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Personalized product recommendations and firm performance

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ABSTRACT

This paper investigates the incentives of e-commerce platforms to show personalized recommendations and its effects on performance. A theoretical framework is developed that characterizes the optimal decision policy of a firm, given current state of shoppers. The key finding is that the firm must always show recommendations to shoppers in the high state above a certain price or value threshold. In the low state, recommending is optimal if the "salience effect" is above a threshold that maximizes discounted future stream of profits. An empirical model provides support to the theoretical findings, highlighting the reputation effects of personalized recommendations, using browsing and purchase data from a Finnish multi-product platform. While recommendations are associated with a 29% increase in firm revenue, relevance of such recommendations potentially boost revenue by a significant 30%. Furthermore, strong evidence is presented that consumer state is endogenous in firm revenue regressions. A three-step IV process extracts the direct effect of consumer state on revenue which shows positive association between reputation effects and firm performance.

1. Introduction

1.1. Motivation

Personalized recommendations have evolved to be an integral part of the online shopping experience. While economics and marketing literature have largely focused on the impact of recommender systems on consumer choices online, information systems and computer science has focused on their algorithmic design and improving efficiency (Adomavicius and Tuzhilin, 2005). However, little research has been done to capture firm incentives that motivate use of recommendation agents in electronic markets. Online platforms today, leverage various sales support tools to improve conversion rate. Two of the most popular are recommender systems (generated by the firm) and online review systems (generated by shoppers). Recommender systems are widely used to inform and persuade shoppers to consider alternative products as they evaluate competing offerings, thereby converting browsers into buyers, increasing loyalty and improving consumer retention (Adomavicius and Tuzhilin, 2005; Adomavicius et al., 2018; Chen et al., 2004; Fleder and Hosanagar, 2009; Haubl and Murray, 2003; Hennig-Thurau et al., 2012; Senecal and Nantel, 2004; Xiao and Benbasat, 2007). While increasing the relevance of a recommendation has been the focus of academic research, it is not clear that maximizing predictive accuracy is the eventual goal of all recommender systems (Hosanagar et al., 2008). Several studies have provided evidence on how online recommendations significantly pull consumers' willingness to pay in the direction of the recommendation (Adomavicius et al., 2018; Senecal and Nantel, 2004; Amatriain and Basilico, 2016; Benlian et al., 2012; Kumar and Benbasat, 2006).

The importance of recommender systems in today's digital world is manifested in the firms' willingness to invest in acquiring and improving these systems, for example, the much publicized Neflix prize that "sought to substantially improve the accuracy of predictions about how much someone is going to enjoy a movie based on their movie preferences".[2]. Firms deploy recommender systems online that are either provided by third-parties or developed in house. In this paper, we focus on the former, where a firm incurs a direct cost as a function of the purchases via recommendations. Recommender systems predict with varying degrees of accuracy what is most relevant for potential buyers and display these predictions as shoppers browse, so as to help them make more informed choices or even to influence consumer preferences (Haubl and Murray, 2003; Hennig-Thurau et al., 2012).

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[2] The million dollar Netflix prize (http://www.netflixprize.com/) was awarded to the team "Bellkor Pragmatic Chaos" in 2009 for improving Netflix's recommendation accuracy by 10%

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This paper investigates the incentives of online platforms to show such recommendations and formally outline conditions under which they might improve performance. Furthermore, the trade-off between relevance of a recommendation and price of the recommended good is examined in detail in the context of firm's reputation. Given the state of the consumer, we examine optimal policies of the firm based on current profits and transition probabilities of shoppers switching between states. State {H,L} is determined by the reputation of firm generated recommendations, where in state H, consumer purchases via recommendations and in state L, via search alone. Deploying recommendations online or allowing consumers to only search is the decision variable in our model, which in equilibrium, is a trade-off between price of the recommended good and relevance of the recommendation to the consumer. The key questions addressed in this paper are: How do personalized recommendations impact firm revenue? Does the relevance of recommendations have an impact on firm revenue? How does reputation of recommendations determine optimal decision policy for online platforms?

