Personalization Trap

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Retail platforms are increasingly capable of gathering and processing large volumes of consumer data, based on which they can personalize product recommendations. Recommended products take prominent positions that facilitate consumer search. Alternatively, the platform can forgo its knowledge from consumer data and sell the prominent positions via sponsored-ad auctions. A fundamental difference between personalization and ad auctions lies in retailers’ use of data, which ultimately impact consumer search and purchase behavior. This research provides a unified model to capture the linkage between data and search and compare these two alternative monetization strategies of a retail platform. We show that data-empowered personalization leads to traps for both consumers and the platform: compared with the case of sponsored ads, under personalized product recommendation, consumers find their best match but are charged with a monopoly price and thus earn zero surplus; the platform extracts all consumer surplus but has to share with the sellers and thus may earn lower profit. We compare platform profitability, consumer welfare, seller surplus under personalization and ad auctions and also study the platform’s targeted advertising strategy. Answers to those questions also shed light on data policy implications.

Keywords: consumer data, retailing, platform, personalization, ad auction, consumer search
1. Introduction

Recent developments in big data and artificial intelligence have empowered retailers such as Amazon and Alibaba to reshape how consumers shop. One of the most important and common practices of retailers is to personalize product recommendations, reducing consumer search and automating their shopping experience. It has been reported that Amazon uses big data to recommend items for its customers based on their past searches and purchases, and it already generated 35 percent of sales through its recommendation engine.\(^1\) Practitioners hype about the potential of this new personalization model in replacing the current profit engine - advertising auction model, in which a retailer can sell the prominent positions via search ad auctions to sellers, and the winners’ product will be recommended to all consumers. In fact, search advertising has become a major revenue source for online retailers. Amazon’s advertising revenue grows at 130% annually and reached $10 billion in 2018.\(^2\)

A fundamental difference between the two – personalization versus ad auctions – lies in data requirements on the retailer side. Whether data is implemented has an ultimate impact on consumer search behavior. The objective of this research is to provide a unified game theory model to capture the linkage between data and consumer search and thereby compare the two alternative monetization strategies of a retail platform. Specifically, we explore when big data is useful for a retailer, and how a retailer’s use of data can impact consumers, sellers and social welfare. Answers to these questions also shed light on data policy implications.

Building on the seminal work by Wolinsky (1986), we consider a model of \(N\) sellers each selling one product to consumers, with the additional feature that transactions take place on a retail platform. The idiosyncratic value of a product to a consumer is originally unknown to both the consumer and the seller. The retail platform decides whether to implement personalized product recommendations or search ad auctions, and sellers set product prices. To implement personalized recommendation, the retailer relies on data analytics and can predict the best match value of any consumer. We show that, under the personalized product recommendation, consumers always get recommended their favorite products. They then have no incentive to continue searching, leaving no incentive for the sellers to lower their price below the monopoly level. Therefore, personalization leads to better matches and the retailer can appropriate part of the benefit through the high monopoly prices charged by the sellers. In contrast, under the search ad auction, the retailer

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induces sellers to bid for the prominent position. Consumers then start their product search from the prominent position. However, such a prominent position does not reveal information about the product value. Hence, consumers may not necessarily obtain their best match from the prominent position, driving them to continue to search for a better product. Consequently, competition among sellers intensifies and leads to lower equilibrium prices (than the monopoly level). The retailer can extract the winning seller’s profit, even though consumer’s surplus is not fully extracted.

We show that for sufficiently large number of sellers in the market, the equilibrium price under personalization is higher than that under the sponsored search ads. In such a market, consumers are worse off under personalization. Sellers, in aggregate, are better off due to the high monopoly prices, even though they share some of the profits with the retail platform. The retailer, however, can be worse off under personalization if the commission fee is relatively low and consumer search cost is relatively high. In general, the total social welfare is higher under personalization than under ad auctions. These results together suggest that, although big data and data analytics can improve social welfare, policy makers have to be cautious about the unbalanced distributions of the welfare gain.

