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Profiting from Selling at a Loss: Customer Big Data Analysis and Personalized Pricing in a Supply Chain

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ABSTRACT

The rapid advancement in information technology has made customer data more accessible, significantly enhancing firms' interest in personalized pricing. This study investigates how personalized pricing and big data analytics capability interact in supply chains using a Stackelberg game-theoretic model. The analysis examines how manufacturers and online platforms strategically determine optimal pricing and big data investment under an agency selling format. The findings are threefold. First, higher big data analytics efficiency does not always lead to increased investment in analytics capability. Second, manufacturers may strategically set base prices below production costs. This strategy incentivizes platforms to invest in analytics capability, which indirectly enhances profitability. Third, platforms do not always benefit from higher analytics efficiency, particularly under moderate efficiency conditions. This research provides managerial insights into the nuanced role of big data capability in pricing strategies.

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1. Introduction

Over the last decade, the increased availability of customer information has fueled interest in personalized pricing [1]. This concept involves firms selling products or providing services at tailored prices according to consumers' valuations [2]. Numerous studies have demonstrated that personalized pricing can enhance profits and market penetration [3]-[7]. In the e-commerce field, platforms such as Meituan, Tmall, and Amazon have started implementing personalized pricing in various ways [4]. For instance, platforms like Meituan, Ele.me, and Xiaohongshu issue full-price coupons of varying amounts to new users, DiDi offers different quotes to distinct users, even if they share the same origin and destination [5]. However, these practices raise concerns around fairness and customer acceptance, which require further investigation. To implement personalized pricing, the platform needs to deploy big data, with Artificial Intelligence (AI) emerging as a new and crucial factor in enabling personalized pricing [8]. AI, trained on big data, enables platforms to estimate consumers' willingness to pay with greater precision [8]. Big data analytics capability provides the database for AI to create an environment for deep learning and analysis, allowing AI to achieve a higher level of intelligence

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[9]. By combining big data analytics capability with AI technologies, companies can better understand consumer behavior and trends. This integration helps them more accurately determine the prices customers are willing to pay. According to a survey of 94 executives from Fortune 1000 companies, 97% of them plan to invest in big data initiatives by 2022. Moreover, 91% indicated growing investment in big data, and 92% have observed tangible business benefits.[1] However, substantial investment by companies does not always translate into accurate big data capability. In other words, firms may not be able to predict customer valuations perfectly; thus, the accuracy of personalized pricing depends on their big data capability.

Based on the preceding discussions, the first research question is proposed: Does greater big data analytics efficiency lead to greater big data capability to implement personalized pricing? For instance, Meituan issues coupons of varying amounts to its potential users based on customer data, such as frequency of use, or offers different prices to users at different levels buying the same product [4]. Online platforms often operate through an agency channel (also known as a marketplace) and charge manufacturers a commission rate for using it to sell directly to consumers [5]. This model is widely adopted by online retailers, such as Taobao and Tmall. Under the agency selling format, can a manufacturer increase its profit by influencing the platform's big data analytics capability and, consequently, its personalized pricing? Therefore, the second research question is: Under the commission channel, will manufacturers incentivize platforms to enhance their big data analytics capability through certain measures? Moreover, this paper also explores how the efficiency of improving big data capability and the unit production cost influence the decisions and profits of supply chain members, constituting the third research question.

To address these questions, we develop a game-theoretic model. In this model, the manufacturer sells through a platform that implements personalized pricing under an agency format. In this scenario, the profit of manufacturers may be threatened by the platform's implementation of personalized pricing, leading manufacturers to minimize this threat by setting a base price to supply products to the platform [9]. Thus, the scenario assumes that the manufacturer influences demand by setting a base price, a departure from previous studies where the online platform adopts uniform pricing. Regarding the platform, it faces a trade-off between the cost of investing in big data capability and the revenue from more accurate personalized pricing when determining an optimal big data capability. By solving the model, the mechanism of personalized pricing with big data capability is examined. This bounded pricing better reflects practical limitations in predictive accuracy. The main findings of this paper are as follows. First, higher big data analytics efficiency may not lead to higher big data capability to implement personalized pricing. It can be seen that even very efficient platforms tend to implement a uniform pricing strategy when unit production costs are high. Second, the manufacturer does behave differently when the platform deploys big data capability to implement personalized pricing. An interesting finding is that the manufacturer may decide on a base price less than his unit production cost to incentivize the platform to implement a more accurate personalized pricing when the efficiency of improving big data capability is moderate. In other words, the manufacturer may be able to earn profits indirectly by selling at a loss. Third, higher big data analytics efficiency may not always benefit the platform. When the efficiency is high, it is intuitive that the platform's profits decrease as the efficiency decreases. Nevertheless, when the efficiency is moderate, the platform's profits will increase as efficiency decreases. However, with the further reduction of efficiency, profits decrease. The reason for this interesting phenomenon is that when efficiency is moderate, the manufacturer sets a lower base price to motivate the platform, which leads to a higher demand. Moreover, in the short term, the impact of customer demand is more significant than the impact of the efficiency reduction, leading to an increase in profits.

The remainder of this paper is organized as follows. Section 2 provides a review of the relevant literature, followed by the presentation of the model in Section 3. Section 4 solves the equilibrium and presents the analysis. Section 5 concludes the paper and suggests possible extensions for future research. All proofs are provided in the Appendix.

2. Literature Review

This paper is most relevant to the literature on personalized pricing. Previous studies on personalized pricing have primarily focused on its profitability [10]-[12], behavior-based pricing [13]-[15], marketing strategies based on personalized pricing

[1] https://www.businesswire.com/news/home/20220103005036/en/NewVantage-Partners-Releases-2022-Data-And-AI-Executive-Survey

[16], [17], and consumer fairness concerns [18]-[20]. Furthermore, personalized pricing has been extensively explored in various industries. In the apparel and fashion industry, most brand manufacturers (e.g., Desigual, Guess, and Marc O'Polo) and retailers (e.g., Zalando and Amazon) utilize coupons and specific promotions to implement customized prices for consumers [21]. Health food providers, such as Unimeal and Healthline, collect customer data (e.g., dining behavior, physical fitness, and health exam records) to customize meal plans and offer tailored price discounts [22]. Additionally, in the transportation sector, Uber charges customers based on what they are "willing to pay," considering factors such as the destination's wealth.[2]

This research primarily relates to the profitability of personalized pricing, with a specific focus on its effects on members' profits in a two-tier supply chain. Generally, personalized pricing is associated with increased profits, as it allows setting prices based on estimates of the maximum individuals are willing to pay, as observed in various studies [23]-[25]. However, conflicting findings in certain research suggest that personalized pricing might adversely affect the profitability of specific members within the supply chain [2], [26], [27]. These disparities imply that the profitability of personalized pricing is context specific. Moreover, existing research often assumes firms perfectly predict customer valuations to implement fully personalized pricing, which is unrealistic in practice [28]. Moreover, all the above papers usually consider a binary comparison, i.e., fully personalized pricing vs. fully uniform pricing, to analyze the profitability of personalized pricing. In contrast, firms rarely achieve fully personalized pricing due to technological limitations. Therefore, this study examines a spectrum of personalized pricing by determining an optimal big data capability and analyzes the impact of bounded personalized pricing on the decisions and profits of supply chain members, an aspect that has not yet been addressed in the existing literature.

This study is also related to the literature on analytics in big data capability. The term 'big data' was first used in 1997 to explain the visualization of data and the challenges it posed for computer systems [29]. Research has shown that big data capabilities provide comprehensive data support for organizations [30] and enhance operational management through data-driven decision-making [31], [32]. From the perspective of transaction cost theory [33], online companies can benefit from big data analytics through higher efficiency in market and managerial transactions, and time. According to the resource-based view [34], big data capability is a distinctive competence when identifying customers and determining the optimal price [35]. Empirical studies also demonstrate that a more robust big data analytics capability has a positive effect on performance [36], [37].

However, some studies indicate that collecting more data does not always lead to better performance. For instance, X. Li and Li [38] found that even if a firm were able to obtain all customer data at no cost, it might not necessarily choose to do so. This is because it could lead to further customer data manipulation, reducing the data quality and ultimately damaging the firm's profitability. Similarly, Du et al. [2] suggested that imposing personalized pricing on the part of consumers can improve the dominant retailer's profits more than imposing personalized pricing on all customers. Firms may not always choose the highest feasible level of big data capability. This study makes a novel contribution by showing how the online platform determines the big data capability of adopting personalized pricing within a two-tier supply chain [2]. To the best of current knowledge, this paper is the first to examine how platforms can deploy big data capability to implement personalized pricing, offering significant practical implications for supply chain members.

Despite these insights, current studies [10]-[15] largely assume perfect personalization or fail to model the endogenous interaction between manufacturers and platforms under capability constraints. Personalized pricing, however, is intrinsically imperfect, and its accuracy is shaped by the platform's big data analytics capability. Building on this premise, this study develops a Stackelberg game model under an agency format that explicitly incorporates bounded personalization and strategic base price setting.

3. The Model

A supply chain is considered in which a manufacturer (denoted as M) sells a single product through an e-commerce platform (denoted as P) under an agency format. In this model, the manufacturer determines the base price $\underline{p}$ (where $0 \leq \underline{p} \leq 1$) and pays the platform a commission rate α (where $0 \leq \alpha \leq 1$) per transaction. The unit production cost is denoted as c, and the base price must ensure non-negative demand, as represented by the demand function defined below.

