The Promise and Peril of Dynamic Targeted Pricing*

Sung H. Ham† Chuan He‡ Dan Zhang§

January 14, 2022

*Authors are listed in alphabetical order, each author contributed equally.

†Assistant Professor of Marketing, Broad College of Business, Michigan State University, East Lansing, MI 48823; email: sungham@msu.edu.

‡Associate Professor, Leeds School of Business, University of Colorado, Boulder, CO 80309; email: chuan.he@colorado.edu.

§Professor, Leeds School of Business, University of Colorado, Boulder, CO 80309; email: dan.zhang@colorado.edu.

The Promise and Peril of Dynamic Targeted Pricing

Abstract

Dynamic pricing is widely adopted in many industries, such as travel and insurance. These industries are also gaining extensive capabilities in identifying and segmenting customers, partly fueled by the increasing availability of data. It is natural to ask whether firms should take advantage of such developments by charging different prices to different customer segments. If so, under what conditions? We seek answers to these highly managerially relevant questions.

We consider a market with two customer segments served by a monopolist. The monopolist can choose among a set of pricing strategies to exploit consumers' inter-temporal preferences and/or inter-segment variations. At one end of the spectrum, the firm can charge a constant price to all customers, which is called static pricing. At the other end of the spectrum, the firm can charge different prices to different customer segments and vary these prices over time, which is referred to as dynamic targeted pricing. We systematically compare these alternative pricing strategies. We show that dynamic pricing without targeting can be more effective than static targeted pricing when customers are not very forward looking, which corroborates the findings in the empirical literature. Interestingly, we find that the monopolist can be worse off when she adopts targeting in addition to dynamic pricing. We conduct laboratory experiments to test several key model predictions. The studies show that individuals behave in a manner consistent with the predictions of our model.

Keywords: Dynamic Pricing, Targeting, Game Theory, Experimental Economics.

1. INTRODUCTION

Marketers routinely tailor their offerings to different consumer segments. For instance, retailers target specific promotions to different customers according to their demographics, degree of loyalty, and life time value; fashion designers and publishing houses offer new products at premium prices but reduce their prices over time, effectively giving discounts to those who are willing to wait. These practices are commonly known as targeted pricing and dynamic pricing,[1] which help firms to price discriminate consumers based on their valuations or time preferences. Consumer heterogeneity in both valuations and time preferences is prevalent in many product categories. For example, this heterogeneity is frequently observed in the consumption of airline tickets, hotel rooms, ski passes, sporting events, and concerts.

Firms' capabilities to identify and target customers has been further enhanced by recent advancements in technologies. As a result, business practitioners are often in possession of vast amounts of customer data. These data enable firms to identify some of their customers, facilitate segmentation, and implement price discrimination. When a firm is able to identify a subset of its customers through marketing intelligence, should the firm take advantage of the information? If the answer is positive, how should the information be used?

The answers to these questions are not trivial. Consider a scenario where a hotel chain acquires customer information from Comic-Con before its annual convention. The information helps to identify some of its potential customers as having high valuations due to their passion for the event. The demand for hotel rooms depends on other demographic factors in addition to valuations. In particular, while some consumers plan ahead and make reservations early, others postpone their reservations. The hotel chain adjusts its rates dynamically to cater to different time preferences. Now, armed with the customer valuation information, the firm can charge a different price to the newly identified customer segment. Should the firm do so? Put differently, can firms benefit from dynamic targeted pricing when some subset of customers are identified? We address these questions in this paper.

Targeted pricing and dynamic pricing are key elements in two of the three research areas identified in Grewal et al. (2011), where they discuss the innovations in retail pricing and promotions. Yet the comparison of the relative effectiveness of targeted pricing and dynamic

[1] To be precise, targeted pricing is defined as offering different prices to different customer segments and dynamic pricing is defined as changing prices over time.

pricing is sparse in the literature. In an empirical study, Khan et al. (2009) show that dynamic pricing contributes more to profitability than targeted pricing. This is an intriguing finding but a theoretical explanation is lacking. The increasing availability of data facilitates customer identification and highlights the pressing need for a better understanding of the trade-offs between dynamic pricing and targeted pricing. Toward that end, we focus on the following two research questions:

Q1: When is dynamic pricing preferred to targeted pricing?

Q2: Does targeting enhance dynamic pricing? If so, under what conditions?

We consider a two-period model with a single seller. Consumers can make a unit purchase of the good in either of the two periods. A discount factor applies to purchases made in the second period. Consumers differ in both their time preferences and valuations. The firm knows the distribution of customer valuations but it can only recognize the valuations of a subset of customers. We assume that the identified customers have a common valuation[2] for the good and the unidentified customers' valuations follow a uniform distribution. The monopolist can price discriminate the consumers based on their heterogeneity in valuation. This entails charging different prices to consumers in different segments. In addition, the monopolist can exploit consumers' intertemporal preferences by charging different prices in the two periods. In sum, the monopolist's pricing policy ranges from charging a single price (static pricing) in both periods to charging four prices across the periods (dynamic targeted pricing).

Regarding Q1, we find that when consumers are not very forward looking, dynamic pricing without targeting (two prices) dominates static targeted pricing. This result echoes the empirical finding of Khan et al. (2009). To understand this result, note that consumer valuations are continuous but they are divided into a small number of segments (often two) for targeting purposes. As such, the effectiveness of targeting is limited by how the segments are defined. On the other hand, when customers are not sufficiently forward looking, dynamic pricing enables the firm to charge two prices to exploit customers' time preferences. Since customers often hold their valuations steady within a given period but discount their val-

[2]This is a simplifying assumption. As we show in Appendix C, our result is robust when the valuations of customers in Segment A are uniformly distributed within a narrow band.

uations from one period to another, dynamic pricing captures consumers' time preferences with relatively little loss.

Regarding Q2, we show that the monopolist can be worse off practicing dynamic targeted pricing rather than engaging in dynamic pricing only. The intuitions are as follows. Dynamic pricing is effective when high valuation customers are willing to pay a high price in the first period; however, some of them may delay their purchases if the second period price is sufficiently low. Targeting separates the two customer segments and may decrease the optimal price charged in the second period. As such, it exacerbates forward looking behavior on the part of high valuation customers. In other words, with targeting, more high valuation customers may choose to strategically wait for a lower price in the second period, thereby undermining the profitability of dynamic pricing. On the other hand, targeted pricing allows the monopolist to exploit valuation heterogeneity across consumer segments. The gain from targeting must be weighed against the reduction of effectiveness of dynamic pricing. Hence, dynamic targeted pricing can indeed hurt the monopolist's bottom line.

Our theory indicates when dynamic pricing is favored over targeted pricing and when targeting can improve dynamic pricing. We conduct two experimental studies using human participants to provide a tightly-controlled empirical test of these theoretical predictions. In the first experimental study, we show that when customers are patient, targeted pricing is preferred over dynamic pricing. However, if customers are impatient, then price skimming through dynamic pricing improves profitability over static targeted pricing. In the second experimental study investigates the role of targeting. We find that targeting improves profits when used in conjunction with dynamic pricing if a high valuation segment of customers can be targeted, but targeting actually reduces profits when the valuation of the targeted segment is moderate. Overall, the participants in our experiments make decisions that closely align with our theoretical predictions.

Related Literature. Our work is related to several streams of literature, including behavior-based pricing (see Fudenberg and Villas-Boas, 2006, for a review), dynamic pricing (Besanko and Winston, 1990), targeted pricing (Shaffer and Zhang, 1995; Chen et al., 2001), and the benefits of additional customer information (Gardete and Bart, 2018).

The initial research on behavior-based pricing (BBP) suggests that BBP hurts firms' profits. For example, Villas-Boas (2004) shows that a monopolist is worse off when it charges different prices to past consumers and new consumers compared to when it charges a uniform price for all consumers. Acquisti and Varian (2005) examine a market with forward-looking consumers who have either high or low valuation for the goods sold by a monopolist. They show that a monopolist never finds it optimal to engage in targeted pricing when the firm can commit to a pricing policy. The negative effect of BBP can extend to a duopoly market. Using a two-period homogeneous-good duopoly model, Chen (1997) shows that behavior-based pricing reduces duopolists' profits. Zhang (2011) notes that BBP reduces competing firms' profits not only through intensified competition but also by inducing them to offer less differentiated products. Under BBP, consumers purchase in each period so long as they gain a non-negative surplus. By contrast, in our model, consumers purchase a single unit over two periods and some consumers can strategically withhold their purchase in the first period. Furthermore, under BBP, firms recognize customers' purchase histories in the second period. In our model, however, firms have perfect knowledge of customer valuation for a segment of consumers from the outset. Therefore, our model is very different from those in the behavior-based pricing literature.

Besanko and Winston (1990) investigate a durable good market where rational consumers can make a unit purchase over a finite number of periods. A monopolist chooses an optimal price in each period. They show that, in equilibrium, the monopolist's pricing policy is characterized by price skimming. Following their work, we model consumer forward looking behavior using a discount factor for future purchases. Unlike Besanko and Winston (1990), however, we consider a non-durable goods market.

Shaffer and Zhang (1995) introduce targeted pricing where duopolistic firms can perfectly recognize their own customers and their rival's customers. Consumer valuations for the competing products follow a uniform distribution. Although the duopolists can identify customer valuations, each firm can only charge two different prices. The key finding is that targeted pricing leads to a prisoner's dilemma and does not improve firms' profits. Chen et al. (2001) extend Shaffer and Zhang (1995) by considering the situation where firms' targeting accuracy ranges from primitive to perfect. It is assumed that the duopolists each face two types of customers, a loyal segment and a switcher segment. The loyal customers are completely price inelastic while the switchers are infinitely price elastic. They show that imperfect targeting can make targeted pricing profitable due to the fact that the mistargeting effect counteracts the competitive effect. We consider both dynamic pricing and targeted pricing and identify the conditions under which dynamic pricing is more profitable than static targeted pricing.

A research question that is related to ours is whether more consumer data is always beneficial, as targeting is often made possible by the available data. Gardete and Bart (2018) show in the context of an advertising game that collecting more consumer data is not necessarily beneficial for either firms or consumers. In line with their result, we show that targeting does not necessarily add value for firms practicing dynamic pricing. However, we consider a different marketing variable (price) instead of advertisement. Moreover, we show that the negative impact of targeting is often negligible, while the potential benefit can be substantial.

Our work contributes to the literature in that it studies the interaction between dynamic pricing and targeted pricing. We compare the effectiveness of dynamic pricing with that of targeted pricing and establish that dynamic targeted pricing is generally profitable for a monopolist. We show that even though a monopolist can suffer loss from dynamic targeted pricing, the potential loss is small whereas the potential gain is substantial. We also show that when the monopolist adopts dynamic targeted pricing, the value of commitment is very limited. These findings have sharp managerial implications and as far as we know, they are new to the literature.

Accordingly, our experiments contribute to the literature in the following ways. First, there is substantial evidence from field studies that targeting customers with promotions may benefit firms. For instance, offering price discounts via coupons (Besanko et al., 2003) and through mobile location targeting in a static context has been found to be an effective tool for marketers in improving sales and profits (Fong et al., 2015; Dubé et al., 2017). Similarly, in dynamic pricing contexts, Khan et al. (2009) show empirically that although the benefits of dynamic pricing may outweigh the benefits of targeted pricing, targeted pricing can still benefit firms. Meanwhile, Zhang et al. (2014) find that targeting within a B2B dynamic pricing context also improves profits. These studies collectively demonstrate the gains associated with targeted pricing. Likewise, we confirm through our experiments that there are substantial gains to targeted pricing. But unlike the extant research in field settings, we show that targeting in dynamic pricing contexts can actually backfire. Hence, this paper contributes to the literature by uniquely documenting both the gains and losses of targeted pricing in dynamic settings.

Second, our experiments differ substantially from the behavioral literature in marketing that examines how consumers respond to dynamic pricing and targeting. This literature does not consider targeting within a dynamic context and isolates the effects of inter-temporal price changes and peer-induced fairness (Li and Jain, 2016). With targeting, Krishna et al. (2007) find that consumers are willing to stay loyal to firms even when they have been targeted with price increases. Alternatively, with dynamic pricing, Feinberg et al. (2002), Haws and Bearden (2006) and Jin et al. (2014) demonstrate that consumers experience negative emotions when prices vary across customers and consumers view this practice to be unfair. Moreover, Wang and Krishna (2012) show that these price differentials reduce a consumer's likelihood to purchase from a firm price discriminating through dynamic pricing. Contrarily, our experiments suggest that targeted pricing in a dynamic context may have negative repercussions for firms even when peer-induced fairness concerns are mitigated.

Finally, we contribute to the experimental economics literature in marketing, which centers on the strategic decision making of firms and consumers. The strategic decision making of firms have been examined in trade promotion decisions (Yuan et al., 2013), duopoly pricing (Amaldoss and He, 2013), distribution channel coordination (Cui and Mallucci, 2016; Ho et al., 2010; Özer et al., 2018), third-party reviews (Kim et al., 2019; Chung et al., 2020) and salesforce management (Chen et al., 2011; Lim and Chen, 2014). On the contrary, strategic consumer decision making has been tested in the context of conspicuous consumption (Amaldoss and Jain, 2005a,b) and auction bidding behavior (Ding et al., 2005). Typically, one of these two strategic parties is simulated by a computer as a design variable. However, in order to test theoretical predictions that require strategic decisions by both parties, we consider a market experiment (Yuan and Han, 2011) that has active participants for both the sellers and buyers. Only a few experimental studies test dynamic pricing strategies within this context and none investigates whether targeted pricing should be implemented by firms that use dynamic pricing.

Yuan and Han (2011) examine dynamic pricing strategies with strategic consumers and find that firms' prices are driven by consumers' price expectations and their willingness to search for better prices. Meanwhile, Mak et al. (2012) show that the pricing strategies of sellers are influenced by strategic buyers who wait and anticipate future markdowns. Relatedly, Mak et al. (2014) find experimental evidence that scarcity could drive buyers to be more myopic, which drives sellers to set and benefit from higher prices from initial offerings. Similarly, Kremer et al. (2017) indicate that sellers can also be myopic when setting prices in the main selling season and the markdown season. These findings collectively indicate that there can be substantial deviations from theory when testing complex pricing strategies. Therefore, we add to this literature by examining whether our predictions about the effectiveness of targeting in a dynamic pricing context can be substantiated with human participants.

The rest of the paper is organized as follows. In Section 2, we lay out the benchmarks in which the monopolist does not engage in targeting. We first analyze the case where the monopolist charges a single price for both periods; we then examine the implications of dynamic pricing. In Section 3, we explore targeting where the monopolist charges a different price to the newly identified customer segment and compare the monopolist's profits under dynamic pricing with those under static targeted pricing. Next, we investigate the monopolist's optimal pricing policy and profits when she employs dynamic targeted pricing. We test several main findings in two laboratory experiments and report the details in Section 4. Finally, we conclude in Section 5 and offer some directions for further research. All proofs are contained in Appendix A. We consider models with price commitment in Appendix B. Appendix C provides numerical studies and model extensions that illustrate the robustness of our key results. Appendix D reports some additional experimental results.

2. BENCHMARKS

Consider a monopolist offering a product to two distinctive customer segments over two periods. The market size is normalized to one, where a proportion α belongs to segment A with a constant product valuation $v_A \in [0, 1]$, while the rest belongs to segment B with product valuation V_B that follows a uniform $[0, 1]$ distribution. To avoid triviality, we assume throughout the paper that $\alpha \in [0, 1)$. Segment A consumers have a common valuation to the monopolist's product. The common valuation[3] can be anywhere in the spectrum, ranging from low to high. By contrast, segment B consumers are heterogeneous in their valuation of the product. Segment A consists of a group of customers whose valuations are identified by the firm through marketing intelligence. The valuations of customers in segment B are not identified, although the distribution of their valuations is common knowledge. All customers

[3]The common valuation assumption is essential for analytical tractability but it is not required for our qualitative results. In Appendix C, we demonstrate that our results hold when segment A consumers' valuations follow a uniform distribution within a narrow band (see $p.\,48$).

arrive at the beginning of the first period. The per unit cost of the product is normalized to 0.[4]

Given the market characteristics, the monopolist can engage in two types of third-degree price discrimination. First, she can adopt intertemporal price discrimination by charging different prices in the two periods. Second, she can use targeted pricing by charging different prices to the two distinct consumer segments. The latter becomes feasible after the identification of customers in segment A. In this section, we present two benchmark cases. The first benchmark examines static pricing, where the monopolist does not engage in price discrimination of any kind. The second benchmark analyzes dynamic pricing without targeting. We introduce targeting in Section 3.

2.1 Static Pricing

In static pricing without targeting, a single price is charged to both segments. For a given static price $p \in [0, 1]$, the revenue is given by

$$\begin{aligned} R^S(\alpha, p) &= \begin{cases} p(1-p)(1-\alpha), & \text{if} \quad p > v_A, \\ p[(1-p)(1-\alpha)+\alpha], & \text{if} \quad p \le v_A, \end{cases} \\ &= \underbrace{p(1-p)(1-\alpha)}_{\text{revenue from segment B}} + \underbrace{\begin{cases} 0, & \text{if} \quad p > v_A, \\ \alpha p, & \text{if} \quad p \le v_A. \end{cases}}_{\text{revenue from segment A}} \end{aligned} \tag{1}$$

The optimal static price can be found by solving the problem

$$R^{S*}(\alpha) = \max_{0 \le p \le 1} R^S(\alpha, p). \tag{2}$$

Lemma 1 *Suppose the seller adopts static pricing without targeting. The optimal static price is given by*

$$p^{S*}(\alpha) = \begin{cases} \frac{1}{2}, & \textit{if} \quad v_A < \frac{1-\sqrt{\alpha(2-\alpha)}}{2(1-\alpha)}, \\ v_A, & \textit{if} \quad \frac{1-\sqrt{\alpha(2-\alpha)}}{2(1-\alpha)} \le v_A \le \frac{1}{2(1-\alpha)}, \\ \frac{1}{2(1-\alpha)}, & \textit{if} \quad v_A > \frac{1}{2(1-\alpha)}. \end{cases} \tag{3}$$

[4] We henceforth use revenue and profit interchangeably.