Our work contributes to the important research stream that investigates the implications of consumer information for firm pricing (e.g., [Villas-Boas 1999], [Fudenberg and Tirole 2000]). Unlike prior studies, we examine a new scenario due to the technological development of big data. The focus here is on retailers’ pricing policies instead of on manufacturers’ pricing. Therefore our research also connects to the literature on channel coordination. In particular, the market structure where multiple manufacturers compete through a common retailer has been studied with the assumption that the retailer has no consumer information because of the lack of data (e.g., [Choi 1991], [Moorthy 1988], [Bernheim and Whinston 1998], [Cachon and Kök 2010]). These studies typically assume a market of two competing manufacturers. We study a more realistic market scenario where more than two manufacturers compete and consumers may search for products to find the best match. Furthermore, except a few analyses (e.g., [Shaffer and Zettelmeyer 2004], [Shaffer and Zettelmeyer 2009]), little attention has been paid to the impact of advertising in this type of retail structure. We enrich this body of research by studying the retailer’s strategy of implementing advertising auctions.

The paper is organized as follows: we introduce the model set-up in Section 2 and provide an equilibrium analysis in Section 3. Section 4 discusses several extensions that include targeted ad auctions. We conclude in Section 5.
2. Model

Consider a retail platform with $M \geq 2$ sellers competing with each other by choosing prices. Sellers’ marginal production costs are assumed to be the same and normalized as zero.

There is a continuum of consumers in the market with the total market size normalized as one. A representative consumer has a match value $v_j$ with seller $j$ for $j \in \{1, \cdots, M\}$. It is common knowledge that $v_j$ is distributed independently over sellers in $[0, \bar{v}]$ according to the distribution function $G$. We assume that $G(v)$ is twice differentiable with $g(v) \equiv G'(v) > 0$ for $v \in [0, \bar{v}]$. In addition, to guarantee equilibrium existence, we use the standard assumptions mentioned by Anderson and Renault (1999), among which, $g(v)$ is log-concave. We also assume that different consumers’ match values for a seller are independent. Given seller $j$’s price $p_j$, the consumer’s utility from purchasing the product from the seller equals

$$u_j = v_j - p_j.$$  

The consumer does not observe her match values $v_j$ nor the prices $p_j$ a priori (Wolinsky 1986). She can search sequentially over the sellers with search cost $0 < c < E[v_j]$. The upper bound on $c$ ensures that the search cost is not too high such that consumers are not interested in searching any seller. Upon paying cost $c$ and visiting seller $j$, she discovers both $v_j$ and $p_j$. The outside option for consumers is normalized as zero.

The platform charges a commission fee of $\delta$ percent of the transaction price for all trades occurred on the platform. In practice, many considerations come into play for setting $\delta$, such as elasticities of supply and demand as well as competition with other platforms. Since we do not endogenize entry nor consider platform competition, we will assume $\delta$ is exogenously given. We discuss the implications of endogenous commission fee in Section 5. The platform collects consumers’ data. We assume that the data is rich enough such that the platform can perfectly infer each consumer’s match value for each seller. The assumption of perfect information on consumer preference simplifies the analysis but is not necessary for our results to go through. We will discuss the implications of imperfect information in Section 5.

For each consumer, the platform can create a prominent position. We assume that the consumer

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3 Notice that log-concavity of $g(v)$ implies log-concavity of $1 - G(v)$ (using Prékopa-Leindler inequality). In the case of monopolistic competition with $M = \infty$, Anderson and Renault (1999) shows that the log-concavity of $1 - G(v)$ guarantees the existence of $p^*$; in the case of oligopoly with $M$ finite, Appendix B in Anderson and Renault (1999) provides additional conditions besides the log-concavity of $g(v)$ to guarantee the existence of $p^*$. For example, in Corollary B1, Anderson and Renault (1999) shows that if $g(v)$ is log-concave and $g'(v) \geq 0$ for $v \in [\underline{v}, \bar{v}]$, $p^*$ exists uniquely; in Corollary B2, Anderson and Renault (1999) shows that if $g(v)$ is log-concave and $2g(v) \geq -g'(\bar{v})/g(\bar{v})$, $p^*$ exists uniquely.
incurs zero search cost to visit the seller on the prominent position, and therefore the consumer will always visit the prominent position first. The consumer incurs $c$ for visiting each other seller afterwards. The platform has three ways to determining which seller to take the prominent position. The first approach is personalized product recommendation, where the platform can utilize its knowledge of consumer preference to select a seller to take the prominent position. In the second approach, the platform can forgo its knowledge of consumer preference and instead, sell the prominent position to the sellers via a second-price sponsored ad auction. In the third approach, the platform utilize its knowledge of consumer preference to hold targeted auctions for each consumer.

