] \right\}, \quad (3)$$

which generates the following first-order necessary conditions:

$$\sum_{k=1}^{K} \lambda^k \sum_{r=1}^{R} \Pr(j \mid p, \Theta^{r,k}) + p_j^{\text{uniform}} \sum_{k=1}^{K} \sum_{r=1}^{R} \lambda^k \frac{\partial \Pr(j \mid p, \Theta^{r,k})}{\partial p_j} = 0. \quad (4)$$

Please see Appendix A for the derivation of the slopes of the probit demand system. Firm j can assess the choice of p_j^{uniform} by studying the corresponding posterior distribution of profits

$$\left\{ p_j^{\text{uniform}} \sum_{k=1}^{K} \lambda^k \frac{1}{R} \Pr(j \mid p, \Theta^{r,k}) \right\}_{r=1}^{R}.$$

We also investigate various forms of mobile discount targeting facilitated by mobile technology. In our application, we can partition consumers into $K = 4$ segments based on their location during the off-peak period (theater A versus theater B) and their recency state (high versus low). Let Ω denote a partition of the $K = 4$ segments. We use the following partitions:

- *Geographic targeting*:

$$\Omega = \{\text{location A, location B}\}$$
$$= \{\{\text{high type in loc. A, low type in loc. A}\}, \{\text{high type in loc. B, low type in loc. B}\}\};$$

- *Behavioral targeting* on type:

$$\Omega = \{\text{high type, low type}\}$$
$$= \{\{\text{high type in loc. A, high type in loc. B}\}, \{\text{low type in loc. A, low type in loc. B}\}\};$$

- *Geobehavioral targeting*:

$$\Omega = \{\text{high type in loc. A, low type in loc. A, high type in loc. B, low type in loc. B}\}.$$

For a given partition with elements $\omega \in \Omega$, firm j's targeted pricing problem consists of picking the vector of prices p_j^{Ω} as follows:

$$p_j^{\Omega} = \arg\max_{p_j} \left\{ \sum_{\omega \in \Omega} p_{j\omega} \sum_{k \in \omega} \lambda^k \mathbb{E}[\Pr(j \mid p_{\omega}, \Theta^{r,k}) \mid \mathbf{D}^k] \right\}$$
$$\approx \arg\max_{p_j} \left\{ \sum_{\omega \in \Omega} p_{j\omega} \sum_{k \in \omega} \lambda^k \frac{1}{R} \sum_{r=1}^{R} \Pr(j \mid p_{\omega}, \Theta^{r,k}) \right\}, \quad (5)$$

which generates the following first-order necessary conditions:

$$\sum_{k \in \omega} \left(\lambda^k \sum_{r=1}^{R} \Pr(j \mid p_{\omega}, \Theta^{r,k}) + p_{j\omega}^{\Omega} \sum_{r=1}^{R} \lambda^k \frac{\partial \Pr(j \mid p_{\omega}, \Theta^{r,k})}{\partial p_j} \right) = 0, \quad \forall\, \omega \in \Omega. \quad (6)$$

Please see Appendix A for the derivation of the slopes of the probit demand system. Firm j can assess the choice of p_j^{Ω} by studying the corresponding posterior distribution of profits

$$\left\{ \sum_{\omega \in \Omega} p_{j\omega}^{\Omega} \sum_{k \in \omega} \lambda^k \frac{1}{R} \Pr(j \mid p, \Theta^{r,k}) \right\}_{r=1}^{R}.$$

In several of our targeting schemes, demand consists of a mixture over different consumer types. Under geographic targeting, demand for theater j in location k is given by

$$S_{j\,|\,k} = \lambda^{(\text{low},k)}\Pr(y = j \mid p_k, \Theta^{(\text{low},k)}) + \lambda^{(\text{high},k)}\Pr(y = j \mid p_k, \Theta^{(\text{low},k)}).$$

Similarly, under type targeting, demand for theater j from type k consumers is given by

$$S_{j|k} = \lambda^{(A,k)}\Pr(y = j \mid p_k, \Theta^{(A,k)}) + \lambda^{(B,k)}\Pr(y = j \mid p_k, \Theta^{(A,k)}).$$

We assume the firms select a pricing structure based on its posterior mean profitability. Since each scenario uses the same posterior distribution of demand parameters, $F_\Theta(\Theta \mid \mathbf{D})$, the posterior distribution of profits will be correlated across scenarios. One must therefore be careful when comparing marginal profit distributions. To account for statistical uncertainty when comparing pricing structures, we use the posterior probability of a profit difference. Consider two scenarios of interest with price vectors p and $\tilde{p}$, respectively. Formally, we want to test whether $\pi_j(p) > \pi_j(\tilde{p})$ conditional on our data $\mathbf{D}$, where $\pi_j(p)$ is firm j's profit when both firms use prices p. We can compute the exact posterior probability that firm j is more profitable in a scenario with prices p than prices $\tilde{p}$ as follows:

$$\text{Prob}(\pi_j(p) > \pi_j(\tilde{p}) \mid \mathbf{D}) = \frac{1}{R}\sum_{r=1}^{R} 1_{\{\pi_j(p \mid \Theta^r) > \pi_j(\tilde{p} \mid \Theta^r)\}}. \quad (7)$$

6.2. Ignoring Competitor Response

In Section 4, we found that a theater could increase its revenue substantially during the off-peak period by issuing mobile discounts. We now compute the optimal mobile discounts during the off-peak period. In practice, firms may run a pilot study to determine the optimal price under the implicit assumption that the competitor's price remains fixed. We now compute each firm's optimal uniform coupon structure, geotargeted coupon structure, behaviorally targeted coupon structure, and geobehaviorally targeted coupon structure. In each case, we first hold the competitor's price at RMB 75 to mimic the format of the typical pilot test. For each coupon structure, we then combine our demand estimates, from Section 5.3, with the corresponding system of first-order necessary conditions, from Section 6.1.

We assume that the off-peak period of demand is an independent market relative to other time slots in the day. We therefore rule out the possibility that low, "early-bird" prices would cannibalize demand at peak periods of the day (e.g., Saturday evening) when the theater typically sells many more tickets at the full price of RMB 75. Solving the full dynamic pricing game where consumers optimally decide when to see a movie during the course of the day is beyond the scope of our data and analysis. Our corporate partners do not believe that most evening consumers would substitute for a showing before noon. Some of the cannibalization would be limited by the fact that only consumers in the mall before noon on a Saturday would ever learn that mobile discounts were offered for the off-peak period (i.e., regular evening moviegoers would not receive such coupons). In addition, cannibalization could be averted by restricting the mobile coupons to apply only to midday showtimes. In spite of these factors, we are unable to test whether cannibalization would occur over the longer term, and this is a limitation of our analysis.

Figure 8 displays each firm's best-response function when each uses a uniform mobile discount during the off-peak period; that is, we plot each firm's optimal uniform mobile discount corresponding to a given rival price. The green arrows indicate where each theater would set its price if it optimized against the assumption that the rival will charge the full RMB 75 ticket price. We can immediately see that each theater would offer a substantial discount of about 70% off the regular RMB 75 box-office price. This type of early-bird discount is comparable to the early-bird rates observed in U.S. theaters during similar off-peak periods of the day. A recent price search on Fandango.com revealed many AMC[14] theaters in shopping malls in large urban areas offering early-bird discounts of more than 60% off the regular evening box-office price on newly released movies. For example, the AMC Van Ness 14 theater in San Francisco posted an early-bird price of \$6.29 for a

Figure 8. Uniform Pricing

Figure 9. Best-Response Functions for Geotargeting

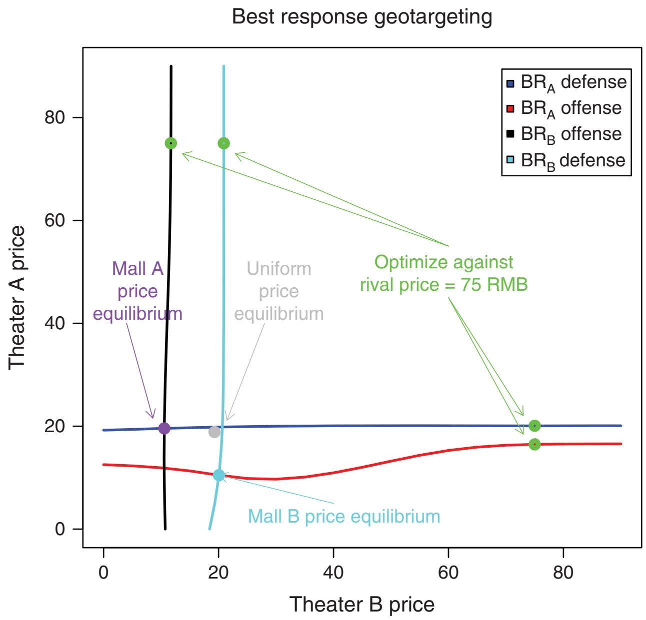
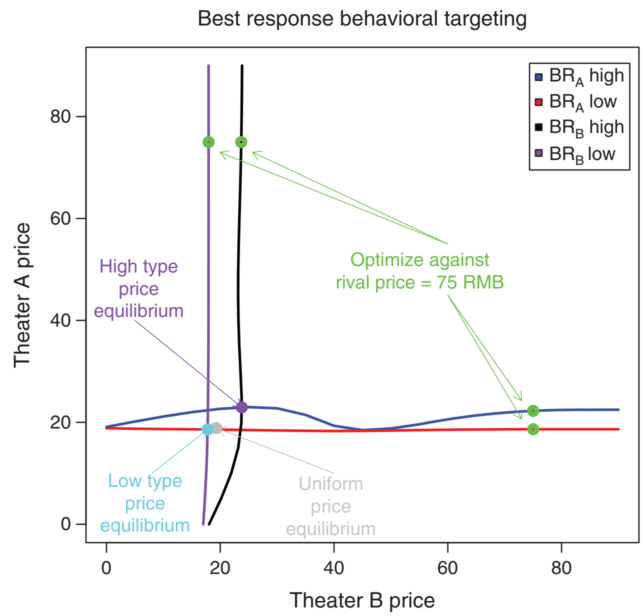


Figure 10. Best-Response Functions for Behavioral Targeting



morning showing of its newly released films, a matinee price of $11.09 for early afternoon shows, and a regular evening price of $16.59 for shows after 7 P.M.[15] This early-bird discount of 62% off the regular evening price is comparable to our optimized 70% discount off the regular price.