1.2. Literature review

As stated by Stiglitz (1989), in the absence of information, products may be viewed as perfect substitutes, but as information becomes available, they may become imperfect substitutes, giving rise to search costs in identifying one's match quality (Stiglitz, 1989). Online markets are often associated with enlarged consideration sets, simply due to larger set of alternatives compared to physical stores (Punj and Moore, 2009; Close and Kukar-Kinney, 2010; Hauser, 2014). This raises consumer search costs as shoppers aim to find the product most relevant to them. Firms recognize the existence of increasing search costs incurred by the consumer with an increase in available information. Therefore, to maximize purchase likelihood and performance, firms adopt numerous strategies with the aim of reducing such costs, such as providing product information on prices, availability, ease of use, to name a few, via online recommendations. As personalized recommendations help guide potential buyers on their search path and lead them to their 'best-matched' good, it builds a reputation of such firm-generated instruments (Fleder and Hosanagar, 2009; Chen et al., 2004; Hosanagar et al., 2008). Relevance of firms' recommendations in the future are dependent on its past performance. Assuming consumers can judge quality with complete accuracy after they have purchased a good, irrelevant recommendations will have a lifetime of only one period. Economic literature has studied extensively the relationship between firm pricing strategy and asymmetric market information. Typically in multi-period games, firms may need to practice predatory or limit pricing in the short-run, so as to maximize future pay-offs under incomplete information (Milgrom and Roberts, 1982a,b; Kreps and Wilson, 1982). It has been established that firms with high quality offerings aim to maintain their reputation, as it is rewarded with high prices and high profits in the long-run (Klein and Leffler, 1981; Shapiro, 1982; Allen, 1984; Houser and Wooders, 2006). A large class of goods do not satisfy the assumption of perfect consumer accuracy (Klein and Leffler, 1979; Dybvig and Spatt, 1980), therefore firms need to take reputation effects into account while choosing optimal policy (Mailath and Samuelson, 2001; Hörner, 2002; Cabral and Hortacsu, 2010). The findings in this study resonate with literature to the extent that showing recommendations to shoppers who strictly buy via search may be costly for the firm, however, may be optimal from the long-term policy design perspective.

Impact of firm reputation is twofold. Firstly, relevant recommendations are more likely to get repeat buyers, especially ones with relatively high search costs. Secondly, they are also more likely to receive new consumers who are dissatisfied with their current options. Therefore, firms with more relevant recommendations, will in the long run have a larger consumer base and in turn higher revenue. Rogerson (1983) shows via number of theory-driven empirical tests that differences in feedback histories lead to differences in the prices of substitutes, across sellers with different feedback aggregates (Rogerson, 1983). One of the key findings of this study is that, in order to switch shoppers from buying via search to recommendations, relevance of a recommendation must be sufficiently high. Therefore, incentivizing those who buy via recommendations is more profitable for the firm in the long run. The empirical analysis in this study points to evidence on consumer state being endogenous to the model which stems from unobserved reputation effects. We show that reputation of firm generated recommendations have a significant positive impact on firm revenue, which translates to clear incentives for firms to improve relevance of product recommendations.

The rest of the paper is arranged as follows. A theoretical framework is developed in Section 2 to formalize conditions under which it is optimal for firms to recommend, given that consumers either purchase via recommendations or search alone. Section 3 provides a description of search and purchase data from a multi-product online platform during 2014–16, which is further used in the empirical analysis in Section 4.

2. Model

In this paper, we study a multi-product online platform's optimal decision policy to show product recommendations at a cost or let consumers obtain product information via search alone. Consider a set-up where the firm offers n products and has the option to show a recommendation at each period for every consumer. Based on the number of 'success events' the firm incurs a cost, C, to a third party that designs the recommendation engine. In other words, for each successful purchase via recommendation, firm pays to the third party a percentage, x of the total price, P_R of recommended product, R. Firms choose to deploy recommendation engines on their platforms either to improve purchase likelihood by showing personalized, relevant product suggestions, or to increase sales diversity by increasing consideration sets of consumers, as they engage in online search. As the firm hosts a number of sellers/ brands on its platform, the recommendation policy is a binary decision variable: to recommend or not, given prices are provided by suppliers individually. For the sake of simplicity, it is assumed that ex-ante, the firm knows the value of good i, V_i.