To summarize, we will consider the following game. First, the platform chooses the product recommendation strategy—whether to use personalized recommendation, second-price ad auction, or targeted ad auction to determine the prominent position for each consumer. Second, all sellers set prices. Third, if the platform has chosen to use auctions, all sellers place their bids. Lastly, consumers search sequentially before making a purchase. Next, we will analyze the equilibrium outcome given each of the platform’s product recommendation strategies, and then compare them. We are only interested in symmetric strategies where all sellers charge the same price in equilibrium.

3. Equilibrium Analysis

3.1. Personalized Recommendation

For a representative consumer, the platform observes her match values with all sellers. We argue that the platform will recommend the seller with the highest match value $v_{\text{max}} \equiv \max_j v_j$ to the consumer by placing the seller on the prominent position. Denote the equilibrium price as $p_P^*$, where the subscript $P$ represents “under personalized recommendation”. In equilibrium, the consumer expects that the prominent seller has the best match. Given the prominent seller’s price $p$, the consumer will stop searching and make a purchase immediately if and only if,

\begin{align}
  v_{\text{max}} - p \geq w(v_{\text{max}}) - p_P^*, \\
  v_{\text{max}} - p \geq 0,
\end{align}

where $w(v_{\text{max}})$ denotes the reservation value from continuing to search and is given by (Weitzman 1979),

$$
\int_{w(v_{\text{max}})}^{v_{\text{max}}} (v - w(v_{\text{max}})) \frac{g(v)}{G(v_{\text{max}})} dv = c.
$$
By definition $w(v_{max}) < v_{max}$ because $c > 0$. This implies that in equilibrium with $p = p^*_p$, condition \( \Pi \) is always satisfied and thus not binding. Let’s first consider local deviations of the seller from the equilibrium price so that condition \( \Pi \) is still satisfied. This will help us pin down the equilibrium price, $p^*_p$. Then, we will check that there is no profitable global deviations as well. Particularly, under local deviations, the seller’s profit function is that,

$$S_P(p) = \frac{1 - \delta}{M} \Pr(v_{max} - p \geq 0) p = \frac{1 - \delta}{M} (1 - G(p)^M) p.$$ 

The equilibrium price satisfies that $p^*_p = \arg \max_p S_P(p)$. One can show that log-concavity of $1 - G(p)$ implies log-concavity of $1 - G(p)^M$, which implies the second-order optimality condition is satisfied. Therefore, $p^*_p$ can be obtained by the first-order optimality condition, which is given by the following equation.

$$p^*_p = \frac{1 - G(p^*_p)^M}{MG(p^*_p)^{M-1}g(p^*_p)}.$$ (3)

To summarize, in equilibrium, each consumer only visits the prominent seller and does not search afterwards. She gets recommended her favorite product but is charged a monopoly price that leaves some consumers unserved. Consequently, the equilibrium price $p^*_p$ does not depend on the search cost as long as it is positive. The intuition is similar to what happens in Diamond Paradox \cite{Diamond1971}—consumers have no incentive to search and thus will not be attracted by other sellers’ potential deviations of price cuts. Given that, sellers have no incentive to lower their price below the monopoly level. This result also means that the platform’s consumer-data-based personalized recommendation enables sellers to achieve collusion on prices.