[2] https://www.bloomberg.com/news/articles/2017-05-19/uber-s-future-may-rely-on-predicting-how-much-you-re-willing-to-pay

Consistent with standard assumptions in operations management literature, the commission rate is assumed to be exogenously determined [39]-[41].

Unlike existing research, this study assumes that the platform cannot always implement perfect personalized pricing, i.e., fully extracting consumer surplus. Each customer's valuation v follows a uniform distribution $U(0,1)$. Their purchase decision depends on utility:

$$U(v) = (1-\theta)\left(v - \underline{p}\right) \tag{3.1}$$

where $\theta \in [0,1]$ quantifies the platform's big data analytics capability, reflecting the accuracy with which it can estimate customer valuations. This analytics capability encompasses the platform's ability to leverage AI and data-driven insights to precisely predict customer valuations and tailor prices accordingly. To differentiate it from perfect personalized pricing, this case is referred to as bounded personalized pricing. If $v \geq \underline{p}$, that is $U(v) \geq 0$, customers will find the purchase worthwhile, and thus decide to buy. Conversely, if $v < \underline{p}$, that is $U(v) < 0$, the customer will not make a purchase. The potential demand in the market is assumed to be standardized to 1. $p(v)$ is defined as the personalized pricing. According to the utility function, it follows that $p(v) = \underline{p} + \theta\left(v - \underline{p}\right)$. Intuitively, if $\theta=1$, then $p(v)=v$, meaning the price a customer pays for the product depends entirely on their valuation. This case corresponds to perfect personalized pricing. In contrast, if $\theta=0$, then $p(v)=p$, indicating that the platform chooses uniform pricing. Otherwise, if the platform determines a big data capability with $0 \leq \theta \leq 1$, then the pricing strategy can be regarded as a mixed-pricing structure. After plugging $p(v)$ into the utility function, the demand is determined by $D=1-\underline{p}$, which is consistent with the model setting in which the manufacturer determines the selling quantity by setting a base price $\underline{p}$. Therefore, is given by:

$$CS = \int_{\underline{p}}^{1} [v - p(v)]dv = \frac{1}{2}(1-\theta)(1-\underline{p})^2 \tag{3.2}$$

Undoubtedly, higher big data capability improves revenue through more accurate personalized pricing, but it also entails greater investment costs. The cost of investing in big data capability is assumed to be $\beta\theta^2$ (where $\beta>0$). Here, β inversely reflects analytics efficiency: a higher β implies lower efficiency (i.e., higher cost). Thus, β is interpreted as the efficiency of improving big data capability; that is, smaller β means higher efficiency. Here, the quadratic cost reflects increasing marginal costs. Such quadratic cost function has been widely used in the literature for analytical tractability [39]. Therefore, the platform faces a trade-off between the cost of investing in the big data capability and the revenue of more accurate personalized pricing when determining an optimal big data capability.

Therefore, the scenario is formulated as a Stackelberg game under the agency selling format. The sequence of events is as follows. First, the manufacturer decides a base price $\underline{p}$ (where $0 \leq \underline{p} \leq 1$) to maximize its profit. Then, the platform determines the big data capability θ (where $0 \leq \theta \leq 1$) to implement bounded personalized pricing with the aim of maximizing its own profit. Finally, consumers decide whether to buy or not.

Based on the model description above, the manufacturer's optimization problem is formulated as

$$\max_{\underline{p}} \quad (1-\alpha)\int_{\underline{p}}^{1} p(v)dv - c\left(1-\underline{p}\right) \qquad s.t. \quad 0 \leq \underline{p} \leq 1 \tag{3.3}$$

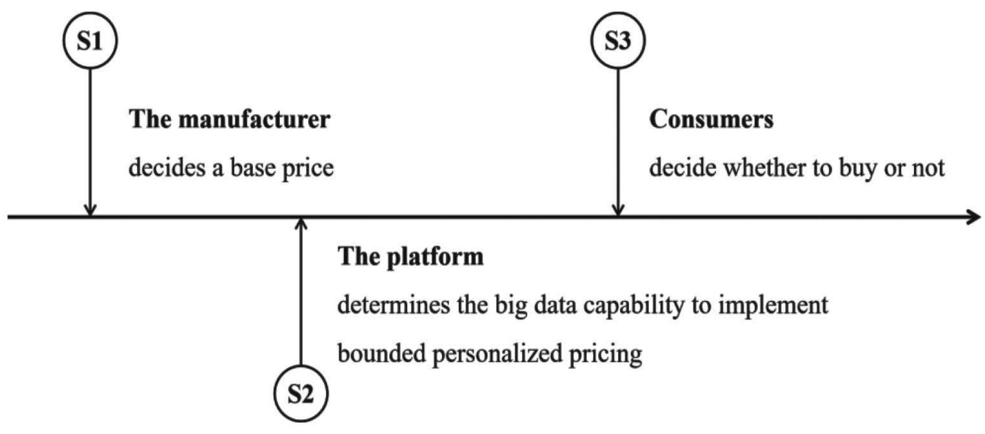


Figure 1. The sequence of events

The manufacturer maximizes profit by balancing two components: revenue from sales and production costs. In Formula (3.3), the first term captures the manufacturer's revenue, while the second term denotes the manufacturer's cost.

The platform’s corresponding problem is formulated as

$$\max_{\theta} \quad \alpha \int_{\underline{p}}^{1} p(v)dv - \beta\theta^2 . \qquad (3.4)$$
$$s.t. \qquad 0 \le \theta \le 1$$

Similarly, the platform aims to maximize its profit as shown above.

4. Model Analysis

The equilibrium is solved using a two-step backward induction approach.

Lemma 1. Given $0 \le \underline{p} \le 1$, the optimal big data capability is characterized as follows.

(1) When the efficiency of improving big data capability is relatively high, i.e., $\beta \le \frac{1}{4}$, it follows that

$$\theta^*\left(\underline{p}\right) = \begin{cases} 1, & 0 \le \underline{p} \le 1 - 2\sqrt{\frac{\beta}{\alpha}} \\ \frac{\alpha(1-\underline{p})^2}{4\beta}, & 1 - 2\sqrt{\frac{\beta}{\alpha}} \le \underline{p} \le 1 \end{cases} \qquad (4.1)$$

(2) When the efficiency of improving big data capability is relatively low, i.e., $\beta > \frac{1}{4}$, then

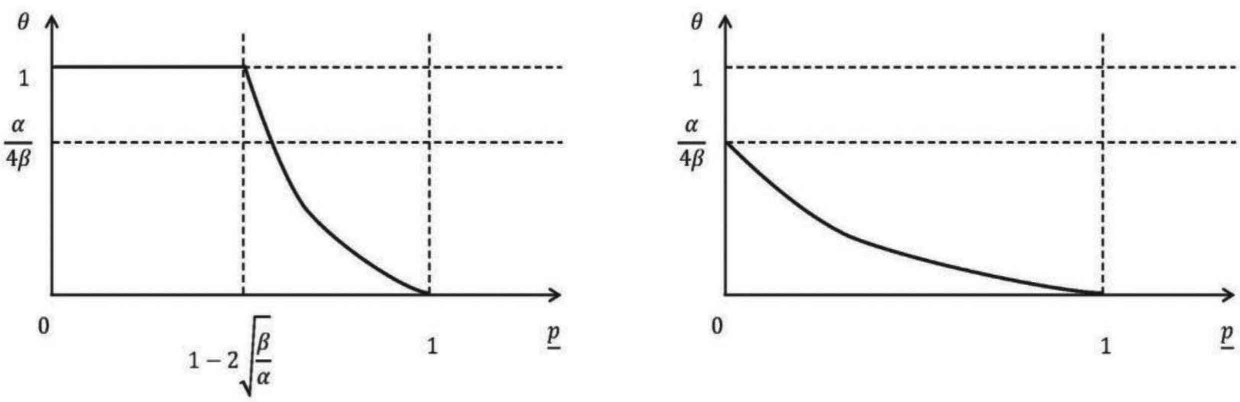
$$\theta^*\left(\underline{p}\right) = \frac{\alpha\left(1-\underline{p}\right)^2}{4\beta}. \qquad (4.2)$$

Figure 2(a) and 2(b) show the monotonicity of θ^* with $\underline{p}$ when $0 < \beta \le \frac{1}{4}$ and $\beta > \frac{1}{4}$, respectively. When the efficiency of improving big data capability is relatively high, i.e., $0 < \beta \le \frac{1}{4}$, the optimal big data capability initially remains constant and then decreases as the base price $\underline{p}$ increases. In this case, the platform, modeled as a rational profit-maximizing agent, selects the highest feasible level of big data capability to implement perfect personalized pricing when the base price $\underline{p}$ is below a certain threshold. However, when the efficiency is relatively low, i.e., $\beta > \frac{1}{4}$, the platform refrains from implementing perfect personalized pricing regardless of the base price. In the latter case, the optimal big data capability consistently declines with the base price $\underline{p}$, following a similar trend to the latter part of Figure 2(a).

In intuitive terms, Lemma 1 shows that the platform’s willingness to invest in big data capability depends jointly on the base price and the efficiency of improving this capability. When the efficiency of improvement is high, the platform can sustain a high capability level for a range of base prices before gradually reducing it. When the efficiency is low, even moderate base prices make further investment unattractive, so the platform systematically scales back its big data capability as the base price increases.

The parameter space (β, c) is divided into five mutually exclusive regions. The definitions of which are provided in Table 2.

Theorem 1. The optimal solutions $\left(\theta^*, \underline{p}^*\right)$ are characterized as follows.