Figure 9 displays each firm's best-response function when both use geotargeted pricing. The green arrows indicate how each firm would price in each of the two geographic markets (near theater A and near theater B, respectively). As expected, each firm would target a lower price in the rival's market than in its own market. Thus, the early-bird rate charged by a theater would be more aggressive in the rival's market.

Figure 10 displays each firm's best-response function when both use behaviorally targeted pricing. The green arrows indicate how each firm would price in each of the two consumer recency segments (high and low). Now we see more symmetry in the theaters' targeting decisions. Both theaters target higher prices to high-recency consumers than low-recency consumers. Furthermore, the price targeted to high-recency customers would be nearly RMB 3 higher than the uniform discount.

In Table 4, we report each theater's anticipated revenues for each targeting structure when each firm, respectively, assumes the rival will not change its price from RMB 75. We also report each firm's realized revenues when both theaters concurrently set prices with incorrect beliefs about competitor prices.

As expected from the theory of monopoly price discrimination, both firms anticipate the higher expected profits from geobehavioral targeting when they ignore competitor response. This is because the geobehavioral prices implement a more granular form of price discrimination. Even though we observe overlap in the posterior credibility intervals of profits across scenarios,[16] a given theater's expected posterior profits are significantly higher when it targets different coupons across segments. For both theaters, there is close to 100% posterior probability that realized revenues will be lower than anticipated under each targeting scheme. For theater A, the expected realized revenues are between 14.5% and 15% lower across the various targeting structures. For theater B, the expected realized revenues are between 3% and 4% lower.

In sum, both theaters would benefit from an early-bird discount. Moreover, as per the literature on monopoly price discrimination, both firms would expect to increase profitability by targeting different early-bird discounts across different consumer segments. However, each theater would also overestimate those incremental profits from targeting during the off-peak period of demand if it pilot tested its targeting under the assumption that the competitor would not also implement a targeting scheme of its own. For theater A, the expected realized posterior profits from geotargeting are lower than those from uniform pricing if theater B also implements geotargeting.

A potential concern with these findings is that the voucher is valid all day, even though it is purchased before noon. We cannot track exactly when the respondent redeemed her voucher and saw a movie. As explained earlier, our corporate partner did not believe many (if any) respondents would leave the mall and then return later in the day during a peak period to see a movie. However, we cannot rule out that some of the

Table 4. Anticipated vs. Realized Profits from Mobile Targeting

	Expected anticipated revenue per messaged consumer (RMB)		Expected realized revenue per messaged consumer (RMB)	
	Theater A	Theater B	Theater A	Theater B
Full price	0.124	0.237	0.124	0.237
	(0.085, 0.171)	(0.162, 0.32)	(0.085, 0.171)	(0.162, 0.32)
Uniform price	2.296	3.026	1.961	2.913
	(1.81, 2.823)	(2.352, 3.86)	(1.46, 2.52)	(2.24, 3.74)
Geotargeting	2.305	3.116	1.956	3.013
	(1.82, 2.837)	(2.428, 3.946)	(1.451, 2.521)	(2.332, 3.835)
Behavioral targeting	2.306	3.054	1.979	2.946
	(1.822, 2.838)	(2.376, 3.884)	(1.473, 2.542)	(2.269, 3.766)
Geobehavioral targeting	2.321	3.15	1.98	3.036
	(1.833, 2.852)	(2.451, 3.979)	(1.47, 2.544)	(2.347, 3.865)

Notes. The anticipated revenues for theater i are $\pi_i(p_i^* \mid p_{-i} = 75)$, and the realized revenues for theater i are $\pi_i(p_i^* \mid p_{-i} = p_{-i}^*)$. The 95% posterior credibility intervals are reported in parentheses.

large profit gains may be cannibalizing demand from later in the day.

6.3. Equilibrium Pricing

Suppose both firms run successive tests over time and adjust their prices accordingly. As one theater implements a new price, it changes the rival's "best response," causing the rival to adjust its price. Recent research (e.g., Doraszelski et al. 2017) found that firms may eventually reach a Nash equilibrium through such repeated pricing interactions with learning. Accordingly, we study the static Nash equilibrium in prices as an approximation of ongoing pricing behavior in this market. The Nash equilibrium assumption allows us to analyze the role of competitive response formally. We assume that the off-peak period of demand is a separate market from the peak periods of demand, such as during the evening.

Like many oligopoly models with empirically realistic demand specifications (e.g., random coefficients logit), it is not possible to prove existence and uniqueness of a Bertrand–Nash price equilibrium for a probit demand oligopoly except under very strong independence assumptions (Mizuno 2003).[17] In our numerical simulations, existence is established by computing a fixed point to the system of necessary conditions. Uniqueness is verified by inspecting each firm's best-response function over the range of prices from RMB 0 to RMB 75.

6.4. Equilibrium Uniform Pricing Results

Results for the uniform equilibrium prices during the off-peak period are displayed in Table 5. Consistent with the experimental results, both firms have strong incentives to reduce their prices. In equilibrium, firm A charges RMB 19.29 per ticket, and firm B charges RMB 18.86 per ticket, drawing in substantial demand, especially from the low consumer segment. These prices are in fact not much different from the pilot-test results discussed in Section 6.3. Note that the best-response curves plotted in Figure 8 indicate that, at least for uniform pricing, neither firms' optimal price is very sensitive to what the rival charges, even though the level of demand would be affected.

6.5. Equilibrium Unilateral Targeting Results

We now explore each theater's incentives to target prices across the different consumer segments during the off-peak period of demand. We begin by investigating what happens when one firm unilaterally runs a targeting campaign while the other firm continues to offer a uniform discount during the off-peak period but is allowed to adjust its uniform price in equilibrium. We compute the Nash equilibrium during the off-peak period for which one firm targets while the other firm sets a uniform price.

The unilateral targeting results are reported in Table 6. The first row repeats the last row of Table 5, indicating the expected revenues per messaged consumer under uniform pricing, which we use as a benchmark. The subsequent rows report each firm's expected revenues when it unilaterally implements targeted mobile coupons. Unlike the case of monopoly price discrimination, a firm does not unambiguously increase its expected profits by unilaterally targeting in equilibrium. Theater A, for instance, is worse off using geotargeting than uniform pricing when theater B uses a uniform pricing strategy. By discounting its price in theater B's local area, theater A triggers a defensive

Table 5. Uniform Price Equilibrium

	Firm A	Firm B
Price	19.2942	18.8641
Share		
High type, location A	0.1896	0.0168
Low type, location A	0.2795	0.0465
High type, location B	0.0005	0.2039
Low type, location B	0.0106	0.2380
Expected profit per messaged consumer	1.9604	2.9133

Table 6. Unilateral Targeting

	Profit per messaged consumer	
	Firm A	Firm B
Uniform	1.96	2.91
	(1.46, 2.52)	(2.24, 3.74)
Geotargeting	1.933	3.01
	(1.45, 2.49)	(2.33, 3.83)
Behavioral targeting	1.97	2.94
	(1.46, 2.53)	(2.26, 3.76)
Geobehavioral targeting	1.98	3.04
	(1.47, 2.55)	(2.35, 3.87)

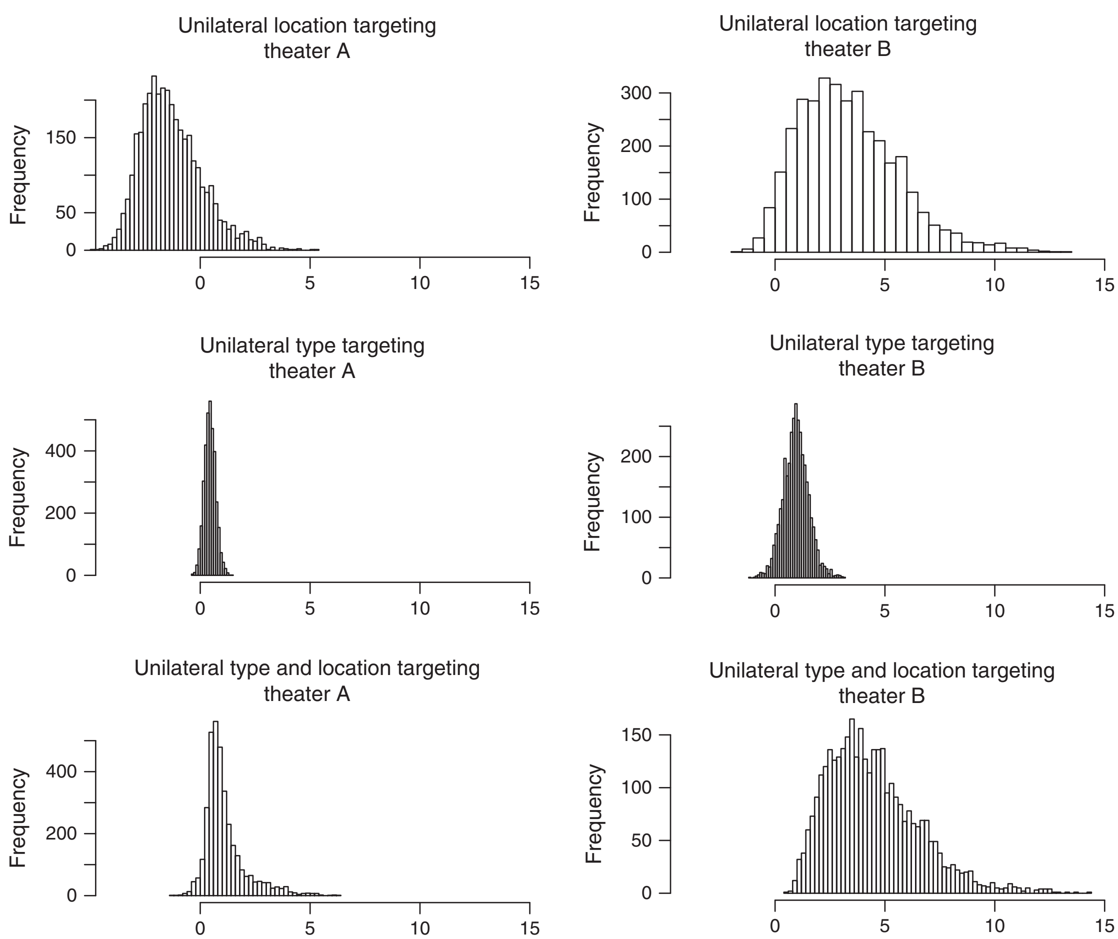
Note. 90% posterior credibility intervals are in parentheses.

reaction, causing theater B to lower its price. Surprisingly, theater A would be better off using a uniform mobile coupon policy than geotargeting once theater B is able to adjust its own price in equilibrium.