The corresponding optimal revenue is

$$R^{S*}(\alpha) = \begin{cases} \frac{1-\alpha}{4}, & \textit{if} \quad v_A < \frac{1-\sqrt{\alpha(2-\alpha)}}{2(1-\alpha)}, \\ v_A[1-(1-\alpha)v_A], & \textit{if} \quad \frac{1-\sqrt{\alpha(2-\alpha)}}{2(1-\alpha)} \leq v_A \leq \frac{1}{2(1-\alpha)}, \\ \frac{1}{4(1-\alpha)}, & \textit{if} \quad v_A > \frac{1}{2(1-\alpha)}. \end{cases} \tag{4}$$

Lemma 1 shows that the monopolist's optimal static price depends on segment A's contribution to the total profits, which in turn hinges on its segment size (α) and valuation (v_A). Specifically, when the contribution is relatively small, the monopolist's optimal price is set to extract the maximum rent from segment B. When segment A's contribution is in some intermediate range, the monopolist optimally sets its price at segment A's valuation. When segment A's contribution is above a threshold, the monopolist's optimal price is set to reap the profits from segment A and the high valuation customers in segment B.

Under static pricing, all consumers purchase in the first period because there is no incentive to delay their purchases. Intuitively, the monopolist can induce some consumers to defer their purchases to the second period by charging a lower price. Due to time discounting, consumers valuations decline in the second period. Thus, only consumers whose valuations are sufficiently low find it worthwhile to wait. We consider these factors in dynamic pricing.

2.2 Dynamic Pricing

In this section, we assume that the seller can perform inter-temporal price discrimination by charging different prices in different periods. Customers use a discount factor $\gamma \in (0, 1)$. By contrast, the seller does not discount its profit in the second period. This assumption captures the idea that firms are often more patient than customers.[5] We further assume that the seller does not commit to a price path. Therefore, the price charged in the second period must be optimal for the residual market in the second period. To obey this assumption, we formulate the problem backwards.

We start with the formulation for the second period problem. Observe that for any pair of prices in the two periods, there exists a critical value θ above which customers purchase in period 1. When $\theta \leq v_A$, consumers in segment A purchase in period 1; when $\theta > v_A$, consumers in segment A either purchase in period 2 or do not purchase at all. For a given

[5]See Levin et al. (2009) and Cachon and Swinney (2009) for a similar assumption.

price p_2, the second period revenue is given by

$$R_2^D(\alpha,\theta,p_2) = (1-\alpha)(\theta-p_2)p_2 + \begin{cases} 0, & \text{if} \quad \theta \le v_A, \text{or } \theta > v_A, p_2 > v_A, \\ \alpha p_2, & \text{if} \quad p_2 \le v_A < \theta. \end{cases} \tag{5}$$

The optimal revenue in the second period is then given by

$$R_2^{D*}(\alpha,\theta) = \max_{0\le p_2 \le \theta} R_2^D(\alpha,\theta,p_2). \tag{6}$$

Let $p_2^{D*}(\alpha,\theta)$ be the maximizer in equation (6); i.e., $R_2^{D*}(\alpha,\theta) = R_2^D(\alpha,\theta,p_2^{D*}(\alpha,\theta))$.

Next, we formulate the first period problem. Given first period price p_1, a customer with valuation θ purchases in the first period if the surplus in the first period is higher than the (discounted) surplus in the second period, i.e.,

$$\theta - p_1 \ge \gamma(\theta - p_2^{D*}(\alpha,\theta)) \qquad \Leftrightarrow \qquad \theta \ge \frac{p_1 - \gamma p_2^{D*}(\alpha,\theta)}{1-\gamma}. \tag{7}$$

For a marginal customer with valuation θ who is indifferent between purchasing in the first period and the second period, equality holds in the above equation. We have

$$p_1(\alpha,\theta) = (1-\gamma)\theta + \gamma p_2^{D*}(\alpha,\theta). \tag{8}$$

We note that the optimization over p_1 can be equivalently stated as an optimization over the marginal valuation θ. It follows that the total revenue is given by

$$R^D(\alpha,\theta) = R_2^{D*}(\alpha,\theta) + \begin{cases} p_1(\alpha,\theta)[\alpha + (1-\alpha)(1-\theta)], & \text{if} \quad \theta \le v_A, \\ p_1(\alpha,\theta)(1-\theta)(1-\alpha), & \text{if} \quad \theta > v_A. \end{cases} \tag{9}$$

The optimal revenue is then given by

$$R^{D*}(\alpha) = \max_{0\le\theta\le 1} R^D(\alpha,\theta). \tag{10}$$

Lemma 2 *Under dynamic pricing, the optimal two-period revenue is given by*

$$R^{D*}(\alpha) = \begin{cases} \frac{(2-\gamma)^2}{4(1-\alpha)(3-2\gamma)}, & \textit{Region 1}, \\ \frac{v_A\left[(2-\gamma)^2-(1-\alpha)(3-2\gamma)v_A\right]}{(2-\gamma)^2}, & \textit{Region 2}, \\ \frac{(2-\gamma)^2-4\alpha(1-\alpha)(1-\gamma)^2}{4(1-\alpha)(3-2\gamma)}, & \textit{Region 3}, \\ \frac{(1-\alpha)(1-\gamma)+2v_A(1+\alpha+\gamma-\alpha\gamma)-(1-\alpha)(3+\gamma)v_A^2}{4}, & \textit{Region 4}, \\ \frac{(1-\alpha)(2-\gamma)^2}{4(3-2\gamma)}, & \textit{Region 5}. \end{cases} \tag{11}$$

The regions are defined in the following table:

Region	*Definition*	*Condition*
Region 1	*Segment A served in period 1 and* $p_1^* < v_A$	$\frac{(2-\gamma)^2}{2(1-\alpha)(3-2\gamma)} < v_A$
Region 2	*Segment A served in period 1 and* $p_1^* = v_A$	$v_{23} < v_A \leq \frac{(2-\gamma)^2}{2(1-\alpha)(3-2\gamma)}$
Region 3	*Segment A served in period 2 and* $p_2^* < v_A$	$\frac{2-\gamma+2\alpha(1-\gamma)}{2(3-2\gamma)(1-\alpha)} < v_A \leq v_{23}$
Region 4	*Segment A served in period 2 and* $p_2^* = v_A$	$v_{45} < v_A \leq \frac{2-\gamma+2\alpha(1-\gamma)}{2(3-2\gamma)(1-\alpha)}$
Region 5	*Segment A not served*	$v_A < v_{45}$

Let $R_i^{D*}(\alpha)$ *denote the revenue in Region* i *for* $i = 1, 2, \ldots, 5$ *as stated in (11). The constant* v_{23} *is the smallest root of the equation* $R_2^{D*}(\alpha) - R_3^{D*}(\alpha) = 0$*, and* v_{45} *is the smallest root of the equation* $R_4^{D*}(\alpha) - R_5^{D*}(\alpha) = 0$*, where* v_A *is treated as the unknown in both equations.*

The regions in Lemma 2 are defined based on whether segment A consumers are served and the price charged to segment A consumers. Note that because of segment A, the revenue function of the seller is not smooth. Since the constants v_{23} and v_{45} are solutions to quadratic equations of v_A, they can be expressed in (complicated) explicit forms. We choose not to do so in the paper for ease of exposition.

Clearly, the implementation of dynamic pricing can be quite involved, as we can see from the optimal dynamic pricing policy and the resulting profits. Indeed, Khan et al. (2009) remark that the computational burden of dynamic optimization is heavy and accounting for cross-sectional heterogeneity in addition to temporal heterogeneity significantly increases the burden. This observation casts some doubt on the benefit of pursuing dynamic targeted pricing and illustrates the importance of understanding the trade-offs between dynamic pricing and targeted pricing. We address these issues in the next section.

3. TARGETING

With the widespread availability of the customer database, firms are endowed with large amounts of individual level customer information. This information allows firms to customize their product offerings and marketing strategies based on certain customer characteristics. Targeted pricing is a prime example of such practice. It is not clear, however, whether targeting adds value when firms are practicing dynamic pricing. In this section, we investigate static targeted pricing and compare static targeted pricing with dynamic pricing. Moreover, we establish when and the extent to which dynamic targeted pricing can be beneficial.

3.1 Static Targeted Pricing

To keep our model parsimonious, we assume that firms possess perfect targeting capability. Our qualitative results remain robust when targeting is imperfect.

Proposition 1 *Under static pricing, targeting improves seller profits.*

The result of Proposition 1 is strong, as it shows that static targeted pricing always dominates static pricing without targeting. Next, we seek to understand the nuanced differences between dynamic pricing and targeted pricing.

Proposition 2 *Dynamic pricing dominates static pricing without targeting. When $\gamma = 0$, dynamic pricing dominates static targeted pricing. Furthermore, there exists a range of v_A and γ values under which dynamic pricing dominates static targeted pricing.*

The first part of Proposition 2 is not surprising. Since dynamic pricing allows the firm to price discriminate, it yields higher profits than static pricing. Dynamic pricing exploits heterogeneity in consumers' intertemporal preferences, while targeted pricing benefits from heterogeneity in valuation across segments. The effectiveness of dynamic pricing depends on consumers' forward looking behavior. At one end of the spectrum, when consumers are myopic ($\gamma = 0$), dynamic pricing attains its maximum effectiveness. At the other end of the spectrum, when consumers are perfectly forward looking ($\gamma = 1$), dynamic pricing is completely ineffective.[6] This is because the monopolist charges a higher price in period 1 and a lower price in period 2 under dynamic pricing.[7] If consumers are myopic, high valuation customers will purchase in period 1 and the remaining customers either purchase in period 2 or leave the market. Therefore, the monopolist extracts as much rent as possible from the high valuation customers. By contrast, when consumers are perfectly forward looking, the high valuation customers will postpone their purchase until the second period and pay the lower price, which renders dynamic pricing moot.

[6] It is straightforward to show that when $\gamma = 1$, the equilibrium prices under dynamic pricing are the same as those under static pricing.

[7] Besanko and Winston (1990) show that price skimming is optimal for the monopolist for a multi-period game.

The second part of Proposition 2 compares the benefit of static targeted pricing with that of dynamic pricing. We find that when consumers are myopic ($\gamma = 0$), dynamic pricing is more effective than targeted pricing. It follows that this result must hold for some $\gamma > 0$ so long as it is below a threshold due to the continuity of the profit function in the parameter γ.[8] We note that this finding echoes the empirical finding of Khan et al. (2009). Furthermore, we show that dynamic pricing dominates static target pricing for a range of v_A and γ values.

To understand the underlying rationale behind this result, we need to illustrate why targeting works and its limitations. The benefit of targeting stems from the fact that it allows firms to price discriminate consumers according to their valuations. For all practical purposes, consumers are classified into discrete segments based on a certain threshold level of valuations. However, consumer valuations generally follow a continuous distribution and discrete segmentation (often dichotomization) suffers from intrinsic arbitrariness. Therefore, targeting cannot fully exploit consumer valuation heterogeneity regardless of how accurate it is.[9]

By contrast, consumers' inter-temporal preferences often fall into different intervals, which can be reasonably well represented by discrete periods. For instance, consider a consumer who is contemplating about purchasing a vacation package. As long as the trip occurs within a certain time frame, her value remains constant. Her value only declines if the trip is postponed beyond her comfort zone. Our model of dynamic pricing closely resembles such stepwise value discounting where consumers hold their values steady over a given period. Hence, dynamic pricing is more effective than static pricing with perfect targeting when consumers are myopic. Furthermore, this result continues to hold even when consumers are mildly forward-looking. Conceivably, there can be situations where consumer discount their values over short intervals. In that case, a multi-period model would be more appropriate than a two-period model. We show that our main insights extend to a multi-period model in Appendix C.

[8]We prove this claim in the Proof for Proposition 2.

[9]For example, in Shaffer and Zhang (1995), consumer valuations of the competing products are uniformly distributed, yet each firm charges only two different prices: a regular (higher) price to consumers who have sufficiently strong preference toward the firm's product, and a discounted price (with targeted coupon) to consumers whose preferences are weak.

3.2 Dynamic Pricing with Perfect Targeting

As in static pricing, the monopolist is not confined to using dynamic pricing only, she can target the two consumer segments with different prices as well. Indeed, as customer databases become ubiquitous, firms increasingly adopt both dynamic pricing and targeting. Casual observation reveals that such practice is common and it is facilitated by customer relationship management. We focus on the case in which the monopolist can target with perfect accuracy. When the monopolist's targeting is perfect, she can accurately identify customers in the A and B segments. As such, she charges v_A and obtains a profit of αv_A from segment A. Her profits from segment B in the two periods are $(1-\alpha)(1-\theta)\, p_{B,1}$ and $(1-\alpha)(\theta - p_{B,2})\, p_{B,2}$, respectively, given the valuation θ of a marginal customer who is indifferent between purchasing in the two periods. It can be shown that the optimal marginal valuation $\theta^* = \frac{2-\gamma}{3-2\gamma}$, with corresponding prices in the two periods $\left(\frac{(2-\gamma)^2}{2(3-2\gamma)}, \frac{2-\gamma}{2(3-2\gamma)}\right)$. The monopolist's optimal total profit from both segments is $\alpha v_A + \frac{(1-\alpha)(2-\gamma)^2}{4(3-2\gamma)}$.

Proposition 3 *Under dynamic pricing and perfect targeting, the monopolist can be worse off when she adopts targeted pricing. Specifically, (i) when* $\frac{2-\gamma+2\alpha(1-\gamma)}{2(3-2\gamma)(1-\alpha)} < v_A \leq v_{23}$ *(Region 3), the monopolist's profits are higher without targeting when*

$$\gamma > \frac{4v_A(1-\alpha) - 2\alpha - 2\sqrt{(1-\alpha)(1-v_A)\left[2-\alpha-4v_A(1-\alpha)\right]}}{2-3\alpha};$$

(ii) when $v_{45} < v_A \leq \frac{2-\gamma+2\alpha(1-\gamma)}{2(3-2\gamma)(1-\alpha)}$ *(Region 4), the monopolist's profits are higher without targeting when* $\gamma_0 < \gamma < \gamma_1$*, where*

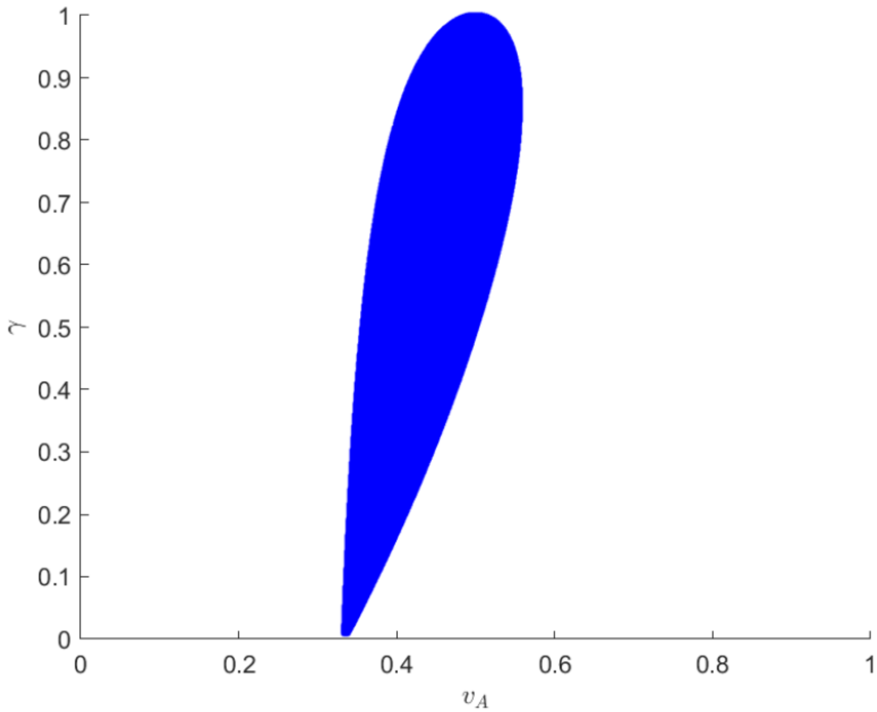
$$\gamma_0 \equiv \frac{(3v_A-1)\left[1+v_A-\sqrt{(1-v_A)(5-9v_A)}\right]}{2\left(4v_A-2v_A^2-1\right)},$$

$$\gamma_1 \equiv \frac{(3v_A-1)\left[1+v_A+\sqrt{(1-v_A)(5-9v_A)}\right]}{2\left(4v_A-2v_A^2-1\right)};$$

(iii) the monopolist's profit is higher with perfect targeting when $\frac{(2-\gamma)^2}{2(1-\alpha)(3-2\gamma)} < v_A$ *(Region 1),* $v_{23} < v_A \leq \frac{(2-\gamma)^2}{2(1-\alpha)(3-2\gamma)}$ *(Region 2), and* $v_A < v_{45}$ *(Region 5).*

Proposition 3 is the key result of our paper and is somewhat counter-intuitive. Since dynamic pricing and targeting both help the firm better price discriminate customers, one would expect that their combined effect is even stronger. Proposition 3 shows that this

FIG. 1. Regions where dynamic pricing without targeting dominates dynamic pricing with perfect targeting; $\alpha = 0.5$



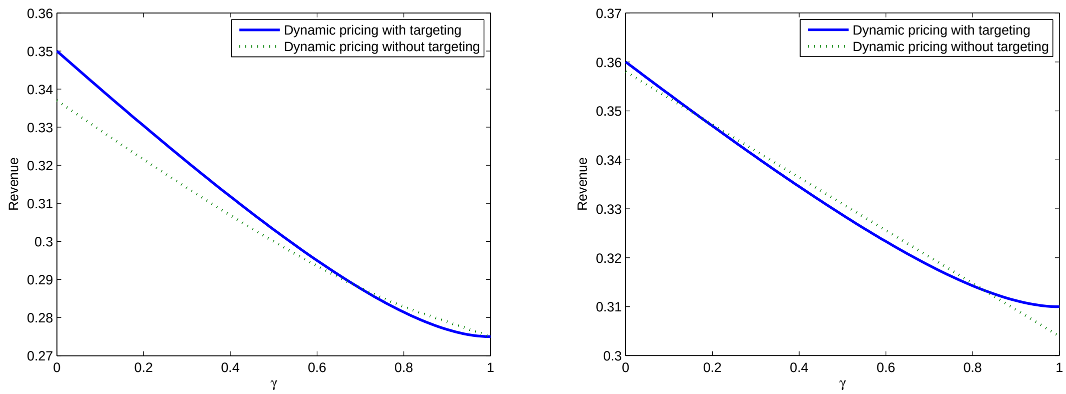
may not be the case – in fact, the firm can be worse off by utilizing both levers for price discrimination. Our result complements the earlier result of Chen and Zhang (2009), which states that targeted pricing can hurt firms under competition. Our result shows that the negative effect can occur even when there is no competition.