In equilibrium, the consumer surplus, retail platform’s profit, a seller’s profit and social welfare are respectively,

$$C_P = \int_{p^*_P}^{\bar{v}} (v - p^*_P) (G(v)^M)’ dv = \bar{v} - p^*_P - \int_{p^*_P}^{\bar{v}} G(v)^M dv,$$

$$R_P = \delta \left( 1 - G(p^*_P)^M \right) p^*_P,$$

$$S_P = \frac{1 - \delta}{M} \left( 1 - G(p^*_P)^M \right) p^*_P,$$

$$W_P = C_P + R_P + MS_P = \bar{v} - \int_{p^*_P}^{\bar{v}} G(v)^M dv - G(p^*_P)^M p^*_P.$$ 

Because in equilibrium, each consumer gets her best match and is charged a monopoly price, $R_P$ is the maximum possible profit the platform can expect.

Lastly, we verify that it is indeed optimal for the platform to recommend consumers’ best match
to them. Since the platform knows a consumer’s match values with all sellers but the consumer only
knows the value of a recommended product, the consumer needs to form belief about whether the
recommended product indeed delivers the highest value, or equivalently speaking, whether there are
other sellers who offer better match values. Suppose the platform deviates to recommend a product
\( j' \) with \( v_{j'} < v_{\max} \) to a consumer. The consumer does not know what \( v_{\max} \) is, and therefore she
cannot detect such deviation and adjust her inference. We rewrite condition (1) by replacing \( v_{\max} \)
with \( v_{j'} \). Irrespective of whether condition (1) is binding or not, such deviation brings no profit
gain to the platform because the platform anyhow at most extract \( p^*_P \) from a consumer. Next,
we consider the seller’s deviation incentive. Since the seller has same information as consumers,
consumers make no inference from price deviation. Suppose a seller deviates to drop the price from
\( p^*_P \), the retail platform has strict incentive to recommend another product given that consumers
would not detect and thus make no inference from the retailer’s deviation. The seller loses profit by
deviation. Consider the seller deviates to a higher price, even the platform recommends its product,
local deviation is not profitable; nor the global deviation that make condition (1) binding. This is
because the seller loses even more demand.

3.2. Sponsored Ad Auctions

For a representative consumer, the platform holds a second-price auction to sell the prominent
position to the sellers. Denote the equilibrium price as \( p^*_A \), where the subscript \( A \) represents “under
ad auctions”. Again, we are interested in the symmetric equilibrium, where all sellers set the same
price and place the same bid and earn an equal share of the market. We solve the equilibrium by
backward induction.

Consider seller \( j \) who sets price \( p_j \). Let’s first analyze his bidding decision. If he wins the auction,
he takes the prominent position. His demand comes from two sources. First, consumers who visit
seller \( j \) for the first time will stop searching and make a purchase if and only if \( v_j - p_j \geq w - p^*_A \),
which happens with probability \( 1 - G(w - p^*_A + p_j) \), where \( w \) denotes the reservation value from
continuing to search and is given by,

\[
\int_{w}^{\infty} (v - w)g(v)dv = c. \tag{4}
\]

Second, consumers who have visited all sellers will return to buy from seller \( j \) if and only if

\[\text{Chakraborty and Harbaugh (2014) impose the same indifference rule in a cheap talk game.} \]
max_k\neq j v_k - p_A^* \leq v_j - p_j < w - p_A^* and v_j - p_j \geq 0, which happens with probability

\[ D_R(p_j) = \int_{p_j}^{w-p_A^*+p_j} G(v + p_A^* - p_j)^{M-1}g(v)dv, \]

where we use \( D_R(p_j) \) to denote the returning demand given seller \( j \)'s price, \( p_j \). To sum up these two sources of demand, we can write down seller \( j \)'s profit excluding the bidding cost, conditioning on that he wins the ad auction:

\[ S_A^{\text{win}}(p_j) = (1 - \delta) \left[ 1 - G(w - p_A^* + p_j) + D_R(p_j) \right] p_j. \]

On the other hand, if seller \( j \) loses the ad auction, his profit function is,

\[ S_A^{\text{lose}}(p_j) = (1 - \delta) \left[ \frac{1}{M - 1} \left( G(w) + \cdots + G(w)^{M-1} \right)^{(1 - G(w) - p_A^* + p_j)) + D_R(p_j)} \right] p_j \]

\[ = (1 - \delta) \left[ \frac{G(w)(1 - G(w)^{M-1})}{(M - 1)(1 - G(w))} \right] (1 - G(w - p_A^* + p_j)) + D_R(p_j) p_j. \]