Figure 11 plots the posterior distribution of the percentage difference in revenues under targeting and uniform pricing for each scenario. Relative to uniform pricing, theater A generates an expected loss of −1.31% with unilateral geographic targeting, but an expected gain of 0.44% under unilateral type targeting, and 1.1% when unilaterally combining type and geographic targeting. By contrast, theater B gains under all three unilateral targeting scenarios, with an expected gain of 3.33% under geographic targeting, 0.94% under type targeting, and 4.45% under both. Figure 11 also visualizes the posterior probability associated with profit differences between pricing scenarios. For instance, there is only a 17% posterior probability that theater A would be more profitable under unilateral geographic targeting than under uniform pricing. By contrast, type targeting and geobehavioral targeting both have more than a 96% posterior probability of being more profitable than uniform pricing for theater A. For theater B, all three unilateral targeting scenarios have at least a 95% posterior probability of being more profitable than uniform pricing.

While we do not report the results for the theater using uniform pricing in Table 5 and Figure 11, the findings are as one might expect. Under geographic targeting, the passive competitor's expected profits fall by 1.24% for theater A and by 0.47% for theater B. These losses reflect the fact that the targeting firm charges substantially lower prices in the rival's market.

Figure 11. Posterior Distribution of the Percentage Difference in Unilateral Revenues per Messaged Consumer Under Targeting vs. Uniform Pricing



Interestingly, the theater using uniform pricing always has a slightly positive expected revenue gain under unilateral behavioral targeting. Under behavioral targeting, the targeting firm raises its price in the high consumer segment, causing some consumers to substitute to the competitor and softening competition. This incremental revenue increases total competitor profits.

In the last row of Table 6, we look at the combination of geobehavioral targeting by allowing firms to price discriminate unilaterally across all four consumer segments. Both firms are unambiguously better off with this finer degree of price discrimination. In summary, both firms would benefit from at least one form of targeting when the rival uses uniform pricing.

6.6. Equilibrium Targeting

We now consider scenarios in which both firms target. Under each targeting scenario, both firms set their prices to satisfy the optimality conditions in Equation (6). From the theoretical literature on competitive price discrimination, we already know that the returns to targeting in equilibrium are not unambiguous.

We first refer back to each firm's best-response function in each of the targeting scenarios, as plotted in Figures 9 and 10.[18] We can immediately see that under geotargeting, we have best-response asymmetry. Each firm considers its own market as the "strong" market and its rival's market as the "weak" market along the entire support. From Corts (1998), we know that the returns to targeting on firm profits are ambiguous in this case. By contrast, under behavioral targeting, we have best-response symmetry. Each firm considers the high market to be strong and the low market to be weak along the entire support. From Holmes (1989), Corts (1998), and Armstrong and Vickers (2001) we know that equilibrium profits can rise in this scenario as long as competition is sufficiently intense in the "strong" market. We already know from Table 3 that the cross-price elasticities are much larger in the high market than in the low market. In fact, cross-price elasticities are nearly zero in the low markets, suggesting almost no competition.

In Table 7, we summarize each firm's equilibrium revenues under each targeting scenario. We report the posterior mean profits for each firm along with the respective 90% posterior credibility intervals. Recall that the correlation in profits between pricing scenarios implies that credibility intervals can be highly overlapping even though one scenario has a very high probability of being more profitable than another.

Beginning with behavioral targeting, both firms' expected equilibrium profits are slightly higher than in their respective unilateral targeting scenarios.[19] Even though we observe overlap in the posterior credibility intervals of profits across scenarios, the posterior probability that a given theater's profits are higher when both engage in behavioral targeting as opposed to when it unilaterally uses behavioral targeting is over 99% for each theater. This result is consistent with the theoretical literature under best-response symmetry. Equilibrium price levels are reported in Table 8. Theaters A and B lower their prices by only 3.6% and 5.8%, respectively, in the low market, where competition is relatively light. By contrast, theaters A and B increase their prices by 18.9% and 26.0%, respectively, in the high market, where competition is relatively intense. Behavioral targeting softens price competition in the high segment. This result is also visualized in Figure 10, where the intersection of the best-response functions in the low market are very close to the uniform price equilibrium, whereas the best-response functions in the high market intersect at substantially higher levels for both theaters. Figure 12 plots the posterior distribution of the percentage difference in revenues under targeting and uniform pricing for each scenario. Both firms strictly benefit from behavioral targeting relative to uniform pricing.

By contrast, under geotargeting, Table 7 reveals that both firms' expected equilibrium profits are lower than in either of their respective unilateral targeting scenarios. The posterior probability that a given theater's profits are higher when both engage in geotargeting as opposed to when it unilaterally uses geotargeting is only 1.1% for theater A and 18.7% for theater B. In this scenario, with best-response asymmetry, the theory is ambiguous, and the results are ultimately an empirical

Table 7. Equilibrium Targeting

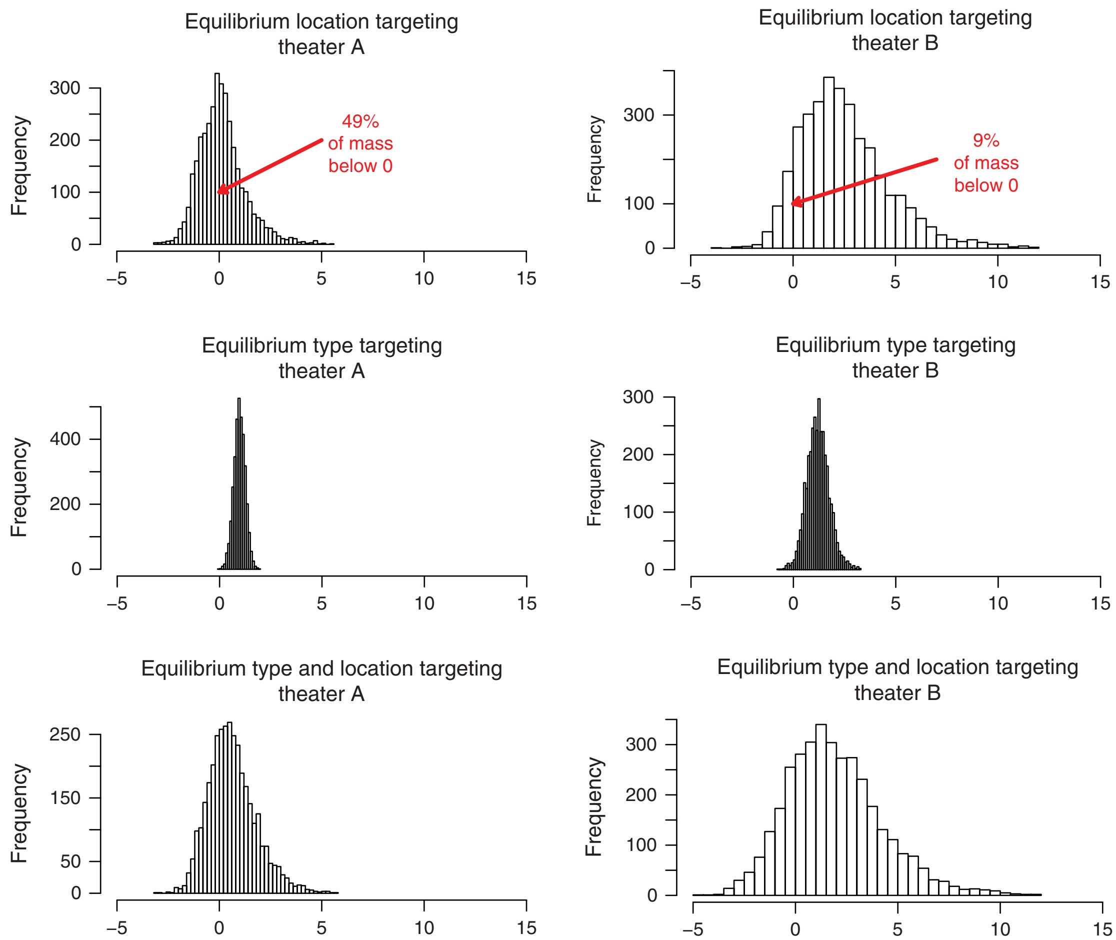
	Expected revenue per messaged consumer (RMB)	
	Theater A	Theater B
Uniform	1.96	2.91
	(1.46, 2.52)	(2.24, 3.74)
Geotargeting	1.96	2.98
	(1.46, 2.53)	(2.3, 3.82)
Behavioral targeting	1.98	2.95
	(1.47, 2.54)	(2.27, 3.77)
Geobehavioral targeting	1.97	2.97
	(1.47, 2.54)	(2.28, 3.8)

Note. 90% posterior credibility intervals are in parentheses.

Table 8. Equilibrium Prices

	Market	Theater A price	Theater B price
Uniform	Pooled	19.294	18.864
Geotargeting	Loc. A	19.575	10.564
	Loc. B	10.485	20.064
Behavioral targeting	High	22.948	23.786
	Low	18.597	17.775
Geobehavioral targeting	Loc. A, high	21.335	10.870
	Loc. A, low	19.146	10.546
	Loc. B, high	5.230	20.595
	Loc. B, low	11.874	19.322

Figure 12. Posterior Distribution of the Percentage Difference in Equilibrium Revenues per Messaged Consumer Under Targeting vs. Uniform Pricing



matter. Theaters A and B raise their prices by only 1.5% and 6.4%, respectively, in their defensive markets. By contrast, they lower their prices by 44% and 45.7%, respectively, in their offensive markets. In other words, each firm launches a massive price attack in the other's local market. While this does not lead to an all-out price war, it severely limits the extent to which firms can benefit from local price discrimination in a competitive environment. This result is also visualized in Figure 9, where the intersection of the best-response functions involve defensive prices that are very close to the uniform price levels, but the offensive prices are considerably lower.[20] Looking at the top panel of Figure 12, we can see that 49% of the posterior probability mass in the distribution of profit differences for geographic targeting relative to uniform pricing is negative for theater A. Just over 9% is negative for theater B.