To illustrate the results in Proposition 3, Figure 1 shows regions where dynamic pricing without targeting dominates dynamic pricing with perfect targeting for $\alpha = 0.5$. It shows that the dominance primarily occurs when v_A is not too far from 0.5. Proposition 3 is counter-intuitive. How can targeting hurt the firm's profits when the firm can perfectly identify customers? Moreover, how can inter-segment price discrimination (targeting) interfere with intra-segment price discrimination (dynamic pricing)? In order to develop some intuition behind this result, we start with Part (ii) of Proposition 3. When the monopolist simultaneously employs dynamic pricing and targeted pricing (with perfect identification), segment A and segment B customers are completely separated and they are each targeted with a different price across the two periods. Note that the second period price under dynamic pricing without targeting is v_A in Region 4. Therefore, with or without targeting, the revenue from segment A is the same. When segment A customers are singled out, the revenue from segment B customers can be either higher or lower under targeting. When customers are myopic, the ability to offer different prices to segment B consumers allows the firm to gain more revenue from the segment. As customers becomes more forward-looking ($\gamma > \gamma_0$), however, targeting segment A customers is counter-productive for the seller. This is because high-valuation segment B customers are more likely to wait for lower prices in the second period. This tendency is less pronounced without targeting. In that case, the presence of segment A customers helps to increase the optimal price in the second period. Put differently, without targeting, high valuation customers in segment B are more likely to purchase in the first period at the higher price, because they know the second period price won't be too low. However, when segment A customers are removed by targeting, high valuation customers in segment B correctly anticipate that the period 2 price will be lower. As such, they are more likely to postpone their purchase to period 2 and pay the lower price. As γ further increases ($\gamma > \gamma_1$), the price stabilization effect of segment A consumers disappears. In fact, the optimal second period price targeted to segment B may even exceed v_A, in which case it is easy to see that dynamic targeted pricing dominates dynamic pricing without targeting. The thresholds γ_0 and γ_1 are moderated by the size of segment A (α). Specifically, a larger α implies a higher impact of separating segment A from segment B customers, hence lower γ_0 and γ_1. Finally, we note that the negative effect of targeting on dynamic pricing is balanced by the gain from exploiting inter-segment price discrimination. However, when the inter-segment heterogeneity is not sufficiently high, the loss from targeting outweighs the gain.

The intuition for Part (ii) of Proposition 3 also applies to Part (i). The dynamics in Region 3 are slightly more involved, because the price at which segment A purchases under dynamic pricing without targeting is less than v_A. Hence, targeting increases revenue from segment A. Note that Region 3 corresponds to a case where v_A is relatively large. Our result shows that as long as γ exceeds a threshold, targeting can cause revenue loss.

We use the following numerical examples to illustrate the intuitions discussed above. In Figure 2(a), we set $\alpha = 0.1$ and $v_A = 0.5$ in Region 3. The adverse effect of targeting on dynamic pricing is lower in this case due to the relatively small weight of segment A in the population. Consequently, the threshold level of γ is reached at 0.692. Note that the revenue

Fig. 2. Revenue comparison between dynamic pricing with targeting and dynamic pricing without targeting



(a) Region 3; $\alpha = 0.1$ and $v_A = 0.5$

(b) Region 4; $\alpha = 0.4$ and $v_A = 0.4$

is the same when $\gamma = 1$ because dynamic pricing reduces to static pricing and $v_A = 0.5$. At $\gamma = 0.692$, the optimal prices without targeting are $p_1^{D*} = 0.582$ and $p_2^{D*} = 0.471$; the optimal prices targeted at segment B are $p_1^* = 0.529$ and $p_2^* = 0.405$.

In Figure 2(b), we set $\alpha = 0.4$ and $v_A = 0.4$ in Region 4. Dynamic pricing without targeting dominates dynamic pricing with perfect targeting for $0.173 < \gamma < 0.827$. At $\gamma = 0.173$, the first and second period prices under dynamic pricing without targeting are $p_1^{D*} = 0.648$ and $p_2^{D*} = 0.4$, respectively; the corresponding prices for segment B under dynamic pricing with perfect targeting are $p_1^* = 0.629$ and $p_2^* = 0.344$. Clearly, the gap between p_1^* and p_2^* is greater than that between p_1^{D*} and p_2^{D*}; $p_2^* < p_2^{D*}$. When $\gamma = 0.827$, $p_1^{D*} = 0.452$ and $p_2^{D*} = 0.4$; $p_1^* = 0.511$ and $p_2^* = 0.436$. Note that $p_1^* - p_2^*$ is still greater than $p_1^{D*} - p_2^{D*}$ but the gap is smaller. Further note that now $p_2^* > p_2^{D*}$.

The fundamental insight of Proposition 3 is that strategic customer behavior reduces the effectiveness of dynamic pricing, whereas targeting can exacerbate consumers' forward looking behavior and thereby hurt firm's profits.

Discussion. In Sections 2 and 3, we have had a thorough examination of the monopolist's pricing strategy. The strategy space spans from static pricing without targeting to dynamic targeted pricing. We obtained a set of interesting results. When consumers are heterogeneous in their valuations, the monopolist is strictly better off when she moves from static pricing without targeting to static targeted pricing. Similarly, she is strictly better off when she chooses dynamic targeted pricing over static targeted pricing, provided that consumers are not perfectly forward looking. The monopolist makes higher profits when she moves from static targeted pricing to dynamic pricing without targeting if consumers are myopic. However, this is not the case when consumers are sufficiently forward looking. When the monopolist adopts targeting in addition to dynamic pricing, she could be worse off (see Figure 1). It is useful to contrast this result to the behavior-based pricing literature. A classic result is that BBP leads to lower profits for firms. We note that under BBP, consumers make a unit purchase in each period. Although firms can offer targeted pricing in the second period based on customers' purchase history, firms cannot identify customers' locations (thereby their net utilities). By contrast, in our model, consumers make a unit purchase over two periods, and firms can offer targeted pricing based on the identification of some customers' values. Furthermore, in our model, targeted pricing is implemented in the first period. Therefore, our insights are driven by a very different mechanism than that of BBP.

The extant literature prescribes commitment as a potent tool for improving the performance of dynamic pricing (e.g., Butz, 1990; Aviv and Pazgal, 2008; Su and Zhang, 2008). In Appendix B, we show that commitment helps improve the performance of dynamic pricing. Nevertheless, the value of commitment is small for dynamic targeted pricing. In Appendix C, we demonstrate the robustness of our results by establishing that these insights extend to a multiple-period setting.

4. EXPERIMENTAL INVESTIGATION

We conduct two incentive-compatible experiments with human participants to test the theoretical predictions. In Experiment 1, we test when dynamic pricing is preferred over targeted pricing. In Experiment 2, we examine when targeting within a dynamic pricing context improves or reduces firm profits.

Throughout the experiments, a triad of human participants make interactive decisions in each round. The triad consists of a representative for the Seller, a representative for customers in Segment $A$and a representative for customers in Segment B. Also, we limit peer-induced fairness, but we do not limit the fairness concerns that may arise from pricing that is incommensurate with costs (Bolton, Warlop, and Alba, 2003; Guo and Jiang, 2016). An extreme example of this classification of unfairness may arise from price gouging. Unfairness may be perceived when firms price to extract all consumer surplus. The targeting feature of pricing tested in our experiments can potentially lead to perceptions of unfairness because firms are predicted to price precisely at the willingness-to-pay for segment A. Finally, profits and revenues are used interchangeably since firm costs are zero.

4.1 Experiment 1: Dynamic Pricing (DP) versus Static Targeted Pricing (STP)

According to theory, the relative profitability of dynamic pricing versus static targeted pricing depends on the patience of customers (discount factor: γ). When customers are impatient, dynamic pricing can be more profitable than static targeted pricing. This is because the benefits of price skimming outweigh the benefits of targeting in static pricing since customers have a strong desire to purchase in the initial period when firms charge higher prices. However, when customers are patient, dynamic pricing does not benefit firms because customers can wait for lower prices in the second period. Hence, static targeted pricing can be more profitable than dynamic pricing in this situation because the benefits of targeting outweigh the benefits of price skimming since customers are willing to wait until the subsequent period to purchase. These predictions are captured in the following hypothesis:

Hypothesis 1 *Profits, in the DP treatment, are higher than the STP treatment when customers are impatient and are lower than the STP treatment when customers are patient.*

We test Hypotheses 1 using an incentive-compatible experiment with 54 human participants. The experiment captures the strategic interaction that takes place between three human players: a representative for the firm, a representative customer for segment A, and a representative customer for segment B. Our experimental manipulation varies the degree of patience in customers. In field settings, it is difficult to assess how customer patience affects profits, but in a controlled laboratory setting, the discount factor can be a design variable. Hence, we assign a smaller discount factor to manipulate impatience and a larger discount factor to manipulate patience. The smaller discount factor substantially reduces the customer's surplus (payout) in the second period. Note that the discount factor only affects customers when dynamic pricing is implemented since there is only one period in the static game.

Consequently, there are three conditions that we test: Static Targeted Pricing (STP),

Table 1. Theoretical Predictions and Means in Experiment 1

Condition	Variable	Theory	Mean	SD	t−test vs. Theory
Static	p_A^{STP}	80.0	70.2	10.7	Diff = −9.8*
Targeted					$SE = 1.29; p = 0.000$
Pricing	p_B^{STP}	50.0	52.7	13.8	Diff = 2.7
(STP)					$SE = 2.48; p = 0.293$
	R^{ST}	415.0	336.1	86.6	Diff = −78.9*
					$SE = 15.67; p = 0.000$
Impatient	p_1^{IDP}	76.0	69.4	10.3	Diff = −6.6*
Dynamic					$SE = 1.67; p = 0.001$
Pricing	p_2^{IDP}	40.0	44.5	14.6	Diff = 4.5*
(IDP)					$SE = 2.09; p = 0.048$
	R^{IDP}	446.4	405.8	91.6	Diff = −40.6*
					$SE = 13.60; p = 0.008$
Patient	p_1^{PDP}	75.5	69.7	16.6	Diff = −5.8*
Dynamic					$SE = 2.67; p = 0.045$
Pricing	p_2^{PDP}	64.8	61.3	19.7	Diff = −3.5
(PDP)					$SE = 2.92; p = 0.250$
	R^{PDP}	357.6	269.1	154.2	Diff = −88.5*
					$SE = 31.24; p = 0.012$

*Significant at the 5% level

Impatient Dynamic Pricing (IDP) and Patient Dynamic Pricing (PDP). We chose a set of parameters that would allow for clear separation between the predictions across these three conditions. Hence, we chose $I = 1$, $\gamma^{IDP} = 0.3$, $\gamma^{PDP} = 0.9$, $v_A = 80$, and $\alpha = 0.3$. Note that we scaled the valuations by 100 for face validity. Also, in order to explain the customer segments more clearly to the participants, we multiplied the proportion of customers by 10. This resulted in 3 customers in segment A and 7 customers in segment B.

After explaining the instructions to the participants, the participants representing the firm in the dynamic pricing conditions chose prices charged in two periods for customers in Segments A and B. Meanwhile, the participants representing the customers in Segments A and B chose whether to purchase at the prices chosen by the sellers. Thus, the prices and the purchases are all chosen by human decision makers and the participants were paid according to the outcomes of their decisions. The predictions for the three conditions are shown in the table below and further details of the experimental procedure can be found in Appendix D.

Results: Given that we did not observe a sharp learning trend, we proceed with the full data and cluster the standard errors to account for within subject correlation because participants make repeated decisions. The predictions and deviations from theory are shown in Table 1. Although deviations from the theoretical predictions exist, there is substantial directional support for the theory. We discuss two specific deviations from theory. First, in the STP condition, the price for segment A is predicted to be equal to A's valuation of 80. However, we see that the observed mean is significantly lower than this value (70.2 vs. 80; $p = 0.000$). Hence, the seller tends to price significantly below Player A's reservation price to ensure purchase. Charging a price equal to A's valuation would result would cause Player A to be indifferent to purchasing. Second, we observe that the revenues observed across the three conditions are all lower than the theoretical predictions. Even though participants have the incentive to maximize their payoffs, achieving optimal revenues remains a formidable task.

Accordingly, theory makes clear predictions about the price differences within a pricing regime (see Table 1). In both of the dynamic pricing conditions (IDP and PDP), the prices are predicted to drop in the subsequent period and we find that this holds true. In particular, the price drops from 69.4 to 44.5 ($p = 0.000$) and from 69.7 to 61.3 ($p = 0.034$) in the IDP and PDP conditions, respectively. Meanwhile, in the STP condition, the targeted price for customers in segment A should be higher than the targeted price for segment B. Indeed, we find that the targeted price is significantly higher as predicted (70.2 vs. 52.7; $p = 0.000$).

We now proceed to formally test the differences across conditions (see Table 2). To begin with, our model predicts that greater impatience renders dynamic pricing more profitable and we find that revenues do increase from 269.1 to 405.8 ($p = 0.000$). When customers are patient (the discount factor is high), the seller is unable to reduce prices much in the subsequent period because high valuation customers will wait until period 2 to purchase. Consistent with this prediction, the period 2 prices in the PDP condition are significantly higher than that in the IDP condition (61.3 vs. 44.5; $p = 0.000$) and the proportion of customers who purchase is lower by 0.19 ($p = 0.000$). However, there is no difference in the period 1 prices (0.922). The period 1 price is equal to 69.4 and 69.7 in the IDP and PDP conditions, respectively. Now we proceed to the tests of Hypothesis 1.

Hypothesis 1 proposed that dynamic pricing would be comparatively more profitable than static targeted pricing when customers are impatient and less profitable when customers are patient. We find that the revenues in the IDP condition exceed the revenues in the STP condition (405.8 vs. 336.1; $p = 0.002$) consistent with theory. As a result, the benefits of

Table 2. t-Tests of Price, Purchase Proportion and Revenue Differences in Experiment 1

Price Differences in a Condition†	**Mean**	**SE**	**t**	**p**	**Theory**
$p_A^{STP} - p_B^{STP}$	17.5*	2.86	6.11	0.000	30.0
$p_1^{IDP} - p_2^{IDP}$	24.9*	2.20	11.36	0.000	36.0
$p_1^{PDP} - p_2^{PDP}$	8.4*	3.62	2.31	0.034	10.8
Price Differences across Conditions	**Mean**	**SE**	**t**	**p**	**Theory**
$p_A^{STP} - p_1^{IDP}$	0.8	2.13	0.36	0.720	4.0
$p_A^{STP} - p_1^{PDP}$	0.5	2.99	0.15	0.879	4.5
$p_1^{IDP} - p_1^{PDP}$	−0.3	3.18	−0.10	0.922	0.5
$p_B^{STP} - p_2^{IDP}$	8.3*	3.28	2.52	0.017	10.0
$p_B^{STP} - p_2^{PDP}$	−8.6*	3.87	−2.23	0.033	−14.8
$p_2^{IDP} - p_2^{PDP}$	−16.9*	3.63	−4.65	0.000	−24.8
Purchase Proportions across Conditions	**Mean**	**SE**	**t**	**p**	**Theory**
$Purchase^{STP} - Purchase^{IDP}$	−0.12*	0.03	−3.54	0.001	−0.08
$Purchase^{STP} - Purchase^{PDP}$	0.08	0.05	1.62	0.114	0.10
$Purchase^{IDP} - Purchase^{PDP}$	0.19*	0.04	4.67	0.000	0.13
Revenue Differences across Conditions	**Mean**	**SE**	**t**	**p**	**Theory**
$R^{IDP} - R^{PDP}$	136.6*	34.40	3.97	0.000	88.8
Hypothesis 1: $R^{IDP} - R^{STP}$	69.6*	20.97	3.32	0.002	31.4
Hypothesis 1: $R^{PDP} - R^{STP}$	−67.0**	35.32	1.90	0.067	−57.4

*Significant at the 5% level; †Paired

**Significant at the 10% level

price skimming exceed the benefits of targeting when customers are impatient. Unit sales are also higher under dynamic pricing. Specifically, the proportion of customers who purchase increases by 0.12 under dynamic pricing ($p = 0.001$). For patient customers, our model predicts the reverse effect — dynamic pricing would be comparatively less profitable than targeted pricing when customers are patient. This is because forward looking customers are willing to wait for the lower prices and delay their purchase. For this reason, the benefits of dynamic pricing are expected to dissipate and static targeted pricing should be more profitable. From Table 3, the revenues in the PDP condition are marginally lower than the STP condition by 67.0 ($p = 0.067$) and the proportion of customers purchasing is directionally lower by 0.08 ($p = 0.114$). The results taken together confirm Hypothesis 1 and indicate that the patience of customers can be a critical factor in determining which pricing regime managers should choose: dynamic pricing or static targeted pricing.

