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Strategical Segmentation: Are High-Value Customers Overvalued?

Runyu Tang
School of Economics and Management, Tsinghua University

Buqu Gao
Department of Economics, Boston University

Yiwei Li, Sheng Liu
Department of Marketing and International Business, Lingnan University

With the wide adoption of marketing segmentation and access to unprecedented amounts of individual-level customer data, firms have become experts in identifying high-value customers and deliver segment-specific offerings. This study attempts to answer a basic question in customer segmentation: should firms focus more on high-value customers than low-value customers in a competitive market? To address this question, we incorporate two key features up to now ignored in the literature with behavior-based pricing (BBP) model: segmentation of the existing customer base, and customer value as a basis for segmentation. Our model results indicate that, counter-intuitively, a larger portion of high-value customers may backfire, because high-value customers attract more intense competition and eventually yields lower profits. Our findings generate fruitful public policy implications: strategical segmentation is beneficial to society when the portion of high-value customers is relatively low. When the portion becomes sufficiently large, the switching costs of the high-value customers begin to soar, which eventually leads to reduced social welfare.

Key words: Segmentation, Customer Value, Behavior-Based Pricing, Market Competition

1. Introduction

Marketing segmentation has long been recognized as a critical strategy in maximizing customer value, increasing competitive advantage, and ultimately boosting profits (Kumar and Reinartz 2016, Natter et al. 2008, Sinha and DeSarbo 1998, Smith 1956). While the business used to report segmentation difficulties in bridging the theories and practices (Belch 1982, Liu et al. 2010), advances in customer information acquisition and processing technology have enabled online companies to implement effective and efficient segmentation strategies (Acquisti and Varian 2005, Boone and Roehm 2002, Chen et al. 2012, Ringel and Skiera 2016). Online merchants such as Netflix and Amazon can segment the customer bases and condition the price offers for each segment by tracking and analyzing customers prior purchase histories, Internet cookies, and browse records (Li and Jain 2015). Such segmentation practices are not the privileges of transactions on the Internet now, offline companies from various industries, including banking, airline, grocery stores, and ride sharing, have also became experts in tracking customers information and offer segment-specific pricing (Menzly and Ozbas 2010, Taylor 2004).

In developing effective marketing segmentation strategies, customer value stands out as one of the most important criteria. Customers can be classified into high-value (low-value) segment, for instances, when they have high (low) income (Armelini et al. 2015), frequent (occasional) purchase (Kumar and Reinartz 2016), strong (weak) relationship with the firm Pan et al. (2006), or low (high) intention to churn (Ascarza et al. 2018). Despite various customer value metrics used across different industries, firms would most likely put more effort in high-value customers (than low-value customers), as intuitively that high-value customers are associated with higher profits. Consequently, the competitors may also implement poaching strategy to steal the firms' high value clients. From a focal firm perspective, it seems that high-value customers bring high monetary return, but such a view needs potential revision if the competitive environments were taken into account. We speculate that as firms compete more fiercely for high-value segment (than low-value segment), they incur significantly higher costs, such as those for deep price discount Anderson and Simester (2004), customized loyalty program Yi and Jeon (2003) and free gifts Liu-Thompkins and Tam (2013), and the considerable costs in winning over the competitors' high-value customers outweigh the realized profits, eventually leading to reduced profits of the firms. And this conjecture underlies the fundamental motivation of setting up our proposed model.

Segmentation strategies for horizontally and vertically differentiated firms can differ. Our proposed model applies to situations where horizontally differentiated firms compete with segment-specific pricing strategy. In examining the externalities of differential pricing strategy, our study also adds to a growing body of literature on behavior-based price (BBP) which differentiates against the new and existing customers of firms (Choe et al. 2017, Li and Jain 2015, Zhang 2011). Different to BBP strategies, marketing segmentation strategies primarily focuses on the existing customer base and further differentiate them into different sub-groups (i.e. segments) based on various customer characteristics such as their demographics and product preferences. Indeed, from the profit maximization perspective, it is vital for the firms to consider not only BBP practices, but also how to implement effective marketing segmentation strategies in contemporary competitive environment. Naturally, BBP framework becomes as a benchmark for the concrete implementation of segment-based pricing.

Specifically, we propose a two-period model with horizontally differentiated competing firms in a duopoly market. The two symmetric firms cover the whole market and compete for (marginal) customers who are uniformly distributed in the Hotelling line. In the first period, each firm offers a uniform price to customers without prior information. While in the second period, the firms have information of both purchase history and customers characteristics. On one hand, the purchase behavior which reveals customers preference for the two competing firms' products, allows the firms to discriminate between the new and existing customers (resembling a basic BBP setting). On the other hand, customer characteristics, such as exogenous customer demographics, enable firms to segment their existing customers into high-value and low-value customers and offer them distinctive prices. It is noteworthy that in our study strategical segmentation has double meanings: the first, we argue that high-value customers are overvalued and thus sellers/policy makers may tactfully maintain a reasonable (instead of the maximum) portion of high-value customers to maximize profit/social welfare; and the second, sellers can strategically influence initial market share via first period pricing decision, which then endogenously determines marketing segments in the second period. Therefore, segmentation can be strategical from sellers' perspective, although the composition of customers is exogenous per se. Furthermore, we have proposed alternative specifications which incorporate more complex features of both the firms and customers. From the customers side, segment-based pricing can lead to perception of unfairness when customers of a certain segment are charged with a higher price than those in other segments. Consequently, customers may not buy products sold at unfair prices. From the firms' side, firms sometimes are not able to implement perfectly accurate segmentation practices, for example, due to lack of appropriate segmentation skills or noisy customer information. The impacts of both customer fairness concern and firms' imperfect segmentation are examined in our model extensions.

Our results suggest that, compared to pure BBP, the total profits for the two sellers generally decrease when segmentation is implemented. This is because the high-value customers (as compared to low-value customers) attract more intense competition between the two sellers, resulting in profit reduction for both sellers. Interestingly, we find that profit is not monotonically decreasing with the size of high-value customers. When the size of high-value customers is relatively small (e.g. less than 27.3% of the customer base) or exceptionally large (e.g. more than 42.9% of the customer base), either high-value customers or low-value customers will not engage in switching in the second stage. Hoping to exploit these non-switching customers, the sellers are incentivized to secure a larger market share in the first stage, leading to intensified competition and therefore decreased overall profits. Interestingly, if the sellers are able maintain a reasonable portion of high-value customers (e.g. 28.1%-40.8% of the customer base), the total profits can increase as the size of high-value customers increases. The rationale is that, with a moderate level of high-value customers, both high- and low-value customers can easily switch to the competing seller, subsequently the sellers have strong motivation to poach each other's customers in the second stage, and tend to secure less market share in the first stage. As a result, competition in the first stage is softened, which in return leads to increased overall profits. These findings can help practitioners determine appropriate segmentation strategies and particularly bring into question regarding the conventional belief that high-value customers are supremely valuable.

Theoretically, our model fills the critical gap between segmentation and BBP literature. If we view firms' discrimination strategy as a continuous spectrum, the left end represents the scenario when firms do not conduct any segmentation and only discriminate against new and existing customers. We refer to this extreme as pure BBP, in which a unique symmetric equilibrium exists (Li and Jain 2015). The right end is the scenario when firms create a distinct segment for every single customer who has purchased from them, and only asymmetric equilibria exist in this setting (Choe et al. 2017). In practice, firms stand in the middle of the spectrum—they divide existing customers into discrete segments based on crude characteristic information from previous patronage. We find that the pure-strategy equilibrium, if achieved, is unique and symmetric, and we delineate its outcome based on the information parameter we propose. In addition, our study enriches the understanding of fairness concern in price discrimination by showing that strong fairness concern may either increase or decrease the sellers' profit, depending on the proportion of high-value customers. While Li and Jain (2015) suggest that customer fairness concern generally leads to increased profits, our work shows that the lower price offered to new customers (in poaching strategies) can trigger serious fairness concerns of the existing customers, leading to potential profit reduction in segment-specific price discrimination.