In the last row of Table 7, we allow each firm to use geobehavioral targeting. Recall that when the theaters ignore competitor response, as in Section 6.2, they anticipate the highest expected profits under geobehavioral targeting. With competitive targeting, both firms realize higher expected equilibrium revenues with coarser price discrimination. Theater A is better off with pure behavioral targeting, and theater B is better off with pure geotargeting.

An interesting empirical question is whether firms would endogenously choose to price discriminate in equilibrium. As in Chen and Iyer (2002), we can also investigate potential asymmetries in each firm's incentives to select a specific targeting scheme based on a specific form of consumer targetability.[21] Consider a two-period game in which each theater first commits to a pricing structure (targeting versus uniform), and then in the second period each theater plays its corresponding Bertrand–Nash pricing strategy.

Table 9 sets up the payoff matrix associated with the 4×4 game in which each firm selects either the uniform pricing strategy or one of the three targeting strategies. One of the three forms of targeting is always a best response for each theater, regardless of the other theater's pricing choice. However, the specific targeting best response varies across competitor actions. For our demand estimates, there is a unique equilibrium in the first stage of the game in which both firms choose behavioral targeting. Conditional on theater B

Table 9. Targeting Choice as a Strategic Game (Each Theater's Expected Revenue per Messaged Consumer)

		Firm B			
		Uniform	Geographic	Behavioral	Geobehavioral
Firm A	Uniform	1.960, 2.913	1.937, 3.007	1.969, 2.940	1.942, 3.041
	Geotargeting	1.933, 2.900	1.963, 2.984	1.956, 2.651	1.958, 2.768
	Behavioral targeting	1.969, 2.919	1.956, 2.383	1.979, 2.948	1.977, 2.722
	Geobehavioral	1.982, 2.905	1.966, 1.501	1.978, 1.882	1.973, 2.968

using behavioral targeting, the posterior probability that theater A could increase its profits by deviating to uniform pricing or geographic targeting is less than 1%; although, it is 40% for geobehavioral targeting. When theater A uses behavioral targeting, the posterior probability that theater B could increase its profits by deviating is less than 3% for uniform, geographic, and geobehavioral targeting. Therefore, in equilibrium, both firms choose behavioral targeting, and the improvement in profits relative to uniform pricing is highly significant.

The equilibrium choice of behavioral targeting is surprising given that both theaters would perceive and realize higher incremental revenues from a richer, geobehavioral targeting scheme in the scenario where they do not anticipate competitor targeting (Table 4). Therefore, in equilibrium, the firms do not select the most granular form of targeting. In fact, theater B derives higher incremental revenues from geotargeting when it does not consider competitor response. When we restrict the theaters to using symmetric targeting rules, they will still always choose targeting over not targeting, as expected. However, in the case of geotargeting, there is a nontrivial probability that a prisoner's dilemma could emerge. Under geotargeting, theater A faces a 48% posterior probability that profits will be lower than in the case where both firms use uniform pricing. For theater B, the posterior probability of lower prices than under uniform pricing is only 9%.

The non-IIA preferences in the multinomial probit demand framework play an important role in our findings. To investigate the role of IIA, we rerun our equilibrium targeting analysis with $\rho = 0$ to eliminate the correlation in preferences. The results are reported in Table B.12 in Appendix B. The most striking difference from above is that targeting on geography reduces theater A's equilibrium profits. This is because setting $\rho = 0$ reduces substitutability for consumers located near theater B, making it harder for theater A to poach consumers. However, setting $\rho = 0$ increases substitutability near theater A, making it easier for theater B to poach consumers. Consequently, theater A has a harder time poaching and, at the same time, needs to intensify its local defensive pricing. Although not reported, when we use the logit demand system that exhibits the IIA property, we actually find that the strategic decision to target on geography versus uniform pricing creates a prisoner's dilemma whereby each firm targets and generates lower equilibrium profits than under uniform pricing. Recall that the logit demand model exhibits inferior fit, based on the posterior marginal likelihood. Therefore, explicitly eliminating the IIA property with an unrestricted, multinomial probit demand is important for our conclusions about the equilibrium implications of targeting.

7. Conclusions

This study provides empirical evidence on the effectiveness of targeted pricing in a competitive market, using a mobile field experiment. Using a novel experimental design that independently varies the actual prices of two competing firms, our approach bridges the gap between applied theory and empirical work to provide several managerially relevant insights and methods. In particular, when the structure of consumer segments creates best-response symmetry and competition is tougher in the strong market, competitive price targeting can soften overall price competition, leading to higher profits than under uniform pricing. By contrast, when consumer segments lead to best-response asymmetry, competitive price targeting can toughen price competition, leading to lower prices and lower profits than under uniform pricing.

In practice, most firms test targeting strategies while holding their competitors' actions fixed. Implicitly, firms are applying the monopoly theory of price discrimination. However, the theory literature on competitive price discrimination shows that monopoly price discrimination may provide the wrong analogy for profitability. We find that firms have a strong unilateral incentive to target pricing in our mobile setting and are not deterred by the threat of competitive response. However, competition moderates the profitability of targeted pricing. Interestingly, competition raises the profitability of behavioral targeting where firms face symmetric pricing incentives that soften price competition. By contrast, competition lowers the profitability of geographic targeting, where firms face asymmetric pricing incentives that toughen price competition. In sum, while competitive targeting does not result in lower profits per se, we do find that firms may misestimate the profitability of targeted pricing by disregarding competitive response.

For our study of movie theaters, a manager would conclude that the returns to behavioral targeting generate larger incremental profits (approximately 1% for each firm) than geotargeting in a competitive market where both firms target their prices. A manager would have reached the opposite conclusion had she disregarded competition. An evaluation of a unilateral targeting scheme in which the competitor does not deviate from its regular box-office pricing overestimates the returns to geotargeting and underestimates the returns to behavioral targeting. As a rule of thumb, the degree of symmetry or asymmetry in a competitor's pricing incentives can provide guidance on the potential direction of bias in a unilateral evaluation. Finally, if we endogenize the choice of how to target, a symmetric behavioral targeting equilibrium emerges even though a more granular geobehavioral targeting is feasible. By contrast, if we ignore competitor response, both firms would unambiguously select geobehavioral targeting.

Our analysis also reveals both the academic and managerial importance of the design of the experiment. We manipulated both firms' actions simultaneously. In practice, most firms have some understanding of their own profits conditional on their competitors' current prices. However, they are unlikely to have knowledge of how their optimal policies would change under counterfactual prices by their competitors. This study demonstrates the importance of strategic considerations when a firm evaluates the adoption of new targeting technologies. We address that the experiment did not contain the best response levels of each firm by using a structural model. This combination of both an experiment and a model offers a pragmatic solution to practitioners who might not be able to test "enough" price points to observe the optimum or equilibrium in a model-free manner. In practice, if a firm was able to test "enough" price points, the equilibrium would be "observed," simplifying the analysis considerably by obviating the need for the demand estimation and price optimization.

The equilibrium analysis at the end of this paper applies to a static, simultaneous-moves pricing game. We have not addressed the potential interdependence between our off-peak period and more popular time slots for movies later in the day. While our corporate partners do not anticipate typical evening movie consumers to start going to early-bird showings, we cannot rule out that our findings would change should such cannibalization arise. An interesting direction for future research would be to conduct experiments like the one herein across multiple time slots and to track subjects over time to see if they change their usual movie theater visiting behavior.

We also do not address the potential endogeneity of the consumer segment definitions that can arise in a multiperiod environment. In practice, as targeting draws more consumers into a theater, it endogenously changes the composition of the "recency" segments. In our application, we define recency based on consumers' visits to the theater at regular box office prices, not based on targeted promotional prices. However, an interesting direction for future research would be to explore how dynamics affect equilibrium targeting and whether firms would continue to profit from behavioral targeting. Moreover, it would be interesting to explore whether behavioral targeting would involve targeting lower prices to firms' strongest local consumers in such a dynamic setting as in Shin and Sudhir (2010). We also assume that consumer locations are exogenous. However, another interesting direction for future research would be to explore whether consumers change their mall visiting behavior in response to their experiences with different degrees of targeted pricing across locations, as in Chen et al. (2017). In this regard, our analysis might be interpreted as the short-term effects of price targeting. Longer term, consumers may strategically alter their location choices to arbitrage the real-time couponing.

Finally, we analyze a very specific form of behavioral targeting based on recency. An interesting direction for future research may be to study alternative forms of behavioral targeting and the conditions under which they toughen versus soften price competition.

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Appendix A. Probit Derivatives

Recall that the expected probability that a consumer chooses alternative j is

$$\Pr(y=j \mid B, X, \Psi) = \Phi(\mu_{z1}^{(1)}, \mu_{z2}^{(1)}; \rho_Z^{(1)}).$$

The matrix of derivatives of the share is as follows:

$$\frac{\partial \mathrm{Prob}(y=j \mid B, X, \Psi)}{\partial X^T} = \frac{\partial \mathrm{Prob}(y=j \mid B, X, \Psi)}{\partial \mu_z^{(j)T}} \frac{\partial \mu_z^{(j)}}{\partial X^T},$$

where

$$\frac{\partial \mu_z^{(j)}}{\partial X'} = \mathrm{diag}(\Sigma_z^{(j)})^{-1/2} \Delta^{(j)} B.$$

It is straightforward to show (see Appendix A.1) that

$$\frac{\partial \Phi(x, y; \rho)}{\partial x} = \phi(x) \Phi\left(\frac{y-\rho x}{\sqrt{1-\rho^2}}\right),$$

and therefore

$$\frac{\partial \Pr(y=j \mid B, X, \Psi)}{\partial \mu_{zi}^{(j)}} = \phi(\mu_{zi}^{(j)}) \Phi\left(\frac{\mu_{z(3-i)}^{(j)} - \rho \mu_{zi}^{(j)}}{\sqrt{1-\rho^2}}\right).$$

A.1. Derivative of Bivariate Gaussian

$$\frac{\partial \Phi(x, y; \rho)}{\partial x} = \int_{\infty}^{y} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left(-\frac{x^2 - 2\rho x v + v^2}{2(1-\rho^2)}\right) dv.$$

If you complete the square inside the exp$(\cdot)$ function, you can isolate the component depending on v

$$\exp\left(-\frac{x^2 - 2\rho x v + v^2}{2(1-\rho^2)}\right) = \exp\left(-\frac{(v - px)^2}{2(1-\rho^2)}\right) \exp\left(-\frac{x^2}{2}\right).$$

We can rewrite the derivative as

$$\frac{\partial \Phi(x, y; \rho)}{\partial x} = \phi(x)\Phi\left(\frac{y - \rho x}{\sqrt{1-\rho^2}}\right).$$

Table B.3. Comparison of Locations

	Location A	Location B
Shopping area (sq. meters)	102,000	120,000
Bus lines	10	10
Visitors (people/day)	53,000	55,000
Number of merchants	650	670
Population (1 km radius)	26,367	24,233

Notes. Shopping mall location statistics were drawn from the respective malls' promotional materials, except for population. The nearby population (within 1 km) was estimated using geographic information system data from the 2010 Census, provided by a research center at the University of Michigan, Ann Arbor.