4.2 Experiment 2: Dynamic Targeted Pricing versus Dynamic Pricing

Our model also addresses the profit implications of targeting within a dynamic pricing context. We turn our attention to varying the valuation of customer segment A assuming that all customers exhibit a moderate degree of patience ($\gamma = 0.6$) and consider a 2×2 experiment with the following factors: the valuation of A (high or moderate) and dynamic pricing regime (no targeting or targeting). Theory makes the prediction that when the valuation of customer segment A is high, dynamic targeted pricing improves profits. However, when the valuation of customer segment A is moderate, targeted pricing can potentially hurt firm profits though the harm is quite minimal. For the former, the rationale is that targeting a high valuation segment that would otherwise pay a lower price will indeed improve profits. With a moderate valuation segment, the benefits of targeting may no longer exist and having less flexibility, due to setting a common price for two segments, causes rigidity in the prices that can actually benefit firms since moderately patient customers will defer purchases to period 2. Being constrained to sell to both segments A and B through dynamic pricing would encourage more segment B customers, who would have strategically delayed their purchase under dynamic targeted pricing, to purchase in period 1 when the price is higher than that in period 2. This, in turn, will favor dynamic pricing when customers are moderately patient. Hence, it is possible for dynamic pricing to outperform dynamic targeted pricing, but the gains are modest. We state the hypotheses formally below:

Hypothesis 2 *Profits are higher in the DTP treatment than the DP treatment when the targeted customers have a high valuation for the product but are lower when the targeted customers only have a moderate valuation.*

The dynamic pricing conditions are DPH and DPM for dynamic pricing with high and moderate valuation customers in segment A, while the dynamic targeted pricing conditions are DTPH and DTPM, respectively for the high and moderate valuation segment A customers. We designed the experiment to allow for a substantial difference in the revenue predictions across the four conditions, but as we observed from theory, the difference between the DPM and DTPM conditions are minimal. Otherwise, the experimental procedure is identical to Experiment 1. There were 78 participants, where human decision makers chose prices for segments A and B and also the purchase decisions for each segment for up to two periods. We focus our discussion on the differences from Experiment 1. Here we examine targeted pricing in a dynamic pricing setting. Instead of manipulating the discount factor, we adjust the valuation of segment A's customers between H-high and M-moderate. Additionally, there are 4 customers in segment A and 6 customers in segment B. We explain the conditions in more detail in Appendix D.

Results: The theory predictions and the deviations from theory are shown in Table 4 in Appendix D. As with Experiment 1, there are some differences from theory, but directionally the results align closely with theory. We proceed by discussing the main observations from Table 4. First, in the DTPH condition, the targeted price for segment A is predicted to be equal to A's valuation of 90 and we see that the observed mean is significantly lower than this value in period 1 (76.4 vs. 90; $p = 0.000$) and period 2 (68.6 vs. 90; $p = 0.000$) when Player A did not purchase in period 1. It appears that participants tend to price significantly below Player A's reservation price to induce purchase as we found in Experiment 1. However, in the DTPM condition, the targeted price for segment A does not differ from the theory predictions (period 1 price difference: 38.0 vs. 40.0; $p = 0.244$ and period 2 price difference: 36.4 vs. 40.0; $p = 0.134$). Hence, firms do not appear to offer a formidable incentive to purchase for segment A when A's valuation is moderate. Second, as in Experiment 1, we observe that the mean revenue is less than the theoretical prediction across all conditions. Now we proceed to discuss the findings in more detail.

We discuss the price change from period 1 to period 2 within each condition; see Table 3. In the DTPH condition, the price decreases from period 1 to period 2 (A: 76.4 to 68.6, $p = 0.014$ and B: 59.3 to 46.9, $p = 0.000$). Although the price decrease was predicted for segment B, it was not predicted for segment A. This result is consistent with our explanation that the Seller tries to lower the price in period 2 to make purchasing more compelling for segment A. Meanwhile, in the DTPM condition, the price for segment A remains unchanged from period 1 to period 2 (38.0 vs. 36.4; $p = 0.491$) and decreases for segment B (53.1 to 45.0; $p = 0.000$). The DTPM condition results are consistent with the theoretical predictions. Distinctively, there is a difference in behavior between DTPH and DTPM when pricing segment A. In particular, the Seller is more willing to reduce prices to encourage purchases when A's valuation is high, but when the valuation is moderate, the Seller prices no differently from A's willingness-to-pay. Meanwhile, for the dynamic pricing conditions, the price decreases, consistent with theory (DPH: 75.9 to 67.5; $p = 0.000$ and DPM: 46.5 to 36.4; $p = 0.000$).

Table 3. t-Tests of Price, Purchase Proportion, and Revenue Differences in Experiment 2

Price Differences in a Condition[†]	**Mean**	**SE**	**t**	**p**	**Theory**
$p_{A1}^{DTPH} - p_{A2}^{DTPH}$	7.9*	2.87	2.74	0.014	0.0
$p_{B1}^{DTPH} - p_{B2}^{DTPH}$	12.4*	2.21	5.62	0.000	15.6
$p_{A1}^{DTPH} - p_{B1}^{DTPH}$	17.1*	2.53	6.77	0.000	50.0
$p_{A2}^{DTPH} - p_{B2}^{DTPH}$	21.7*	4.11	5.29	0.000	51.1
$p_{A1}^{DTPM} - p_{A2}^{DTPM}$	1.6	2.27	0.70	0.491	0.0
$p_{B1}^{DTPM} - p_{B2}^{DTPM}$	8.1*	1.57	5.13	0.000	15.6
$p_{A1}^{DTPM} - p_{B1}^{DTPM}$	−15.1*	2.03	−7.44	0.000	14.4
$p_{A2}^{DTPM} - p_{B2}^{DTPM}$	−8.6*	2.63	−3.27	0.004	−1.1
$p_{1}^{DPH} - p_{2}^{DPH}$	8.5*	1.65	5.13	0.000	10.0
$p_{1}^{DPM} - p_{2}^{DPM}$	10.2*	2.26	4.50	0.000	12.0
Price Differences across Conditions	**Mean**	**SE**	**t**	**p**	**Theory**
$p_{A1}^{DTPH} - p_{A1}^{DTPM}$	38.4*	1.97	19.49	0.000	50.0
$p_{A2}^{DTPH} - p_{A2}^{DTPM}$	32.1*	3.49	9.19	0.000	50.0
$p_{B1}^{DTPH} - p_{B1}^{DTPM}$	6.2*	2.37	2.61	0.013	0.0
$p_{B2}^{DTPH} - p_{B2}^{DTPM}$	1.8	3.12	0.58	0.564	0.0
$p_{1}^{DPH} - p_{1}^{DPM}$	29.4*	2.38	12.35	0.000	34.3
$p_{2}^{DPH} - p_{2}^{DPM}$	31.1*	2.81	11.07	0.000	36.3
$p_{A1}^{DTPH} - p_{1}^{DPH}$	0.5	1.87	0.26	0.794	3.7
$p_{B1}^{DTPH} - p_{1}^{DPH}$	−16.7*	2.47	−6.76	0.000	−31.9
$p_{B2}^{DTPH} - p_{2}^{DPH}$	−20.6*	3.41	−6.04	0.000	−37.5
$p_{A1}^{DTPM} - p_{1}^{DPM}$	−8.5*	2.46	−3.46	0.001	−12.0
$p_{B1}^{DTPM} - p_{1}^{DPM}$	6.6*	2.28	2.88	0.007	2.4
$p_{B2}^{DTPM} - p_{2}^{DPM}$	8.7*	2.45	3.88	0.001	−1.1
Purchase Proportions across Conditions	**Mean**	**SE**	**t**	**p**	**Theory**
$Purchase^{DTPH} - Purchase^{DTPM}$	0.11*	0.04	3.13	0.003	0.00
$Purchase^{DPH} - Purchase^{DPM}$	−0.17*	0.05	−3.44	0.001	−0.22
$Purchase^{DTPH} - Purchase^{DPH}$	0.16*	0.04	4.44	0.000	0.22
$Purchase^{DTPM} - Purchase^{DPM}$	−0.11*	0.05	−2.41	0.021	0.01
Revenue Differences across Conditions	**Mean**	**SE**	**t**	**p**	**Theory**
$R^{DTPH} - R^{DTPM}$	204.4*	18.70	10.93	0.000	200.0
$R^{DPH} - R^{DPM}$	76.8*	25.68	2.99	0.005	92.5
Hypothesis 3: $R^{DTPH} - R^{DPH}$	70.1*	27.15	2.58	0.014	105.2
Hypothesis 4: $R^{DTPM} - R^{DPM}$	−57.5*	16.50	−3.49	0.001	−2.3

*Significant at the 5% level   [†]Paired

Next, we consider differences in the decision variables across the conditions. We begin by comparing the DTPH to DTPM condition. The revenue is predicted to be 200 points higher in the high valuation condition over the moderate valuation condition and we find strong support for this result (mean difference: 204.4 and $p = 0.000$). It is evident that participants recognize that the targeted price for segment A differs and participants adjust their price to extract surplus from consumers. Sellers also price skim from period 1 to period 2 when selling to segment B. In the dynamic pricing conditions, we obtain a similar pattern of results. Theory predicts that the revenue will be higher in the DPH condition by 92.5 points and our results indicate that the revenue is higher by 76.8 ($p = 0.005$). Accordingly, the period 1 price and the period 2 price in the DPH condition are both higher than that in the DPM condition (period 1 prices: 75.9 vs. 46.5, $p = 0.000$ and period 2 prices: 67.5 vs. 36.4, $p = 0.000$). Thus, there is strong support that the participants recognize the manipulations and adjust their prices to maximize revenues.

We now compare the revenues predicted by Hypothesis 2. Hypothesis 2 formulates that targeted pricing increases revenues when valuations for segment A are sufficiently high and we find significant support for this prediction. The mean revenue difference between the DTPH and the DPH condition is found to be 70.1 ($p = 0.014$). Hence, we confirm that Hypothesis 2 holds and sellers can benefit substantially from dynamic targeted pricing. On the other hand, Hypothesis 2 also predicts the opposite effect when valuations for segment A are moderate, where targeted pricing can actually reduce revenues. We find that the DPM condition revenues are indeed greater than the DTPM revenues (343.2 vs. 266.4; $p = 0.001$). However, the predicted revenue difference between the DPM and DTPM conditions was only 2.3 points, but we ascertain that dynamic pricing outperforms dynamic targeted pricing by 57.5 points — this difference is significantly higher than the theoretical prediction ($p = 0.000$). Due to the large magnitude of this result, we discuss this further below.

The benefit of dynamic pricing when segment A's valuation is moderate is predicted to be driven by the rigidity in the period 2 price under dynamic pricing as the Seller sells to both segments A and B, which encourages more customers from segment B to purchase in period 1. However, when we compare the period 2 price in the DPM condition to the period 2 price for segment B in the DTPM condition we find that the price is lower by 8.7 ($p = 0.001$) when it is expected to be higher by 1.1. This indicates the following: First, the purchase proportion difference between the DTPM and DPM conditions is negative and equal to 0.11 when theory predicts a positive difference (0.01). The reduction in purchases stems from the price for segment B being significantly higher than predicted in the DTPM condition in period 2. From a theoretical standpoint, the change in the purchase proportion should arise from segment B and is predicted to be quite small, but the higher price causes even less customers to purchase. For this reason, the revenue generated from segment B decreases by 22.9 ($p = 0.011$) from the DTPM to the DPM condition. Second, the revenue from segment A decreases by 34.7 ($p = 0.021$) from the DTPM to the DPM condition. The proportion of customers who purchase does not change across the two conditions, but the purchase price is significantly different. In particular, the purchase price for segment A in the DTPM condition decreases by 8.4 ($p = 0.001$) when compared to the DPM condition. Even with this larger than expected difference, we still find strong directional support for the theory.

Although we have deciphered where the additional losses from the DTPM condition stem from, we have not provided a comprehensive explanation for the results. Based on the revenue loss from segment A and B, it is evident that bounded rationality may be a behavioral driver of the results. Throughout both of the experiments, the prices differ from the point predictions and the revenues are substantially lower than predicted, which indicate that bounded rationality is a factor in decision making. Moreover, the manager's decision is more complex under dynamic targeted pricing because the manager's decision space requires choosing up to four prices instead of two. As a result, the benefits of dynamic targeted pricing, when the gains are minimal, may be negated by bounded rationality and should be implemented with caution.

Additionally, we have shown that segment A is sensitive to unfairness concerns when prices are based on willingness-to-pay. These concerns are exacerbated under targeted pricing because segment A customers are singled out. It also appears though that Sellers rationally anticipate fairness concerns more appropriately when A's valuation is high, but not when it is moderate. One possible explanation for this finding is that targeting when A's valuation is high results in a price premium charged to A (the mean price charged to A is greater than the mean price charged to B), but when A's valuation is moderate, the result is a price discount relented to A (the mean price charged to A is lower than the mean price charged to B). From a psychological standpoint, Sellers may be more willing to reduce prices to account for unfairness when charging a premium as opposed to providing a discount, since Sellers may feel that the price is already fair.

5. CONCLUSIONS

Dynamic pricing and targeted pricing are price discrimination devices that rely on the understanding of consumer preferences. It is not clear especially in this digital age (Kannan et al., 2017), however, what the trade-offs are between dynamic pricing and targeted pricing and whether the concurrent deployment of these two price discrimination devices necessarily benefits firms under all circumstances. Thus, a careful investigation of the inter-relationship of dynamic pricing and targeted pricing sheds light on how firms can take advantage of the increasing capability in customer identification and segmentation. We take an initial step toward this direction and our research generates several interesting insights.

First, dynamic pricing is more profitable to the monopolist than static targeted pricing provided that consumers are not too forward looking. Second, although the monopolist can be worse off when she employs targeting in addition to dynamic pricing, she generally benefits from doing so. This is because targeting allows the monopolist to price discriminate consumers based on their valuations, but targeting can reduce the effectiveness of dynamic pricing. The net benefit (loss) from dynamic targeted pricing hinges on the trade-off between these two forces.

We test our key findings in two laboratory, incentive-aligned (Dong, Ding, Grewal, and Zhao, 2011) experiments. In the first experimental study, we examine whether static targeted pricing can be more profitable than dynamic pricing. In the second experimental study, we explore whether simultaneously implementing targeting and dynamic pricing can hurt a firm's bottom line. Both targeting and dynamic pricing are complex, data-driven pricing strategies. Our experiments lend support to our theoretical predictions by demonstrating that individuals behave largely in a manner consistent with the predictions of our model.

This paper studies the interaction between dynamic pricing and targeted pricing for a monopolist. The natural next step is to extend our model to a competitive setting such as (Chen, Joshi, Raju, and Zhang, 2009; Kopalle and Lehmann, 2015; Wei and Huang, 2019). Such an extension requires simplification in some aspects of the model, given the potential complexity of the analysis. The current model restricts the consumers to make a unit purchase over two periods. It would be interesting to relax the restriction and allow consumers to make a purchase in both periods or purchase multiple units. These assumptions can be more applicable to certain product categories and market conditions. For instance, the current model is appropriate for perishable or non-perishable goods that are infrequently purchased (e.g., life insurance). Frequently purchased product categories require an alternative assumption. It would also be interesting to examine further, the conditions when targeted advertising may not be beneficial for firms (Liu, 2020). Finally, exploring how partial knowledge of targeting accuracy can affect our results is a very interesting avenue for future research. We believe that further research along these lines will prove fruitful.

References

Acquisti, Alessandro, Hal R Varian. 2005. Conditioning prices on purchase history. *Marketing Science* **24**(3) 367–381.

Amaldoss, Wilfred, Chuan He. 2013. Pricing prototypical products. *Marketing Science* **32**(5) 733–752.

Amaldoss, Wilfred, Sanjay Jain. 2005a. Conspicuous consumption and sophisticated thinking. *Management science* **51**(10) 1449–1466.

Amaldoss, Wilfred, Sanjay Jain. 2005b. Pricing of conspicuous goods: A competitive analysis of social effects. *Journal of Marketing Research* **42**(1) 30–42.

Aviv, Y., A. Pazgal. 2008. Optimal pricing of seasonal products in the presence of forward-looking consumers. *Manufacturing and Service Operations Management* **10**(3) 339–359.

Besanko, D., W. L. Winston. 1990. Optimal price skimming by a monopolist facing rational customers. *Management Science* **36**(5) 555–567.

Besanko, David, Jean-Pierre Dubé, Sachin Gupta. 2003. Competitive price discrimination strategies in a vertical channel using aggregate retail data. *Management Science* **49**(9) 1121–1138.

Bolton, Lisa E, Luk Warlop, Joseph W Alba. 2003. Consumer perceptions of price (un) fairness. *Journal of consumer research* **29**(4) 474–491.

Butz, D. A. 1990. Durable-good monopoly and best-price provisions. *The American Economic Review* **80**(5) 1062–1076.

Cachon, G., R. Swinney. 2009. Purchasing, pricing and quick response in the presence of strategic consumers. *Management Science* **55**(3) 497–511.

Chen, Hua, Sung H Ham, Noah Lim. 2011. Designing multiperson tournaments with asymmetric contestants: An experimental study. *Management Science* **57**(5) 864–883.

Chen, Y., C. Narasimhan, Z.J. Zhang. 2001. Individual marketing with imperfect targetability. *Marketing Science* **20**(1) 23–41.