Our findings not only generate fruitful managerial implications regarding strategical segmentation, but also shed light on public policy issues in potential regulation of segmentation practices in industry. Our model results suggest that when firms have low level of high-value segments , strategical segmentation is beneficial to the society as a whole. When the proportion of high-value customers is relatively small, no high-value customers engage in switching behavior, and therefore the total switches decreases as the proportion of high-value customers increases, which leads to a higher social welfare. However, when the ratio of high-value customers is sufficiently large, the customers in the high-value segment engage in switching behavior, and the switch of high-value segment to the competitor is particularly wasteful from a societal perspective, and thus significantly decreases social welfare. In extreme cases, when high-value customers are getting close to half of the customer base, the social welfare can be even lower than that in pure BBP strategy when no extra segmentation is conducted at all. This finding again challenges our general belief that the society will be straightly better off when there are more high-value customers. Interestingly, our finding is roughly consistent with predictions of the Pareto Principle or 80/20 rule that in a typical business approximately 80 percent of sales come from about 20 percent of high-value customers (Schwartz et al. 2014, Stathacopoulos 2006). To a certain degree we believe that, a smaller portion of high-value customers retained by a firm are most valuable to the whole society.

The rest of the paper is organized as follows. In next section, we review the relevant literature and discuss in detail the theory behind our analytical inquiry. We then describe our analytical setting in Section 4.1 and its extensions in Section 4.3, which serve as the basis for the contributions and present the results. We finally conclude the paper and also discuss directions for future research.

2. Literature Review

Customer segmentation has been widely accepted as an important component for both business operations and strategies, ranging from conventional marketing mix design, such as pricing, adverting, and promotion, to the creation of competitive advantages (Anderson and Jolson 1980, Liu-Thompkins and Tam 2013, Natter et al. 2008, Smith 1956). The enduring popularity of segmentation in both industry and academia shows how deeply strategical segmentation has connected with the core corporate values, for instances, an effective customer segmentation system can usually lead to enhanced customer satisfaction (Wu et al. 2006), repeated purchases (Ailawadi et al. 2014), and improved profitability (Bock and Uncles 2002). While much of the extant literature has focused predominantly on how a focal firm can improve her segmentation practices (in various contexts), very limited research has been conducted to understand the externality of segmentation practices on her competitor. Indeed, when competing firms decide which specific segments they wish to target, the overlap in the segments targeted by firms with undifferentiated products and similar pricing can trigger intense competition. In investigating the externalities of strategical segmentation, Behavior-Based Pricing (BBP) is the most relevant benchmark.

2.1. Behavior-Based Pricing

Behavior-Based Pricing (BBP) primarily describes that firms distinguish the prices offered to the existing customers with that to the new customers, due to a better understanding of the purchasing behaviors of existing customers. For an instance, a firm can exploit its loyal customers (i.e. existing customers) by charging a higher price to them, and at the mean time poach competitors' previous customers (i.e. the new customers of the focal firm) by offering them a lower price (Villas-boas 1999). The typical analytical set-up is a duopoly model with two horizontally differentiated firms and two-period-lived customers (Acquisti and Varian 2005, Villas-boas 1999, Zhang 2011). In the first period, both firms offer plain pricing to their customers without any prior knowledge about them. While in the second period, firms understand the behavioral differences between their existing customers and the competitors' customers, and thus distinguish the price offers to them.

Our analytical specification extends this conventional set-up by allowing the firms to conduct segmentation practices, i.e. to further differentiate the price offers to their existing customers, due to an enhanced understanding of customers based on not only purchase behaviors (which typically differentiate the existing customers with new customers), but also various customer characteristics that enables the firms to further differentiate high-value customers with low-value customers. Such extension is significant, and consistent with the basic idea of marketing segmentation which has a primary focus on how to properly categorize existing customers, and also in line with the routine practices in Customer Relationship Management (CRM) where retaining existing customers is a first-order issue for firms (Becker et al. 2009, Reinartz et al. 2004). There are two streams of discussions on the profitability of BBP, which serve as good basis for us to understand the bottom-line outcomes of pricing segmentation with customer information. A more conventional perspective is that BBP strategy intensifies the competition more than when they use simpler pricing strategies, and it therefore hurts the profits of the firms (Choe et al. 2017, Esteves and Reggiani 2014, Thisse and Vives 1988, Zhang 2011). However, another stream of literature is in support of BBP and suggests various circumstances in which BBP strategy can increase profits. Some examples include Rhee and Thomadsen (2016) which argue BBP can be profitable to firms in vertically differentiated markets, Jing (2016), and Shin and Sudhir (2010) show that sufficiently high heterogeneity in customer value (e.g. in terms of purchase quantity) can also lead to profitable BBP strategy.

2.2. Customer Value

Our primary contribution applies to customer value. Customer value is usually considered as a major source for competitive advantage in modern times, as indicated by a shift from firms' attempts to improve the organization internally, to outward orientation towards customers (Slater and Narver 2000, Woodruff 1997). By adopting customer value delivery orientation, managers start to explore various dimensions of customer value, for example, some firms believe customers' satisfaction in response to evaluations of the use experiences of a product creates customer value (Woodruff 1997), and some other firms suggest that (Yi and Jeon 2003) customer value is derived from their loyalty to the firms. While many firms reply on attitudinal (e.g. satisfaction, loyalty) outcome to define customer value, it is also becoming popular for firms to use behavioral outcome to measure customer values, such as through purchasing frequency (Kumar and Reinartz 2016), monetary expenses (Lam et al. 2004), as well as composite indexes like recency-frequency-monetary (RFM) value (Fader et al. 2005). Even though different firms can have different measurements towards customer value, firms commonly believe higher-value customers leads to higher profitability (Rust et al. 2011, Woodruff 1997), and therefore it is preferred to acquire and retain a larger high-value customer base. However, if we deviate from a focal firm's view and also consider the competitors' action, we need to rethink this common belief. Shin and Sudhir (2010) is one of the very few studies that brings the consideration of customer value into a competitive market. Based on the BBP model structure, the study argues there exists heterogeneity of customer values, and it is optimal to reward one's own customers (instead of competitor's customers) under symmetric competition. Indeed, marketers not only observe heterogeneity of customer values between existing and new (competitor's) customers, but also within the existing customer base per se, and this is essentially why segmentation is meaningful. By investigating the role of customer value in a competitive framework, our study bridges segmentation with BBP literature, and allows us to re-evaluate the common belief that higher-value customers always leads to higher profitability.

2.3. Customer Fairness Concern

An important extension of BBP scenarios is concerned with customer fairness. It is natural that price discrimination can trigger price comparisons among customers (Anderson and Simester 2008, Ho and Su 2009, Li and Jain 2015, Xia et al. 2004), one may easily compares her price with that of her friends, and in most cases feels unfair if she found out she was charged with a higher price, and therefore not make the purchase. While such peer-induced fairness seems to harm customers purchasing intention, Li and Jain (2015) found peer-induced fairness is somehow beneficial to the firms, in the sense that it softens the price competition, and thus firms can profit from BBP practices when customers are highly concerned with fairness. The peer-induced fairness concerns are largely driven by social comparison (Bearden and Etzel 1982, Festinger 1954) which is made between an ego and his surrounding peers who are in similar circumstances. In real-business scenarios, as social comparison creates an explicit and powerful reference or benchmark for an individual to evaluate his well-being (with respect to that of his peers), our model extensions also incorporate the salient peer-induced fairness. Such self-centric comparisons are usually in the purpose of preventing unfair treatment, which is termed as self-centered inequity aversion (Fehr and Schmidt 1999). The inequity aversion in theory suggests aversion against either a higher price, or a lower price. Our paper mainly considers the lowest price (being behind) aversion (Li and Jain 2015, Lee and Fay 2017), because in real life, customers exhibit a stronger disutility from being behind than from being ahead (Ho and Su 2009). Also, A survey from American shoppers show that 76% American adults feel unhappy if they know other customers have lower prices, but think it is acceptable that other customers are charged with higher prices otherwise (Turow et al. 2005).