(a) When $\beta \le \frac{1}{4}\alpha$ (b) When $\beta > \frac{1}{4}\alpha$

Figure 2. Platform’s optimal big data capability given different base prices

$$\left(\theta^*,\ \underline{p}^*\right)=\begin{cases}\left(1,\dfrac{c}{1-\alpha}\right), & (\beta,c)\in\ I\\ \left(1,1-2\sqrt{\dfrac{\beta}{\alpha}}\right), & (\beta,c)\in\ II\\ \left(\dfrac{\alpha\left(1-\underline{p}_1\right)^2}{4\beta},\underline{p}_1\right), & (\beta,c)\in\ III\\ \left(\dfrac{\alpha}{4\beta},0\right), & (\beta,c)\in\ IV\\ (0,1), & (\beta,c)\in\ V\end{cases}\tag{4.3}$$

Figure 3 illustrates the structure of the optimal decisions as outlined in Theorem 1. The results are analyzed under two distinct efficiency scenarios. First, the optimal decisions are examined when the efficiency of improving big data capability is high (β is small). The results indicate that when the unit production cost is low, i.e., $(\beta,c)\in I$, the manufacturer increases the base price as the unit production cost increases, but the platform optimally selects its big data capability to maximize its profit under efficiency and cost constraints. When the production cost per unit is moderate, i.e., $(\beta,c)\in II$, the manufacturer sets a base price independent of production cost, exactly at the level that incentivizes the platform to fully invest in analytics capability. However, the platform chooses an appropriate big data capability to implement bounded personalized pricing when the unit production cost is relatively high, i.e., $(\beta,c)\in III$, and it even adopts uniform pricing with no big data capability when the unit production cost is high, i.e., $(\beta,c)\in V$. Second, the structure of the optimal decisions when the efficiency of improving big data capability is low (β is large) is largely the same as in the first case. The only difference is that the platform will not implement perfect personalized pricing even if the manufacturer sets a very low base price, i.e., $(\beta,c)\in IV$. This is because the platform needs to spend a lot of cost to obtain a higher big data capability, which leads to spending more to achieve perfect personalized pricing, which is not as profitable as implementing bounded personalized pricing. These five regions respectively correspond to distinct scenarios in which the platform adopts uniform pricing (Regions *I* and *II*), bounded personalized pricing (Regions *III* and *IV*) and perfect personalized pricing (Region *V*). At the same time, it is found that the market does not exist when $c>1$. Overall, Theorem 1 and Figure 3 jointly indicate that small changes in production cost or efficiency can shift the system across different pricing regimes. Managers should therefore recognize that the optimal base price and big data capability are not adjusted smoothly, but switch across distinct regions, leading to qualitatively different pricing and investment behaviors.

The findings clarify that higher big data analytics efficiency does not necessarily translate into greater investment in analytics capability (θ). In particular, even highly efficient platforms may adopt uniform pricing when unit production costs are high, while moderately efficient platforms may select intermediate values of θ to balance costs and benefits.

Based on the above analysis, an intriguing phenomenon is uncovered: the optimal base price can fall below the production cost c when $(\beta,c)\in IV$. In other words, the manufacturer offers a very low base price, even at a loss, in order to incentivize the platform to improve its big data capability. The following Theorem 2 studies when the manufacturer may have a loss to incentivize the platform to implement personalized pricing.

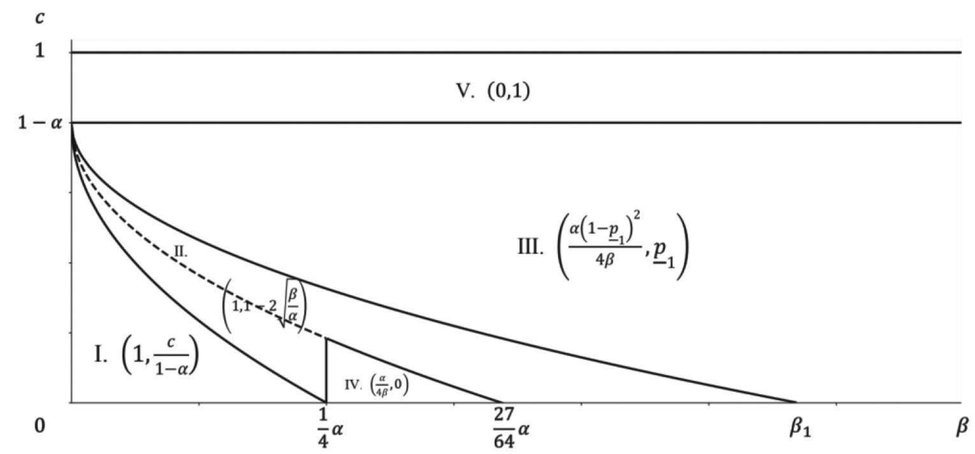


Figure 3. Optimal decisions of base price and data capability at different efficiency and cost levels

Theorem 2. The manufacturer's optimal base price is lower than the unit cost, i.e., $\underline{p}^* < c$, only if $\underline{\beta} < \beta < \overline{\beta}$ and $0 < c < \overline{c}$.

Figure 4 takes $\alpha=0.2$ as an example to compare the manufacturer's optimal base price and the unit production cost across all combinations of β and c. The grey area indicates the region where the optimal base price is lower than the production cost, implying that the manufacturer may incur a loss to motivate the platform to adopt personalized pricing. These counterintuitive results happen only at moderate levels of β. The reasons are as follows. In the agency model, when the efficiency of improving big data capability is high (β is small), the platform is highly motivated to obtain customer profiles. Even if the manufacturer offers a higher base price than the unit production cost, the platform is willing to improve big data capability. When the efficiency is very low (β is large), the platform is less active in obtaining customer profiles. At this time, the manufacturer cannot obtain profits by offering a lower base price, so it will provide a higher base price than the unit production cost to maintain profits. However, when the efficiency is moderate (β is moderate), the manufacturer will incentivize the platform to improve big data capability by lowering the base price. Because of the lower base price, more customers are willing to buy the product, making the platform willing to enhance its big data capability to earn higher profits, which in turn allows the manufacturer to generate higher demand and earn higher profits by charging commissions. In this case, it is found that there exist regions where the manufacturer may set a base price lower than the unit production cost to incentivize the platform to implement personalized pricing. In other words, in the grey area, manufacturers may earn profits while selling at a loss.

Theorem 2 indicates that at moderate efficiency levels, a manufacturer may deliberately set the base price below production cost to motivate the platform's investment in analytics, because the resulting demand expansion can raise commission revenues enough to offset unit-level losses.

The following propositions describe how production cost per unit c and big data analytics efficiency β impact supply chain members.

Theorem 3. (1) The optimal θ^* decreases with c, while the optimal base price $\underline{p}^*$ increases with c, i.e., $\frac{\partial\theta^*}{\partial c} < 0$ and $\frac{\partial \underline{p}^*}{\partial c} > 0$.

(2-1) If the unit production cost c is low, the optimal θ^* decreases with β, while the optimal base price $\underline{p}^*$ first decreases and then increases with β, i.e., $\frac{\partial\theta^*}{\partial\beta} < 0$, $\frac{\partial \underline{p}^*}{\partial\beta} < 0$ first and then $\frac{\partial \underline{p}^*}{\partial\beta} > 0$.

(2-2) If the unit production cost c is high, both the optimal θ^* and the optimal base price $\underline{p}^*$ are independent of β.

Theorem 3 elucidates the impact of β and c on the optimal base price and big data capability. Intuitively, with the increase in unit production cost c, the manufacturer will decide a higher base price, which will lower the motivation of the platform to improve big data capability, so that the platform will decide a smaller big data capability.

Interestingly, the optimal base price is non-monotonic in β. Specifically, the base price first decreases and then increases with β. This phenomenon arises because, when efficiency is relatively high, the manufacturer lowers the base price to stimulate platform investment in big data capability, thereby boosting demand and profit. However, when efficiency is low, the manufacturer anticipates that the platform will not invest in analytics, and instead raises the base price to secure higher per-unit revenue. When the

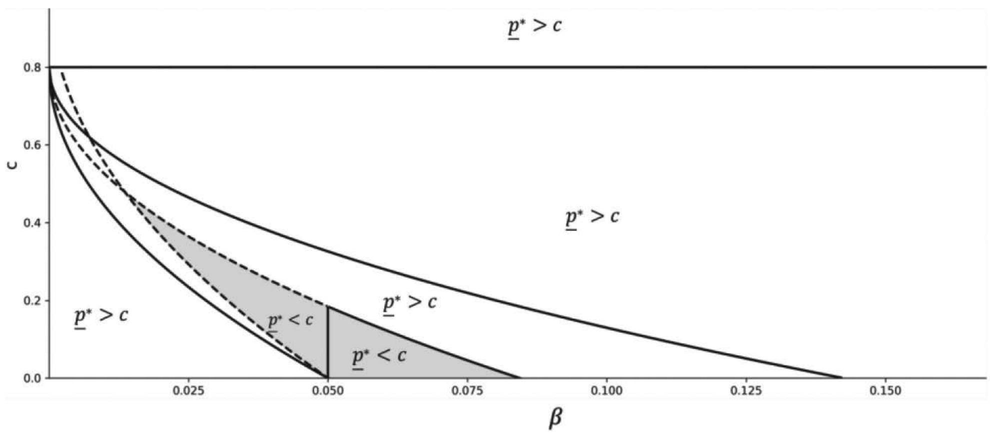


Figure 4. Manufacturer's base price compared with production cost when $\alpha=0.2$.

unit production cost is high, i.e., $1-\alpha<c<1$, the platform adopts uniform pricing. Otherwise, when the unit production cost is low, with the decrease in efficiency (increase in β), the platform will determine a smaller big data capability, which is consistent with intuition.