Chen, Yongmin. 1997. Paying customers to switch. *Journal of Economics & Management Strategy* **6**(4) 877–897.

Chen, Yuxin, Yogesh V Joshi, Jagmohan S Raju, Z John Zhang. 2009. A theory of combative advertising. *Marketing Science* **28**(1) 1–19.

Chen, Yuxin, Z John Zhang. 2009. Dynamic targeted pricing with strategic consumers. *International Journal of Industrial Organization* **27**(1) 43–50.

Chung, Kevin, Keehyung Kim, Noah Lim. 2020. Social structures and reputation in expert review systems. *Management Science* **66**(7) 3249–3276.

Cui, Tony Haitao, Paola Mallucci. 2016. Fairness ideals in distribution channels. *Journal of Marketing Research* **53**(6) 969–987.

Ding, Min, Jehoshua Eliashberg, Joel Huber, Ritesh Saini. 2005. Emotional bidders—an analytical and experimental examination of consumers' behavior in a priceline-like reverse auction. *Management Science* **51**(3) 352–364.

Dong, Songting, Min Ding, Rajdeep Grewal, Ping Zhao. 2011. Functional forms of the satisfaction–loyalty relationship. *International journal of research in marketing* **28**(1) 38–50.

Dubé, Jean-Pierre, Zheng Fang, Nathan Fong, Xueming Luo. 2017. Competitive price targeting with smartphone coupons. *Marketing Science* **36**(6) 944–975.

Feinberg, Fred M, Aradhna Krishna, Z John Zhang. 2002. Do we care what others get? a behaviorist approach to targeted promotions. *Journal of Marketing research* **39**(3) 277–291.

Fong, Nathan M, Zheng Fang, Xueming Luo. 2015. Geo-conquesting: Competitive locational targeting of mobile promotions. *Journal of Marketing Research* **52**(5) 726–735.

Fudenberg, Drew, J Miguel Villas-Boas. 2006. Behavior-based price discrimination and customer recognition. *Handbook on economics and information systems* **1** 377–436.

Gardete, Pedro M, Yakov Bart. 2018. Tailored cheap talk: The effects of privacy policy on ad content and market outcomes. *Marketing Science* **37**(5) 733–752.

Grewal, D., K. L. Ailawadi, D. Gauri, K. Hall, P. Kopalle, J. R. Robertson. 2011. Innovations in retail pricing and promotions. *Journal of Retailing* **87S**(1,2011) S43–S52.

Guo, Xiaomeng, Baojun Jiang. 2016. Signaling through price and quality to consumers with fairness concerns. *Journal of Marketing Research* **53**(6) 988–1000.

Haws, Kelly L, William O Bearden. 2006. Dynamic pricing and consumer fairness perceptions. *Journal of Consumer Research* **33**(3) 304–311.

Ho, Teck-Hua, Noah Lim, Tony Haitao Cui. 2010. Reference dependence in multilocation newsvendor models: A structural analysis. *Management Science* **56**(11) 1891–1910.

Jin, Liyin, Yanqun He, Ying Zhang. 2014. How power states influence consumers' perceptions of price unfairness. *Journal of Consumer Research* **40**(5) 818–833.

Kannan, PK, et al. 2017. Digital marketing: A framework, review and research agenda. *International Journal of Research in Marketing* **34**(1) 22–45.

Khan, Romana, Michael Lewis, Vishal Singh. 2009. Dynamic customer management and the value of one-to-one marketing. *Marketing Science* **28**(6) 1063–1079.

Kim, Keehyung, Kevin Chung, Noah Lim. 2019. Third-party reviews and quality provision. *Management Science* **65**(6) 2695–2716.

Kopalle, Praveen K, Donald R Lehmann. 2015. The truth hurts: How customers may lose from honest advertising. *International Journal of Research in Marketing* **32**(3) 251–262.

Kremer, Mirko, Benny Mantin, Anton Ovchinnikov. 2017. Dynamic pricing in the presence of myopic and strategic consumers: Theory and experiment. *Production and Operations Management* **26**(1) 116–133.

Krishna, Aradhna, Fred M Feinberg, Z John Zhang. 2007. Should price increases be targeted?—pricing power and selective vs. across-the-board price increases. *Management Science* **53**(9) 1407–1422.

Levin, Y., J. McGill, M. Nediak. 2009. Dynamic pricing in the presence of strategic consumers and oligopolistic competition. *Management Science* **55**(1) 32–46.

Li, Krista J, Sanjay Jain. 2016. Behavior-based pricing: An analysis of the impact of peer-induced fairness. *Management Science* **62**(9) 2705–2721.

Lim, Noah, Hua Chen. 2014. When do group incentives for salespeople work? *Journal of Marketing Research* **51**(3) 320–334.

Liu, Xingyi. 2020. De-targeting to signal quality. *International Journal of Research in Marketing* .

Mak, Vincent, Amnon Rapoport, Eyran J Gisches. 2012. Competitive dynamic pricing with alternating offers: Theory and experiment. *Games and Economic Behavior* **75**(1) 250–264.

Mak, Vincent, Amnon Rapoport, Eyran J Gisches, Jiaojie Han. 2014. Purchasing scarce products under dynamic pricing: An experimental investigation. *Manufacturing & Service Operations Management* **16**(3) 425–438.

Özer, Özalp, Upender Subramanian, Yu Wang. 2018. Information sharing, advice provision, or delegation: what leads to higher trust and trustworthiness? *Management Science* **64**(1) 474–493.

Rossi, Peter E, Robert E McCulloch, Greg M Allenby. 1996. The value of purchase history data in target marketing. *Marketing Science* **15**(4) 321–340.

Shaffer, Greg, Z John Zhang. 1995. Competitive coupon targeting. *Marketing Science* **14**(4) 395–416.

Su, X., F. Zhang. 2008. Strategic customer behavior, commitment, and supply chain performance. *Management Science* **54**(10) 1759–1773.

Villas-Boas, J Miguel. 2004. Price cycles in markets with customer recognition. *RAND Journal of Economics* **35**(3) 486–501.

Wang, Yu, Aradhna Krishna. 2012. Enticing for me but unfair to her: Can targeted pricing evoke socially conscious behavior? *Journal of consumer Psychology* **22**(3) 433–442.

Wei, Yuansheng, Pei Huang. 2019. A model of product compatibility introduction with consumer recognition. *International Journal of Research in Marketing* **36**(4) 613–629.

Yuan, Hong, Miguel I Gómez, Vithala R Rao. 2013. Trade promotion decisions under demand uncertainty: A market experiment approach. *Management Science* **59**(7) 1709–1724.

Yuan, Hong, Song Han. 2011. The effects of consumers' price expectations on sellers' dynamic pricing strategies. *Journal of Marketing Research* **48**(1) 48–61.

Zhang, Jonathan Z, Oded Netzer, Asim Ansari. 2014. Dynamic targeted pricing in b2b relationships. *Marketing Science* **33**(3) 317–337.

Zhang, Juanjuan. 2011. The perils of behavior-based personalization. *Marketing Science* **30**(1) 170–186.

APPENDIX A: PROOFS

Lemma 1: Optimal price and profits under static pricing without targeting

Proof. The first derivative of the profit function with respect to p is given by

$$\frac{\partial R^S(\alpha,p)}{\partial p} = \begin{cases} (1-\alpha)(1-2p), & \text{if } p > v_A, \\ 1-2(1-\alpha)p, & \text{if } p \le v_A. \end{cases} \tag{A–1}$$

The profit function is piecewise concave with breakpoint v_A. Solving the first order condition and taking into account the breakpoint v_A yields the result stated in the lemma. ■

Lemma 2: Optimal profits under dynamic pricing without targeting

Proof. Recall that the optimal two-period revenue is given by

$$R^{D*}(\alpha) = \max_{0\le\theta\le 1} R^D(\alpha,\theta), \tag{A–2}$$

$$R^D(\alpha,\theta) = R_2^{D*}(\alpha,\theta) + \begin{cases} p_1(\alpha,\theta)[\alpha+(1-\alpha)(1-\theta)], & \text{if } \ \theta \le v_A, \\ p_1(\alpha,\theta)(1-\theta)(1-\alpha), & \text{if } \ \theta > v_A. \end{cases} \tag{A–3}$$

The solution for the second period problem is given by

$$p_2^{D*}(\alpha,\theta) = \begin{cases} \frac{\theta}{2}, & \text{if } \ \theta \le v_A, \text{or } \theta > v_A, v_A \le \frac{(1-\alpha)\theta+\alpha-\sqrt{\alpha[2(1-\alpha)\theta+\alpha]}}{2(1-\alpha)}, \\ v_A, & \text{if } \ \frac{(1-\alpha)\theta+\alpha-\sqrt{\alpha[2(1-\alpha)\theta+\alpha]}}{2(1-\alpha)} < v_A \le \frac{(1-\alpha)\theta+\alpha}{2(1-\alpha)}, \theta > v_A, \\ \frac{(1-\alpha)\theta+\alpha}{2(1-\alpha)}, & \text{if } \ v_A > \frac{(1-\alpha)\theta+\alpha}{2(1-\alpha)}, \theta > v_A. \end{cases} \tag{A–4}$$

The corresponding optimal revenue is given by

$$R_2^{D*}(\alpha,\theta) = \begin{cases} \frac{(1-\alpha)\theta^2}{4}, & \text{if } \ \theta \le v_A, \text{or } \theta > v_A, v_A \le \frac{(1-\alpha)\theta+\alpha-\sqrt{\alpha[2(1-\alpha)\theta+\alpha]}}{2(1-\alpha)}, \\ v_A[(1-\alpha)(\theta-v_A)+\alpha], & \text{if } \ \frac{(1-\alpha)\theta+\alpha-\sqrt{\alpha[2(1-\alpha)\theta+\alpha]}}{2(1-\alpha)} < v_A \le \frac{(1-\alpha)\theta+\alpha}{2(1-\alpha)}, \theta > v_A, \\ \frac{[(1-\alpha)\theta+\alpha]^2}{4(1-\alpha)}, & \text{if } \ v_A > \frac{(1-\alpha)\theta+\alpha}{2(1-\alpha)}, \theta > v_A. \end{cases} \tag{A–5}$$

Next, we solve the first period problem. There are five cases to be considered based on the price at which consumers in segment A purchase the product. Throughout, we use θ to denote the valuation of a marginal customer who is indifferent between purchasing in the two periods.

Case 1: Segment A purchases in period 1 at price $p_1 < v_A$.

The optimal price in period 2 is $p_2^{D*}(\alpha,\theta) = \frac{\theta}{2}$. It can be shown that the first period price can be written as $\frac{1}{2}(2-\gamma)\theta$. The the two-period revenue is given by

$$R^D(\alpha,\theta) = \frac{1}{2}(2-\gamma)\theta[(1-\alpha)(1-\theta)+\alpha] + \frac{1}{4}(1-\alpha)\theta^2.$$

Solving the first order condition for θ, we obtain $\theta^*(\alpha) = \frac{2-\gamma}{(1-\alpha)(3-2\gamma)}$. The corresponding revenue is $\frac{(2-\gamma)^2}{4(1-\alpha)(3-2\gamma)}$.

Case 2: Segment A purchases in period 1 at price $p_1 = v_A$.

The optimal price in period 2 is $p_2^{D*}(\alpha,\theta) = \frac{\theta}{2}$. When the first period price is v_A, it can be shown that $\theta^* = \frac{2v_A}{2-\gamma}$. The corresponding revenue is $\frac{v_A[(2-\gamma)^2-(1-\alpha)(3-2\gamma)v_A]}{(2-\gamma)^2}$.

Case 3: Segment A purchases in period 2 at price $p_2 < v_A$.

The optimal price in period 2 is $p_2^{D*}(\alpha,\theta) = \frac{(1-\alpha)\theta+\alpha}{2(1-\alpha)}$. It follows that the first period price can be written as $p_1^{D*}(\alpha,\theta) = \frac{\alpha\gamma}{2(1-\alpha)} + \frac{(2-\gamma)\theta}{2}$. The first period revenue is given by

$$(1-\alpha)(1-\theta)p_1^{D*}(\alpha,\theta) + p_2^{D*}(\alpha,\theta)[\alpha + (1-\alpha)(\theta - p_2^{D*}(\alpha,\theta))].$$

Solving the first order condition for θ, we obtain $\theta^* = \frac{2-\alpha-\gamma}{(1-\alpha)(3-2\gamma)}$. The corresponding revenue is $\frac{(2-\gamma)^2-4\alpha(1-\alpha)(1-\gamma)^2}{4(1-\alpha)(3-2\gamma)}$.

Case 4: Segment A purchases in period 2 at price $p_2 = v_A$.

The first period price can be written as $p_1^{D*}(\alpha,\theta) = (1-\gamma)\theta + \gamma v_A$. The two period revenue is given by

$$(1-\alpha)(1-\theta)p_1^{D*}(\alpha,\theta) + v_A(\alpha + (1-\alpha)(\theta - v_A));$$

Solving the first order condition for θ, we obtain $\theta^* = \frac{1+v_A}{2}$. The corresponding revenue is $\frac{(1-\alpha)(1-\gamma)+2v_A(1+\alpha+\gamma-\alpha\gamma)-(1-\alpha)(3+\gamma)v_A^2}{4}$.

Case 5: Segment A not served.

In this case, we solve a two-period pricing problem for segment B and obtain the optimal revenue $\frac{(1-\alpha)(2-\gamma)^2}{4(3-2\gamma)}$.

It remains to show which case dominates in the optimal solution, which can be accomplished by comparing the revenue from each case, taking into account the boundary conditions. For example, for case one, the boundary condition is that the optimal period 1 price p_1^* is less than v_A. We should also point out that the revenue function is not smooth everywhere. In particular, the non-smoothness occurs when switching from Case 2 to Case 3, and when switching from Case 4 to Case 5. The boundaries in the non-smooth cases can be found by comparing the revenue from the neighboring cases, which involves solving quadratic equations of v_A. This completes the proof. ■

Proposition 1: Profits comparison between static pricing with and without targeting

Proof. We prove this proposition in two parts.

Part 1: *Under static pricing, targeted pricing leads to seller profits at least as high as the profits without targeting for any targeting accuracy $I \in [0,1]$.*

For any price $p \in [0,1]$, we have

$$\begin{aligned}
R^{ST*}(\alpha, I) &= \alpha R^{S*}(\beta_A) + (1-\alpha) R^{S*}(1-\beta_B) \\
&\geq \alpha R^{S}(p, \beta_A) + (1-\alpha) R^{S}(p, 1-\beta_B) \\
&= \begin{cases} \alpha p(1-p)(1-\beta_A) + (1-\alpha)p(1-p)\beta_B, & \text{if } p > v_A, \\ \alpha p[(1-p)(1-\beta_A) + \beta_A] + (1-\alpha)p[(1-p)\beta_B + 1 - \beta_B], & \text{if } p \leq v_A \end{cases} \\
&= \begin{cases} p(1-p)[\alpha(1-\beta_A) + (1-\alpha)\beta_B], & \text{if } p > v_A, \\ p(1-p)[\alpha(1-\beta_A) + (1-\alpha)\beta_B] + p[\alpha\beta_A + (1-\alpha)(1-\beta_B)], & \text{if } p \leq v_A \end{cases} \\
&= \begin{cases} p(1-p)(1-\alpha), & \text{if } p > v_A, \\ p(1-p)(1-\alpha) + \alpha p, & \text{if } p \leq v_A \end{cases} \\
&= R^{S}(p, \alpha).
\end{aligned} \tag{A–6}$$

It immediately follows that

$$R^{ST*}(\alpha, I) \geq \max_{0 \leq p \leq 1} R^{S}(\alpha, p) = R^{S*}(\alpha). \tag{A–7}$$

Part 2: *The profits under static targeted pricing $R^{ST*}(\alpha, I)$ increase in the targeting accuracy I.*

The profit function under static targeted pricing is piecewise continuous. We prove the result by showing that the profit function is increasing in I for each piece.

To simplify notation, let

$$v_1(\alpha) = \frac{1 - \sqrt{\alpha(2-\alpha)}}{2(1-\alpha)}, \quad v_2(\alpha) = \frac{1}{2(1-\alpha)}. \tag{A–8}$$

Observe that $v_1(\alpha)$ is decreasing in α, while $v_2(\alpha)$ is increasing in α. We also point out that

$$\beta_A = \alpha + (1-\alpha)I \geq \alpha - \alpha I = 1 - \beta_B. \tag{A–9}$$

It follows that

$$v_1(\beta_A) \leq v_1(1-\beta_B) \leq v_2(1-\beta_B) \leq v_2(\beta_A). \tag{A–10}$$

There are five cases depending on the value of v_A.

Case 1: $v_A < v_1(\beta_A)$

Using Lemma 1, we have

$$\begin{aligned} R^{ST*}(\alpha, I) &= \alpha R^{S*}(\beta_A) + (1-\alpha)R^{S*}(1-\beta_B) \\ &= \frac{\alpha(1-\beta_A)}{4} + \frac{(1-\alpha)\beta_B}{4} \\ &= \frac{1-\alpha}{4}. \end{aligned} \tag{A–11}$$

In this case, the profit function does not change with I.

Case 2: $v_1(\beta_A) \leq v_A \leq v_1(1-\beta_B)$

$$\begin{aligned} R^{ST*}(\alpha, I) &= \alpha[v_A(1-(1-\beta_A)v_A] + \frac{(1-\alpha)\beta_B}{4} \\ &= \alpha[v_A(1-v_A+\beta_A v_A)] + \frac{(1-\alpha)\beta_B}{4}. \end{aligned} \tag{A–12}$$

Since both β_A and β_B increase in I, the profit function increases in I in this case.