3. The model

We propose a two-period model with two symmetric sellers (feminine) selling horizontally differentiated non-durable products. The customers (masculine) are uniformly distributed along the Hotelling line $[0, 1]$. Seller a locates at point 0 and seller b locates at point 1. The customers and the sellers evaluate the future with discount factor δ_c and δ_s respectively. Marginal production costs are normalized to zero and fixed costs are disregarded. In each period, each customer buys one unit of good from either seller a or b. A customer locating at θ gets per-period utility $v - \theta q - p_a$ when buying from seller a and $v - (1-\theta)q - p_b$ when buying from seller b. q is the marginal travel cost, p_i is the price charged by seller i, and v is the direct utility from consumption. We further assume v is sufficiently large so that the market is fully covered.

In the first period, each seller offers a uniform price to customers because no information is available yet to tailor prices. In the second period, each seller observes whether the customer has purchased from her, which reveals the customer's preference for the two sellers/products. Based on that, the sellers can adopt "behavior-based pricing": They divide the entire pool of customers into existing customers and new customers, and charge new customers a price potentially different from their existing customers.

Importantly, we assume the sellers can further partition their existing customers into low-value and high-value segments based on customer characteristics revealed in historical data. This is a realistic assumption due to the recent development of segmentation techniques. For example, the customers with more frequent visits, more intense in-store searching, larger spending in historical transactions, or stronger relationship with the firm exhibit stronger intention to buy from the seller, and hence may be labeled as higher value. Specifically in our model, each seller knows at the beginning of the second period whether the distance of an existing customer from her is less than α.[1] If so, she labels the customer as high value; otherwise, she labels the customer as low value. α is exogenously determined by the information structure of market data. Commonly, the Pareto Principle or 80/20 rule is insightful in segmentation practices such that, in a typical business approximately 80 percent of sales come from about 20 percent of high-value customers (Schwartz et al. 2014, Stathacopoulos 2006). We therefore further assume $0 \le \alpha \le 1/2$ to be consistent with the ratio of the high-value customers. Our model allows the sellers to conduct segment-based pricing in the second period, i.e., charge different prices to new customers, high-value existing customers, and low-value existing customers. We relax some key assumptions of our model in section 4.3 by taking into account the possibility of imperfect segmentation practices (e.g. noisy information or technology constraint) and (heterogeneous) fairness concerns that customers may have in response to price discrimination.

[1] One can think the seller's information acquisition as a signalling process by the customer. The customer within radius α from the seller automatically sends a private signal h to the seller when purchasing from her in the first period. Those who did not purchase from the seller in the first period, or who are away from the seller by more than α do not send any signal to her. It is noteworthy that customers' preferences are stationary and not influenced by the information parameter α.

3.1. The second period

By backward induction, our analysis begins with the second period. In the second period, each seller can segment customers based on transaction history and additional user data. The information parameter α captures the segmentation outcome. Let θ_0 be the marginal customer who is indifferent between choosing seller a and seller b in the first period. For the ease of exposition, we focus on the case $\alpha < \theta_0 < 1-\alpha$ in the following discussion. Analysis of the other cases is deferred to Appendix A.1 and we can show that these cases do not arise in equilibrium. Given our specification, seller a (resp. b) obtains three customer segments: Customers in $[0,\ \alpha)$ (resp. $(1-\alpha,\ 1]$) are high-value existing customers, those in $(\alpha,\ \theta_0)$ (resp. $(\theta_0,\ 1-\alpha)$) are low-value existing customers, and those in $(\theta_0,\ 1]$ (resp. $[0,\ \theta_0)$) are new customers. Existing customers in each segment may be poached by the competing seller. The market structure is shown in Figure 1. Labels "a" and "b" on top of the Hotelling line indicate where the corresponding customers buy from.

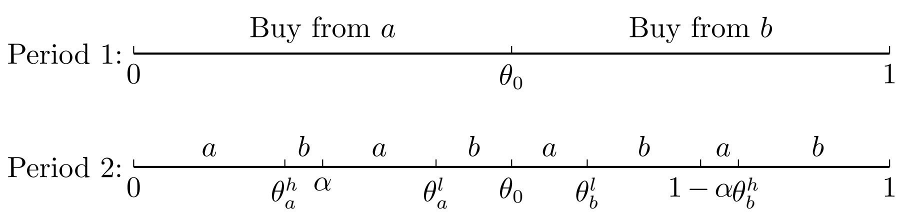


Figure 1 Market Structure in two periods with three segments

The marginal customer in the high-value segment of seller a, located at θ_a^h, is indifferent between buying from seller a at price p_{2a}^h and switching to buy from seller b at price p_{2b}^n in the second period. That is, $v-\theta_a^h q - p_{2a}^h = v-(1-\theta_a^h)q - p_{2b}^n$. The marginal customer in the low-value segment of seller a, located at θ_a^l, is indifferent between buying from seller a at price p_{2a}^l and switching to buy from seller b at price p_{2b}^n in the second period. That is, $v-\theta_a^l q - p_{2a}^l = v-(1-\theta_a^l)q - p_{2b}^n$. The marginal customers for seller b behave symmetrically. As a consequence, the second-period profit function for each seller are

$$\pi_{2a} = p_{2a}^h \theta_a^h + p_{2a}^l(\theta_a^l - \alpha) + p_{2a}^n(\theta_b^l - \theta_0 + \theta_b^h - (1-\alpha)),$$
$$\pi_{2b} = p_{2b}^h(1-\theta_b^h) + p_{2b}^l(1-\alpha-\theta_b^l) + p_{2b}^n(\alpha - \theta_a^l + \alpha - \theta_a^h).$$

We can obtain the best response functions for each seller by taking derivatives of the profit function with respect to prices. Combining the two sellers' best response functions, we can solve the second-period equilibrium in each contingency of α and θ_0. The detailed equilibrium strategies can be found in Appendix A.1. We take seller a's territory (i.e., customers in $[0,\ \theta_0]$) as an example to illustrate the equilibrium outcome.

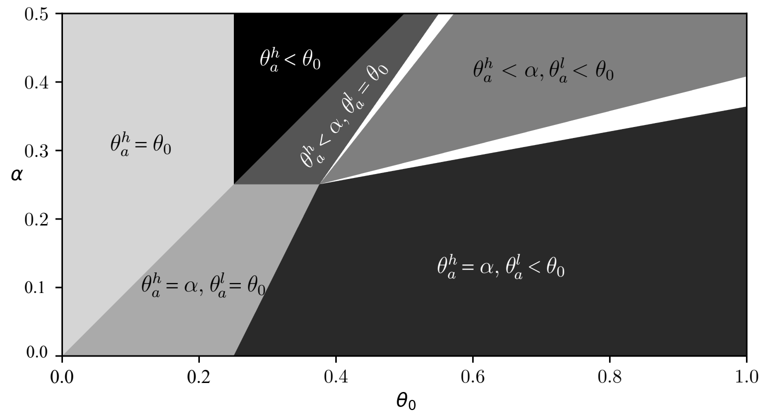


Figure 2 **Equilibrium in the second period for customers in** $[0,\ \theta_0]$

Figure 2 depicts the region of α and θ_0 where a second-period equilibrium exists on $[0,\ \theta_0]$. When $\alpha > \theta_0$, existing customers for seller a cannot be further differentiated in the second period and all are classified as high-value customers. An interesting case in this scenario is that, when the initial market share is small (i.e., $\theta_0 < 0.25$), seller a retains all of her existing customers. The main scenario we focus on is when $\alpha \leq \theta_0$, and the equilibrium may involve four different kinds of customer switching depending on α and θ_0. In the bottom-right (resp. top-left) region, where seller a has a small (resp. large) high-value segment but a large (resp. small) low-value segment, switching only happens in the low-value (resp. high-value) segment in equilibrium. In the top-right (resp. bottom-left) region, when both segments are large (resp. small), there will be switching customers in both (resp. no) segments. It is noteworthy that there are two white areas where no pure strategy equilibrium exists. For example, seller a may want to induce switching in both segments, whereas seller b may want to poach a single segment and give up the other. The conflict of interests leaves no pure strategy equilibrium in these areas.