V_i is made of two components. One is the baseline utility derived from good i, which is constant for the entire mass of consumers. The other component varies as it is dependent on individual match quality that consumers ascertain through search and learning. This paper investigates specifically under which circumstances it is optimal for the firm to recommend, given the state of the consumer, $s \in \{H, L\}$. Consumers typically have varying degrees of trust on product recommendations offered by different platforms. The model assumes that in state H, consumer buys the recommended good, while in state L consumer buys the searched good. The state implicitly reflects the reputation of the firm recommender system to the consumer. Intuitively, if a recommender system consistently recommends the most relevant products to the consumer, then it would have a good reputation. In that case, recommendations would influence choice to a greater extent than would be the case if it often recommends irrelevant products. One of the central assumptions of the model based on Hosanagar et al. (2008) is that, a consumer's satisfaction with the recommender system on a retailer website is assumed to be reflected in her purchase behavior. In other words, if the retailer offers relevant recommendations to consumers, they are more likely to click on them and ultimately purchase the recommended good, thereby developing a sense of trust in such recommendations. This, in turn, improves the reputation of the underlying recommender system over a period of time. Therefore, purchases through recommendations signal a higher reputation of the firm's recommender system as compared to purchases via search.

Purchase likelihood and firm's performance heavily depend on the state of the consumer, therefore, in designing optimal policy firms have to determine when it is profitable to incentivize consumers moving from one state to another. The current state of a consumer is determined by her action in the previous period: if she is in state H in period t and purchases the recommended good, in period $t+1$ she remains in state H, however, if she purchases a good that was not a recommendation, with probability q, she transitions to state L. Similarly, if consumer is in state L in period t, purchases a good that was not recommended, she remains in state L and if she does purchase a recommended good, with probability $q^{'}$ she transitions to state H. $q, q^{'}$ are transition probabilities that represent the persistence of reputation of recommendations on the said platform. Without loss of generality, it is assumed $q = q^{'} = 1$ which studies the extreme case when reputation effects are extremely persistent. This means that when a consumer in state L views a product recommendation with a high perceived match quality, she immediately transitions to state H, while a consumer in state H immediately transitions to state L when presented with an irrelevant recommendation.

Recommendations are assumed to have a *salience effect*, δ_S (Hosanagar et al., 2008) which can be interpreted as a temporary boost in perceived match quality of a good. Now, consumer states are largely indicative of the relevance of recommendations, hence their reputation. Intuitively, if a recommendation engine structurally shows relevant recommendations, it will have a good reputation and in turn impact consumer choice to a larger extent than if it shows irrelevant recommendations. This leads to a key assumption $\delta_H > \delta_L$.

The utility of the consumer purchasing good i in period t is given as:

$$U_{it} = v_{i,t} + 1\delta_{s,t} + \epsilon_{i,t} \tag{1}$$

where $1 = 1$ if i is a recommended good and $\epsilon_{i,t}$ captures all the factors that affect utility, but are not observable to the firm.

It is assumed that $\epsilon_{i,t}$ is i.i.d type-I extreme value distributed, which represents the idiosyncratic tastes of consumers for good i observable just before purchase. Then following a multinomial logit specification, the probability of buying good i in period t can be expressed as:

$$Pr\left\{i, t \middle| S\right\} = \frac{e^{v_{i,t}+1\delta_{s,t}}}{1 + \sum e^{v_{i,t}+1\delta_{s,t}}} \tag{2}$$

The firm's objective, as below, is to maximize the expected discounted future stream of profits with a decision policy that affects consumer choice per period:

$$\max_D E\left(\prod[D]\right) = E\sum_{t=1}^{\infty}\beta_t(p_t - 1C_t) \tag{3}$$

where $\beta \in [0, 1]$ is the discount factor, p the price and C the cost incurred by the firm to show recommendations on its platform, when it is following policy D.