Under the second-price auction, seller \( j \) will bid

\[ b_A(p_j) = S_A^{\text{win}}(p_j) - S_A^{\text{lose}}(p_j) = (1 - \delta) \left[ 1 - \frac{G(w)(1 - G(w)^{M-1})}{(M - 1)(1 - G(w))} \right] (1 - G(w - p_A^* + p_j)) p_j. \]

Other sellers will bid \( b_A(p_A^*) \) in equilibrium. Given the bids, we can write down seller \( j \)'s profit function as follows,

\[ S_A(p_j) = \begin{cases} S_A^{\text{win}}(p_j) - b_A(p_A^*) & \text{if } b_A(p_j) \geq b_A(p_A^*) \\ S_A^{\text{lose}}(p_j) & \text{otherwise.} \end{cases} \]

Let’s denote \( p_A^{\text{win}} = \arg \max_p S_A^{\text{win}}(p), \ p_A^{\text{lose}} = \arg \max_p S_A^{\text{lose}}(p) \) and \( p_A^b = \arg \max_p b_A(p) \). By Anderson and Renault (1999)’s standard assumption on \( G \), we can show that \( p_A^{\text{win}}, p_A^{\text{lose}} \) and \( p_A^b \) are interior solutions to the first-order optimality conditions. Moreover, Armstrong et al. (2009) have shown that the returning demand \( D_R(p_j) \) is less elastic than the demand from the first visits, \( 1 - G(w - p_A^* + p_j) \). Comparing the expressions of \( S_A^{\text{win}}(p_j), S_A^{\text{lose}}(p_j) \) and \( b_A(p_j) \), apparently, \( S_A^{\text{lose}}(p_j) \) has the largest proportion of demand coming from returning demand, and \( b_A(p_j) \) has the least—in fact, zero—proportion of demand coming from returning demand. Therefore, we must have that \( p_A^{\text{lose}} \geq p_A^{\text{win}} \geq p_A^b \). Based on this relationship, it is then easy to show that, the equilibrium price is given by \( p_A^* = \arg \max_{p_A} S_A(p_j) = p_A^{\text{win}} \), which can be further determined by the following equation.

\[ p_A^* = \frac{1 - G(w) + \int_{p_A^*}^{w} G(v)^{M-1}g(v)dv}{g(w) - \int_{p_A^*}^{w} G(v)^{M-1}g'(v)dv}. \]
Following Wolinsky (1986), we require $p^*_A < w$, otherwise in equilibrium consumers will choose the outside option directly and not participate in the market. This imposes an upper bound on the search cost $c$.

In equilibrium, the consumer surplus, retail platform’s profit, a seller’s profit and social welfare are respectively,

$$C_A = c + w - p^*_A,$$

$$R_A = \delta \left( 1 - G(p^*_A)M \right) p^*_A + b_A(p^*_A),$$

$$= \delta \left( 1 - G(p^*_A)M \right) p^*_A + (1 - \delta) \left( 1 - \frac{M}{M-1}G(w) + \frac{1}{M-1}G(w)^M \right) p^*_A,$$

$$S_A = (1 - \delta) \left[ \frac{1}{M-1}G(w) - \frac{1}{M}G(p^*_A)^M - \frac{1}{M(M-1)}G(w)^M \right] p^*_A,$$

$$W_A = C_A + R_A + MS_A = c + w - G(p^*_A)^M p^*_A,$$

where the retail platform’s profit comes from two parts: commission and advertising revenue.

### 3.3. Comparisons

To facilitate the comparison between the two recommendation strategies, let’s first analyze the market of monopolistic competition with a sufficiently large number of sellers.

**Monopolistic Competition**

By equation (3) it is easy to show that $p^*_P$ increases with $M$ and $p^*_P \to \varpi$ as $M \to \infty$. This is quite intuitive because consumers are expected to get a better match as $M$ increases, which enables the sellers to charge higher prices. On the other hand, by equation (5), we have that $p^*_P$ decreases with $M$ and $p^*_A \to (1 - G(w))/g(w) < \varpi$ as $M \to \infty$. This is also intuitive because higher $M$ leads to more intense competition and thus a lower equilibrium price. These two observations together imply that for sufficiently large $M$, we have $p^*_P > p^*_A$, as formalized by the following proposition.