3.2. The first period

We then move to solve the first-period game. In the first period, the marginal customer located at θ_0 rationally anticipates that he will (non-strictly) switch to the other seller in the second period. The reasoning is that, if he strictly prefers to stay with the same seller in period 2, the seller can increase profit by charging him (and the whole segment he belongs to) more in that period until he is indifferent between switching and staying. Therefore, if this customer buys from seller a at price p_{1a} in period 1, he will switch to seller b at price p_{2b}^n in period 2. His first-period utility is $v - \theta_0 q - p_{1a} + \delta_c(v - (1-\theta_0)q - p_{2b}^n)$. If the customer buys from seller b at price p_{1b} in period 1, he will switch to seller a at price p_{2a}^n in period 2, and his first-period utility is $v - (1-\theta_0)q - p_{1b} + \delta_c(v - \theta_0 q - p_{2a}^n)$. Under the rational expectation assumption, the customers' anticipated prices should equal the equilibrium prices. Since the marginal customer is indifferent between buying from seller a and seller b in period 1, the two options should generate the same utility. Thus we can get θ_0 as a function of p_{1a} and p_{1b}.

In the first period, the sellers maximize their total discounted profit, given by

$$\pi_a = p_{1a}\theta_0 + \delta_s \pi_{2a},$$

$$\pi_b = p_{1b}(1-\theta_0) + \delta_s \pi_{2b}.$$

The first-period best responses are easily obtained by taking derivatives of the profit functions with respect to p_{1a} and p_{1b}. The equilibrium prices are listed in Table 1.

Table 1 The optimal first- and second-period price

Range of α	$[0,\ \frac{3}{11}]$	$[\frac{-15+12\sqrt{2}}{7},\ \frac{39+12\sqrt{2}}{137}]$	$[\frac{3}{7},\ \frac{1}{2}]$
p_{1a}, p_{1b}	$\frac{3+\delta_c-4\alpha\delta_s}{3}q$	$\frac{3-\delta_c-\delta_s+2\alpha\delta_s}{3}q$	$\frac{3-3\delta_c+2(2-5\alpha)\delta_s}{3}q$
p^h_{2a}, p^h_{2b}	$\frac{4(1-2\alpha)}{3}q$	$\frac{3+\alpha}{6}q$	$\frac{1+2\alpha}{3}q$
p^l_{2a}, p^l_{2b}	$\frac{2(1-2\alpha)}{3}q$	$\frac{3-5\alpha}{6}q$	$\frac{4\alpha-1}{3}q$
p^n_{2a}, p^n_{2b}	$\frac{1-2\alpha}{3}q$	$\frac{\alpha}{3}q$	$\frac{4\alpha-1}{3}q$

Proposition 1. *When $\alpha \in [0,\ \frac{3}{11}] \cup [\frac{-15+12\sqrt{2}}{7},\ \frac{39+12\sqrt{2}}{137}] \cup [\frac{3}{7},\ \frac{1}{2}]$, the equilibrium exists and is unique and symmetric. The first-period price decreases with α when only one segment has switching customers, and increases with α when both segments have switching customers. Moreover, the first-period price is negative when only the high-value segment has switching customers and when both the customers and the sellers are sufficiently patient.*

Proposition 1 characterizes the equilibrium properties. It first shows that the equilibrium, if achievable, is unique and symmetric. In contrast, Choe et al. (2017) show that the market only involves two asymmetric equilibria under first-degree price discrimination in the second period. The difference in our results are driven by the fundamental difference in the information structure. Their model essentially induces a continuum of segments and the sellers' benefit of customer information changes continuously in the initial market share. But in our model, the marginal informational value of expanding initial market share is mostly zero under discrete segments and hence the first-period equilibrium resembles more closely to the case of uniform pricing.

Proposition 1 also highlights interesting properties of the equilibrium strategies. Table 1 illustrates that there are three different scenarios in equilibrium, depending on the information parameter α. Intuitively, when α is either very small or very large, poaching concentrates on each seller's core segment. When α is very large, i.e., $3/7$ $(0.429) < \alpha < 0.5$, the sellers only poach their rival's high-value customers. The low-value segment will never switch in equilibrium. As α increases, each seller's low-value segment shrinks and attracts less competition. Thus the sellers can charge a higher second-period price to their low-value segment. To exploit this pricing advantage, they have stronger incentive to expand the low-value segment, which is equivalent to expanding the initial market share. Hence, the first-period price decreases with α. Notably, if both the customers and the sellers are sufficiently patient, the first-period market expansion can be so aggressive that the first-period price is negative. This is in sharp contrast to the work of Choe et al. (2017), where the first-period price is always positive.

When α is very small, i.e., $\alpha < 3/11$ (0.273), a seller refrains from poaching her competitor's high-value customers and switching only happens in each seller's low-value segment. Thus the first-order effect of a larger α is more retained high-value customers. To exploit this effect, the sellers would like to raise the price for the high-value segment. Prices prevalent to a seller's existing customers would be higher if she takes a larger initial market share, because her competitor would be able to poach a sufficient amount of low-value customers with a less aggressive price. Therefore, as α increases, the sellers have stronger incentive to expand the initial market share and the first-period price decreases.

When α is moderate, i.e., $(-15+12\sqrt{2})/7$ (0.281) $< \alpha < (39+12\sqrt{2})/137$ (0.408), both segments have switching customers. In particular, seller a's high-value customers $[\theta_a^h,\ \alpha]$ will switch to seller b and seller b's high-value customers $[1-\alpha,\ \theta_b^h]$ will switch to seller a. Thus the first-order effect of a larger α is a larger volume of new customers. To exploit this effect, the sellers desire a higher poaching price. A seller can set a higher poaching price if her initial market share is smaller, because her product would be attractive to more of her competitor's existing customers.[2] Therefore, as α increases, the sellers are less willing to expand the initial market share and the first-period price increases.

The optimal profits in both periods are listed in the following Table 2. Summing up the profits

Table 2 The optimal profit in each period

Range of α	$[0,\ \frac{3}{11})$	$[\frac{-15+12\sqrt{2}}{7},\ \frac{39+12\sqrt{2}}{137}]$	$[\frac{3}{7},\ \frac{1}{2}]$
π_{1a}, π_{1b}	$\frac{3+\delta_c-4\alpha\delta_s}{6}q$	$\frac{3-\delta_c-\delta_s+2\alpha\delta_s}{6}q$	$\frac{3-3\delta_c+(4-10\alpha)\delta_s}{6}q$
π_{2a}, π_{2b}	$\frac{-28\alpha^2+4\alpha+5}{18}q$	$\frac{9-12\alpha+17\alpha^2}{36}q$	$\frac{-4\alpha^2+14\alpha-1}{18}q$

in two periods, we obtain the optimal total profit in the three scenarios, given in the following proposition.