Theorem 4. (1) Both the optimal profit of the manufacturer π_M^* and the optimal profit of the platform π_P^* decrease with c, i.e., $\frac{\partial \pi_M^*}{\partial c} < 0$ and $\frac{\partial \pi_P^*}{\partial c} < 0$.

(2-1) If $\frac{1}{3}(1-\alpha) < c \leq 1-\alpha$, the optimal profit of the manufacturer π_M^* decreases with β, while the optimal profit of the platform π_P^* first decreases, then increases and finally decreases with β, i.e., $\frac{\partial \pi_M^*}{\partial \beta} < 0$, $\frac{\partial \pi_P^*}{\partial \beta} < 0$ first, then $\frac{\partial \pi_P^*}{\partial \beta} > 0$ and finally $\frac{\partial \pi_P^*}{\partial \beta} < 0$.

(2-2) Otherwise, both the optimal profit of the manufacturer π_M^* and the optimal profit of the platform π_P^* decrease with β.

Theorem 4 shows the impact of β and c on the profits of the platform and the manufacturer. Intuitively, an increase in unit production cost or a decrease in the efficiency of improving big data capability leads to a reduction in profits for both members.

An interesting phenomenon arises when the unit production cost is moderate, i.e., $\frac{1}{3}(1-\alpha) < c \leq 1-\alpha$. As efficiency decreases, the manufacturer's profit declines monotonically, while the platform's profit first falls, then rises, and eventually falls again. Figure 5 shows how π_P varies with β when $\alpha=0.5$ and $c=0.2$, and it is not difficult to find that the variation of π_P is non-monotonic. After analysis, it is found that the non-monotonicity of the platform's profits can be explained as follows. First, when the efficiency of improving big data capability is high, according to Theorem 3, the optimal base price has nothing to do with the efficiency and does not affect the demand, so the profits of the two members both decrease with the decrease of efficiency. Then, when the efficiency of improving the big data capability is in the intermediate stage, according to Theorem 2, the manufacturer wants to incentivize the platform to improve its big data capability by lowering the base price. The lower base price leads to more customers willing to buy the product. At this point, the impact of customer demand outweighs the impact of lower efficiency in the short run, leading to more profits for the platform even in the face of lower efficiency. However, as efficiency continues to decrease, the manufacturer no longer incentivizes platforms by lowering the base price. The negative effects of reduced efficiency outweigh the positive effects of increased customer demand, ultimately leading to a decrease in platform profits.

Theorem 5. (1) The optimal consumer surplus CS^* decreases with c, i.e., $\frac{\partial CS^*}{\partial c} < 0$.

(2-1) If $0 \leq c \leq \left(1-\frac{4}{3\sqrt{3}}\right)(1-\alpha)$, the optimal consumer surplus CS^* first increases and then decreases with β, i.e., $\frac{\partial CS^*}{\partial \beta} > 0$ first and then $\frac{\partial CS^*}{\partial \beta} < 0$.

(2-2) Otherwise, the optimal consumer surplus CS^* decreases with β, i.e., $\frac{\partial CS^*}{\partial \beta} < 0$.

Theorem 5 shows the impact of β and c on consumer surplus. Surprisingly, consumer surplus decreases as the unit production cost increases. The underlying logic is as follows. An increase in production cost leads to an increase in the base price offered by the manufacturer, which not only leads to a smaller big data capability but also a lower customer demand. Overall, although individual consumer surplus increases with unit production cost, the total consumer surplus declines due to a more substantial drop in overall demand.

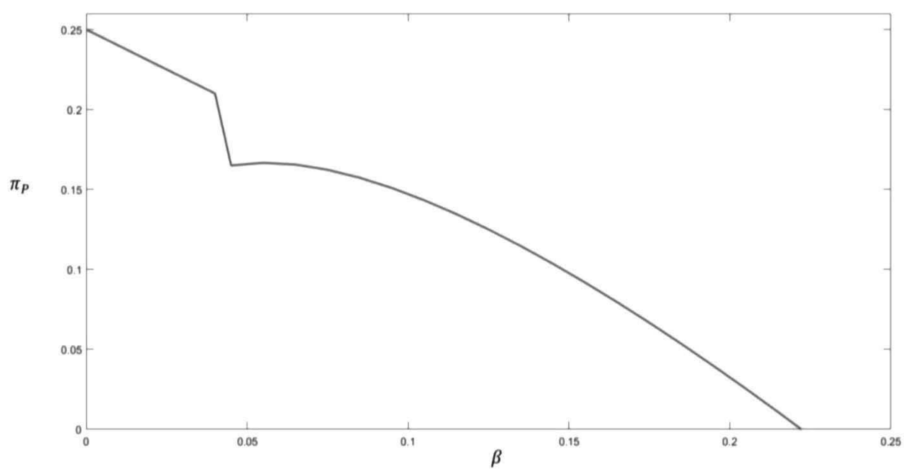


Figure 5. Platform profit curve of π_P when $\alpha=0.5$ and $c=0.2$.

Similarly, the impact of the efficiency of improving big data capability on consumer surplus is also influenced by demand. When the unit production cost is low, the total consumer surplus first increases and then decreases as efficiency decreases because the customer demand first remains unchanged and then decreases with the decrease of efficiency. When the unit production cost is high, customer demand decreases with the reduction of efficiency, so the total consumer surplus also decreases.

To enhance clarity, Appendix A (Table 4) summarizes each theorem, its main result, and the associated managerial implication.

Numerical illustration. To illustrate the model's mechanics, consider a setting with a fixed commission rate α=0.2.

We compare three efficiency levels with different unit production cost c and the big data efficiency parameter β. Solving the Stackelberg game yields the equilibrium shown below:

Let the unit production cost be c=0.01 and the big data efficiency parameter be β=0.08. Solving the model under these values yields the equilibrium base price $\underline{p}^*$=0 and big data capability θ=0.625, which corresponds to Region IV in Theorem 1, where a positive but bounded big data capability is optimal. In this case we have $\underline{p}^*<c$, so the manufacturer sells below its unit production cost while the platform invests in a strictly positive level of analytics capability. This numerical outcome illustrates that below-cost pricing arises endogenously in the moderate-efficiency, bounded-personalization regime, rather than being imposed ad hoc. It also shows how the base price can be used as a strategic instrument to induce platform investment in big data capability and implement bounded personalized pricing, in line with the loss-leader logic described in Theorem 2.

In addition to this bounded-personalization case, Table 1 also reports a Region II outcome in which the platform fully invests in big data capability θ=1 and implements perfectly personalized pricing, while the equilibrium still satisfies $\underline{p}^*<c$. This second instance confirms that the mechanism in Theorem 2 is not confined to the bounded-personalization regime: even under full personalization the manufacturer may rationally set a below-cost base price in order to expand demand and recover profit through commissions. Taken together, the Region II and Region IV rows in Table 1 provide numerical support for the loss-leader conditions identified in Theorem 2 under both fully personalized and bounded personalized pricing.

To highlight the comparative-statics results in Theorems 3 and 4, consider the rows in Table 1 that share the same unit production cost c in the moderate-cost band $\frac{1}{3}(1-\alpha) < c \leq 1-\alpha$ but differ in the efficiency parameter β. Along this path, the equilibrium base price $\underline{p}^*$ first decreases and then increases as β rises, while both the manufacturer's and the platform's profits π_M^* and π_P^* decline monotonically. The initial reduction in $\underline{p}^*$ reflects the manufacturer's incentive to subsidize the platform's analytics investment when efficiency is still moderate, whereas the subsequent increase in $\underline{p}^*$ appears once further deterioration in efficiency makes additional subsidies unprofitable. This pattern reproduces the non-monotonic response of the base price and the downward trend in profits that are characterized analytically in Theorems 3 and 4.

Taken together, the numerical illustration reinforces the main conclusions and managerial implications developed earlier in the paper. First, it concretely shows how small changes in production cost and analytics efficiency can shift the system across the five regions in Theorem 1, leading to sharp transitions between full, bounded, and no personalization, as discussed in the main results. Second, it confirms that in a moderate-efficiency window the manufacturer can optimally adopt a loss-leader base price to stimulate the platform's investment in big data capability, expand demand, and improve joint performance, echoing the agency-channel insight that manufacturers may profit indirectly by selling at a loss. Overall, the numerical results underline that big data capability

Table 1. Equilibrium outcomes under illustrative cost and efficiency levels

(β, c)	θ^*	$\underline{p}^*$	π_M^*	π_P^*	Region
(0.01, 0.4)	1	0.5	0.1	0.06500	I
(0.03, 0.4)	1	0.22540	0.06984	0.06492	II
(0.4, 0.4)	0.008	0.74800	0.05020	0.03772	III
(0.08, 0.01)	0.625	0	0.24000	0.03125	IV
(0.1, 0.9)	0	1	0	0	V

should be treated as a strategic, efficiency-dependent lever: managers need to balance the quality and cost of analytics, rather than mechanically pushing for the highest possible level of personalization.