Case 3: $v_1(1-\beta_B) \leq v_A \leq v_2(1-\beta_B)$

$$\begin{aligned} R^{ST*}(\alpha, I) &= \alpha[v_A(1-(1-\beta_A)v_A)] + (1-\alpha)[v_A(1-\beta_B)v_A] \\ &= v_A[1-(1-\alpha)v_A]. \end{aligned} \tag{A–13}$$

It follows that the profit function does not change with I in this case.

Case 4: $v_2(1-\beta_B) \leq v_A \leq v_2(\beta_A)$

$$R^{ST*}(\alpha, I) = \alpha[v_A(1-(1-\beta_A)v_A)] + \frac{1-\alpha}{4\beta_B}. \tag{A–14}$$

Taking derivative with respect to I, we have

$$\frac{\partial R^{ST*}(\alpha, I)}{\partial I} = (1-\alpha)\left[v_A^2 - \frac{\alpha}{4(1-\alpha+\alpha I)^2}\right]. \tag{A–15}$$

Note that $v_A \geq v_2(1-\beta_B)$ can be written as $v_A \geq \frac{1}{2(1-\alpha+\alpha I)}$. This implies that the partial derivative is nonnegative. Hence, the profit function increases in I in this case.

Case 5: $v_A \geq v_2(\beta_A)$

$$R^{ST*}(\alpha, I) = \frac{\alpha}{4(1-\beta_A)} + \frac{1-\alpha}{4\beta_B}$$
$$= \frac{1-\alpha+(2\alpha-1)I}{4(1-\alpha)[1-\alpha+(2\alpha-1)I-\alpha I^2]}. \tag{A–16}$$

Taking derivative with respect to I, we have

$$\frac{\partial R^{ST*}(\alpha, I)}{\partial I} = \frac{\alpha I[2-2\alpha(1-I)-I]}{4(1-\alpha)(1-I)^2(1-\alpha(1-I))^2} = \frac{\alpha I[1-\alpha(1-I)+(1-\alpha)(1-I)]}{4(1-\alpha)(1-I)^2(1-\alpha(1-I))^2} \geq 0. \tag{A–17}$$

Therefore, the profit function is increasing in I in this case.

Combining cases above yields the desired result. ■

Proposition 2: Profits comparison between dynamic pricing without targeting and static pricing

Proof. The result that dynamic pricing dominates static pricing without targeting is straightforward since $R^{D*}(\lambda) \geq R^D(\lambda, 1) = R^{S*}(\alpha)$ for any $\lambda = \alpha/(1-\alpha)$.

To show that dynamic pricing dominates static targeted pricing for $\gamma = 0$, we note that the optimal prices for segments A and B under static targeted pricing are v_A and $1/2$, respectively. First, if $v_A \geq 1/2$, we can show that the revenue from static targeted pricing is dominated by the dynamic pricing revenue from the price pair $(p_1, p_2) = (v_A, 1/2)$. Since $\gamma = 0$, under the price pair $(v_A, 1/2)$, segment A purchases at price v_A in the first period, while segment B customers with valuation above v_A purchase the first period at price v_A and segment B customers with valuations between v_A and $1/2$ purchases in the second period at price $1/2$. It follows that the revenue under the price pair $(v_A, 1/2)$ is at least as high as the revenue from static targeted pricing, since the revenue from segment A matches that from static targeted pricing, while the revenue from segment B is higher. Similarly, if $v_A < 1/2$, the revenue from static targeted pricing is dominated by the dynamic pricing revenue from the price pair $(p_1, p_2) = (1/2, v_A)$.

To show the last part of the proposition, consider the price pair $(v_A+\Delta, v_A)$ under dynamic pricing for $\Delta < 1 - v_A$. Note that the revenue for segment A is the same under dynamic pricing and static targeted pricing. So we only need to compare the revenue from segment B. To ensure that there are customers who purchase at the price $v_A + \Delta$, we require that the valuation cutoff for the first period purchase is less than 1:

$$\frac{\Delta}{1-\gamma} + v_A < 1 \Leftrightarrow \gamma < 1 - \frac{\Delta}{1-v_A}. \tag{A–18}$$

The revenue is given by

$$\begin{aligned}&(1-\alpha)\left[(v_A+\Delta)\left(1-\frac{\Delta}{1-\gamma}-v_A\right)+\frac{\Delta}{1-\gamma}v_A\right]\\ &=(1-\alpha)\left[v_A+\Delta-\Delta v_A-v_A^2-\frac{\Delta^2}{1-\gamma}\right].\end{aligned}$$

The result holds as long as there are values of v_A, Δ and γ such that the terms within the square brackets is above 1/4. Taking $(v_A, \Delta, \gamma) = (1/2, 1/4, 1/4)$, the terms within the square backets is $7/24 > 1/4$. Since the terms within the brackets is continuous in (v_A, Δ, γ), there are ranges of (v_A, Δ, γ) such that the value is above 1/4. This completes the proof. ■

Proposition 3: Profits comparison between dynamic pricing without targeting and dynamic pricing with perfect targeting

Proof.

(i) Recall that the monopolist's profit from dynamic pricing with perfect targeting is $R^{DT*}(\alpha, 1) = \alpha v_A + \frac{(1-\alpha)(2-\gamma)^2}{4(3-2\gamma)}$. When the monopolist does not engage in targeted pricing, her profit is $R_3^{D*}(\alpha) = \frac{(2-\gamma)^2-4\alpha(1-\alpha)(1-\gamma)^2}{4(1-\alpha)(3-2\gamma)}$ in Region 3 ($\frac{2-\gamma+2\alpha(1-\gamma)}{2(3-2\gamma)(1-\alpha)} < v_A \leq v_{23}$). Comparing $R^{DT*}(\alpha, 1)$ with $R_3^{D*}(\alpha)$, we obtain $R^{DT*}(\alpha, 1) < R_3^{D*}(\alpha)$ when $\gamma > \frac{4v_A(1-\alpha)-2\alpha-2\sqrt{(1-\alpha)(1-v_A)(2-\alpha-4v_A(1-\alpha))}}{2-3\alpha}$.

(ii) The monopolist's profit is $R_4^{D*}(\alpha) = \frac{(1-\alpha)(1-\gamma)+2v_A(1+\alpha+\gamma-\alpha\gamma)-(1-\alpha)(3+\gamma)v_A^2}{4}$ in Region 4 ($v_{45} < v_A \leq \frac{2-\gamma+2\alpha(1-\gamma)}{2(3-2\gamma)(1-\alpha)}$). Comparing $R^{DT*}(\alpha, 1)$ with $R_4^{D*}(\alpha)$ shows that $R^{DT*}(\alpha, 1) < R_4^{D*}(\alpha)$ when $\frac{(3v_A-1)\left[1+v_A-\sqrt{(1-v_A)(5-9v_A)}\right]}{2\left(4v_A-2v_A^2-1\right)} < \gamma < \frac{(3v_A-1)\left[1+v_A+\sqrt{(1-v_A)(5-9v_A)}\right]}{2\left(4v_A-2v_A^2-1\right)}$.

(iii) It is easy to verify that $R^{DT*}(\alpha, 1) > R_1^{D*}(\alpha), R_2^{D*}(\alpha)$ and $R_5^{D*}(\alpha)$.

■

APPENDIX B: COMMITMENT

In this Appendix, we consider the role of price commitment. The extant literature prescribes commitment as a potent tool for improving the performance of dynamic pricing (e.g., Butz, 1990; Aviv and Pazgal, 2008; Su and Zhang, 2008). However, commitment often suffers from dynamic inconsistency, which makes credible implementation difficult. That begs the question whether there are viable alternatives to commitment. When firms develop the capability to segment customers, can targeting be a complement or substitute to commitment? If so, to what degree? In this section, we first consider the baseline case of dynamic pricing with commitment, then examine how much targeting can add in the presence of commitment. We also explore the extent to which commitment can improve dynamic pricing in the presence of targeting.

Dynamic Pricing with Commitment

We assume that the seller can commit to a price path at the beginning of the selling horizon. The pricing optimization problem can be written as[10]

$$R^{C*}(\alpha) = \max_{1 \geq \theta \geq p_2 \geq 0} R^C(\alpha, \theta, p_2), \tag{B–1}$$

where

$$R^C(\alpha, \theta, p_2) = \begin{cases} [(1-\alpha)(1-\theta)+\alpha][(1-\gamma)\theta+\gamma p_2]+(1-\alpha)(\theta-p_2)p_2, & \text{if} \quad \theta \leq v_A, \\ (1-\alpha)(1-\theta)[(1-\gamma)\theta+\gamma p_2]+[(1-\alpha)(\theta-p_2)+\alpha]\,p_2, & \text{if} \quad \theta > v_A, p_2 \leq v_A, \\ (1-\alpha)(1-\theta)[(1-\gamma)\theta+\gamma p_2]+(1-\alpha)(\theta-p_2)p_2, & \text{if} \quad \theta > v_A, p_2 > v_A. \end{cases} \tag{B–2}$$

From top to bottom, the three cases correspond to segment A served in period 1, segment A served in period 2, and segment A not served, respectively. To facilitate exposition, we

[10]Recall that $p_1 = (1-\gamma)\theta + \gamma p_2$. When the monopolist can commit to a price path, her two-period profits can be expressed in p_2 only with the above substitution. The optimal prices from this maximization problem would not be subgame perfect and they are valid provided that the commitment is credible.

can separate the profits from segment A and segment B and rewrite the above expression as

$$R^C(\alpha,\theta,p_2) = \underbrace{(1-\alpha)\left[(1-\theta)((1-\gamma)\theta+\gamma p_2)+(\theta-p_2)p_2\right]}_{\text{Revenue from segment B}}$$

$$+\underbrace{\begin{cases} \alpha\left[(1-\gamma)\,\theta+\gamma p_2\right], & \text{if} \quad \theta \le v_A, \\ \alpha p_2, & \text{if} \quad \theta > v_A, p_2 \le v_A, \\ 0, & \text{if} \quad \theta > v_A, p_2 > v_A. \end{cases}}_{\text{Revenue from segment A}} \tag{B–3}$$

Lemma B–1 *Under dynamic pricing with commitment, the optimal two-period revenue is given by*

$$R^{C*}(\alpha) = \begin{cases} \frac{1}{(1-\alpha)(3+\gamma)}, & \textit{Region 1}, \\ \frac{v_A[4-v_A(1-\alpha)(3+\gamma)]}{4}, & \textit{Region 2}, \\ \frac{1-\alpha(1-\alpha)(1-\gamma)}{(1-\alpha)(3+\gamma)}, & \textit{Region 3}, \\ \frac{(1-\alpha)(1-\gamma)+2v_A(1+\alpha+\gamma-\alpha\gamma)-(1-\alpha)(3+\gamma)v_A^2}{4}, & \textit{Region 4}, \\ \frac{1-\alpha}{3+\gamma}, & \textit{Region 5}. \end{cases} \tag{B–4}$$

The regions are defined in the following table:

Region	*Definition*	*Condition*
Region 1	*Segment A served in period 1 and* $p_1^* < v_A$	$\frac{2}{(1-\alpha)(3+\gamma)} < v_A$
Region 2	*Segment A served in period 1 and* $p_1^* = v_A$	$w_{23} < v_A \le \frac{2}{(1-\alpha)(3+\gamma)}$
Region 3	*Segment A served in period 2 and* $p_2^* < v_A$	$\frac{1+\alpha+\gamma-\alpha\gamma}{(1-\alpha)(3+\gamma)} < v_A \le w_{23}$
Region 4	*Segment A served in period 2 and* $p_2^* = v_A$	$w_{45} < v_A \le \frac{1+\alpha+\gamma-\alpha\gamma}{(1-\alpha)(3+\gamma)}$
Region 5	*Segment A not served*	$v_A < w_{45}$

Let $R_i^{C*}(\alpha)$ *denote the revenue in Region* i *for* $i = 1, 2, \ldots, 5$ *as stated in (B–4). The constant* w_{23} *is the smallest root of the equation* $R_2^{C*}(\alpha) - R_3^{C*}(\alpha) = 0$*, and* v_{45} *is the smallest root of the equation* $R_4^{C*}(\alpha) - R_5^{C*}(\alpha) = 0$*, where* v_A *is treated as the unknown in both equations.*

Proof. There are five cases to be considered based on the price at which consumers in segment A purchase the product. Throughout, we use θ to denote the valuation of a marginal customer who is indifferent between purchasing in the two periods.

Case 1: Segment A purchases in period 1 at price $p_1 < v_A$.

For given θ and p_2, the first period price is given by $(1-\gamma)\theta + \gamma p_2$. The revenue function can be written as

$$R^C(\alpha, \theta, p_2) = [(1-\alpha)(1-\theta) + \alpha][(1-\gamma)\theta + \gamma p_2] + (1-\alpha)p_2(\theta - p_2).$$

Solving first order conditions with respect to θ and p_2, we obtain

$$\theta^* = \frac{2+\gamma}{(1-\alpha)(3+\gamma)}, p_2^* = \frac{1+\gamma}{(1-\alpha)(3+\gamma)}.$$

The expression for optimal revenue follows by plugging θ^* and p_2^* in the revenue function.

Case 2: Segment A purchases in period 1 at price $p_1 = v_A$.

Since $p_1^* = v_A$, we can write θ as a function of p_2 as $\theta = \frac{v_A - \gamma p_2}{1-\gamma}$. The revenue function is given by

$$R^C(\alpha, \theta, p_2) = [(1-\alpha)(1-\theta) + \alpha]v_A + (1-\alpha)p_2(\theta - p_2).$$

Plugging the expression of θ and solve the first order condition with respect to p_2, we obtain $p_2^* = \frac{(1+\gamma)v_A}{2}$. The expression for optimal revenue is given by evaluating the revenue function using p_2^*.

Case 3: Segment A purchases in period 2 at price $p_2 < v_A$.

For given θ and p_2, the first period price is given by $(1-\gamma)\theta + \gamma p_2$. The revenue function can be written as

$$R^C(\alpha, \theta, p_2) = (1-\alpha)(1-\theta)[(1-\gamma)\theta + \gamma p_2] + [\alpha + (1-\alpha)(\theta - p_2)]p_2.$$

Solving first order conditions with respect to θ and p_2, we obtain

$$\theta^* = \frac{2-\alpha+\gamma-\alpha\gamma}{(1-\alpha)(3+\gamma)}, p_2^* = \frac{1+\alpha+\gamma-\alpha\gamma}{(1-\alpha)(3+\gamma)}.$$

The expression for optimal revenue follows by plugging θ^* and p_2^* in the revenue function.

Case 4: Segment A purchases in period 2 at price $p_2 = v_A$.

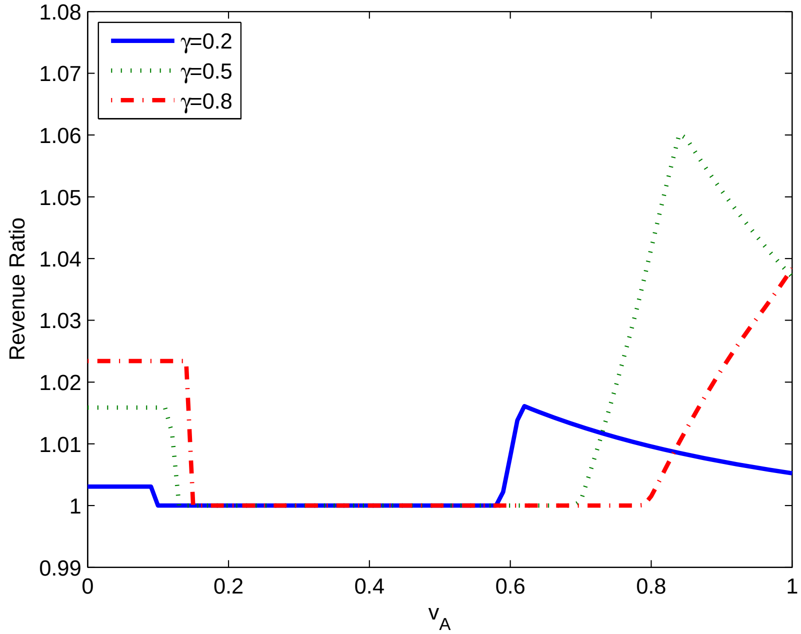
The first period price is given by $(1-\gamma)\theta + \gamma v_A$. The revenue function can be written as

$$R^C(\alpha, \theta, v_A) = (1-\alpha)(1-\theta)[(1-\gamma)\theta + \gamma v_A)] + v_A[\alpha + (1-\alpha)(\theta - v_A)].$$

Solving the first order condition with respect to θ we obtain $\theta^* = \frac{1+v_A}{2}$. The revenue expression follows by plugging θ^* into the revenue function above.

Case 5: Segment A not served.

FIG. 3. Revenue ratio between dynamic pricing with commitment and dynamic pricing without commitment; $\alpha = 0.4$



This case involves solving the two period pricing problem with commitment for segment B.

It remains to show which case dominates in the optimal solution, which can be accomplished by comparing the revenue from each case, taking into account the boundary conditions. We omit the details. This completes the proof. ■

Before proceeding, we comment that when $\gamma = 0$, the value of commitment is 0. This is because there is no shift in demand between the two periods for a given first period price, hence the second period price is necessarily optimal for the residual demand after period one. This argument does not hold for $\gamma > 0$.

Figure 3 shows the revenue ratio between dynamic pricing with commitment and dynamic pricing without commitment. Since we do not consider targeting at this point, the parameter I is irrelevant. The value of α is 0.4. The figure confirms that commitment can bring significant benefit, increasing revenue by more than 6% for cases shown in the graph. Furthermore, there exists a range of intermediate values of v_A for which the value of commitment is 0. This is not surprising. Commitment is valuable because it mitigates strategic customer behavior.