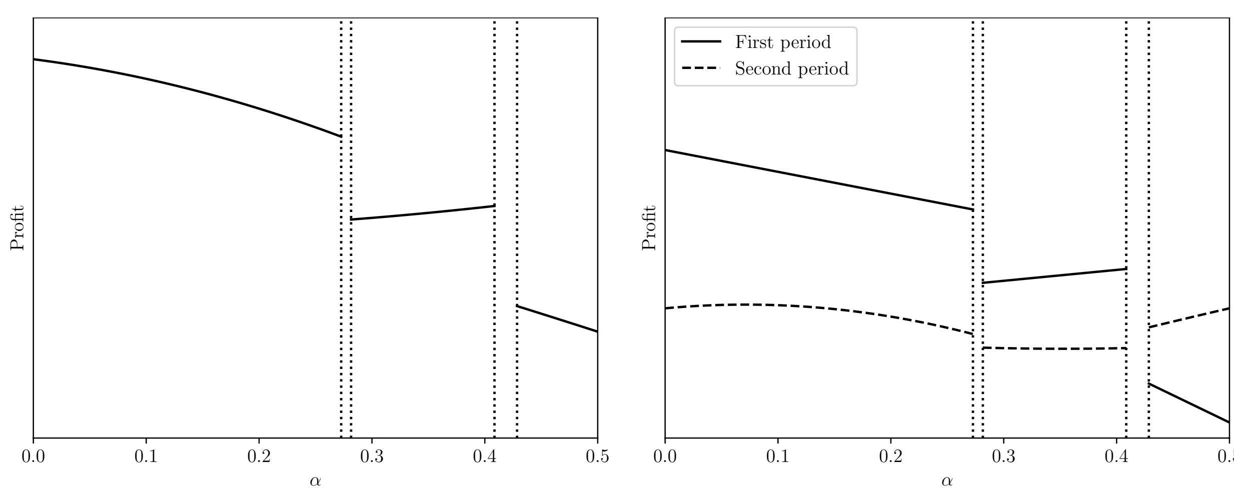
[2] In the case where only the high-value segment has switching customers (i.e. $0.429 < \alpha < 0.5$), an increase in α also leads to a first-order increase of new customer volume. However, initial market share has no impact on the size of switching customers and hence does not affect poaching prices. It is worth emphasizing the difference in reasoning for the two cases.

Proposition 2. *The optimal total profits are*

$$\pi_a = \pi_b = \begin{cases} \dfrac{1}{18} q \left[\left(-28\alpha^2 - 8\alpha + 5 \right) \delta_s + 3\delta_c + 9 \right], & 0 \le \alpha < \dfrac{3}{11}, \\ \dfrac{1}{36} q \left[\left(17\alpha^2 + 3 \right) \delta_s - 6\delta_c + 18 \right], & \dfrac{-15 + 12\sqrt{2}}{7} \le \alpha < \dfrac{39 + 12\sqrt{2}}{137}, \\ \dfrac{1}{18} q \left[\left(-4\alpha^2 - 16\alpha + 11 \right) \delta_s - 9\delta_c + 9 \right], & \dfrac{3}{7} \le \alpha < \dfrac{1}{2}. \end{cases}$$

The optimal profit decreases with α when only one segment has switching customers, and increases with α when both segments have switching customers.

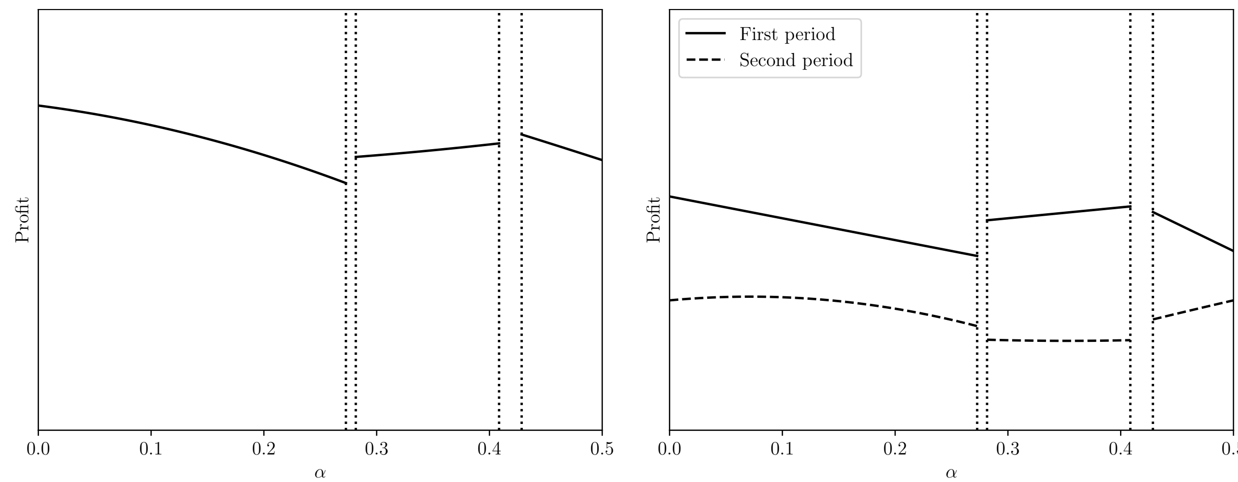
To better understand the properties of seller profit, we present numerical examples for two special cases. Figure 3 depicts the case that the customers and the sellers are equally patient ($\delta_c = \delta_s = 0.7$), whereas Figure 4 depicts the case that the customers are myopic—they only care about current utility when making decisions ($\delta_c = 0,\ \delta_s = 0.7$). As is consistent with the usual intuition, the highest profit is obtained at $\alpha = 0$ in both cases, where sellers conduct pure BBP. When $\alpha > 0$, market segmentation induces more intense competition between the two sellers, which reduces each seller's total profit relative to $\alpha = 0$. From Figure 3b and 4b, we can also see that the second-period profit is not very sensitive to α relative to the first-period profit. This is because the second-period demand changes in response to prices, whereas the first-period demand is fixed at 1/2 for each seller in equilibrium. The elastic second-period demand moderates the impact of varying market segmentation. Consequently, the change of total profit in α is mainly driven by the change of first-period profit, and given that the first-period market share is fixed, the trend of total profit is exactly the same as the first-period price.



(a) The total profit for seller a with $\delta_c = \delta_s = 0.7$

(b) The first and second period profit for seller a with $\delta_c = \delta_s = 0.7$

Figure 3 Profit for seller a when customers and sellers are equally patient



(a) The total profit for seller a with $\delta_c = 0, \delta_s = 0.7$

(b) The first and second period profit for seller a with $\delta_c = 0, \delta_s = 0.7$

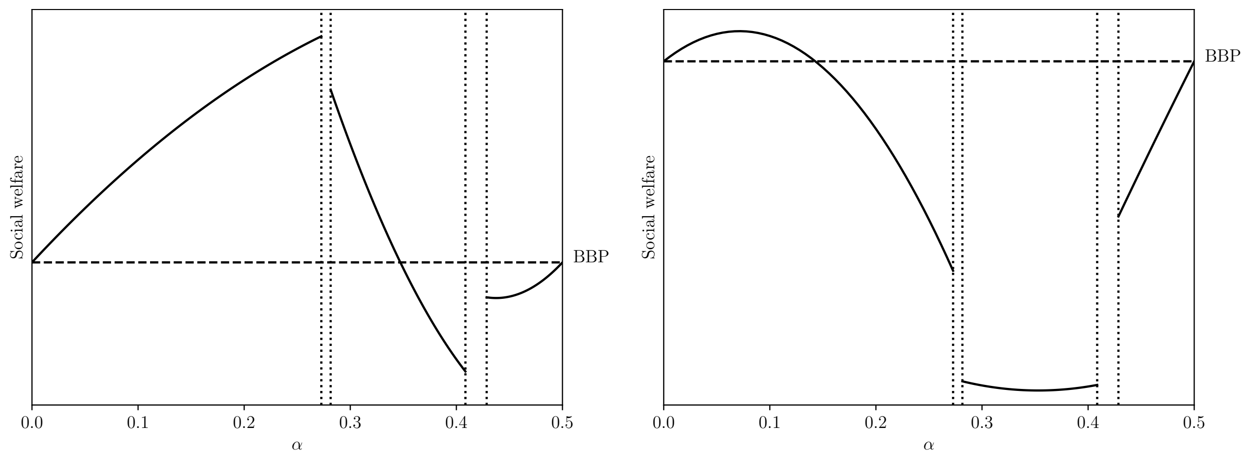
Figure 4 Profit for seller a when customers are myopic

Finally, we explore the properties of social welfare and customer surplus under segment-based pricing.