Appendix B. Supplemental Figures and Tables

Table B.1. Summary Statistics

Segment	ARPU	MOU	SMS	GPRS	N
Loc. A and	109.96	771.54	205.23	90,127.72	4,450
high	−85.19	−720.44	−279.56	−217,276	
Loc. A and	111.02	772.97	202	85,707.8	4,461
low	−92.06	−726.6	−224.21	−132,691	
Loc. B and	110.22	766.16	212.39	94,731.77	4,550
high	−92.14	−709.3	−327.51	−274,771.8	
Loc. B and	112.19	774.46	206.72	90,548	4,539
low	−87.47	−711.54	−271.03	−206,697.4	
High	110.09	768.82	208.85	92,455.32	9,000
	−88.77	−714.82	−304.76	−248,021	
Low	111.61	773.72	204.38	88,148.87	9,000
	−89.77	−719.03	−248.93	−174,008.4	
Location A	110.49	772.26	203.61	87,915.03	8,911
	−88.69	−723.52	−253.37	−179,981.3	
Location B	111.2	770.31	209.56	92,642.42	9,089
	−89.84	−710.42	−300.64	−243,174.3	
All	110.85	771.27	206.61	90,302.1	18,000
	−89.27	−716.93	−278.26	−214,243.91	

Notes. ARPU, Average revenue per user; MOU, average minutes used per month; SMS, average number of SMS messages sent per month; GPRS, average kilobytes downloaded per month.

Table B.2. Mobile Usage Randomization Checks

	ARPU	MOU	SMS	GPRS	Combined
Unadjusted $p < 0.05$	6	0	0	0	6
Adjusted $p < 0.05$	0	0	0	0	0
Number of comparisons	36	36	36	36	144
Unadjusted rate (%)	17	0	0	0	4
Adjusted rate (%)	0	0	0	0	0

Notes. Randomization checks for the assignment of pricing treatments were performed using consumers' historical mobile usage variables presented in Table B.1. Unadjusted $p < 0.05$ and adjusted $p < 0.05$ count the number of pairwise comparisons between experimental cells where average mobile usages had statistically significant differences. The corresponding rates divide the counts by the number of comparisons. The unadjusted p-values find differences at an overall rate expected by chance. Adjusted p-values use Tukey's honest significant difference adjustments for multiple comparisons of pairwise means. The adjusted p-values find no significant differences. ARPU, Average revenue per user; MOU, average minutes used per month; SMS, average number of SMS messages sent per month; GPRS, average kilobytes downloaded per month.