**Proposition 1 (Equilibrium Price):** For sufficiently large number of sellers in the market, the equilibrium price under personalization is higher than that under the sponsored ads.

Compared with the case of sponsored ads, consumers get better match under personalization, but are expected to pay a higher price. To facilitate comparison, let’s define the total seller profit as the sum of all sellers’ profits.
Proposition 2 (Welfare Analysis): For sufficiently large number of sellers in the market, compared with the case of sponsored ads,

- consumer surplus is lower under personalization;
- retail profit is lower under personalization if commission fee is relatively low and search cost is relatively high;
- total seller profit is higher under personalization;
- social welfare is higher under personalization.

Proof: First, notice that as $M \to \infty$, $C_P \to 0$ and $C_A \to c + w - (1 - G(w))/g(w) > 0$. By continuity of $C_P$ and $C_A$ with respect to $M$, we have the first result. Second, notice that as $M \to \infty$, $R_P \to \delta \overline{v}$ and $R_A \to \delta(1-G(w))/g(w) + (1-\delta)(1-G(w))^2/g(w)$. By taking derivatives and utilizing log-concavity of $1-G$, it is easy to show that as $M \to \infty$, $R_P - R_A$ increases with $\delta$ and decreases with $c$. Moreover, as $\delta \to 0$, $R_P \to 0$ and $R_A \to (1-G(w))^2/g(w) > 0$. This implies the second result. Lastly, as $M \to \infty$, $M \cdot S_P \to (1-\delta)\overline{v}$, $M \cdot S_A \to (1-\delta)(G(w) - G(p^*_A))p^*_A < (1-\delta)\overline{v}$, $W_P \to \overline{v}$ and $W_A \to c + w < \overline{v}$. This implies the third and last results. 

Even though consumers get their best match under personalization, they are charged a monopolistic price and have no incentive to search no matter how small the search cost is as long as it is positive. On the other hand, consumers do not necessarily get their best match from the prominent position under sponsored ads, which incentivizes them to search and leads to more competition among sellers and thus lower equilibrium prices. Consequently in a monopolistic competitive market, the consumer surplus is lower under personalization.

For the retail platform, even though its personalization strategy enables sellers to charge monopolistic prices, it only appropriates $\delta$ fraction of benefit of the personalization and the sellers take the other $1-\delta$ fraction. On the other hand, the retail platform is unable to extract consumer surplus via a monopoly price under sponsored ads, but the ads auction enables it to extract profits from sellers which can more than compensate the loss from the consumer side. Consequently, in a monopolistic competitive market, the retail platform is lower under personalization.

Next, we explore the case with small number of sellers by analyzing the market of oligopolistic competition. The analytical comparison between the two product recommendation strategies is difficult because in general we cannot solve the equilibrium prices $p^*_P$ and $p^*_A$ explicitly from equations (3) and (5). We will resort to a specific distribution of $G$ and numeric studies.
Oligopolistic Competition

For numeric studies, we will focus on the uniform distribution with $G(v) = v$ for $v \in [0, 1]$, which satisfies $g(v) > 0$ for $v \in [0, 1]$ and the standard assumption on $G$ by Anderson and Renault (1999). We have normalized the upper bound $\bar{v}$ to 1 without loss of generality. According to equation (4), we can solve $w = 1 - \sqrt{2c}$. We cannot solve $p^*_p$ or $p^*_A$ explicitly under uniform distribution.

Figure 1 plots the relationship between the equilibrium prices and the number of sellers. The active market participation condition, $p^*_A < w$ implies $c < 1/8$ for the uniform distribution. Given the range of $c$, we find that $p^*_A < p^*_p$ for any $M \geq 2$, as shown by the two cases of $c = 0.01$ and $c = 0.12$ in the figure. This implies that it seems the finding from Proposition 1 can be extended to the case with small number of sellers—personalization leads to a higher price than sponsored ads, at least under uniform distribution of the match values.