PROPOSITION 3. *Compared to pure BBP, segment-based pricing yields higher social welfare when α is low, but brings lower social welfare when α is high.*

Following the convention, we define social welfare as the sum of total customer surplus and sellers' total profit. In the most efficient case, the market should always be split evenly between the two sellers with the left half buying from seller a and the right half buying from seller b. As our equilibrium is always symmetric, the first-period market achieves full efficiency. However, sellers' competition leads to inefficient switching in the second period.

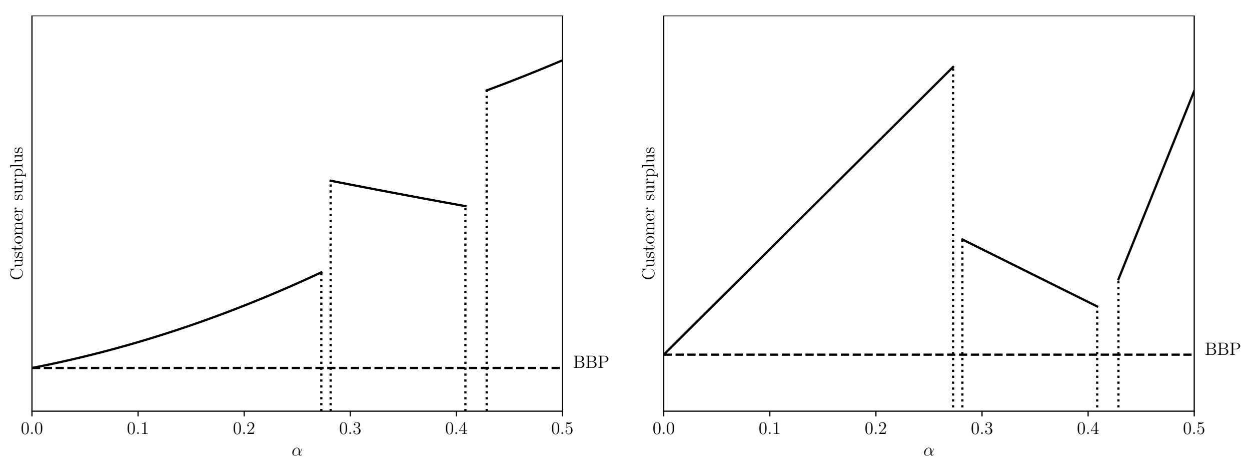
Figure 5 explicitly compares the social welfare under pure BBP and segment-based pricing. When $\delta_s = \delta_c$, transfers between the customers and the sellers have no real impact, and the social welfare is negatively correlated with the customers' traveling costs. When α is small (i.e. $\alpha < 0.347$), switching only happens in the low-value segment. Segmentation can be used to tailor prices to these customers and hence there is less switching compared to pure BBP. It follows that social welfare is higher under segment-based pricing. When α is large (i.e. $\alpha > 0.347$), the customers located close to one seller may switch to the distant competing seller. Such behavior causes a significant social welfare loss and may thus lead to a lower social welfare than pure BBP. When δ_c is small relative to δ_s, the shape of social welfare is mainly determined by the sellers' second-period profit. In the special case $\delta_c = 0$, segment-based pricing causes a lower social welfare than pure BBP after $\alpha = 0.143$.



(a) The social welfare when $\delta_c = 0.7, \delta_s = 0.7$ (b) The social welfare when when $\delta_c = 0, \delta_s = 0.7$

Figure 5 The social welfare and the comparison with pure BBP

PROPOSITION 4. *Compared to pure BBP, segment-based pricing always yields a higher total customer surplus, The total customer surplus decreases with α when both segments have switching customers, and increases with α otherwise.*



(a) The total customer surplus when $\delta_c = 0.7, \delta_s = 0.7$ (b) The total customer surplus when when $\delta_c = 0, \delta_s = 0.7$

Figure 6 The total customer surplus and the comparison with pure BBP

Figure 6 illustrates the total customer surplus under segment-based pricing. The total customer surplus is always higher than that under pure BBP, because segmentation brings overall stronger competition and thus the customers pay less on average. The total customer surplus naturally has the opposite trend in α compared to the total profit.

4. Model Extensions

In this section, we relax some of assumptions and extend them to more generalized settings. From the perspective of the customers, they may have (heterogenous) fairness concerns if they were offered different prices for the same product. For example, while some customers seldom make price comparisons, some customers are sensitive to the price differences and may switch to the other firm if they feel they are treated unfairly. Therefore, we extend our model settings to incorporate such (heterogenous) customer fairness concerns in subsection 4.1 and 4.2. From the perspective of firms, in empirical business scenarios they sometimes were not able to conduct perfectly accurate segmentation, such as due to inaccurate customers' signals (information) and the firms' lack of technology to conduct data-driven segmentation practices. We resolve this imperfect segmentation issue by allowing the existence of segmentation errors in the model as discussed in subsection 4.3. In all extensions, the main pricing strategies' properties we find in the previous section still hold.

4.1. The model with fairness

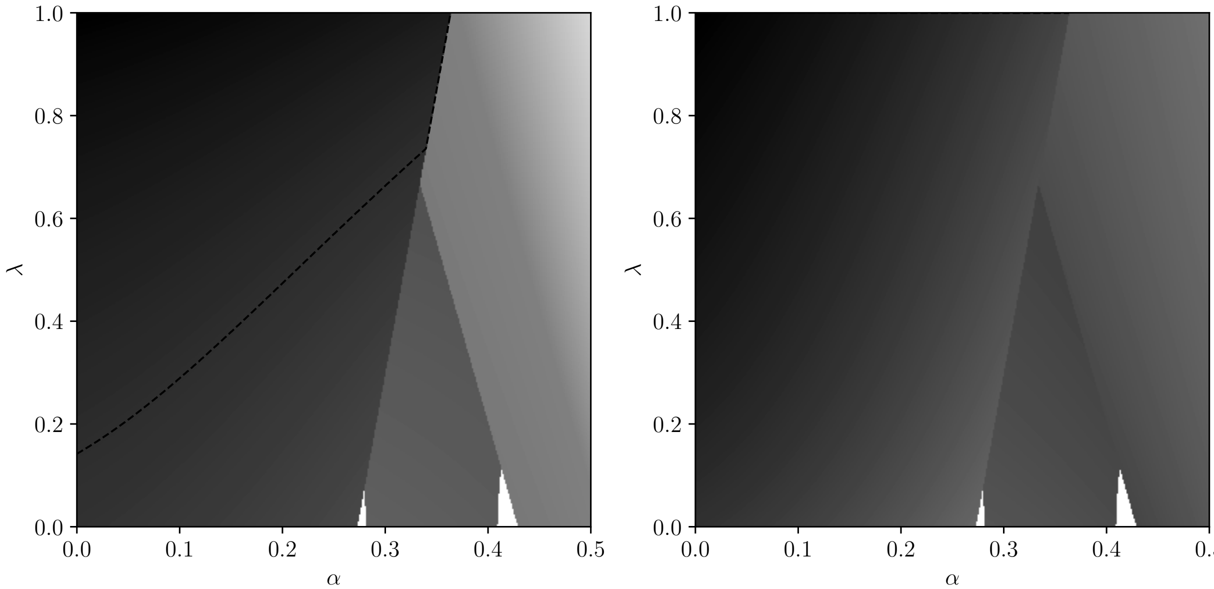
The customers are offered different prices even if they buy the same product from the same seller. Such price discrimination may stir fairness aversion. Following Li and Jain (2015), we assume when the customer pays a price higher than the lowest market price offered by the same seller, the customer perceives a negative utility proportional to this price difference. To be specific, the utility of the customer who locates at θ and buys from seller a is $v - \theta q - p_a - \lambda \max\{p_a - p_a^{min}, 0\}$, where p_a is the price he actually pays to seller a and p_a^{min} is the lowest market price seller a offers in the same period. The parameter λ represents the strength of customers' fairness concern and $\lambda \in [0,1]$.[3] When $\lambda = 0$, customers do not care about others' prices and the current setting degenerates to the base model. Recent studies show that disadvantageously discriminated consumers are more concerned about price fairness than those who are advantageously discriminated (Fehr and Schmidt 1999, Li and Jain 2015). Therefore, we only consider the fairness concern coming from customers paying higher prices.