6. Discussion and Implications

With the rapid development of modern information technology, it has become significantly easier to collect customer data, which has intensified firms' interest in personalized pricing [8]. This study investigates how platforms determine the optimal level of big data analytics capability under bounded personalization within an agency channel. Regarding Research Question 1, higher big data analytics efficiency does not necessarily translate into a higher chosen capability level for implementing personalized pricing, especially when production costs are high. Specifically, when big data analytics efficiency is very high and the unit production cost of the product is low, the platform, modelled as a rational profit-maximizing agent, tends to allocate the maximum feasible investment in big data capability so as to increase the precision of personalization [4]. As efficiency declines and costs rise, it reduces investment, and when unit cost is very high, it refrains from investing and implements uniform pricing [9], [10]. Turning to Research Question 2, the manufacturer will have a loss (the base price is lower than the unit production cost) to incentivize the platform to implement personalized pricing when the efficiency of improving big data analytics capability is moderate. This is because the manufacturer sacrifices part of the base price to motivate the platform to improve the big data analytics capability. As the base price is reduced, customer demand increases [4], [23]. In the case of efficiency in the moderate, the platform is willing to improve the big data analytics capability, so manufacturers can earn greater profits by charging commissions [21]. This allows manufacturers to earn profits indirectly by selling at a loss. With respect to Research Question 3, higher big data analytics efficiency may not always benefit the platform. When efficiency is moderate, the manufacturer optimally lowers the base price to encourage the platform's investment in big data capability, which raises demand [17]. In the short run, this demand expansion can more than offset the negative effect of lower efficiency on price discrimination, leading to higher platform profit even as efficiency declines [25].

At the same time, production cost and analytics efficiency jointly determine the equilibrium base price, the platform's investment level, and the profit allocation between parties [29]. As efficiency and cost vary, the base price and capability move across distinct regimes rather than changing smoothly, which generates the non-monotonic patterns in both prices and profits.

By embedding bounded personalization in a Stackelberg framework, the analysis moves beyond a simple comparison between uniform and fully personalized pricing. The personalization parameter captures a continuum of feasible precision levels under realistic capability constraints, and the results clarify when it is rational for manufacturers to sacrifice part of their margin to induce platform investment and improve overall channel performance [31].

6. Conclusion

First, platform managers should carefully evaluate the cost–benefit trade-off of investing in personalization rather than indiscriminately pursuing high levels of it. Personalized pricing can be implemented in full when big data analytics efficiency is high and unit production cost is low. Otherwise, managers should consider whether and how to adjust big data analytics efficiency, rather than mandating personalized pricing. Second, manufacturers operating within an agency channel should dynamically adjust their base prices according to the platforms' willingness and capability to invest in big data analytics. Manufacturers might strategically lower their base prices below production costs. This incentivizes the platform's investment in enhanced big data analytics, which ultimately increases overall profitability. Third, higher big data analytics efficiency may not always benefit the platform. Platform managers must carefully assess how improvements in big data analytics efficiency affect profitability and make targeted investments based on specific operational contexts. Platform managers cannot simply increase the efficiency of their big data capability when they want to intensify personalized pricing. Instead, they should formulate a strategy to adjust efficiency upward or downward, depending on their specific situation.

Furthermore, as personalized pricing becomes more widely adopted, it is essential for platforms to integrate ethical considerations into their strategic decisions. Key concerns include data privacy, fairness, and transparency. Managers must ensure that big data analytics and pricing mechanisms comply with relevant data protection regulations and reflect ethical data usage. For instance, Netflix uses behavioral data to optimize content recommendations but deliberately avoids using sensitive attributes such as race or gender in pricing or visibility algorithms, aligning its practices with the General Data Protection Regulation (GDPR).[3] Meituan adjusted its personalized pricing strategy after being criticized for offering different prices to users based on purchase history, a practice referred to as "data-enabled price discrimination." The platform responded by improving algorithmic transparency and allowing users to opt out of personalized pricing, in accordance with the Personal Information Protection Law (PIPL).[4] These practices underscore the importance of aligning technological efficiency with ethical responsibility. Maintaining transparency and regulatory compliance helps foster trust and long-term engagement in data-driven platforms.

This research also points to several promising avenues for future exploration. Firstly, while the current analysis considers a simplified supply chain structure without competition, real-world scenarios typically involve intense competition. Future research could explicitly integrate competitive dynamics among multiple platforms or manufacturers, examining how such interactions affect personalized pricing strategies, analytics investment decisions, and overall profitability. Secondly, a fixed, externally determined commission rate has been assumed. Extending the model to allow dynamic commission rates determined through negotiation between manufacturers and platforms could provide richer insights into optimal personalized pricing and analytics strategies. Additionally, empirical validation using real-world industry data would significantly enhance the practical applicability of the theoretical results, offering deeper managerial insights and verifying the robustness of the conclusions in practical contexts. Lastly, considering growing consumer concerns around privacy and fairness, future studies could empirically investigate how different levels of customer privacy protection and transparent pricing policies affect consumer acceptance of personalized pricing. For instance, future research might examine the effectiveness of anonymized data practices and clear communication strategies (e.g., explaining tiered pricing discounts based on purchase history) in reducing consumer resistance. Additionally, compliance with regulations like GDPR ensures ethical data usage while maintaining consumer trust. A valuable future research direction is examining empirically how varying degrees of customer privacy protection influence consumer acceptance of personalized pricing, thus helping firms balance analytics capabilities with ethical business practices.

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Appendix A

In Appendix A, the relevant tables are compiled.

Table 2. The parameter space (β, c)

Region	Space
I	$0 < c < \left(1 - 2\sqrt{\frac{\beta}{\alpha}}\right)(1-\alpha)$
II	$\left\{\left(1 - 2\sqrt{\frac{\beta}{\alpha}}\right)(1-\alpha) < c < \left(1 - \frac{8}{3}\sqrt{\frac{\beta}{3\alpha}}\right)(1-\alpha), 0 < \beta < \frac{1}{4}\alpha\right\} \cup \left\{\left(1 - \frac{8}{3}\sqrt{\frac{\beta}{3\alpha}}\right)(1-\alpha) < c < c_1\right\}$
III	$c_1 < c < 1-\alpha$
IV	$\left(1 - 2\sqrt{\frac{\beta}{\alpha}}\right)(1-\alpha) < c < \left(1 - \frac{8}{3}\sqrt{\frac{\beta}{3\alpha}}\right)(1-\alpha)$, $\frac{1}{4}\alpha < \beta < \frac{27}{64}\alpha$
V	$1-\alpha < c < 1$

Table 3. Notions and their values

Notions	Value	Theorem
c_1	$2(1-\alpha-c_1)\sqrt{\frac{\beta}{\alpha}} - \frac{2\beta(1-\alpha)}{\alpha} - \frac{(1-\underline{p}_1)\left\{(-1+\underline{p}_1)^3\alpha^2+\left[1-\underline{p}_1{}^3+3\underline{p}_1{}^2-(3+8\beta)\underline{p}_1\right]\alpha-8\beta(c_1-\underline{p}_1)\right\}}{8\beta} = 0$	Theorem 1
$\underline{p}_1$	$\frac{-(1-\alpha)\alpha}{2\beta}(1-\underline{p}_1)^3 - 2(1-\alpha)\underline{p}_1 + (1-\alpha) + c = 0$	Theorem 1
β_1	the β value when c_1=0	Theorem 1
$\underline{\beta}$	$\frac{\alpha(1-c)^2}{4}$	Theorem 2
$\overline{\beta}$	β_1	Theorem 2
$\overline{c}$	$\frac{(3\sqrt{3}-4)(1-\alpha)}{3\sqrt{3}-4(1-\alpha)}$	Theorem 2

Table 4. Summary of main propositions and managerial implications

Theorem	Main result	Managerial implication
Theorem 1	Characterizes the optimal base price and big data capability across five parameter regions defined by production cost and efficiency, leading to uniform, bounded personalized, or perfect pricing.	The optimal pricing and investment regime depends on cost and efficiency conditions; managers should identify which region their operations fall into before choosing strategies.
Theorem 2	Shows that the manufacturer's optimal base price can be lower than the unit production cost in certain regions with moderate efficiency, while still allowing the manufacturer to earn profit via commissions.	Manufacturers in agency channels may rationally adopt below-cost base prices to induce platform investment in big data capability and increase overall channel profit.
Theorem 3	Describes how the optimal base price and big data capability change with production cost and efficiency; the base price increases with cost, while the capability generally decreases with cost and can be non-monotonic in efficiency.	Changes in production cost or analytics efficiency systematically shift pricing and investment incentives; firms should anticipate these shifts when costs or technology change.
Theorem 4	Analyzes how the profits of the manufacturer and the platform respond to cost and efficiency; in particular, the platform's profit can be non-monotonic in efficiency when production cost is moderate.	Improvements in efficiency do not uniformly benefit all parties; platforms should carefully evaluate whether additional investment in analytics will increase or reduce profit.
Theorem 5	Examines how consumer surplus varies with production cost and efficiency, showing that higher cost and lower efficiency can reduce total consumer surplus, with non-monotonic patterns in some regions.	The impact of personalization and big data capability on consumers depends on cost and efficiency; managers and regulators should consider these effects when designing or governing personalization strategies.

Appendix B

In Appendix B, the previous theorems and propositions are proved.

Proof of Lemma 1. The problem is solved for the personalized pricing model using backward induction. First, given base price $\underline{p}$, the platform decides a big data capability to maximize its profit. Due to $\frac{\partial^2 \pi_P(\theta)}{\partial^2 \theta} = -2\beta < 0$, solving the first order condition $\frac{\partial \pi_P(\theta)}{\partial \theta} = -2\beta\theta + \frac{1}{2}\alpha(1-\underline{p})^2 = 0$ yields $\theta_1 = \frac{\alpha(1-\underline{p})^2}{4\beta}$. Due to $\theta_1 - 1 = \frac{\alpha(1-\underline{p})^2 - 4\beta}{4\beta}$, two cases can be distinguished.