Figure 2 compares the retail platform’s profits under the two product recommendation strategies. The left panel shows the case with $M = \infty$. As implied by the second result in Proposition 2 the platform’s optimal product recommendation strategy should be sponsored ads when the commission fee is relatively low and search cost is relatively high, and personalization otherwise. On the right panel of Figure 2 we also plot the case of duopoly competition with $M = 2$. We can see that the duopoly competition case is qualitatively similar with the monopolistic competition case, except that under duopoly, sponsored ads are even more preferred.

Figure 3 compares consumer surplus, total seller profit and social welfare under the two product recommendation strategies. Similar to Figure 1, we make the plots for two cases: relatively low search cost with $c = 0.01$ and relatively high search cost with $c = 0.12$. We find that some of the findings in Proposition 2 get reserved for the case with small number of sellers. Particularly, with small number of sellers, consumer surplus could be higher under personalization when the search cost is relatively high; social surplus could be higher under sponsored ads when the search cost is
relatively low. We also find that it seems the third result in Proposition 2 can be extended to the case with small number of sellers—personalization leads to higher total seller profit than sponsored ads.

4. DISCUSSIONS

4.1. Targeted Ad Auctions

With the advent of data analytics, the retail platform can use perfect information on consumers’ match values and hold targeted ad auctions among sellers. Even improved targetability may deliver potential benefits, retail platforms like Amazon have not yet rolled out targeted ad auctions at large. Wider adoptions of targeted ad auctions may be influenced by recent policy changes regarding stringent consumer data protection (e.g., the General Data Protection Regulation and the California Consumer Privacy Act). To contribute to the ongoing debate over this new and controversial practice, we discuss potential market outcomes under targeted ad auctions.

We assume that it can offer the finest segmentation of consumers by allowing sellers to target each individual consumer by disclosing all relevant information of consumers, such as their demographics and behavioral characteristics to all sellers. To summarize, we assume that for a representative

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As argued by Levin and Milgrom (2010), the retail platform may not want to disclose all the information to sellers, because this creates many thin submarkets and thus reduce advertising revenue. It is beyond the scope of the paper to study the optimal targeted sponsored ads auctions; moreover, this is not a concern for a monopolistic competitive market with sufficiently large number of sellers.
Figure 3: Consumer surplus, total seller profit and social welfare under two alternative product recommendation strategies.
consumer, the platform discloses her match values to all sellers and then holds a second-price auction to sell the prominent position to the sellers. Again, we are interested in the symmetric equilibrium, where all sellers set the same price $p^*_T$.

If multiple sellers with the same price submit the same highest bid, the retail platform is indifferent in choosing one of them as the winner. We impose the tie-breaking rule that in this case the retailer will choose the seller with the highest match value as the winner. In another word, we assume that given the retail platform earns the same profit among multiple sellers, he will choose the one that maximizes consumer surplus. Given this tie-breaking rule, we are interested in the following equilibrium. For each consumer, the seller with the highest match value wins the auction; consumers believe the prominent seller has the highest match value and thus do not search. In the following, we first solve the sellers’ bids and then their equilibrium price.

Suppose seller $j$ deviates from $p^*_T$ to set price $p_j$. Let’s first analyze his bidding decision for a representative consumer. If he wins the auction, he takes the prominent position, and the consumer believes he has the highest match value. Therefore, the consumer stops searching if and only if $v_j - p_j \geq w(v_j) - p^*_T$. We know $v_j > w(v_j)$, so in equilibrium with $p_j = p^*_T$, this condition is always satisfied. By the same argument as with the case of personalized product recommendation, we only need to consider local deviations of $p_j$ around $p^*_T$ such that $v_j - p_j \geq w(v_j) - p^*_T$ holds. Given the consumer stops searching, he makes a purchase if and only if $v_j \geq p_j$. Therefore, the seller’s profit from the consumer excluding the bidding cost is $(1 - \delta)1(v_j \geq p_j) p_j$; on the other hand, if the seller loses the ad auction, his profit from the consumer is zero. Under the second-price auction, the seller will bid