When v_A is at an intermediate value, it helps to stabilize the price in the second period, even when the firm does not commit. Therefore, commitment does not affect the optimal dynamic pricing policy for intermediate value of v_A. Interestingly, the value of commitment is not necessarily increasing in γ. In particular, for high values of v_A, commitment brings the most value when $\gamma = 0.5$, compared with the case where $\gamma = 0.8$.

Dynamic Targeted Pricing with Commitment

This section considers the case where the seller adopts dynamic targeted pricing and can commit to future prices. The total optimal revenue is given by

$$R^{CT*}(\alpha, I) = \alpha R^{C*}(\beta_A) + (1-\alpha)R^{C*}(1-\beta_B). \tag{B–5}$$

Since the price charged in each segment under dynamic targeted pricing without commitment is also feasible under dynamic targeted pricing with commitment, we have the following result.

Proposition B–1 *(i) Dynamic targeted pricing with commitment dominates dynamic targeted pricing without commitment for any targeting accuracy $I \in [0,1]$. (ii) With commitment, dynamic targeted pricing dominates dynamic pricing without targeting for any targeting accuracy $I \in [0,1]$.*

Proof. Fix $I \in [0,1]$, and let (θ^*, p_2^*) be the optimal solution for dynamic pricing without targeting; i.e., $R^{C*}(\alpha) = R^C(\alpha, \theta^*, p_2^*)$.

We have

$$\begin{aligned} R^{CT*}(\alpha, I) &= \alpha R^{C*}(\beta_A) + (1-\alpha)R^{C*}(1-\beta_B) \\ &\geq \alpha R^{C*}(\beta_A, \theta^*, p_2^*) + (1-\alpha)R^{C*}(1-\beta_B, \theta^*, p_2^*). \end{aligned} \tag{B–6}$$

In the above, the inequality follows since (θ^*, p_2^*) is not necessarily optimal in each of the targeted segment. After some algebra, we can show that the last expression is the same as $R^C(\alpha, p_1^*, p_2^*)$. This completes the proof. ■

Proposition B–1 shows that commitment is generally profit enhancing. An interesting follow-up question is how much the monopolist can benefit from commitment above and beyond dynamic targeted pricing.

Proposition B–2 *With perfect targeting ($I = 1$), the gain from dynamic targeted pricing with commitment relative to dynamic targeted pricing without commitment is bounded by 2.4%. The bound is tight at $\alpha = 0$ and $\gamma = 3/4$.*

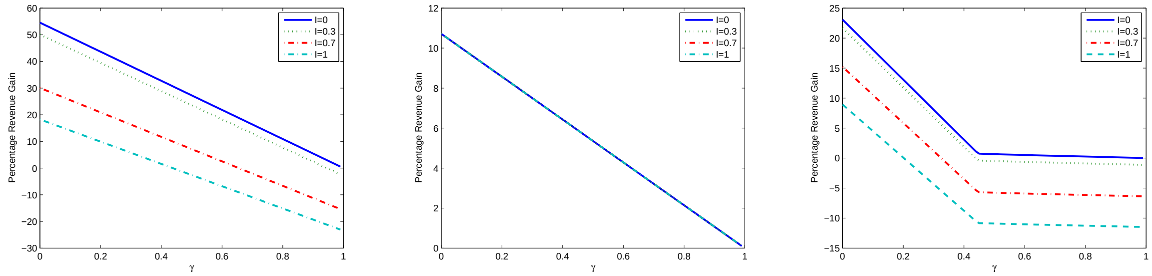
Proof. When $I = 1$, the optimal profit from dynamic targeted pricing without commitment is $R^{DT*}(\alpha, 1) = \alpha v_A + \frac{(1-\alpha)(2-\gamma)^2}{4(3-2\gamma)}$, and the profit from dynamic targeted pricing with commitment is $R^{CT*}(\alpha, 1) = \alpha v_A + \frac{1-\alpha}{3+\gamma}$. The profit gain from commitment is given by

$$\begin{aligned}
\frac{R^{CT*}(\alpha,1) - R^{DT*}(\alpha,1)}{R^{DT*}(\alpha,1)} &= \frac{R^{CT*}(\alpha,1)}{R^{DT*}(\alpha,1)} - 1 \\
&= \frac{\alpha v_A + \frac{1-\alpha}{3+\gamma}}{\alpha v_A + \frac{(1-\alpha)(2-\gamma)^2}{4(3-2\gamma)}} - 1 \\
&\leq \frac{\frac{1}{3+\gamma}}{\frac{(2-\gamma)^2}{4(3-2\gamma)}} - 1 \qquad \text{(B–7)} \\
&\leq \frac{3}{125} \\
&= 2.4\%.
\end{aligned}$$

In the above, the first inequality follows by taking $\alpha = 0$, and the second inequality follows by taking $\gamma = \frac{3}{4}$. Note that the term $\frac{\frac{1}{3+\gamma}}{\frac{(2-\gamma)^2}{4(3-2\gamma)}}$ attains its maximum at $\gamma = \frac{3}{4}$. This completes the proof. ■

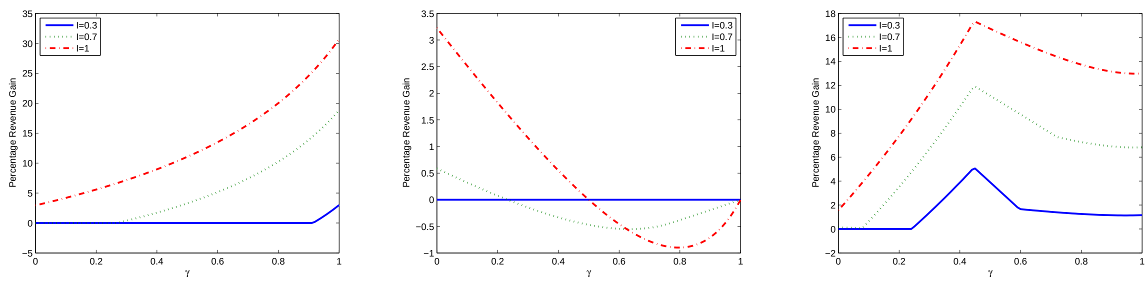
Proposition B–2 is striking. It shows that when targeting is perfect, commitment adds little value to dynamic targeted pricing. This result seems to suggest that commitment and targeting are substitutable in mitigating strategic customer behavior. The truth is quite the opposite. While commitment mitigates strategic customer behavior, targeting exacerbates it. As we have shown in Proposition 3, dynamic targeted pricing can hurt the firm's bottom line because targeting may undermine the effectiveness of dynamic pricing. This potential adverse effect of targeting is largely offset by commitment. Therefore, commitment and targeting are complementary. Later, in our numerical studies (Figure 7), we shall see that under dynamic pricing, the value of commitment and targeting is greater than the sum of the value of targeting without commitment and commitment without targeting. Nevertheless, even if the monopolist can make credible commitment when she adopts dynamic targeted pricing, the gain from doing so is very limited. This is because targeting has far higher value than that of commitment. Previous literature (e.g., Aviv and Pazgal 2008) demonstrates that commitment can significantly enhance firms' profits. Indeed, in the context of our model, commitment can improve the monopolist's profit by up to 6% under dynamic pricing without targeting (Figure 3). However, it is difficult to make credible commitment. Fortunately, Proposition B–2 shows that when the monopolist can achieve a high level of targeting accuracy, commitment is of limited value.

Fig. 4. Revenue gains of dynamic pricing compared with static targeted pricing; $\alpha = 0.4$.



(a) $v_A = 0.2$ (b) $v_A = 0.5$ (c) $v_A = 0.8$

Fig. 5. Revenue gains of dynamic pricing with targeting compared with dynamic pricing without targeting; $\alpha = 0.4$.



(a) $v_A = 0.2$ (b) $v_A = 0.5$ (c) $v_A = 0.8$

APPENDIX C: NUMERICAL ANALYSIS AND MODEL EXTENSIONS

We derived our key results using parsimonious models that are analytically tractable. As always, parsimony is achieved by making simplifying assumptions. In this section, we use numerical studies to demonstrate that our insights are robust when the simplifying assumptions are relaxed. We also extend our analysis for dynamic pricing and dynamic targeted pricing to a multi-period setting.

Numerical Analysis

We first investigate the value of dynamic pricing compared with static targeted pricing. Proposition 2 establishes that dynamic pricing dominates static targeted pricing when customers are myopic ($\gamma = 0$). What happens when customers are forward looking? Figure 4 plots the revenue gains of dynamic pricing compared with static targeted pricing for different values of γ. The value of α is fixed at 0.4, and we consider three different values of v_A: 0.2, 0.5, and 0.8. Not surprisingly, as customers become more forward looking, the revenue gains decrease. When γ is high enough, the revenue gains can be negative, indicating revenue losses. This is intuitive. When γ approaches 1, dynamic pricing is completely ineffective and produces the same revenues as static pricing without targeting. We note that the magnitude of revenue gains from dynamic pricing can be quite large, reaching more than 50% for the cases we considered. This suggests that static targeted pricing can be far inferior to dynamic pricing. We also observe that the revenue gains are decreasing in targeting accuracy I, because static targeted pricing becomes more effective as I increases. Through a numerical study, we verify that all these insights hold when the selling horizon is divided into multiple periods and a different price is charged in each period.

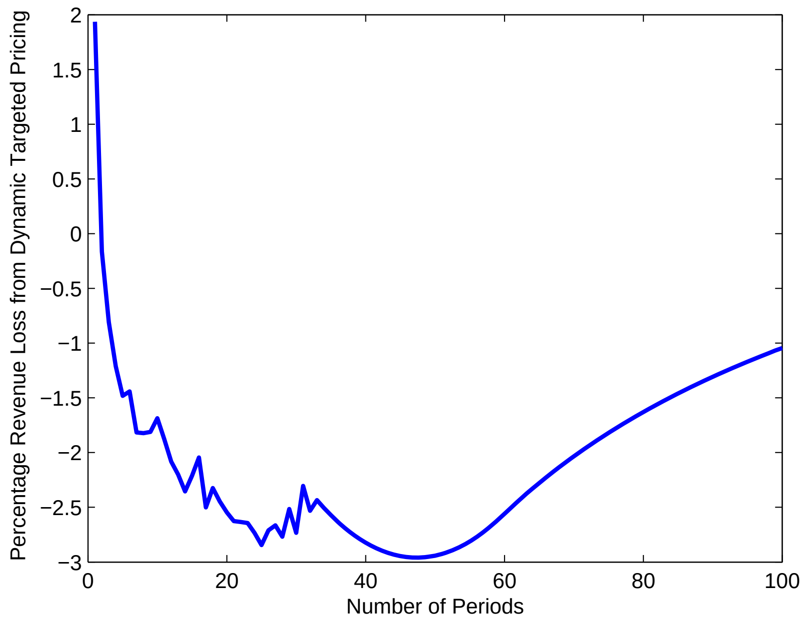
Next, we compare dynamic targeted pricing with dynamic pricing without targeting. Figure 5 shows the revenue gains of dynamic targeted pricing vis-à-vis dynamic pricing without targeting. We again fix α at 0.4 and report results for different v_A values. As expected, when v_A takes an intermediate value, the revenue gains can be negative. Note however that the magnitude of the revenue loss is rather small — less than 1% for the cases considered. On the other hand, we observe huge revenue gains from targeting, reaching almost 30% in some instances. We observe the same pattern for other parameter combinations. The revenue gains are non-monotone in γ, except for $v_A = 0.2$. For $v_A = 0.5$, the revenue gains first decrease and then increase in γ, while the opposite trends are observed for $v_A = 0.8$. The complex patterns reflect the different magnitudes of impact of customers' forward looking behavior on revenues. One observation from our numerical results is that targeting tends to be the least effective for intermediate values of v_A. Indeed, negative revenue gains for dynamic targeted pricing are only observed here for $v_A = 0.5$.

We also perform numerical analysis where the valuation of segment A follows a uniform distribution on $[v - \mu, v + \mu]$, where $v \in [0, 1]$, and μ is a small positive constant. In a two period setting with $\alpha = 0.4$ and $\gamma = 0.8$, we can show that the negative revenue gain from dynamic targeted pricing persists when $v = 0.4$ and $\mu = 0.01$. Therefore, our main result holds when the valuation of segment A follows a uniform distribution within a narrow band.

The negative revenue gain of dynamic targeted pricing compared with dynamic pricing persists in a multi-period setting.[11] To illustrate this point, we compare the revenue from

[11] See Appendix C for details of the analysis.

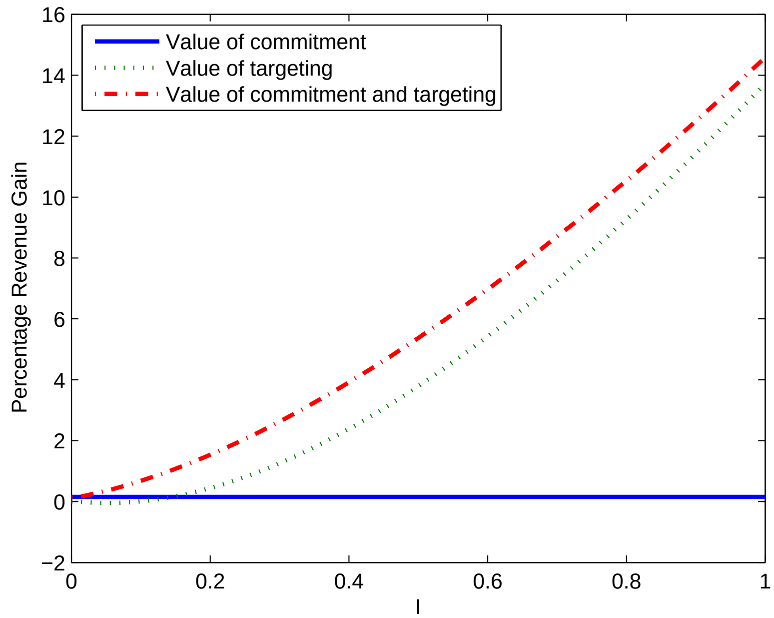
FIG. 6. The revenue loss from dynamic targeted pricing compared with dynamic pricing without targeting



dynamic pricing and dynamic targeted pricing when the selling horizon is divided into T periods of equal length. The per-period discount factor is given by $\gamma = e^{\frac{\delta}{T}}$. We take $\alpha = 0.4$, $v_A = 0.4$, and $\delta = 0.19382$. The δ value is taken to ensure that $\gamma = 0.8$ when $T = 2$. Figure 6 shows the percentage revenue loss of dynamic targeted pricing compared with dynamic pricing without targeting. Observe that there is significant revenue loss (close to 3%) even when the number of periods is 40. This clearly shows that the negative revenue gain from targeting is not driven by the two-period assumption in our main analysis. The main driver of the result, separating segment A customers lowers prices for segment B later in the selling horizon, remains in effect in a multi-period setting.

Finally, we investigate the value of targeting versus commitment. Figure 7 shows the relative revenue gains of dynamic pricing with commitment, dynamic targeted pricing, and dynamic targeted pricing with commitment, respectively, compared with dynamic pricing without commitment. The most salient observation is that dynamic targeted pricing reaps most of the benefits that can be achieved through both targeting and price commitment, except when I is very small. Hence, the value of price commitment on top of targeting is

FIG. 7. The value of targeting and commitment; $\alpha = 0.4$, $v_A = 0.8$, and $\gamma = 0.8$.



small. This suggests that our earlier observation for $I = 1$ is quite robust. Although price commitment always brings positive revenue gains, it can miss huge revenue potential in the absence of targeting. In this sense, targeting capability is more valuable than commitment capability. On the other hand, the full potential of targeting can only be realized when combined with dynamic pricing; our earlier discussion suggests that static targeted pricing is dominated by dynamic pricing when consumers are not too forward looking.

Multi-Period Dynamic Targeted Pricing

Our main analysis on dynamic targeted pricing assumes that the selling horizon is divided into two periods. Here we consider an extension where the selling horizon is divided into equal intervals. We assume the targeting accuracy $I = 1$. It follows that the revenue from segment A consumers is αv_A. Next, we discuss the dynamic pricing problem for segment B. The time horizon $[0, \tau]$ is divided into T equal periods with the per period discount factor $\gamma = e^{-\delta\left(\frac{\tau}{T}\right)}$. The monopolist maximizes total revenue from segment B during the T selling periods by setting different prices in different periods. We assume the monopolist does not commit to future price. The seller's revenue maximization problem can be formulated as follows.

In period t, let θ_t denote the maximum willingness to pay for consumers remaining on the market. Let the $v_t(\theta_t)$ be the maximum future revenue from segment B given state θ_t. For each $t < T$, the optimality equations can be written as

$$v_t(\theta_t) = \max_{0 \le p_t \le \theta_t} \left\{ p_t(\theta_t - \theta_{t+1}) + v_{t+1}(\theta_{t+1}) \right\}. \tag{C–1}$$

In the above, θ_{t+1} represents the willingness to pay of a consumer who is indifferent between purchasing in period t at price p_t and purchasing in period $t+1$ at the price $p^*_{t+1}(\theta_{t+1})$. Here, $p^*_{t+1}(\theta_{t+1})$ is the optimal price in period $t+1$ given state θ_{t+1}. The marginal valuation satisfies

$$\theta_{t+1} - p_t = \gamma\left(\theta_{t+1} - p^*_{t+1}(\theta_{t+1})\right). \tag{C–2}$$

In the last period, all consumers with willingness to pay higher than the price, purchase. Hence, we have

$$v_T(\theta_T) = \max_{0 \le p_T \le \theta_T} p_T(\theta_T - p_T). \tag{C–3}$$

Lemma B–2 *An optimal solution to the dynamic program defined in (C–1)–(C–3) is given by*

$$\begin{aligned} v_t(\theta_t) &= B_t\theta_t^2, && \forall t = 1, \ldots, T, \\ p^*_t(\theta_t) &= A_t\theta_t, && \forall t = 1, \ldots, T, \end{aligned}$$

where

$$\begin{aligned} A_T &= \frac{1}{2}, \quad B_T = \frac{1}{4}, \\ A_t &= \frac{(\gamma A_{t+1} - \gamma + 1)^2}{2\gamma(A_{t+1} - 1) - 2(B_{t+1} - 1)}, && \forall t = 1, \ldots, T-1, \\ B_t &= A_t\left(1 - \frac{A_t}{\gamma(A_{t+1} - 1) + 1}\right) + B_{t+1}\left(\frac{A_t}{\gamma(A_{t+1} - 1) + 1}\right)^2, && \forall t = 1, \ldots, T-1. \end{aligned}$$

Proof. The proof is by induction. We first solve the problem for period T defined in (C–3). It can be easily checked that $p^*_T(\theta_T) = \frac{\theta_T}{2}$ and $v_T(\theta_T) = \frac{\theta_T^2}{4}$. Hence the proposition holds for $t = T$.