(1) When $\underline{p} \le 1 - 2\sqrt{\frac{\beta}{\alpha}}$, $\theta_1 \le 1$, π_P increases in $\theta \in (0,1)$, so $\theta^*\left(\underline{p}\right) = 1$.

(2) When $1 - 2\sqrt{\frac{\beta}{\alpha}} < \underline{p} \le 1$, π_P first increases in $\theta \in (0, \theta_1)$ and then decreases in $\theta \in (\theta_1, 1)$, so $\theta^*\left(\underline{p}\right) = \theta_1 = \frac{\alpha(1-\underline{p})^2}{4\beta}$.

To sum up, the following can be summarized

$$\theta^* = \begin{cases} 1, & \underline{p} \le 1 - 2\sqrt{\frac{\beta}{\alpha}} \\ \frac{\alpha(1-\underline{p})^2}{4\beta}, & 1 - 2\sqrt{\frac{\beta}{\alpha}} \le \underline{p} \le 1 \end{cases} \quad (A1)$$

Proof of Theorem 1. Plugging θ^* in Lemma 1 into the profit of manufacturer, the following cases are obtained.

(1) When $0 < \beta < \frac{1}{4}\alpha$, i.e., $\theta_1 > 0$, the following result holds

$$\pi_M^* = \begin{cases} -\frac{1}{2}(1-\alpha)\underline{p}^2 + c\underline{p} + \frac{1}{2}(1-\alpha) - c, & 0 \le \underline{p} \le 1 - 2\sqrt{\frac{\beta}{\alpha}} \\ \frac{\alpha(1-\alpha)(1-\underline{p})^4}{8\beta} + (1-\alpha)\underline{p}\left(1-\underline{p}\right) - c\left(1-\underline{p}\right), & 1 - 2\sqrt{\frac{\beta}{\alpha}} \le \underline{p} \le 1 \end{cases} \quad (A2)$$

It can be verified that the first line is a concave function of $\underline{p}$, then solving the first order condition of the first line (i.e., $\frac{\partial \pi_M}{\partial \underline{p}} = -(1-\alpha)\underline{p} + c = 0$) yields $\underline{p}_0 = \frac{c}{1-\alpha}$. However, the second line is more complex. By solving the second order condition of the second line (i.e.,$\frac{\partial^2 \pi_M}{\partial^2 \underline{p}} = \frac{3(1-\alpha)\alpha(1-\underline{p})^2}{2\beta} - 2 + 2\alpha$), $\underline{p}_2 = 1 - 2\sqrt{\frac{\beta}{3\alpha}} \le 1$ is obtained and a root larger than 1 is discarded. Plugging $\underline{p}_2 = 1 - 2\sqrt{\frac{\beta}{3\alpha}}$, $\underline{p}_3 = 1 - 2\sqrt{\frac{\beta}{\alpha}}$ and $\underline{p}_5 = 1$ into the first order condition of the second line (i.e. $\frac{\partial \pi_M}{\partial \underline{p}} = g(\underline{p}) = \frac{-(1-\alpha)\alpha}{2\beta}(1-\underline{p})^3 - 2(1-\alpha)\underline{p} + (1-\alpha) + c$), $g\left(1 - 2\sqrt{\frac{\beta}{3\alpha}}\right) = (1-\alpha)\left(\frac{8}{3}\sqrt{\frac{\beta}{3\alpha}} - 1\right) + c$, $g\left(1 - 2\sqrt{\frac{\beta}{\alpha}}\right) = c - (1-\alpha)$ and $g(1) = c - (1-\alpha)$ are derived. Then, by comparing these values, also considering $\underline{p}_0$ and $1 - 2\sqrt{\frac{\beta}{\alpha}}$, the following cases are obtained.

(1-1) If $0 < c \le \left(1 - 2\sqrt{\frac{\beta}{\alpha}}\right)(1-\alpha)$, $\underline{p}_0 \le \underline{p}_2$, $g\left(1 - 2\sqrt{\frac{\beta}{\alpha}}\right) < 0$ and $g\left(1 - 2\sqrt{\frac{\beta}{3\alpha}}\right) < 0$. In this case, π_M first increases in $\underline{p} \in \left(0, \frac{c}{1-\alpha}\right)$, and then decreases in $\underline{p} \in \left(\frac{c}{1-\alpha}, 1\right)$, so $\underline{p}^* = \frac{c}{1-\alpha}$, $\theta^*\left(\underline{p}\right) = 1$.

(1-2) If $\left(1 - 2\sqrt{\frac{\beta}{\alpha}}\right)(1-\alpha) < c \le c_1$, $\underline{p}_0 > \underline{p}_2$, $g\left(1 - 2\sqrt{\frac{\beta}{\alpha}}\right) < 0$ and $g\left(1 - 2\sqrt{\frac{\beta}{3\alpha}}\right) < 0$. In this case, π_M first increases in $\underline{p} \in \left(0, 1 - 2\sqrt{\frac{\beta}{\alpha}}\right)$, and then decreases in $\underline{p} \in \left(1 - 2\sqrt{\frac{\beta}{\alpha}}, 1\right)$, $\underline{p}^* = 1 - 2\sqrt{\frac{\beta}{\alpha}}$, $\theta^*\left(\underline{p}\right) = 1$.

(1-3) If $c_1 < c \le (1-\alpha)$, $\underline{p}_0 > \underline{p}_2$, $g\left(1 - 2\sqrt{\frac{\beta}{\alpha}}\right) < 0$ and $g\left(1 - 2\sqrt{\frac{\beta}{3\alpha}}\right) > 0$. In this case, π_M first increases in $\underline{p} \in \left(0, 1 - 2\sqrt{\frac{\beta}{\alpha}}\right)$, then decreases and then increases in $\underline{p} \in \left(1 - 2\sqrt{\frac{\beta}{\alpha}}, 1 - 2\sqrt{\frac{\beta}{3\alpha}}\right)$, and finally increases and then decreases in $\underline{p} \in \left(1-2\sqrt{\frac{\beta}{3\alpha}}, 1\right)$. $\pi_M\left(1-2\sqrt{\frac{\beta}{3\alpha}}\right) - \pi_M\left(1-2\sqrt{\frac{\beta}{\alpha}}\right) > 0$ and $\pi_M\left(\underline{p_1}\right) - \pi_M\left(1-2\sqrt{\frac{\beta}{3\alpha}}\right) > 0$, so $\underline{p}^* = \underline{p_1}$, $\theta^*\left(\underline{p}\right) = \frac{\alpha(1-\underline{p_1})^2}{4\beta}$. $\underline{p_1}$ satisfies the formula $g(\underline{p_1}) = \frac{-(1-\alpha)\alpha}{2\beta}(1-\underline{p_1})^3 - 2(1-\alpha)\underline{p_1} + (1-\alpha) + c = 0$.

(1-4) If $(1-\alpha) < c < 1$, $\underline{p_0} > \underline{p_2}$, $g\left(1-2\sqrt{\frac{\beta}{\alpha}}\right) > 0$ and $g\left(1-2\sqrt{\frac{\beta}{3\alpha}}\right) > 0$. In this case, π_M increases in $\underline{p} \in (0,1)$, so $\underline{p}^* = 1$, $\theta^*\left(\underline{p}\right) = 0$.

(2) When $\beta \geq \frac{1}{4}\alpha$, i.e., $\theta_1 < 0$, the following result holds:

$$\pi_M^* = \frac{(1-\alpha)\alpha(1-\underline{p})^4}{8\beta} + (1-\alpha)\underline{p}\left(1-\underline{p}\right) - c\left(1-\underline{p}\right), \quad 0 \leq \underline{p} \leq 1 \tag{A3}$$

By solving the second order condition (i.e., $\frac{\partial^2\pi_M}{\partial^2\underline{p}} = \frac{3(1-\alpha)\alpha(1-\underline{p})^2}{2\beta} - 2 + 2\alpha = 0$), $\underline{p_2} = 1-2\sqrt{\frac{\beta}{3\alpha}} \leq 1$ is obtained and a root larger than 1 is discarded. Plugging $\underline{p_2} = 1-2\sqrt{\frac{\beta}{3\alpha}}$, $\underline{p_4} = 0$ and $\underline{p_5} = 1$ into the first order condition (i.e., $\frac{\partial\pi_M}{\partial\underline{p}} = g(\underline{p}) = \frac{-(1-\alpha)\alpha}{2\beta}(1-\underline{p})^3 - 2(1-\alpha)\underline{p} + (1-\alpha) + c$), $g\left(1-2\sqrt{\frac{\beta}{3\alpha}}\right) = (1-\alpha)\left(\frac{8}{3}\sqrt{\frac{\beta}{3\alpha}} - 1\right) + c$, $g(0) = \frac{-(1-\alpha)\alpha}{(2\beta)} + (1-\alpha) + c$ and $g(1) = c - (1-\alpha)$ are derived.

Then, by comparing these values, the following cases are obtained.

(2-1) If $c < c_1$, $g\left(1-2\sqrt{\frac{\beta}{\alpha}}\right) < 0$, so $\pi_M\left(\underline{p_1}\right)$ decreases in $\underline{\mathrm{p}} \in (0,1)$. In this case, $\underline{p}^* = 0$, $\theta^*\left(\underline{p}\right) = \frac{\alpha}{4\beta}$.