Let $P(D)_{t,s,s'}$ be the probability of next period state being $s^{'}$ when current period state is s and $\pi(D)_{t,s}$ denote the current period profit from following policy D_t. Then lifetime profit functions in state $\in \{H,L\}$can be expressed as the following Bellman equations:

$$\prod_H\left(D\right) = \pi_H + \beta\left[P_{HH}\left(D\right)\prod_H\left(D\right) + P_{HL}\prod_L\left(D\right)\right] \tag{4}$$

$$\prod_L\left(D\right) = \pi_L + \beta\left[P_{LL}\left(D\right)\prod_H\left(D\right) + P_{LH}\prod_L\left(D\right)\right] \tag{5}$$

Recommendation policies have varying considerations depending on both present and future state of the consumer. The trade-off between firm revenue and relevance to buyer must be taken into account, while recommending in each state. In this framework, the firm has four exhaustive policies to consider:

	Policy Specifications
D1	Recommend in H Recommend in L
D2	Recommend in H Search option in L
D3	Search option in H Recommend in L
D4	Search option in H Search option in L

To determine Eqs. (4) and (5), per period profits and transition probabilities are derived as follows:

Policy **D1**

$$\begin{aligned} P_{HH} &= \frac{e^{V_R+\delta_H}}{e^{V_R+\delta_H} + e_S^V + 1} \\ P_{LL} &= \frac{e^{V_S} + 1}{e^{V_R+\delta_L} + e^{V_S} + 1} \\ \pi_H &= \frac{e^{V_R+\delta_H}\left(P_R - C_R\right) + e^{V_S}P_S}{e^{V_R+\delta_H} + e^{V_S} + 1} \\ \pi_S &= \frac{e^{V_R+\delta_L}\left(P_R - C_R\right) + e^{V_S}P_S}{e^{V_R+\delta_L} + e^{V_S} + 1} \end{aligned} \tag{6}$$

Policy **D2**

$$\begin{aligned} P_{HH} &= \frac{e^{V_R+\delta_H}}{e^{V_R+\delta_H} + e^{V_S} + 1} \\ P_{LL} &= \frac{e^{V_S} + 1}{e^{V_R} + e^{V_S} + 1} \\ \pi_H &= \frac{e^{V_R+\delta_H}\left(P_R - C_R\right) + e^{V_S}P_S}{e^{V_R+\delta_H} + e^{V_S} + 1} \\ \pi_S &= \frac{e^{V_R}\left(P_R - C_R\right) + e^{V_S}P_S}{e^{V_R} + e^{V_S} + 1} \end{aligned} \tag{7}$$

Policy **D3**

$$\begin{aligned} P_{HH} &= \frac{e^{V_S}}{e^{V_R} + e^{V_S} + 1} \\ P_{LL} &= \frac{e^{V_S} + 1}{e^{V_R+\delta_L} + e^{V_S} + 1} \\ \pi_H &= \frac{e^{V_R}\left(P_R - C_R\right) + e^{V_S}P_S}{e^{V_R} + e^{V_S} + 1} \\ \pi_S &= \frac{e^{V_R+\delta_L}\left(P_R - C_R\right) + e^{V_S}P_S}{e^{V_R+\delta_L} + e^{V_S} + 1} \end{aligned} \tag{8}$$

Policy **D4**

$$\begin{aligned} P_{HH} &= \frac{e^{V_S}}{e^{V_R} + e^{V_S} + 1} \\ P_{LL} &= \frac{e^{V_R} + 1}{e^{V_R} + e^{V_S} + 1} \\ \pi_H &= \frac{e^{V_R}\left(P_R - C_R\right) + e^{V_S}P_S}{e^{V_R} + e^{V_S} + 1} \\ \pi_S &= \frac{e^{V_R}\left(P_R - C_R\right) + e^{V_S}P_S}{e^{V_R} + e^{V_S} + 1} \end{aligned} \tag{9}$$

Given a specific policy choice in state i, pair-wise comparisons are made between policy combinations in state j. In other words, we compare policies D1 and D3 in state H, when the firm definitely chooses to recommend in state L and D2 and D4 in state H, when the firm definitely chooses to not recommend or only have the search option in state L. This leads to the following conditions:

Condition 1: Given, firm always recommends in state L, it will recommend also in state H, if and only if $\prod_H(D3) - \prod_H(D1) < 0$.

Condition 2: Given, firm never recommends in state L, it will recommend in state H, if and only if $\prod_H(D4) - \prod_H(D2) < 0$.