For the inductive step, assume the result holds for $t+1$ for some $t < T$; i.e.,

$$\begin{aligned} p^*_{t+1}(\theta_{t+1}) &\equiv A_{t+1}\theta_{t+1}, \\ v_{t+1}(\theta_{t+1}) &\equiv B_{t+1}\theta_{t+1}^2. \end{aligned}$$

Using the above equations in (C–1), we obtain

$$v_t(\theta_t) = \max_{0 \le p_t \le \theta_t} \left\{ p_t(\theta_t - \theta_{t+1}) + B_{t+1}\theta_{t+1}^2 \right\}. \tag{C–4}$$

The marginal valuation θ_{t+1} satisfies

$$\theta_{t+1} - p_t = \gamma(\theta_{t+1} - A_{t+1}\theta_{t+1}), \tag{C–5}$$

which yields $\theta_{t+1} = \frac{p_t}{\gamma(A_{t+1}-1)+1}$. It follows that

$$v_t(\theta_t) = \max_{0 \le p_t \le \theta_t} \left\{ p_t\left(\theta_t - \frac{p_t}{\gamma(A_{t+1}-1)+1}\right) + B_{t+1}\left(\frac{p_t}{\gamma(A_{t+1}-1)+1}\right)^2 \right\}. \tag{C–6}$$

From which we obtain

$$\begin{aligned} p_t^*(\theta_t) &= \frac{\theta_t(\gamma A_{t+1} - \gamma + 1)^2}{2\gamma(A_{t+1}-1) - 2(B_{t+1}-1)} \\ &= A_t\theta_t. \end{aligned} \tag{C–7}$$

Substitute $p_t^*(\theta_t) = A_t\theta_t$ into $v_t(\theta_t)$, we have

$$\begin{aligned} v_t(\theta_t) &= A_t\theta_t\left(\theta_t - \frac{A_t\theta_t}{\gamma(A_{t+1}-1)+1}\right) + B_{t+1}\left(\frac{A_t\theta_t}{\gamma(A_{t+1}-1)+1}\right)^2 \\ &= \left[A_t\left(1 - \frac{A_t}{\gamma(A_{t+1}-1)+1}\right) + B_{t+1}\left(\frac{A_t}{\gamma(A_{t+1}-1)+1}\right)^2\right]\theta_t^2 \\ &= B_t\theta_t^2. \end{aligned} \tag{C–8}$$

Hence the recursion holds for period t. This completes the proof. ■

Using the result of Lemma B–2, the optimal revenue under dynamic targeted pricing is given by $\alpha v_A + (1-\alpha)B_1$.

Multi-Period Dynamic Pricing without Targeting

This section considers multi-period dynamic pricing without targeting. We again assume the time horizon $[0, \tau]$ is divided into T equal periods with the per period discount factor $\gamma = e^{-\delta\left(\frac{\tau}{T}\right)}$. The monopolist maximizes total revenue during the T selling periods by setting different prices in different periods. We assume the monopolist does not commit to future price. The seller's revenue maximization problem can be formulated as follows.

In period t, let θ_t denote the maximum willingness to pay for consumers remaining on the market. Let the $u_t(\theta_t)$ be the maximum future revenue given state θ_t. For each $t < T$, the optimality equations can be written as

$$u_t(\theta_t) = \max_{0 \le p_t \le \theta_t} \{p_t(\theta_t - \theta_{t+1}) + \alpha v_A \mathrm{I}\{\theta_t > v_A \ge \theta_{t+1}\} + u_{t+1}(\theta_{t+1})\}. \tag{C–9}$$

The indicator function $\mathrm{I}\{\cdot\}$ takes the value 1 if the condition in the curly bracket is true and 0 otherwise. The value θ_{t+1} represents the willingness to pay of a consumer who is indifferent between purchasing in period t at price p_t and purchasing in period $t+1$ at the price $p^{\dagger}_{t+1}(\theta_{t+1})$. Here, $p^{\dagger}_{t+1}(\theta_{t+1})$ is the optimal price in period $t+1$ given state θ_{t+1}. The marginal valuation satisfies

$$\theta_{t+1} - p_t = \gamma\left(\theta_{t+1} - p^{\dagger}_{t+1}(\theta_{t+1})\right). \tag{C–10}$$

In the last period, all consumers with willingness to pay higher than the price, purchase. Hence, we have

$$u_T(\theta_T) = \max_{0 \le p_T \le \theta_T} p_T(\theta_T - p_T) + \alpha v_A \mathrm{I}\{\theta_T > v_A \ge p_T\}. \tag{C–11}$$

The dynamic program defined in (C–9)–(C–11) does not admit a simple closed-form solution. However, since it is a dynamic program with one-dimensional state and action spaces, it can be easily solved by a numerical procedure.

APPENDIX D: ADDITIONAL EXPERIMENTAL DETAILS

Experiment 1: As stated previously, our experiments are market experiments (Yuan and Han, 2011). Hence, we allow for the firm, segment A, and segment B to make active decisions in a strategic game. This means that the computer does not simulate any decisions in the experiment and a human participant will assume the roles shown above. We use a representative customer approach and allow for a participant to make decisions on behalf of the segment that they represent.

This approach offers three main advantages. First, the interaction between strategic firms and strategic customers can be captured more efficiently since we do not require as many participants to simulate the consumer market because each entity can be represented by one participant. Second, the mapping between theory and customer segments are more closely aligned. For segment A, the valuations and preferences are assumed to be identical and so having a representative for the segment reduces the noise that can arise from individual level differences within the segment. For segment B, we can account for individual level differences through a representative as we do for segment A, but the valuation levels differ according to a uniform distribution. By allowing for a representative customer to represent segment B, the indifference point (or the minimum valuation) of the customer purchasing in segment B that arises due to the uniform distribution assumption can be identified with greater precision because we actually observe this point in this experiment. Third, the decision makers for segment B are more actively engaged when making purchase decisions. With discretized valuations assigned to each participant, those with low or high values have very simple decisions since these participants will never or always purchase. In our experiment, the representative customer chooses the indifference point for the segment and is less likely to feel that their decision is inconsequential.

54 participants took part in Experiment 1 with 18 participants in each of the three conditions. Participants received both course credit and payment (an average of $17) for their decisions. We designed the experiment to ensure significant separation between the point predictions across the three conditions. Upon arriving for the experiment, participants were provided with instructions that were read out loud by the experimenter. The participants were informed that they would be randomly and anonymously grouped into threes and that each participant would be randomly assigned a role as the Seller, Player A, or Player B.

Then, the participants were told that the grouping procedure would be repeated in each round. Therefore, the groupings and roles would change across the eight decision rounds.

Next, we described each role and the decisions required in each role. We began with a description of the Seller. The Seller would determine the price for a product that would be sold to both Player A and Player B, where Player A would represent 3 customers who value the product at 80 and Player B would represent 7 customers whose valuations for the product would be uniformly distributed between 0 and 100. The Seller could choose integer prices from 0 to 100 and both Player A and Player B would observe the price or prices before deciding whether to purchase from the Seller. If participants were in the dynamic pricing conditions, then Sellers would choose prices in period 2, assuming that not all of the customers purchased in period 1. Players A and B would then make their subsequent purchase decisions. Note that Sellers would be informed about the purchases from period 1 in period 2, but both Player A and Player B would not be informed about the purchases made by the other player until the end of the round. In this way, we limited the overlap in the information that Player A and Player B would have about each other when making purchase decisions. Player A and Player B would know their own decision, but would not know the decision of the other party until the completion of the round. This design limits peer-induced fairness concerns that we discussed previously.

Static Targeted Pricing Condition (STP): In the STP Condition, there is only one period. The Seller chooses a separate price, in integers, for each segment from 0 to 100. The assumption in this condition and throughout our experiments is that targeting is perfect ($I = 1$) consistent with theory. We assume, as in the model, that the targeting costs and the unit costs are both equal to zero. The Seller chooses one price for Player A and another price for Player B. Then, Players A and B make their purchase decisions simultaneously. Player A's purchase decision as a representative for segment A is fairly straightforward. If the targeted price is not greater than 80, Player A is predicted to purchase. Player A's points will then be equal to segment A's consumer surplus: $3 \times \left(80 - p_A^{ST}\right)$. Player B also observes the price chosen for segment B and makes a purchase decision. Since valuations of customers represented by Player B are uniformly distributed between 0 and 100, Player B chooses the minimum valuation level at which customers purchase, v_B^{STP}. The selection of v_B^{STP} determines the share of customers in segment B that purchases and their resultant consumer surplus. Therefore, Player B's points will equal the consumer surplus from segment B: $7 \times \frac{100-v_B^{STP}}{100} \times \left(\frac{100+v_B^{STP}}{2} - p_B^{STP}\right)$. The middle quantity represents the proportion of customers in segment B that purchase and the last term is the average customer surplus. Note that the players earn zero points if no purchase is made from the segment they represent. To help participants understand the selection of v_B^{STP}, we worked examples and also provided a revenue chart with different combinations of prices and v_B^{STP}. The Seller's points would then be equal to the sum of the revenue generated from Players A and B if purchases are made: $3 \times p_A^{STP} + 7 \times \frac{100-v_B^{STP}}{100} \times p_B^{STP}$. Otherwise, the Seller would receive zero points from the segments that do not purchase. The points were then converted at a rate of 100 points to \$1 for both experiments.

Impatient and Patient Dynamic Pricing Conditions (IDP and PDP): There is no targeting in these conditions, but rather the Seller determines one price for both Player A and Player B in period 1 and another price for those customers who did not purchase in period 2. Although both Player A and Player B have the option of purchasing the product in period 1, they can strategically wait until period 2 to make their purchase. However, if a particular customer purchases in period 1, then that customer would not be eligible to purchase in period 2. Similarly, Player B would determine whether to purchase in period 1 and if Player B chooses to purchase then Player B would choose the minimum valuation level (v_{B1}^{DP}) at which customers in the group purchases in period 1. However, those customers with a valuation at or above the valuation level chosen by Player B would not be eligible to purchase again in period 2. Therefore, if customers in segment B purchase in both periods, then the following must hold: $v_{B1}^{DP} > v_{B2}^{DP}$. After the period 1 decisions, the Seller would then determine the price in period 2, but both Player A and Player B (if eligible to purchase) would have their points reduced by the discount factor of $\gamma = 0.3$ (0.9) in the Impatient Dynamic Pricing Condition — IDP (Patient Dynamic Pricing Condition — PDP). In period 2, Player A would then decide to purchase if no purchase was made in period 1, but the earned points would be reduced by the discount factor γ. Accordingly, Player B would also decide to purchase and would choose the minimum valuation level at which customers in B would purchase. Note that if Player B purchased at a valuation level of v_{B1}^{DP} in period 1 and chose a valuation level of v_{B2}^{DP} in period 2, then those customers with a valuation between v_{B2}^{DP} and v_{B1}^{DP} would purchase in period 2 and the earned points would be reduced by the discount factor, γ. The points for Player A would be equal to $3 \times \left(80 - p_1^{DP}\right)$ if purchasing in period 1 or $3\gamma \times \left(80 - p_2^{DP}\right)$ if purchasing in period 2. Player B's points would be equal to $7 \times \frac{100-v_{B1}^{DP}}{100} \times \left(\frac{100+v_{B1}^{DP}}{2} - p_1^{DP}\right) + 7\gamma \times \frac{v_{B1}^{DP}-v_{B2}^{DP}}{100} \times \left(\frac{v_{B1}^{DP}+v_{B2}^{DP}}{2} - p_2^{DP}\right)$ if purchases occur in both periods. The Seller's points would then be equal to the following if Player A purchases in period 1 and Player B purchases in both periods: $3 \times p_1^{DP} + 7 \times \frac{100-v_{B1}^{DP}}{100} \times p_1^{DP} + 7 \times \frac{v_{B1}^{DP}-v_{B2}^{DP}}{100} \times p_2^{DP}$. As with the STP condition, we worked through examples and a provided a chart so that participants understood the decisions clearly.

Experiment 2: There were 78 participants across the four conditions in Experiment 2. The participants received both course credit and cash (an average of \$16). The four conditions are described in greater detail below.

Dynamic Targeted Pricing Conditions (DTPH and DTPM): These conditions are very similar to the STP condition in Experiment 1. However, the firm can choose prices in period 2 if some customers do not purchase in period 1. In this way, the firm can choose up to four prices in this experiment (two for segment A and two for segment B). If all of the customers purchase in period 1, then the firm would only choose two prices and this would reflect the STP condition. If, however, customers purchase in period 2, the second period points will be reduced by a factor of 0.6. Player A's points are equal to $4 \times \left(90 - p_{A1}^{DTP}\right)$ if Player A purchases in period 1 and $0.6 \times 4 \times \left(90 - p_{A2}^{DTP}\right)$ if Player A purchases in period 2. Similarly, Player B's points are equal to $6 \times \frac{100-v_{B1}^{DTP}}{100} \times \left(\frac{100+v_{B1}^{DTP}}{2} - p_{B1}^{DTP}\right) + 0.6 \times 6 \times \frac{v_{B1}^{DTP}-v_{B2}^{DTP}}{100} \times \left(\frac{v_{B1}^{DTP}+v_{B2}^{DTP}}{2} - p_{B2}^{DTP}\right)$ if purchases occur in both periods. The points for the Seller will then be $4 \times p_{A1}^{DTP} + 6 \times \frac{100-v_{B1}^{DTP}}{100} \times p_{B1}^{DTP} + 6 \times \frac{v_{B1}^{DTP}-v_{B2}^{DTP}}{100} \times p_{B2}^{DTP}$ if Player A purchases in period 1 and Player B purchases in both periods.

Dynamic Pricing Conditions (DPH and DPM): These conditions are identical in procedure to the IDP and PDP conditions and the only difference is that the valuation of segment A customers are either 90 (DPH) or 40 (DPM) while the discount factor remains 0.6 across all conditions.

We chose a set of parameters that would allow for clear separation between predictions across these four conditions. However, the benefit of dynamic pricing when valuations are moderate is expected to be small. With this constraint, we chose $I = 1$, $\gamma = 0.6$, $v_A^H = 90$, $v_A^M = 40$, $V_B = 100$ and $\alpha = 0.4$. We also multiplied the proportion of customers by 10 and scaled the valuations by 100 to explain the market more clearly to the participants.

Table 4. Theoretical Predictions and Means in Experiment 2

Condition	Variable	Theory	Mean	SD	t-test vs. Theory
Dynamic Targeted Pricing High Valuation (DTPH)	p_{A1}^{DTPH}	90.0	76.4	8.5	Diff $= -13.6^*$
					$SE = 1.06; p = 0.000$
	p_{B1}^{DTPH}	54.4	59.3	12.2	Diff $= 4.9^*$
					$SE = 1.91; p = 0.020$
	p_{A2}^{DTPH}	90.0	68.6	14.2	Diff $= -21.4^*$
					$SE = 2.59; p = 0.000$
	p_{B2}^{DTPH}	38.8	46.9	17.2	Diff $= 8.0^*$
					$SE = 2.55; p = 0.006$
	R^{DTPH}	523.3	413.3	109.9	Diff $= -110.0^*$
					$SE = 15.55; p = 0.000$
Dynamic Targeted Pricing Moderate Valuation (DTPM)	p_{A1}^{DTPM}	40.0	38.0	9.7	Diff $= -2.0$
					$SE = 1.64; p = 0.244$
	p_{B1}^{DTPM}	54.4	53.1	10.1	Diff $= -1.3$
					$SE = 1.35; p = 0.351$
	p_{A2}^{DTPM}	40.0	36.4	12.4	Diff $= -3.6$
					$SE = 2.27; p = 0.134$
	p_{B2}^{DTPM}	38.9	45.0	11.5	Diff $= 6.1^*$
					$SE = 1.73; p = 0.002$
	R^{DTPM}	323.3	208.9	65.4	Diff $= -114.4^*$
					$SE = 10.01; p = 0.000$
Dynamic Pricing High Valuation (DPH)	p_1^{DPH}	86.3	75.9	10.0	Diff $= -10.4^*$
					$SE = 1.52; p = 0.000$
	p_2^{DPH}	76.3	67.5	12.9	Diff $= -8.8^*$
					$SE = 2.21; p = 0.001$
	R^{DPH}	418.1	343.2	139.4	Diff $= -74.9^*$
					$SE = 21.88; p = 0.003$
Dynamic Pricing Moderate Valuation (DPM)	p_1^{DPM}	52.0	46.5	11.6	Diff $= -5.5^*$
					$SE = 1.80; p = 0.008$
	p_2^{DPM}	40.0	36.4	8.7	Diff $= -3.6^*$
					$SE = 1.69; p = 0.046$
	R^{DPM}	325.6	266.4	83.2	Diff $= -59.2^*$
					$SE = 12.88; p = 0.000$

*Significant at the 5% level