Figure B.1. Offensive Purchase Rates vs. Logit and Probit Predicted Rates

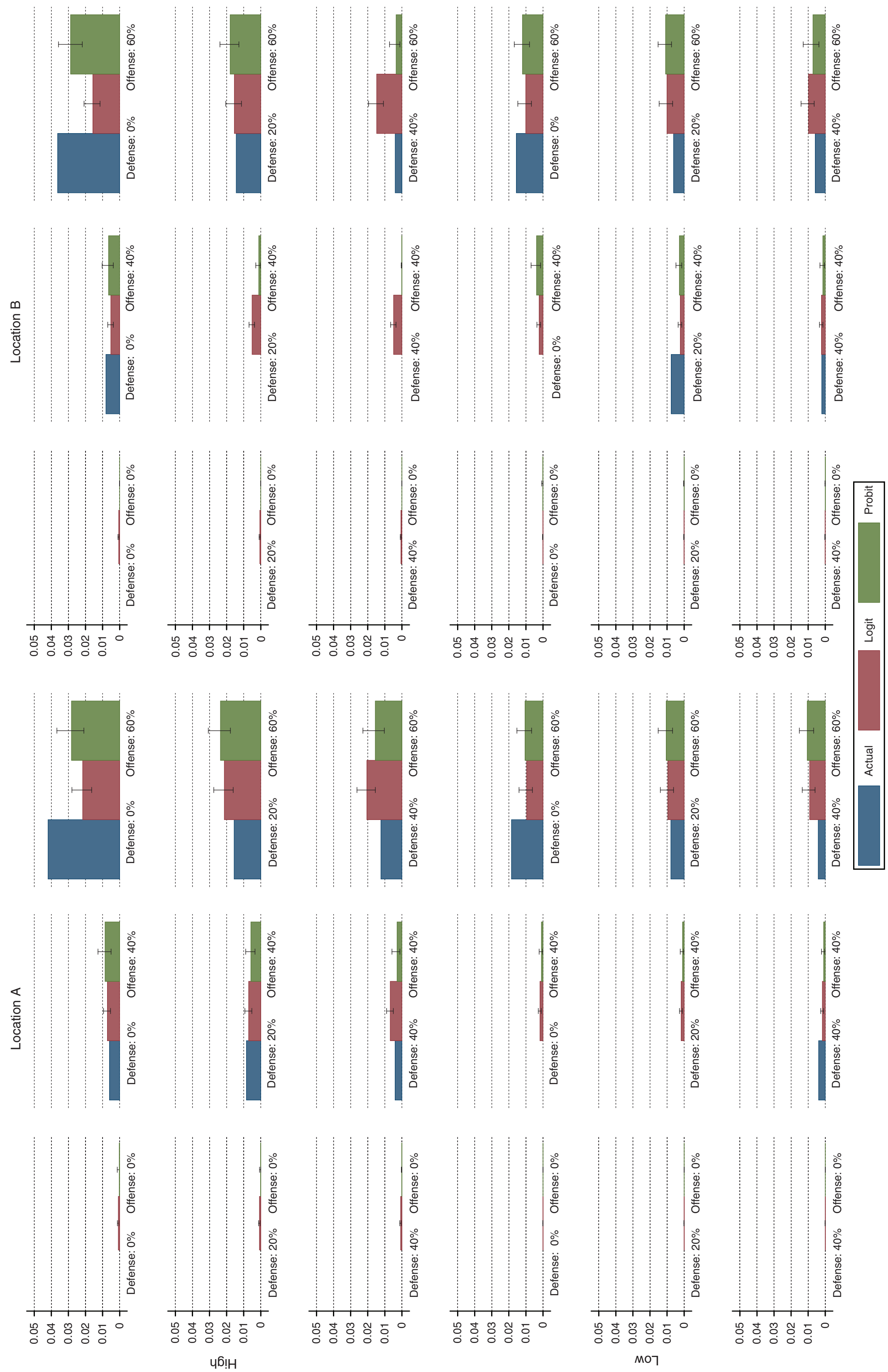

Figure B.2. Defensive Purchase Rates vs. Logit and Probit Predicted Rates

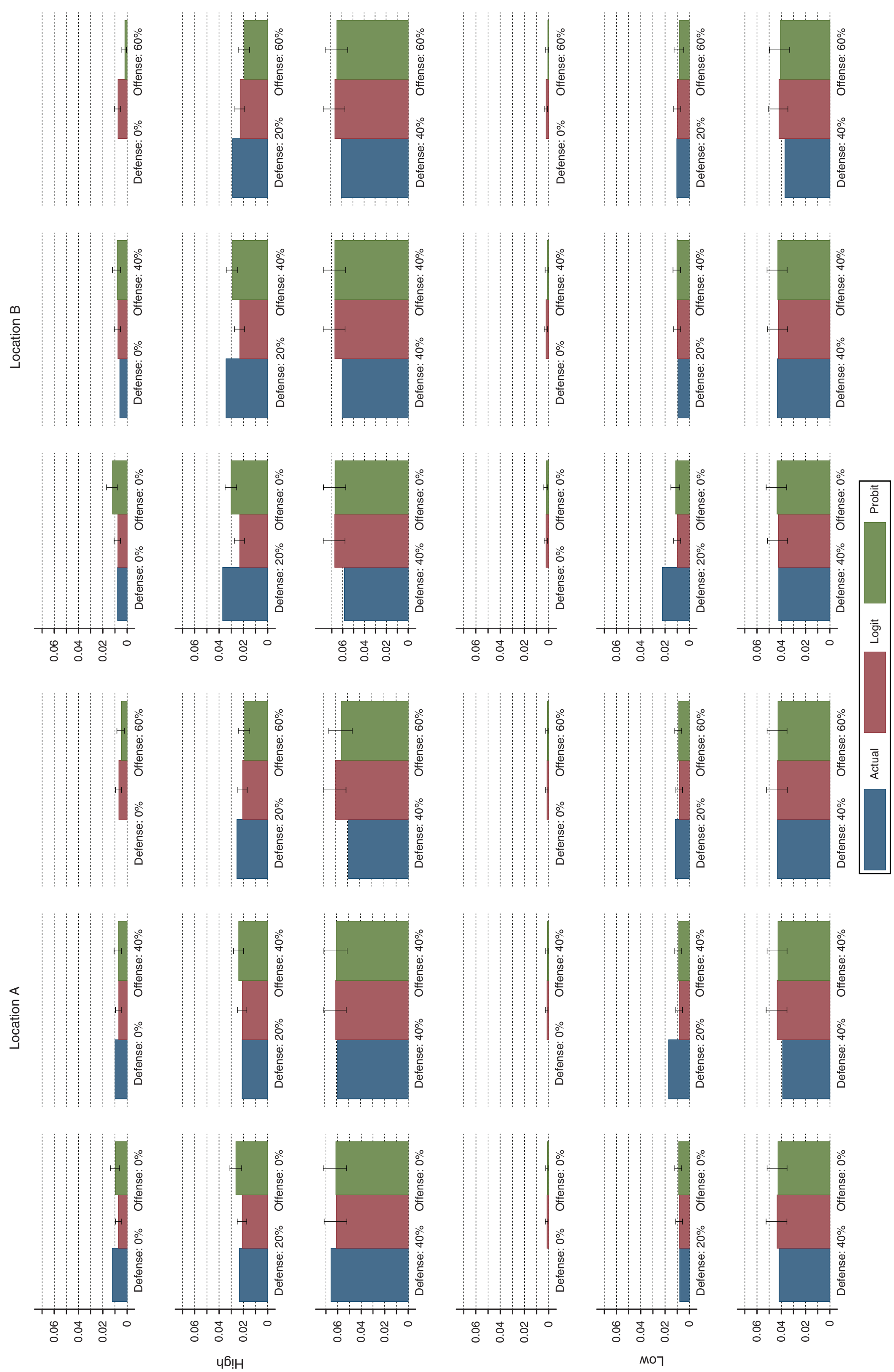

Table B.4. Aggregate Purchase Rates for Offensive Promotions

	Offensive discount					
Defensive discount	A 0%	B 40%	C 60%	D (B) – (A)	E (C) – (A)	F (C) – (B)
1. 0%	0.0000	0.0035^{**}	0.0280^{**}	0.0035^{**}	0.0280^{**}	0.0245^{**}
	(0.0000)	(0.0013)	(0.0037)	(0.0013)	(0.0037)	(0.0039)
2. 20%	0.0000	0.0040^{**}	0.0110^{**}	0.0040^{**}	0.0110^{**}	0.0070^{*}
	(0.0000)	(0.0014)	(0.0023)	(0.0014)	(0.0023)	(0.0027)
3. 40%	0.0000	0.0025^{*}	0.0065^{**}	0.0025^{*}	0.0065^{**}	$0.0040^{\dagger}$
	(0.0000)	(0.0011)	(0.0018)	(0.0011)	(0.0018)	(0.0021)
4. (2) – (1)	0.0000	0.0005	-0.0170^{**}	0.0005	-0.0170^{**}	-0.0175^{**}
	(0.0000)	(0.0019)	(0.0044)	(0.0019)	(0.0044)	(0.0048)
5. (3) – (1)	0.0000	−0.0010	-0.0215^{**}	−0.0010	-0.0215^{**}	-0.0205^{**}
	(0.0000)	(0.0017)	(0.0041)	(0.0017)	(0.0041)	(0.0045)
6. (3) – (2)	0.0000	−0.0015	−0.0045	−0.0015	−0.0045	−0.0030
	(0.0000)	(0.0018)	(0.0029)	(0.0018)	(0.0029)	(0.0035)

Notes. Means and differences are computed using experimental sample weights. Standard errors for differences in proportions and all p-values are computed using conventional normal approximation. Since the approximation can perform poorly for very small proportions, we also test using several alternatives, including linear regression (conventional and robust standard errors), nonparametric bootstrap, and permutation testing, all of which obtain similar results (available from the authors on request). The sample size is 2,000 per cell ($N = 18{,}000$ total). Standard errors are in parentheses.

$^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$.

Table B.5. Aggregate Purchase Rates for Offensive Promotions (Weighted)

	Offensive discount					
Defensive discount	A 0%	B 40%	C 60%	D (B) – (A)	E (C) – (A)	F (C) – (B)
1. 0%	0.0000	0.0021^{**}	0.0237^{**}	0.0021^{**}	0.0237^{**}	0.0216^{**}
	(0.0000)	(0.0008)	(0.0034)	(0.0008)	(0.0034)	(0.0035)
2. 20%	0.0000	0.0041^{*}	0.0094^{**}	0.0041^{*}	0.0094^{**}	0.0053^{*}
	(0.0000)	(0.0016)	(0.0022)	(0.0016)	(0.0022)	(0.0027)
3. 40%	0.0000	0.0027^{*}	0.0060^{**}	0.0027^{*}	0.0060^{**}	0.0033
	(0.0000)	(0.0013)	(0.0018)	(0.0013)	(0.0018)	(0.0022)
4. (2) – (1)	0.0000	0.0020	-0.0142^{**}	0.0020	-0.0142^{**}	-0.0163^{**}
	(0.0000)	(0.0018)	(0.0040)	(0.0018)	(0.0040)	(0.0044)
5. (3) – (1)	0.0000	0.0006	-0.0177^{**}	0.0006	-0.0177^{**}	-0.0183^{**}
	(0.0000)	(0.0015)	(0.0039)	(0.0015)	(0.0039)	(0.0041)
6. (3) – (2)	0.0000	−0.0014	−0.0034	−0.0014	−0.0034	−0.0020
	(0.0000)	(0.0020)	(0.0028)	(0.0020)	(0.0028)	(0.0035)

Notes. Means and differences are computed using population weights for high/low behavioral segments (locations A and B weighted equally). Standard errors for differences in proportions and all p-values are computed using conventional normal approximation. Since the approximation can perform poorly for very small proportions, we also test using several alternatives, including linear regression (conventional and robust standard errors), nonparametric bootstrap, and permutation testing, all of which obtain similar results (available from the authors on request). The sample size is 2,000 per cell ($N = 18{,}000$ total). Standard errors are in parentheses.

$^{*}p < 0.05$; $^{**}p < 0.01$.

Table B.6. Aggregate Purchase Rates for Defensive Promotions

	Offensive discount					
Defensive discount	A 0%	B 40%	C 60%	D (B) – (A)	E (C) – (A)	F (C) – (B)
1. 0%	0.0050^{**}	0.0040^{**}	0.0000	−0.0010	-0.0050^{**}	-0.0040^{**}
	(0.0016)	(0.0014)	(0.0000)	(0.0021)	(0.0016)	(0.0014)
2. 20%	0.0225^{**}	0.0205^{**}	0.0190^{**}	−0.0020	−0.0035	−0.0015
	(0.0033)	(0.0032)	(0.0031)	(0.0046)	(0.0045)	(0.0044)
3. 40%	0.0520^{**}	0.0505^{**}	0.0475^{**}	−0.0015	−0.0045	−0.0030
	(0.0050)	(0.0049)	(0.0048)	(0.0070)	(0.0069)	(0.0068)
4. (2) – (1)	0.0175^{**}	0.0165^{**}	0.0190^{**}	−0.0010	0.0015	0.0025
	(0.0037)	(0.0035)	(0.0031)	(0.0051)	(0.0048)	(0.0046)
5. (3) – (1)	0.0470^{**}	0.0465^{**}	0.0475^{**}	−0.0005	0.0005	0.0010
	(0.0052)	(0.0051)	(0.0048)	(0.0073)	(0.0071)	(0.0070)
6. (3) – (2)	0.0295^{**}	0.0300^{**}	0.0285^{**}	0.0005	−0.0010	−0.0015
	(0.0060)	(0.0058)	(0.0057)	(0.0083)	(0.0082)	(0.0081)

$^{**}p < 0.01$.

Table B.7. Aggregate Purchase Rates for Defensive Promotions (Weighted)

	Offensive discount					
Defensive discount	A 0%	B 40%	C 60%	D (B) – (A)	E (C) – (A)	F (C) – (B)
1. 0%	0.0031**	0.0024**	0.0000	−0.0006	−0.0031**	−0.0024**
	(0.0010)	(0.0009)	(0.0000)	(0.0013)	(0.0010)	(0.0009)
2. 20%	0.0195**	0.0173**	0.0158**	−0.0022	−0.0037	−0.0015
	(0.0032)	(0.0029)	(0.0028)	(0.0043)	(0.0042)	(0.0040)
3. 40%	0.0481**	0.0468**	0.0444**	−0.0013	−0.0037	−0.0024
	(0.0050)	(0.0049)	(0.0048)	(0.0070)	(0.0070)	(0.0069)
4. (2) – (1)	0.0165**	0.0149**	0.0158**	−0.0016	−0.0007	0.0009
	(0.0033)	(0.0031)	(0.0028)	(0.0045)	(0.0043)	(0.0041)
5. (3) – (1)	0.0450**	0.0443**	0.0444**	−0.0007	−0.0007	0.0001
	(0.0051)	(0.0050)	(0.0048)	(0.0071)	(0.0070)	(0.0070)
6. (3) – (2)	0.0285**	0.0294**	0.0286**	0.0009	0.0000	−0.0008
	(0.0059)	(0.0057)	(0.0056)	(0.0082)	(0.0081)	(0.0080)

$^{**}p < 0.01$.

Table B.8. Purchase Rates for Location A High Types

	Offensive discount					
Defensive discount	A 0%	B 40%	C 60%	D (B) – (A)	E (C) – (A)	F (C) – (B)
			Offensive response			
1. 0%	0.0000	0.0060†	0.0419**	0.0060†	0.0419**	0.0360**
	(0.0000)	(0.0034)	(0.0092)	(0.0034)	(0.0092)	(0.0098)
2. 20%	0.0000	0.0084*	0.0156**	0.0084*	0.0156**	0.0072
	(0.0000)	(0.0042)	(0.0055)	(0.0042)	(0.0055)	(0.0069)
3. 40%	0.0000	0.0040	0.0123*	0.0040	0.0123*	0.0083
	(0.0000)	(0.0028)	(0.0050)	(0.0028)	(0.0050)	(0.0057)
4. (2) – (1)	0.0000	0.0024	−0.0263*	0.0024	−0.0263*	−0.0288*
	(0.0000)	(0.0054)	(0.0107)	(0.0054)	(0.0107)	(0.0120)
5. (3) – (1)	0.0000	−0.0020	−0.0296**	−0.0020	−0.0296**	−0.0276*
	(0.0000)	(0.0044)	(0.0104)	(0.0044)	(0.0104)	(0.0113)
6. (3) – (2)	0.0000	−0.0044	−0.0033	−0.0044	−0.0033	0.0011
	(0.0000)	(0.0050)	(0.0074)	(0.0050)	(0.0074)	(0.0090)
			Defensive response			
1. 0%	0.0123*	0.0100*	0.0000	−0.0023	−0.0123*	−0.0100*
	(0.0050)	(0.0044)	(0.0000)	(0.0067)	(0.0050)	(0.0044)
2. 20%	0.0233**	0.0210**	0.0253**	−0.0023	0.0020	0.0043
	(0.0067)	(0.0066)	(0.0069)	(0.0094)	(0.0096)	(0.0096)
3. 40%	0.0657**	0.0595**	0.0492**	−0.0062	−0.0165	−0.0103
	(0.0112)	(0.0105)	(0.0098)	(0.0154)	(0.0149)	(0.0144)
4. (2) – (1)	0.0111	0.0110	0.0253**	0.0000	0.0143	0.0143
	(0.0083)	(0.0079)	(0.0069)	(0.0115)	(0.0108)	(0.0105)
5. (3) – (1)	0.0534**	0.0496**	0.0492**	−0.0039	−0.0043	−0.0004
	(0.0123)	(0.0114)	(0.0098)	(0.0168)	(0.0157)	(0.0151)
6. (3) – (2)	0.0424**	0.0385**	0.0238*	−0.0038	−0.0185	−0.0147
	(0.0131)	(0.0124)	(0.0120)	(0.0180)	(0.0177)	(0.0173)

$^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$.