$$b_T(v_j, p_j) = (1 - \delta)1(v_j \geq p_j)p_j.$$ 

Next, we calculate the seller’s profit function. There are three cases to consider. First, $p_j > p^*_T$, in which case the seller will win the auction as long as $v_j \geq p_j$. The seller’s profit is then,

$$S_T(p_j) = (1 - G(p_j))(1 - \delta)[p_j - (1 - G(p^*_T)^{M-1})p^*_T].$$

Second, $p_j < p^*_T$, in which case the seller will win the auction if and only if $v_j \geq p_j$ and $v_k < p^*_T$ for $\forall k \neq j$. The seller’s profit is then,

$$S_T(p_j) = (1 - G(p_j)) G(p^*_T)^{M-1}(1 - \delta)p_j.$$  

\[\text{Notice that even though sellers have superior information over consumers about their match values, sellers cannot use prices to signal their private information, because no price discrimination is allowed and thus at an aggregated level, all sellers are of the same type.}\]
Lastly, \( p_j = p_T^* \), in which case the seller will make positive profits in an auction only if he is the only bidder. The seller’s profit is then,

\[
S_T(p_j) = (1 - G(p_T^*)) G(p_T^*)^{M-1}(1 - \delta)p_T^*.
\]

To summarize, the seller’s profit function is,

\[
S_T(p_j) = \begin{cases} 
(1 - G(p_j)) G(p_T^*)^{M-1}(1 - \delta)p_j, & \text{if } p_j \leq p_T^*, \\
(1 - G(p_j))(1 - \delta) [p_j - (1 - G(p_T^*)^{M-1}) p_T^*], & \text{otherwise}.
\end{cases}
\]

There is no pure strategy price equilibrium. The intuition is as follows: if a seller sticks to the equilibrium price, then the sellers earns profit if and only if no other sellers comes. If the seller deviates to a higher price, he then can make profit even other sellers come. If the seller deviates to a lower price, he wins if no other sellers is present. Upon winning, the seller can obtain higher demand because the consumers is more likely to be able to afford the product due to the lower price. In summary, the seller may deviate to set either a price or a low price. Next, we discuss the mixed strategy price equilibrium. We compare the price level under sponsored ad auctions and under targeted ad auctions. The equilibrium price in the case of sponsored ads is lower than the lower bound of the support of mixed strategy under targeted ads. This is because a price as in the sponsored ads will trigger consumers to search with probability one. Hence, consumers would expect a higher price level if ad auctions become targeted.

4.2. Endogenous Commission Fees

Our analysis compares platform profitability under personalization and sponsored ads auctions by treating commission fees that a retail platform appropriates from sellers to be exogenously given. Endogenizing commission fees potentially leads to two effects. First, the platform could potentially charge a higher commission fee and earns a higher profit because sellers earn higher profit under personalized product recommendation compared with the case of sponsored ads. Second, if sellers choose commission fees as financial incentives to get their products recommended, the platform may bias personalized recommendation toward a more profitable product, which may hurt consumers.

5. Concluding Remarks

Big data on retail platforms has profoundly influenced retailers in multiple dimensions: better demand and supply forecast, price discrimination, new product design, etc. In this research, we
The first goal of the research is to provide a unified framework to build the linkage between data and consumer search. Then we examine how a retailer’s use of data determines the creation and distribution of the total social surplus among the retail platform, consumers and sellers. Data-empowered personalization may end up a *de facto* collusive outcome: sellers all charge monopoly prices and consumers purchase the recommended product that delivers the highest match value without search. The retailer appropriates surplus from consumers through product efficiency. Personalization traps consumers while benefiting sellers. Without heavily relying on data, the retailer can still hold ad auctions in which all sellers compete for the prominent position so that consumers search it first. This regime results in lower-than-monopoly price level. Consumers actually can benefit from product inefficiency and costly search. In this case, the retailer appropriates surplus from sellers. Lastly, we explore possible targeted ad auctions and give a discussion on price levels under targeted and non-targeted ad auctions.

On a final note, our examination of the change in the split of social welfare among consumers, sellers and retail platform when data can be vastly used for personalized recommendation can potentially contribute to ongoing debates regarding new consumer data protection policies across the globe.
REFERENCES