(2-2) If $c_1 < c \leq \left(\frac{\alpha-2\beta}{2\beta}\right)(1-\alpha)$, $g\left(1-2\sqrt{\frac{\beta}{\alpha}}\right) > 0$ and $g(0) \leq 0$, so π_M first decreases, then increases, and finally decreases in $\underline{p} \in (0,1)$. In this case, $\underline{p}^* = \underline{p_1}$, $\theta^*\left(\underline{p}\right) = \frac{\alpha(1-\underline{p_1})^2}{4\beta}$. $\underline{p_1}$ satisfies the formula $g(\underline{p_1}) = \frac{-(1-\alpha)\alpha}{2\beta}(1-\underline{p_1})^3 - 2(1-\alpha)\underline{p_1} + (1-\alpha) + c = 0$.

(2-3) If $\left(\frac{\alpha-2\beta}{2\beta}\right)(1-\alpha) < c \leq (1-\alpha)$, $g(0) > 0$ and $g(1) \leq 0$, so π_M first increases in $\underline{p} \in \left(0, \underline{p_1}\right)$, and then decreases in $\underline{p} \in \left(\underline{p_1}, 1\right)$. In this case, $\underline{p}^* = \underline{p_1}$, $\theta^*\left(\underline{p}\right) = \frac{\alpha(1-\underline{p_1})^2}{4\beta}$. $\underline{p_1}$ satisfies the formula $g(\underline{p_1}) = \frac{-(1-\alpha)\alpha}{2\beta}(1-\underline{p_1})^3 - 2(1-\alpha)\underline{p_1} + (1-\alpha) + c = 0$.

(2-4) If $(1-\alpha) \leq c < 1$, $g(1) > 0$, so π_M increases in $\underline{p} \in (0,1)$. In this case, $\underline{p}^* = 1$, $\theta^*\left(\underline{p}\right) = 0$.

According to the analysis of the above cases, the following sets are defined.

$$\begin{cases} I = & 0 < c < \left(1-2\sqrt{\frac{\beta}{\alpha}}\right)(1-\alpha) \\ II = & \left\{\left(1-2\sqrt{\frac{\beta}{\alpha}}\right)(1-\alpha) < c < c_1, 0 < \beta < \frac{1}{4}\alpha\right\} \\ III = & \{c_1 < c < 1-\alpha\} \\ IV = & \left\{\left(1-2\sqrt{\frac{\beta}{\alpha}}\right)(1-\alpha) < c < c_1, \frac{1}{4}\alpha < \beta < \frac{27}{64}\alpha\right\} \\ V = & \{1-\alpha < c < 1\} \end{cases} \tag{A3}$$

Then the desired result follows as shown in Theorem 1.

Proof of Theorem 2. The values of $\underline{p}$ and c are compared in each of the five ranges.

(1) When $(\beta, c) \in I$, then $\underline{p}^* = \frac{c}{1-\alpha}$. It can be verified that $\underline{p}$ is larger than c.

(2) When $(\beta, c) \in II$, then $\underline{p}^* = 1-2\sqrt{\frac{\beta}{\alpha}}$ and $\underline{p}^* - c = 1-2\sqrt{\frac{\beta}{\alpha}} - c$. When $\frac{\alpha(1-c)^2}{4} < \frac{27\alpha(1-\alpha-c)^2}{64(1-\alpha)^2}$, that is $0 < c < \frac{(3\sqrt{3}-4)(1-\alpha)}{3\sqrt{3}-4(1-\alpha)}$, it can be verified that if $\frac{\alpha(1-\alpha-c)^2}{4(1-\alpha)^2} < \beta \leq \frac{\alpha}{4}(1-c)^2$, $\underline{p} \geq c$, and if $\frac{\alpha}{4}(1-c)^2 < \beta < \frac{27\alpha(1-\alpha-c)^2}{64(1-\alpha)^2}$, $\underline{p} < c$. Otherwise, $\underline{p} \geq c$.

(3) When $(\beta, c) \in III$, then $\underline{p}^* = \underline{p}_1$. $\underline{p}_1$ satisfies the formula $g(\underline{p}_1) = \frac{-(1-\alpha)\alpha}{2\beta}(1-\underline{p}_1)^3 - 2(1-\alpha)\underline{p}_1 + (1-\alpha) + c = 0$. By solving the second order condition of $g\left(\underline{p}\right)$ (i.e., $\frac{\partial g(\underline{p})}{\partial \underline{p}} = h\left(\underline{p}\right) = \frac{3(1-\alpha)\alpha(1-\underline{p})^2}{2\beta} - (1-2\alpha)$), it follows that $g\left(\underline{p}_1\right) > 0$ in $\underline{p} \in \left(0, \underline{p}_1\right)$, $g\left(\underline{p}_1\right) < 0$ in $\underline{p} \in \left(\underline{p}_1, 1\right)$, and $h\left(\underline{p}_1\right) < 0$. Plugging c into the first order condition and second order condition, it is obtained that there is no such a c in $c \in (0,1)$ that satisfies both the conditions $g(c) < 0$ and $h(c) < 0$, so $\underline{p}$ is larger than c.

(4) When $(\beta, c) \in IV$, $\underline{p}^* = 0$, $\underline{p}$ is always less than c.

(5) When $(\beta, c) \in V$, $\underline{p}^* = 1$, $\underline{p}$ is always larger than c.

Then the desired result follows as shown in Theorem 2.

Proof of Theorem 3. The monotonicity of the equilibrium base price and big data capability with respect to and is established case by case according to the results in Theorem 1.

(1) When $(\beta, c) \in I$, then $\left(\theta^*, \underline{p}^*\right) = \left(1, \frac{c}{1-\alpha}\right)$. It can be verified that $\underline{p}^*$ increases with c while θ^* is independent of c; moreover, both $\underline{p}^*$ and θ^* are independent of β.

(2) When $(\beta, c) \in II$, then $\left(\theta^*, \underline{p}^*\right) = \left(1, 1 - 2\sqrt{\frac{\beta}{\alpha}}\right)$. It can be verified that $\underline{p}^*$ decreases with β while θ^* is independent of β; moreover, both $\underline{p}^*$ and θ^* are independent of c.

(3) When $(\beta, c) \in III$, then $\left(\theta^*, \underline{p}^*\right) = \left(\frac{\alpha(1-\underline{p}_1)^2}{4\beta}, \underline{p}_1\right)$. $\underline{p}_1$ satisfies the formula $g(\underline{p}_1) = \frac{-(1-\alpha)\alpha}{2\beta}(1-\underline{p}_1)^3 - 2(1-\alpha)\underline{p}_1 + (1-\alpha) + c = 0$. By taking the derivative of both sides of this equation with respect to β and c, it is obtained that $\frac{\partial \underline{p}_1}{\partial \beta} = \frac{\alpha(1-\underline{p}_1)^3}{\beta[4\beta - 3\alpha(1-\underline{p}_1)^2]} > 0$ and $\frac{\partial \underline{p}_1}{\partial \beta} = \frac{2\beta}{(1-\alpha)[4\beta - 3\alpha(1-\underline{p}_1)^2]} > 0$. At the same time, it can be verified that $\underline{p}_1$ and θ are negatively correlated. So $\underline{p}^*$ increases with c while θ^* decreases with c; moreover, $\underline{p}^*$ increases with β while θ^* decreases with β.

(4) When $(\beta, c) \in IV$, then $\left(\theta^*, \underline{p}^*\right) = \left(\frac{\alpha}{4\beta}, 0\right)$. It can be verified that $\underline{p}^*$ is independent of β while θ^* decreases with β; moreover, both $\underline{p}^*$ and θ^* are independent of c.

(5) When $(\beta, c) \in V$, then $\left(\theta^*, \underline{p}^*\right) = (0,1)$. Both $\underline{p}^*$ and θ^* are independent of c and β.

Next, the impact of c on $\underline{p}^*$ and θ^* is analyzed.

(1) When $0 < \beta < \frac{\alpha}{4}$, the path of the equilibrium solutions is $I \rightarrow II \rightarrow III \rightarrow V$. Therefore, $\underline{p}^*$ first increases with c, then remains independent of c, then increases with c, and finally remains independent of c, but θ^* first remains independent of c, then decreases with c, and finally remains independent of c.

(2) When $\frac{\alpha}{4} \leq \beta < \beta_1$, the path of the equilibrium solutions is $IV \rightarrow III \rightarrow V$. Therefore, $\underline{p}^*$ first is independent of c, then increases with c, and then remains independent of c, but θ^* first is independent of c, then decreases with c, and then remains independent of c.

(3) When $\beta \geq \beta_1$, the path of the equilibrium solutions is $III \rightarrow V$. Therefore, $\underline{p}^*$ first increases with c, and then remains independent of c, but θ^* decreases with c, and then remains independent of c.

Finally, the impact of β on $\underline{p}^*$ and θ^* are analyzed.

(1) When $0 < c \leq c_2$, the path of the equilibrium solutions is $I \rightarrow II \rightarrow IV \rightarrow III$. Therefore, $\underline{p}^*$ first remains independent of β, then decreases with β, then is independent of β, and then increases with β, but θ^* first remains independent of β, and then decreases with β. c_2 is the value of c when $c_2 = c_1\left(\frac{1}{4}\alpha\right)$.

(2) When $c_2 < c \leq (1-\alpha)$, the path of the equilibrium solutions is $I \rightarrow II \rightarrow III$. Therefore, $\underline{p}^*$ first remains independent of β, then decreases with β, and then increases with β, but θ^* first remains independent of β, and then decreases with β.