From Eq. (4), we can express Condition 1 as:

$$\frac{\pi_H{}^{D3}\left(1-\beta P_{LL}^{D3}\right)+\pi_L^{D3}\beta P_{HL}^{D3}}{1-\beta\left(P_{HH}{}^{D3}+P_{LL}^{D3}\right)+\beta^2\left(P_{HH}{}^{D3}P_{LL}^{D3}-P_{LH}^{D3}P_{HL}^{D3}\right)}-\frac{\pi_H{}^{D1}\left(1-\beta P_{LL}^{D1}\right)+\pi_L^{D1}\beta P_{HL}^{D1}}{1-\beta\left(P_{HH}{}^{D1}+P_{LL}^{D1}\right)+\beta^2\left(P_{HH}{}^{D1}P_{LL}^{D1}-P_{LH}^{D1}P_{HL}^{D1}\right)}<0$$

and Condition 2 as:

$$\frac{\pi_H{}^{D4}\left(1-\beta P_{LL}^{D4}\right)+\pi_L^{D4}\beta P_{HL}^{D4}}{1-\beta\left(P_{HH}{}^{D4}+P_{LL}^{D4}\right)+\beta^2\left(P_{HH}{}^{D4}P_{LL}^{D4}-P_{LH}^{D4}P_{HL}^{D4}\right)}-\frac{\pi_H{}^{D2}\left(1-\beta P_{LL}^{D2}\right)+\pi_L^{D2}\beta P_{HL}^{D2}}{1-\beta\left(P_{HH}{}^{D2}+P_{LL}^{D2}\right)+\beta^2\left(P_{HH}{}^{D2}P_{LL}^{D2}-P_{LH}^{D2}P_{HL}^{D2}\right)}<0$$

The above conditions must be satisfied such that there exists a $[P_R^*, x^*]$ (where, $C_R = xP_R$), for which it is globally optimal for the firm to recommend in state H, irrespective of the choice in state L. For simplicity, it is assumed in this set-up that the firm knows consumers' initial state. As described so far, the payoff function of the retailer is dependent on three key variables in each state, namely, value of the good being sampled via search or recommendation (V_S, V_R), price of the good being sampled via search or recommendation (P_S, P_R) and the salience effect state (δ_s). In order to outline the optimal policy decision of the firm, the relationships between these variables are studied in detail, based on the pair-wise comparison of the policy combinations as per conditions (1) and (2). In that, few notable cases are examined to pin down the optimal price, value and salience thresholds computationally, both for state H and L.

Case 1: $V_S > V_R$.

This is a trivial case. Firms in this scenario have no incentive to show recommendations for one of two reasons: 1) consumer derives lower utility from recommendations. This may be due to lower costs in time spent on search, or greater awareness of the firm's product offering; 2) there are costs associated with deploying a recommendation agent on the firm's retail platform. Typically every online platform invests in personalized recommendations either developing the algorithms in-house or commits to a subscription with external service providers. So, if consumers get higher utility from searching themselves and the firm needs to bear a cost of recommending, then it is not profitable to show recommendations.

Case 2a: $V_R > V_S; P_R > P_S$.

When consumers derive higher utility from purchasing a recommended good and the corresponding price is sufficiently high, it is profitable for the firm to recommend. In this case, not only is the purchase likelihood high, but also the willingness to pay. This leads to the following proposition:

Proposition 1. *When $V_R > V_S$, it is optimal for seller to recommend when P_R is sufficiently high, such that $\frac{P_R}{P_S} > \overline{P}$*

where, $\overline{P}$= max[$\prod_H(D3) - \prod_H(D1)$, $\prod_H(D4) - \prod_H(D2)$], where D1, D2, D3 and D4 represent the set of exhaustive policy specifications for the firm. In other words, $\overline{P}$ is determined via the inequality conditions specified in **Condition 1** *and* **Condition 2**, *wherein pair-wise comparisons are made between firm's payoff functions in state j, given specific policy choice in state i.*