Table B.9. Purchase Rates for Location A Low Types

	Offensive discount					
Defensive discount	A 0%	B 40%	C 60%	D (B) – (A)	E (C) – (A)	F (C) – (B)
			Offensive response			
1. 0%	0.0000	0.0000	0.0185**	0.0000	0.0185**	0.0185**
	(0.0000)	(0.0000)	(0.0061)	(0.0000)	(0.0061)	(0.0061)
2. 20%	0.0000	0.0000	0.0078*	0.0000	0.0078*	0.0078*
	(0.0000)	(0.0000)	(0.0039)	(0.0000)	(0.0039)	(0.0039)
3. 40%	0.0000	0.0039	0.0041	0.0039	0.0041	0.0002
	(0.0000)	(0.0027)	(0.0029)	(0.0027)	(0.0029)	(0.0040)
4. (2) – (1)	0.0000	0.0000	−0.0107	0.0000	−0.0107	−0.0107
	(0.0000)	(0.0000)	(0.0072)	(0.0000)	(0.0072)	(0.0072)
5. (3) – (1)	0.0000	0.0039	−0.0144*	0.0039	−0.0144*	−0.0182*
	(0.0000)	(0.0027)	(0.0068)	(0.0027)	(0.0068)	(0.0073)
6. (3) – (2)	0.0000	0.0039	−0.0037	0.0039	−0.0037	−0.0075
	(0.0000)	(0.0027)	(0.0048)	(0.0027)	(0.0048)	(0.0056)
			Defensive response			
1. 0%	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
2. 20%	0.0079*	0.0170**	0.0117*	0.0091	0.0037	−0.0053
	(0.0039)	(0.0060)	(0.0047)	(0.0071)	(0.0062)	(0.0076)
3. 40%	0.0418**	0.0388**	0.0432**	−0.0030	0.0014	0.0044
	(0.0092)	(0.0085)	(0.0092)	(0.0125)	(0.0130)	(0.0126)
4. (2) – (1)	0.0079*	0.0170**	0.0117*	0.0091	0.0037	−0.0053
	(0.0039)	(0.0060)	(0.0047)	(0.0071)	(0.0062)	(0.0076)
5. (3) – (1)	0.0418**	0.0388**	0.0432**	−0.0030	0.0014	0.0044
	(0.0092)	(0.0085)	(0.0092)	(0.0125)	(0.0130)	(0.0126)
6. (3) – (2)	0.0339**	0.0219*	0.0316**	−0.0121	−0.0024	0.0097
	(0.0100)	(0.0104)	(0.0104)	(0.0144)	(0.0144)	(0.0147)

$^{*}p < 0.05$; $^{**}p < 0.01$.

Table B.10. Purchase Rates for Location B High Types

	Offensive discount					
Defensive discount	A 0%	B 40%	C 60%	D (B) – (A)	E (C) – (A)	F (C) – (B)
			Offensive response			
1. 0%	0.0000	0.0080*	0.0363**	0.0080*	0.0363**	0.0283**
	(0.0000)	(0.0040)	(0.0082)	(0.0040)	(0.0082)	(0.0091)
2. 20%	0.0000	0.0000	0.0144**	0.0000	0.0144**	0.0144**
	(0.0000)	(0.0000)	(0.0054)	(0.0000)	(0.0054)	(0.0054)
3. 40%	0.0000	0.0000	0.0039	0.0000	0.0039	0.0039
	(0.0000)	(0.0000)	(0.0028)	(0.0000)	(0.0028)	(0.0028)
4. (2) – (1)	0.0000	−0.0080*	−0.0220*	−0.0080*	−0.0220*	−0.0139
	(0.0000)	(0.0040)	(0.0098)	(0.0040)	(0.0098)	(0.0106)
5. (3) – (1)	0.0000	−0.0080*	−0.0324**	−0.0080*	−0.0324**	−0.0244*
	(0.0000)	(0.0040)	(0.0086)	(0.0040)	(0.0086)	(0.0095)
6. (3) – (2)	0.0000	0.0000	−0.0105†	0.0000	−0.0105†	−0.0105†
	(0.0000)	(0.0000)	(0.0061)	(0.0000)	(0.0061)	(0.0061)
			Defensive response			
1. 0%	0.0078*	0.0060†	0.0000	−0.0018	−0.0078*	−0.0060†
	(0.0039)	(0.0035)	(0.0000)	(0.0052)	(0.0039)	(0.0035)
2. 20%	0.0370**	0.0344**	0.0287**	−0.0027	−0.0083	−0.0056
	(0.0086)	(0.0080)	(0.0076)	(0.0117)	(0.0114)	(0.0110)
3. 40%	0.0585**	0.0605**	0.0605**	0.0020	0.0021	0.0001
	(0.0104)	(0.0107)	(0.0105)	(0.0149)	(0.0148)	(0.0150)
4. (2) – (1)	0.0292**	0.0283**	0.0287**	−0.0009	−0.0005	0.0004
	(0.0094)	(0.0087)	(0.0076)	(0.0128)	(0.0121)	(0.0115)
5. (3) – (1)	0.0507**	0.0545**	0.0605**	0.0038	0.0099	0.0061
	(0.0111)	(0.0113)	(0.0105)	(0.0158)	(0.0153)	(0.0154)
6. (3) – (2)	0.0214	0.0261†	0.0318*	0.0047	0.0104	0.0057
	(0.0134)	(0.0133)	(0.0130)	(0.0189)	(0.0187)	(0.0186)

$^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$.

Table B.11. Purchase Rates for Location B Low Types

	Offensive discount					
Defensive discount	A 0%	B 40%	C 60%	D (B) – (A)	E (C) – (A)	F (C) – (B)
			Offensive response			
1. 0%	0.0000	0.0000	0.0156^{**}	0.0000	0.0156^{**}	0.0156^{**}
	(0.0000)	(0.0000)	(0.0055)	(0.0000)	(0.0055)	(0.0055)
2. 20%	0.0000	0.0076^{*}	$0.0062^{\dagger}$	0.0076^{*}	$0.0062^{\dagger}$	−0.0014
	(0.0000)	(0.0038)	(0.0036)	(0.0038)	(0.0036)	(0.0052)
3. 40%	0.0000	0.0021	$0.0058^{\dagger}$	0.0021	$0.0058^{\dagger}$	0.0038
	(0.0000)	(0.0021)	(0.0034)	(0.0021)	(0.0034)	(0.0039)
4. (2) – (1)	0.0000	0.0076^{*}	−0.0094	0.0076^{*}	−0.0094	-0.0170^{*}
	(0.0000)	(0.0038)	(0.0065)	(0.0038)	(0.0065)	(0.0075)
5. (3) – (1)	0.0000	0.0021	−0.0098	0.0021	−0.0098	$-0.0118^{\dagger}$
	(0.0000)	(0.0021)	(0.0064)	(0.0021)	(0.0064)	(0.0067)
6. (3) – (2)	0.0000	−0.0055	−0.0003	−0.0055	−0.0003	0.0052
	(0.0000)	(0.0043)	(0.0049)	(0.0043)	(0.0049)	(0.0065)
			Defensive response			
1. 0%	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
2. 20%	0.0223^{**}	0.0095^{*}	0.0103^{*}	−0.0128	−0.0120	0.0009
	(0.0066)	(0.0042)	(0.0046)	(0.0079)	(0.0081)	(0.0062)
3. 40%	0.0421^{**}	0.0433^{**}	0.0370^{**}	0.0012	−0.0052	−0.0063
	(0.0088)	(0.0092)	(0.0083)	(0.0128)	(0.0121)	(0.0124)
4. (2) – (1)	0.0223^{**}	0.0095^{*}	0.0103^{*}	−0.0128	−0.0120	0.0009
	(0.0066)	(0.0042)	(0.0046)	(0.0079)	(0.0081)	(0.0062)
5. (3) – (1)	0.0421^{**}	0.0433^{**}	0.0370^{**}	0.0012	−0.0052	−0.0063
	(0.0088)	(0.0092)	(0.0083)	(0.0128)	(0.0121)	(0.0124)
6. (3) – (2)	$0.0199^{\dagger}$	0.0338^{**}	0.0267^{**}	0.0140	0.0068	−0.0072
	(0.0110)	(0.0102)	(0.0095)	(0.0150)	(0.0145)	(0.0139)

$^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$.

Table B.12. Equilibrium Targeting with $\rho = 0$

	Firm A profit per messaged consumer	Firm B profit per messaged consumer
Uniform	2.22	2.93
Location	2.19	3.00
Type	2.23	2.96
Type and location	2.20	3.03

Endnotes

[1] A geofence is a digital perimeter defining the geographic boundaries of a market. In our setting, we use a 500-meter radius around each of the two shopping malls.

[2] Past work has found that such RFM (recency, frequency, and monetary value) measures provide useful segmentation variables by proxying for differences in consumers' lifetime values (Fader et al. 2005).

[3] Chen et al. (2017) also relax the usual "full market coverage" assumption by including a mass of marginal consumers who would not buy from either firm in the uniform price equilibrium. As long as the category expansion effects are not too large and price competition is not "too strong" in this neutral market, equilibrium profits can still increase under location targeting.

[4] In this experiment, we do not vary the price per message sent, treating it as exogenous. We can derive each theater's incremental revenues per message sent and, hence, demand for messaging services. However, the set of consumers for SMSs spans a much broader range of markets than theaters, such as gaming, apps, call services, restaurants, travel, education, and news. Each of these markets likely has different SMS demand due to differences in the degree of competition and the magnitude of incremental revenue potential. In sum, our data are not suitable for studying the mobile platform's pricing incentives for access to SMS messaging.

[5] In 2006, AMC launched early-bird pricing across all its theaters in the United States. See, for instance, Moviefone (2006).

[6] We used the population weights to correct for the fact that the high and low recency consumer segments have different sizes at the population level.