(3) When $(1-\alpha) < c < 1$, the path of the equilibrium solutions is V. Therefore, both $\underline{p}^*$ and θ^* are independent of β.

Proof of Theorem 4. Similarly, the monotonicity of the equilibrium profits with respect to c and β is established case by case according to the results in Theorem 3.

(1) When $(\beta, c) \in I$ then $\pi_P^* = \frac{\alpha[(1-\alpha)^2 - c^2]}{2(1-\alpha)^2} - \beta$ and $\pi_M^* = \frac{c^2}{2(1-\alpha)} + \frac{1-\alpha}{2} - c$. It can be verified that both π_P^* and π_M^* decrease with c; moreover, π_P^* decreases with β while π_M^* remains independent of β.

(2) When $(\beta, c) \in II$, then $\pi_P^* = 2\alpha\sqrt{\frac{\beta}{\alpha}} - 3\beta$ and $\pi_M^* = 2\sqrt{\frac{\beta}{\alpha}}\left(1 - \sqrt{\frac{\beta}{\alpha}} - c\right)$. π_P^* remains independent of c, while π_M^* decreases with c; moreover, π_M^* decreases with β, while the correlation between π_P^* and β exhibits different

relationships across ranges of c. When $0 < c \leq \frac{1}{3}(1-\alpha)$, π_P^* decreases with β. When $\frac{1}{3}(1-\alpha) < c \leq \left(1-\frac{8}{9\sqrt{3}}(1-\alpha)\right)$, π_P^* first increases with β, and then decreases with β. When $\left(1-\frac{8}{9\sqrt{3}}(1-\alpha)\right) < c < 1-\alpha$, π_P^* increases with β.

(3) When $(\beta, c) \in \mathit{III}$, then $\pi_P^* = \frac{\alpha^2(1-\underline{p}_1)^4}{16\beta} + \alpha\underline{p}_1\left(1-\underline{p}_1\right)$ and $\pi_M^* = \frac{(1-\alpha)\alpha(1-\underline{p}_1)^4}{16\beta} + (1-\alpha)\underline{p}_1\left(1-\underline{p}_1\right) - c\left(1-\underline{p}_1\right)$. $\underline{P}_1$ satisfies the formula $g(\underline{p}_1) = \frac{-(1-\alpha)\alpha}{2\beta}(1-\underline{p}_1)^3 - 2(1-\alpha)\underline{p}_1 + (1-\alpha) + c = 0$. By taking the derivative of $\pi_P(\theta)$ *and* $\pi_M\left(\underline{p}\right)$ with respect to c and β, it is obtained that $\frac{\partial \pi_P(\theta)}{\partial \beta} = \frac{\alpha^2(1-\underline{p}_1)^3[-\alpha(1-\underline{p}_1)^3+12\beta-28\beta\underline{p}_1]}{16\beta^3[4\beta-3\alpha(1-\underline{p}_1)^2]} < 0$, $\frac{\partial \pi_M\left(\underline{p}\right)}{\partial \beta} = \frac{\alpha(1-\underline{p}_1)^3[1-\alpha+3c-4(1-\alpha)\underline{p}_1]}{4\beta[4\beta-3\alpha(1-\underline{p}_1)^2]} < 0$, $\frac{\partial \pi_P(\theta)}{\partial c} = \frac{-\alpha^2(1-\underline{p}_1)^3+4\alpha\beta-8\alpha\beta\underline{p}_1}{2(1-\alpha)[4\beta-3\alpha(1-\underline{p}_1)^2]} < 0$ and $\frac{\partial \pi_M\left(\underline{p}_1\right)}{\partial c} = \frac{-6\beta(1-\alpha)-\alpha(4-\alpha)(1-\underline{p}_1)^3}{(1-\alpha)[4\beta-3\alpha(1-\underline{p}_1)^2]} < 0$. So, both $\pi_P(\theta^*)$ and $\pi_M\left(\underline{p}^*\right)$ decrease with c and β.

(4) When $(\beta, c) \in \mathit{IV}$, then $\pi_P^* = \frac{\alpha^2}{16\beta}$ and $\pi_M^* = \frac{\alpha(1-\alpha)}{8\beta} - c$. It can be verified that π_P^* remains independent of c, while π_M^* decreases with c; moreover, both π_P^* and π_M^* decrease with β.

(5) When $(\beta, c) \in \mathit{V}$, then $\pi_P^* = 0$ and $\pi_M^* = 0$. It can be verified that both π_P^* and π_M^* are independent of c and β.

Next, the impact of c on π_P^* and π_M^* is analyzed.

(1) When $0 < \beta < \frac{1}{4}\alpha$, the path of the equilibrium solutions is $\mathit{I} \to \mathit{II} \to \mathit{III} \to \mathit{V}$. Therefore, π_P^* first decreases with c, then remains independent of c, then decreases with c, and finally remains independent of c, while π_M^* first decreases with c, and then remains independent of c.

(2) When $\frac{1}{4}\alpha \leq \beta < \beta_1$, the path of the equilibrium solutions is $\mathit{IV} \to \mathit{III} \to \mathit{V}$. Therefore, π_P^* first remains independent of c, then decreases with c, and finally remains independent of c, while π_M^* first decreases with c, and then remains independent of c.

(3) When $\beta \geq \beta_1$, the path of the equilibrium solutions is $\mathit{III} \to \mathit{V}$. Therefore, π_P^* first decreases with c, and then remains independent of c, while π_M^* first decreases with c, and then remains independent of c.

Finally, the impact of β on π_P^* and π_M^* are analyzed.

(1) When $0 < c \leq c_2$, the path of the equilibrium solutions is $\mathit{I} \to \mathit{II} \to \mathit{IV} \to \mathit{III}$. Therefore, both π_P^* and π_M^* decrease with β.

(2) When $c_2 < c \leq \frac{1}{3}(1-\alpha)$, the path of the equilibrium solutions is $\mathit{I} \to \mathit{II} \to \mathit{III}$. Therefore, both π_P^* and π_M^* decrease with β.

(3) When $\frac{1}{3}(1-\alpha) < c \leq (1-\alpha)$, the path of the equilibrium solutions is $\mathit{I} \to \mathit{II} \to \mathit{III}$. Therefore, π_P^* first decreases with β, then increases with β, and finally decreases with β, while π_M^* decreases with β.

(4) When $(1-\alpha) < c < 1$, the path of the equilibrium solutions is IV. Therefore, both π_P^* and π_M^* are independent of β.

Proof of Theorem 5. Similarly, the monotonicity of consumer surplus with respect to c and β is derived case by case according to the results in Theorem 3.

(1) When $(\beta, c) \in \mathit{I}$, then $CS^* = 0$. It can be verified that consumer surplus remains independent of c and β.

(2) When $(\beta, c) \in \mathit{II}$, then $CS^* = 0$. It can be verified that consumer surplus remains independent of c and β.

(3) When $(\beta, c) \in \mathit{III}$, then $CS^* = \frac{1}{2}[1-\frac{\alpha(1-\underline{p}_1)^2}{4\beta}](1-\underline{p}_1)^2$. $\underline{P}_1$ satisfies the formula $g(\underline{p}_1) = \frac{-(1-\alpha)\alpha}{2\beta}(1-\underline{p}_1)^3 - 2(1-\alpha)\underline{p}_1 + (1-\alpha) + c = 0$. By solving the first order condition (i.e., $\frac{\partial CS}{\partial c} = \frac{2\beta(1-\underline{p}_1)[\alpha(1-\underline{p}_1)^2-2\beta]}{(1-\alpha)[4\beta-3\alpha(1-\underline{p}_1)^2]} < 0$, $\frac{\partial CS}{\partial \beta} = \frac{8\beta^2(1-\underline{p}_1)[\alpha(1-\underline{p}_1)^2-4\beta]+(1-\underline{p}_1)^2(1-\alpha)[\alpha(1-\underline{p}_1)^2-4\beta][4\beta-3\alpha(1-\underline{p}_1)^2]}{8(1-\alpha)\beta^2[4\beta-3\alpha(1-\underline{p}_1)^2]} < 0$), it is obtained that consumer surplus decreases with c and β.

(4) When $(\beta, c) \in \mathit{IV}$, then $CS^* = \frac{1}{2}\left(1-\frac{\alpha}{4\beta}\right)$. It can be verified that consumer surplus remains independent of c; moreover, consumer surplus increases with β.

(5) When $(\beta, c) \in \mathit{V}$, then $CS^* = 0$. It can be verified that consumer surplus remains independent of c and β.

Next, the impact of c on consumer surplus is analyzed.

(1) When $0 < \beta \leq \frac{1}{4}\alpha$, the path of consumer surplus is $\mathit{I} \to \mathit{II} \to \mathit{III} \to \mathit{V}$. Therefore, consumer surplus decreases with c.

(2) When $\frac{1}{4}\alpha < \beta < 1$, the path of consumer surplus is $\mathit{IV} \to \mathit{III} \to \mathit{V}$. Therefore, consumer surplus decreases with c.

Finally, the analysis examines the impact of β on consumer surplus.

(1) When $0 < c \leq c_2$, the path of consumer surplus is $\mathit{I} \to \mathit{II} \to \mathit{IV} \to \mathit{III}$. Therefore, consumer surplus first increases with β and then decreases with β.

(2) When $c_2 < c \leq (1-\alpha)$, the path of consumer surplus is $\mathit{I} \to \mathit{II} \to \mathit{III}$. Therefore, consumer surplus decreases with β.

(3) When $(1-\alpha) < c < 0$, the path of consumer surplus is V. Therefore, consumer surplus remains independent of β.