Fig. 1 depicts **Condition 1** and **Condition 2** for Case 2a. It is evident

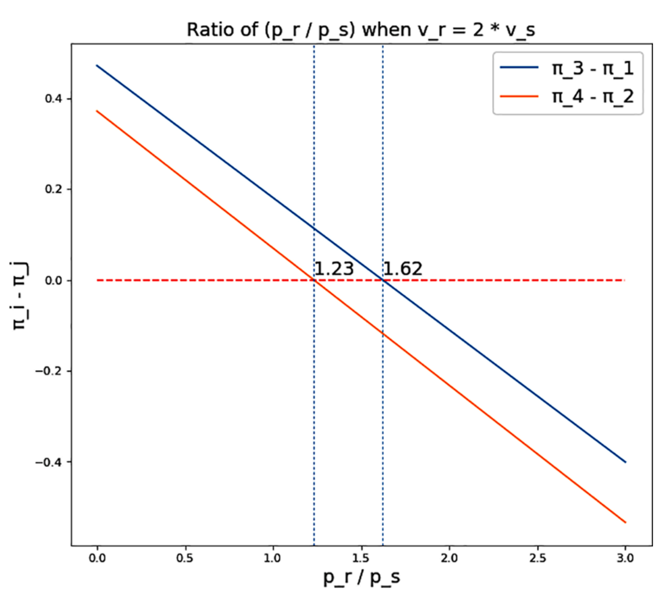

Fig. 1. Case 2a.

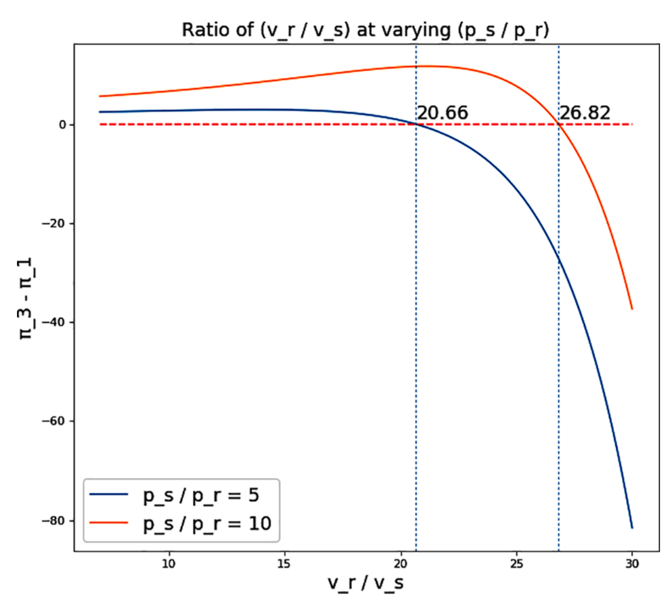

Fig. 2. Case 2b: Comparing D3 and D1.

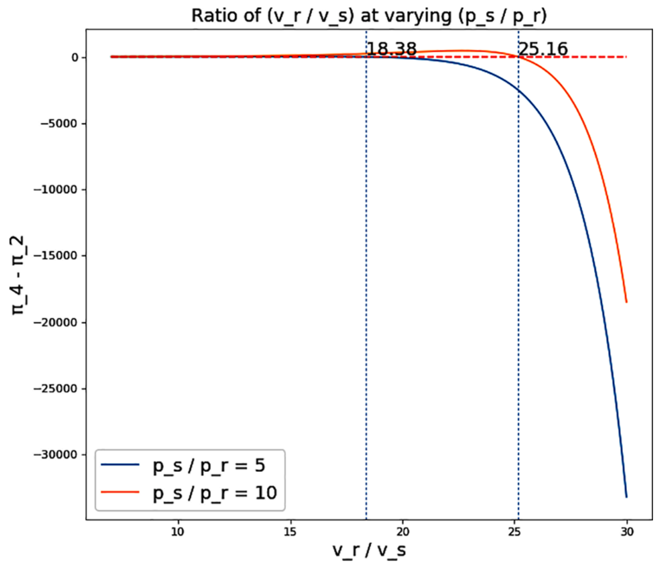

Fig. 3. Case 2b: Comparing D4 and D2.

that as P_R increases, the resultant expressions derived from the above conditions keep decreasing. By simulation, it is possible to derive the optimal value of $\overline{P} = 1.62$, that would make recommending profitable for the firm in either state, {H,L}. As firms improve the relevance of product recommendations, their value to potential shoppers increase. Relevant recommendations help convert potential buyers to paying consumers. However, firm's performance depends on the trade-off between value of the recommendation itself and its price. This trade-off is essentially quantified according to Proposition 1.

Case 2b: $V_R > V_S; P_S > P_R$.