The market structure is similar to the one illustrated in Figure 1. The marginal customer in each segment can be solved in the same way as before. Note that, in a symmetric equilibrium, the poaching price offered to new customers must be weakly smaller than any price offered to existing customers. Thus the marginal customer in seller a's high-value segment θ_a^h is indifferent between buying from seller a at price p_{2a}^h and switching to seller b at price p_{2b}^n. That is, $v - \theta_a^h q - p_{2a}^h - \lambda \max\{0, p_{2a}^h - p_{2a}^n\} = v - (1-\theta_a^h)q - p_{2b}^n$. The marginal customer in seller a's low-value segment θ_a^l is indifferent between buying from seller a at price p_{2a}^l and switching to seller b at price p_{2b}^n. That is, $v - \theta_a^l q - p_{2a}^l - \lambda \max\{0, p_{2a}^l - p_{2a}^n\} = v - (1-\theta_a^l)q - p_{2b}^n$. The remaining steps to solve the optimal pricing strategy are the same as those in Section 3.

Figure 7 illustrates the dependence of switching on underlying parameters. There are three different scenarios depending on α and λ: Switching happens only in the low-value segment (small

[3] If $\lambda > 1$, the customers would pay more than one dollar to avoid a one-dollar price difference, which is not plausible. This assumption is well adopted in the literature, see Li and Jain (2015), for example.

α), in both segments (moderate α and small λ), or only in the high-value segment (large α). As λ increases, the scenario of switching in both segments becomes less likely. Indeed, when the customers exhibit stronger fairness concern, competing in both segments is less profitable to the sellers, because it leads to a larger price dispersion compared to competing in only one segment.



(a) The total profit for seller a with $\delta_c = 0.7, \delta_s = 0.7$ (b) The total profit for seller a with $\delta_c = 0, \delta_s = 0.7$

Figure 7 The total profit for seller a

Note. A darker color indicates a higher profit. The white areas are where no symmetric equilibrium exists. The top-left region which enclosed by the dashed curve depicts where the total profit under segment-based pricing exceeds that of plain pricing.

PROPOSITION 5. *The total profit decreases with the strength of fairness concern when only the high-value segment has switching customers, and increases with the strength of fairness concern when only the low-value segment has switching customers.*

Intuitively, when the fairness concern is stronger, competition in the second period also becomes more intense, because the poaching price can attract more switching customers who are averse to the high prices charged by their previous seller. In the meantime, the intensity of first-period competition is decreasing in the strength of fairness concern when only the low-value segment has switching customers, because sellers are unwilling to acquire customers who are more difficult to retain in the future. Therefore, a stronger fairness concern decreases the second-period profit, but increases the first-period profit. Consistent with Li and Jain (2015), the overall effect is a higher total profit over two periods.

The novelty of our result is that, when only the high-value segment has switching customers, the total profit decreases with λ. The reasoning is as follows. First, when the fairness concern becomes stronger, the second-period competition intensifies. Moreover, as the low-value segment does not switch, a larger low-value segment is more preferable when the second-period competition is more intense. A larger first-period market share immediately increases the volume of low-value segment. As a result, when λ is larger, the sellers will provide a lower first-period price to compete for the market share, which leads to a lower first-period profit as well as a lower total profit.

To stress the profitability of segment-based pricing, we take the plain pricing setting as a comparison benchmark, where each seller can only offer a uniform price in each period. In this setting, the equilibrium price equals q in both periods. The total profit for each seller is $(1+\delta_s)q/2$. In the case of equally patient customers and sellers, segment-based pricing can improve profit relative to plain pricing. Specifically, profit improvement happens when the fairness concern is strong and when the high-value segment is small, depicted by the top-left region enclosed by the dashed curve in Figure 7a. However, when the customers are myopic, segment-based pricing always yields a lower profit than plain pricing.

4.2. Heterogeneous fairness concern

The customers may have heterogeneous degree of fairness concern. Some customers only care if the quality deserves the price but others feel angry when offered an “unfair” price (Guo and Jiang 2016). Moreover, customers often express their fairness concern in other places (e.g., online forums or platforms). Thus it is hard for small sellers to collect information and estimate the strength of such concern. In this section, we assume customers’ fairness concern is heterogeneous and $\lambda \sim U[0,\ \lambda_m]$, where λ_m is the customers’ maximum strength of fairness concern.

The customers’ choices structure is similar to section 4.1, but more complex. Customers located in several intervals may choose both a and b with positive probability. The second period market structure for customers in $[0,\ \theta_0]$ is illustrated in Figure 8.

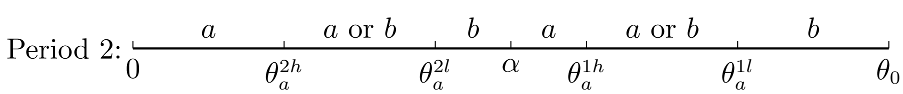


Figure 8 Market structure in the second period with segmentation error

In the second period, for the high-value segment, the customers located in $[0,\ \theta_a^{2h}]$ will definitely buy from seller a, and the customers in $[\theta_a^{2l},\ \alpha]$ will switch to seller b. The customers in $[\theta_a^{2h},\ \theta_a^{2l}]$ may buy from seller a or seller b depending on their fairness concern. They buy from seller a if

$$\theta q - p_{2a}^h - \lambda(p_{2a}^h - p_{2a}^n) \geq (1-\theta)q - p_{2b}^n.$$

Denote by Pr_{ah}^a the probability of seller a’s high-value customer buying from seller a, then we have

$$Pr_{ah}^a = \frac{(2\theta-1)q - p_{2a}^h + p_{2b}^n}{\lambda_m(p_{2a}^h - p_{2a}^n)}.$$

Similarly, for the low-value segment, customers in $[\alpha,\ \theta_a^{1h}]$ will definitely buy from seller a, those in $[\theta_a^{1l},\ \theta_0]$ will switch to seller b, and the rest low-value customers will choose to buy from a with probability

$$Pr_{al}^a = \frac{(2\theta-1)q - p_{2a}^l + p_{2b}^n}{\lambda_m(p_{2a}^l - p_{2a}^n)}.$$