[7] The full set of sales figures and tests for promotional effects for conventional geofencing (defensive firm) are reported in Appendix B, Table B.7. Alternative methods of testing differences in mean purchase rates are described in Appendix B, Table B.4.

[8] This finding is consistent with Fong et al. (2015). The full set of sales figures and tests for promotional effects for geoconquesting (offensive firm) are reported in Appendix B, Table B.5.

[9] These gains are computed using the population weights to correct for differences in the population size of each location.

[10] For instance, Chintagunta et al. (2005) simulate monopoly targeting using household-level estimates obtained from an instrumental variables estimator to resolve the endogeneity in observational price variation.

[11] The trimming avoids very small-valued draws that could lead to numerical problems with the calculation of the harmonic mean.

[12] Theater A has a capacity of 1,200 seats per show, and theater B has a capacity of 2,000 seats per show. With four shows per day and mobile subscribers representing 75% of the total mall traffic on a typical Saturday afternoon, the theaters are less than half full for the average show.

[13] Return bus fare between the theaters is RMB 4 and requires 20 minutes of travel time. So the benefits of arbitraging across locations seems offset by the travel and hassle costs.

[14] As of March 2016, AMC is the largest U.S. chain with 387 theaters (Malcolm 2016).

[15] Accessed on Fandango.com on June 11, 2016.

[16] Recall that profits are correlated across scenarios because they use the same posterior distribution of demand parameters.

[17] In addition to the correlated errors, our demand specification differs from the standard independent probit because it is a discrete mixture of the probit demands in the two geographic and two consumer type segments.

[18] Each firm's best responses are computed numerically using R's built-in "optim" function.

[19] We solve for the equilibrium prices satisfying the system of first-order conditions in each scenario using the Newton solver in the nonlinear equation solver package "nleqslv" in R.

[20] That profits do not unambiguously decrease relative to uniform pricing is different from the prisoner's dilemma finding in Shaffer and Zhang (1995). The current model differs in two ways. First, we do not assume full coverage, meaning that there is an outside option that softens the profit impact of lower prices. Second, we do not allow perfect targeting in the sense that a firm cannot target a consumer based on her random utility shock.

[21] This is not identical to Chen and Iyer (2002), as the authors endogenize the degree of addressability, whereas we merely offer the firms a discrete choice between targeting schemes.

References

Armstrong M, Vickers J (2001) Competitive price discrimination. *RAND J. Econom.* 32:1–27.

Berry ST (1994) Estimating discrete-choice models of product differentiation. *RAND J. Econom.* 25:242–262.

Besanko D, Dubé J-P, Gupta S (2003) Competitive price discrimination strategies in a vertical channel with aggregate data. *Management Sci.* 49:1121–1138.

Borenstein S (1985) Price discrimination in free-entry markets. *RAND J. Econom.* 16:380–397.

Borenstein S, Rose N (1994) Competition and price dispersion in the U.S. airline industry. *J. Political Econom.* 102:653–683.

Borenstein S, Shepard A (1994) Competition and price dispersion in the U.S. airline industry. *J. Political Econom.* 102:653–683.

Borzekowski R, Thomadsen R, Taragin C (2009) Competition and price discrimination in the market for mailing lists. *Quant. Marketing Econom.* 7:147–179.

Busse M, Rysman M (2005) Competition and price discrimination in yellow pages advertising. *RAND J. Econom.* 36:378–390.

Chen Y, Iyer G (2002) Consumer addressability and customized pricing. *Marketing Sci.* 21:197–208.

Chen Y, Li X, Sun M (2017) Competitive mobile geo targeting. *Marketing Sci.* 36(5):666–682.

Chintagunta P, Dubé J-P, Goh KY (2005) Beyond the endogeneity bias: The effect of unmeasured brand characteristics on household-level brand choice models. *Management Sci.* 51: 832–849.

Corts KS (1998) Third-degree price discrimination in oligopoly: All-out competition and strategic commitment. *RAND J. Econom.* 29:306–323.

Danaher PJ, Smith MS, Ranasinghe K, Danaher TS (2015) Where, when and how long: Factors that influence the redemption of mobile phone coupons. *J. Marketing Res.* 52:710–725.

Doraszelski U, Lewis G, Pakes A (2017) Just starting out: Learning and equilibrium in a new market. Working paper, University of Pennsylvania, Philadelphia.

Dubé JP, Luo X, Fang Z (2017) Self-signaling and pro-social behavior: A cause marketing mobile field experiment. *Marketing Sci.* 36(2):161–186.

eMarketer (2015) Marketers boost efforts to reach coupon clippers via mobile. Accessed July 13, 2016, http://www.emarketer.com/Article/Marketers-Boost-Efforts-Reach-Coupon-Clippers-via-Mobile/1012488.

Fader PS, Hardie BGS, Lee KL (2005) RFM and CLV: Using iso-value curves for customer base analysis. *J. Marketing Res.* 42:415–430.

Fong NM, Fang Z, Luo X (2015) Geo-conquesting: Competitive locational targeting of mobile promotions. *J. Marketing Res.* 52: 726–735.

Fudenberg D, Villas-Boas JM (2006) Behavior-based price discrimination and customer recognition. Hendershott T, ed. *Handbooks in Information Systems: Economics and Information Systems*, Vol. 1 (Emerald Group Publishing, Bingley, UK), 377–436.

Ghose A, Goldfarb A, Han SP (2013) How is the mobile Internet different? Search costs and local activities. *Inform. Systems Res.* 24:613–631.

Goldberg PK, Verboven F (2005) Market integration and convergence to the law of one price: Evidence from the European car market. *J. Internat. Econom.* 65:49–73.

GSMA (2015) The mobile economy 2015. Accessed July 13, 2016, http://www.gsmamobileeconomy.com/GSMA_Global_Mobile_Economy_Report_2015.pdf.

Holmes TJ (1989) The effects of third-degree price discrimination in oligopoly markets. *Amer. Econom. Rev.* 79:244–250.

Hudson-Maggio L (2014) What is geo-conquesting, and how can it drive campaign results? Accessed July 13, 2016, http://blog.cmglocalsolutions.com/what-is-geo-conquesting-and-how-can-it-drive-campaign-results.

Juniper Research (2014) Mobile coupon users to surpass 1 billion by 2019. Accessed July 13, 2016, http://www.juniperresearch.com/press-release/coupons-pr1.

Lazar MJ (2015) One-click savings: A quick look at 2015 mobile coupon statistics. Accessed July 13, 2016, http://www.trueship.com/blog/2015/03/24/one-click-savings-a-quick-look-at-2015-mobile-coupon-statistics/#.V4ZJQusrJD8.

Luo X, Andrews M, Fang Z, Phang CW (2014) Mobile targeting. *Management Sci.* 60:1738–1756.

Malcolm H (2016) AMC Theatres buys Carmike Cinemas to create largest chain. *USA Today* (March 4). https://www.usatoday.com/story/money/2016/03/04/amc-theatres-to-acquire-carmike-cinemas/81309104/.

McCulloch R, Rossi PE (1994) An exact likelihood analysis of the multinomial probit model. *J. Econometrics* 64:207–240.

Mizuno T (2003) On the existence of a unique price equilibrium for models of product differentiation. *Internat. J. Indust. Organ.* 21:761–793.

Mobile Marketing Association (2016a) Location terminology guide: The language of location. Accessed July 14, 2016, http://www.mmaglobal.com/documents/location-terminology-guide.

Mobile Marketing Association (2016b) Using location for audience targeting: A perspective issued by the MMA on behalf of the MMA NA Location Committee Audience Working Group. Accessed July 4, 2016, http://national.yp.com/downloads/using_location_for_audience_targeting.pdf.

Moviefone (2006) The early bird catches the cheapest movie at AMC. Accessed July 4, 2016, http://www.moviefone.com/2006/07/13/the-early-bird-catches-the-cheapest-movie-at-amc/.

Nevo A, Wolfram C (2002) Why do manufacturers issue coupons? An empirical analysis of breakfast cereals. *RAND J. Econom.* 33: 319–339.

Newton MA, Raftery AE (1994) Approximate Bayesian inference with the weighted likelihood bootstrap. *J. Roy. Statist. Soc.: Ser. B* 56:3–48.

Pancras J, Sudhir K (2007) Optimal marketing strategies for a customer data intermediary. *J. Marketing Res.* 44:560–578.

Pigou A (1920) *The Economics of Welfare* (MacMillan, London).

PwC (2013) Total retail survey. https://www.pwc.com/gx/en/industries/retail-consumer/total-retail.html.

Rocket Fuel (2015) Rocket Fuel proves digital ads influence physical activity, drives 41.3% lift in store visits with programmatic targeting. Report, Rocket Fuel, Redwood City, CA.

Shaffer G, Zhang ZJ (1995) Competitive coupon targeting. *Marketing Sci.* 14:395–416.

Shepard A (1991) Price discrimination and retail configuration. *J. Political Econom.* 99:30–53.

Shin J, Sudhir K (2010) A customer management dilemma: When is it profitable to reward own customers. *Marketing Sci.* 29:671–689.

Stole LA (2007) Price discrimination and imperfect competition. Armstrong M, Porter R, eds. *Handbook of Industrial Organization*, Vol. 3 (North-Holland, Amsterdam), 2221–2299.

Thinknear (2015) Thinknear case study: Whole Foods Market partners with Thinknear to drive store visits. Accessed July 4, 2016, http://www.thinknear.com/wp-content/uploads/2015/06/Case-Study-Whole-Foods-Thinknear.pdf.

Thisse JF, Vives X (1988) On the strategic choice of spatial price policy. *Amer. Econom. Rev.* 78:122–137.

Varian HR (1989) Price discrimination. Schmalensee R, Willig R, eds. *Handbook of Industrial Organization*, Vol. 1 (North-Holland, Amsterdam), 597–654.

Walsh M (2013) 'Geo-conquesting' drives higher mobile click rates. *Online Media Daily* (May 17), http://www.mediapost.com/publications/article/200578/geo-conquesting-drives-higher-mobile-click-rates.html?edition.

xAd (2013) Mobile-location insights: Q2 2013. http://www.mmaglobal.com/files/xAd_Q2_2013_Report_Final.pdf.

YP Marketing Solutions (2015) Mobile retargeting, optimization and hitting the ROI bullseye. Accessed December 1, 2015, http://national.yp.com/downloads/MMS_Chicago.pdf.