Therefore, the second-period profit for seller a is

$$\begin{aligned}\pi_2^a = & p_{2a}^h\left[\theta_a^{2h} + \int_{\theta_a^{2h}}^{\theta_a^{2l}} Pr_{ah}^a \mathrm{d}\theta\right] + p_{2a}^l\left[\theta_a^{1h} - \alpha + \int_{\theta_a^{1h}}^{\theta_a^{1l}} Pr_{al}^a \mathrm{d}\theta\right] \\ & + p_{2a}^n\left[\theta_b^{2l} - \theta_b^0 + \int_{\theta_b^{2l}}^{\theta_b^{2h}} Pr_{bh}^a \mathrm{d}\theta + \theta_b^{1l} - \theta_0 + \int_{\theta_b^{1l}}^{\theta_b^{1h}} Pr_{bl}^a \mathrm{d}\theta\right].\end{aligned}$$

where

$$Pr_{bh}^a = 1 - \frac{(1-2\theta)q - p_{2b}^h + p_{2a}^n}{\lambda_m(p_{2b}^h - p_{2b}^n)}, \quad Pr_{bl}^a = 1 - \frac{(1-2\theta)q - p_{2b}^l + p_{2a}^n}{\lambda_m(p_{2b}^l - p_{2b}^n)}.$$

We can solve for seller a's best response by taking derivatives with respect to $p_{2a}^h, p_{2a}^l, p_{2a}^n$ and combine the two sellers best responses to find the second-period equilibrium strategies. Then, by using similar techniques to Section 3, we can get the pure strategy equilibrium.

When customers have heterogeneous fairness concern, we find that our previous results still hold. The heterogeneous fairness concern model with uniform fairness concern strength on $[0,\ \lambda]$ is equivalent to a homogeneous fairness concern model with fairness concern strength $\lambda_m/2$. It further implies that the sellers can use the average fairness concern strength to derive the optimal pricing policies.

4.3. Segmentation with error

Although the advanced big data technology enables the sellers to do segmentation, it is still impossible to perfectly match customers' information to their actual value. Thus the sellers often make false negative and false positive mistakes. On the one hand, some of the high-value customers in $[0,\ (1-\alpha)\theta_0]$ may be wrongly classified as low value and offered a price p_2^l. On the other hand, some low-value customers may be offered a price p_2^h because they are labeled as high value. To capture the segmentation error, we assume the probability of misclassification is ϵ for both cases. ϵ is a small number less than 0.5.

The market structure is similar to that in Figure 1. As the two sellers are symmetric, we take seller a as an illustrating example without loss of generality. We use the same parameters convention to that in previous sections. With probability ϵ, the customers in $[0,\ \alpha]$ are labeled as low-value customers. The wrongly labeled high-value customers are offered with a lower price p_{2a}^l, and will definitely buy from seller a. For the rest of the high-value segment, the correctly labeled customers in $[\theta_a^h,\ \alpha]$ will switch to the competitor, and those in $[0,\ \theta_a^h]$ will not switch. For the low-value segment, with probability ϵ, the customers in $[\alpha,\ \theta_0]$ are labeled as high-value customers and offered a higher price p_{2a}^h. Those who are offered a higher price will be poached by the competitor. The correctly labeled customers in $[\alpha,\ \theta_a^l]$ will keep buying from seller a, but those in $[\theta_a^l,\ \theta_0]$ will switch to seller b. In summary, the profit function for seller a and seller b are

$$\begin{aligned}
\pi_2^a =& p_{2a}^h(1-\epsilon)\theta_a^h + p_{2a}^l\epsilon\alpha + p_{2a}^l(1-\epsilon)(\theta_a^l-\alpha) \\
&+ p_{2a}^n[(\theta_b^1-\theta_0) + \epsilon(1-\alpha-\theta_b^l) + (1-\epsilon)(\theta_b^h-1+\alpha)], \\
\pi_2^b =& p_{2b}^h(1-\epsilon)(1-\theta_b^h) + p_{2b}^l\epsilon\alpha + p_{2b}^l(1-\epsilon)(1-\alpha-\theta_b^l) \\
&+ p_{2b}^n[\theta_0-\theta_a^l + \epsilon(\theta_a^l-\alpha) + (1-\epsilon)(\alpha-\theta_a^h)].
\end{aligned}$$

In a similar fashion to that in Section 4.2, we can solve the first period problem, and derive the optimal pricing strategies and the corresponding optimal profits. The detailed calculation and results are included in Appendix 5.

Proposition 6. *The total profit for each seller increases with the segmentation error.*

Intriguingly, we find the profits for both sellers in equilibrium increase with the segmentation error. When the signal error is higher, the pricing discrimination is less effective and the competition between the two sellers is less intense, which leads to a higher profit. Additionally, when $\epsilon = \frac{1}{2}$, the sellers have no information on the customers' valuation level, and the segment-based pricing degenerates into pure BBP pricing, which leads to the highest profit.

5. Conclusion

Our study has been motivated by several simple observations. First, the segmentation strategy is widely adopted by firms across different industries. Second, with the blooming IT development nowadays, firms are able to acquire and analyze customer information and offer segment-specific marketing mixes. Third, the current understanding of customer value from a focal firm's perspective has overlooked the possibility of fierce competition involved. Lastly, there a gap between BBP and segmentation literature. The former emphasizes the discrimination between the existing and new (competitor's) customers, whereas the later focuses on value creation for the existing customers.

We address a basic but controversial question in understanding customer value: should a firm focus on high-value customers when she competes with others? And if the answer is "it depends", under what conditions the firm should or should not seize her high-value customers? By integrating the conventional BBP model with customer value information, our model results suggest high-value customers will most likely backfire where there is competition. Since high-value customers trigger more intense competition than low-value customers, the total profits for both firms can decrease as the portion of high-value segment increases. And the only condition for high-value customers to be more profitable is that when both high- and low-value customers engage in switching in the second stage. In this case, firms have strong motivation to poach competing firm's customers and therefore relax their competition in the first period, resulting in increased profits.

While pure BBP strategy and first-order discrimination pricing strategy were discussed in the literature, empirically, it is common for firms to segment their customers into several large distinct groups, where there exist different symmetric market structures in equilibrium, depending on the customer value information (i.e. the classification of high-value vs. low-value customers). Furthermore, in the model extensions which incorporates customers' fairness concern, we find that it is possible to have profit decreasing in fairness concern, which is in sharp contrast to Li and Jain (2015). When there are switching customers in low-value segment, a stronger fairness concern intensifies the second-period but softens the first-period competition, which leads to higher total profit. However, when only high-value segment exhibits switching customers, a stronger fairness concern makes competition in both periods more intense, which results in a lower total profit.

Our findings on the one hand provide key managerial insights on the understanding of when high-value customers may backfire or be profitable in a competitive environment, on the other hand shed light on potential public policy in regulating segmentation practices in the industry. We find that strategical segmentation is beneficial to the whole society when the percentile of high-value customers is relatively low and achieves higher social welfare than BBP strategies. However, when the ratio of high-value customers becomes sufficiently large, the costs associated with the switching behavior of the high-value customers are substantial and thus lead to decreased social welfare. In extreme cases (e.g. when high-value customers are getting close to half of the customer base), the social welfare with strategical segmentation can be even lower than that with BBP strategies. These findings can help the government and legal practitioners to think about effective control on the industrial segmentation practices in the competitive business environment.

There could be potential limitations of our model, for example we assume the information structure of customer value (captured by parameter α) is exogenously determined, while empirically customer segmentation can be jointed determined by both endogenous factors and exogenous factors (e.g. customer demographics). For example, firms could endogenously alter α through various service encounters, such as firms' designed pop-up ads which easily influence customers' historical browsing behavior, and firms' recommendation systems which have the potential to influence customers' product preferences and overall satisfaction towards the firms, therefore the information parameter can be more complex in nature than it is now. Customer value itself, assumed to be uniformly distributed in our model, can also be influenced by prior consumption. That being said, our theoretical model generates several empirically testable hypotheses for further research, we hope that our study not only provides suggestive answers for some questions but also stimulates future research.

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