Proposition 2. *When $P_S > P_R$, it is optimal for seller to recommend if and only if V_R is sufficiently large, such that $\frac{V_R}{V_S} > \overline{V}$*

where, $\overline{V}$ can be obtained from **Condition 1***: $\prod_H(D3) - \prod_H(D1) < 0$ and* **Condition 2***: $\prod_H(D4) - \prod_H(D2) < 0$. The result may seem counter-intuitive as recommending a lower priced good over a high priced good should never be profitable for the firm. However, a fraction of potential buyers value product recommendations only if they are able to get a better deal in terms of price through a recommendation. Given that firms are incurring costs to show recommendations in order to boost sales and retain consumers who are highly likely to buy via recommendations, they may find it profitable to suggest a lower priced product if it guarantees a successful purchase. This is relevant especially if firms are in earlier stages of the maturity curve in the electronic commerce environment. During this phase improving consumer engagement on the platform is crucial and if value of recommendations is high enough for the shopper, ($\overline{V}$) that it increases likelihood of purchase significantly, then it would still be profitable for the firm.*

Figs. 2 and 3 respectively depict **Condition 1** and **Condition 2** for Case 2b. It is evident that as V_R increases, the resultant expressions derived from the above conditions keep decreasing. Interestingly, as the gap between the high priced option that the consumer samples via search and the low priced recommendation widens, $\overline{V}$ decreases at a slightly slower rate. For a very low P_R and a very high P_S, the threshold at which it starts becoming profitable for the firm to recommend is comparatively much higher. Simulating several scenarios, it is possible to pin down the optimal value of $\overline{V} = 20.66$, that would make recommending profitable for the firm in either state when $P_S/P_R = 5$. In summation, when price of the recommended good is sufficiently high, recommending is always profitable. But even when the recommended option is lower priced compared to the searched option, it would still be profitable to recommended as long as value of the recommendation to the shopper is sufficiently high.

Given the model structure, it is arguably easier for the firm to make a choice in state H than L, as consumers will buy the recommended product in H, by definition. However, in state L, firm has no incentive to show recommendations if considering short-term gains only. In other words, irrespective of the price, recommending may be less profitable in terms of per-period profits. In state H, the per-period performance objective is dominant when deciding optimal firm policy, while in state L firm policy should ideally aim at restoring its reputation so as to optimize long-term profits, even if it is sub-optimal in the short run. This implies that if $\delta_H > \delta_L$, then firms might have incentive to potentially switch consumers from state L to H in the next period. So, the objective of the firm is twofold: not only does it aim to improve performance via the recommendation policy, but also improve reputation of the firm in terms of relevance of its offering to consumers. As shown already, policies D1 and D2 are profitable in state H as compared to D3 and D4. Using similar methodology that leads to Propositions 1 and 2, we now compare policies D1 and D2 in state L, when the firm definitely chooses to recommend in state H. This leads to the following condition:

Condition 3: Given, firm always recommends in state H, it will recommend also in state L, if and only if $\prod_H(D2) - \prod_H(D1) < 0$. Simulating several scenarios as per the following cases leads to Proposition 3.

Case 3a: $V_R > V_S; P_R > P_S$.

This case is trivial as the firm will always recommend if potential buyers derive higher utility from a product recommendation compared to searching themselves. Moreover if the recommended alternative is also priced higher, it is the obvious choice. A typical case when a shopper would opt for this alternative in the low state is if she becomes aware of a new product via recommendation. Firms often tend to increase sales diversity by recommending new products to potential buyers. In this case the firm not only has a higher current profit since $P_R > P_S$, but also higher future returns as $V_R > V_S$ would imply $\delta_H > \delta_L$.

Case 3b: $V_R > V_S; P_S > P_R$.

Proposition 3. *When $P_S > P_R$, it is optimal for seller to recommend if and only if δ_H is sufficiently large, such that $\frac{\delta_H}{\delta_L} > \overline{\delta}$*

where $\overline{\delta}$ can be derived from $\prod_H(D2) - \prod_H(D1) < 0$ as specified in **Condition 3***. The result may seem surprising at the outset. If the search option is higher priced and a shopper is in state L, then ideally the firm should not recommend. However, as objective of the firm is to maximize expected discounted future stream of per-period profits, therefore in some cases it may the optimal choice. By definition, $\delta_H > \delta_L$ as $V_R > V_S$, so there must be a δ_H such that if a shopper switches state form L to H, all future profits are high*

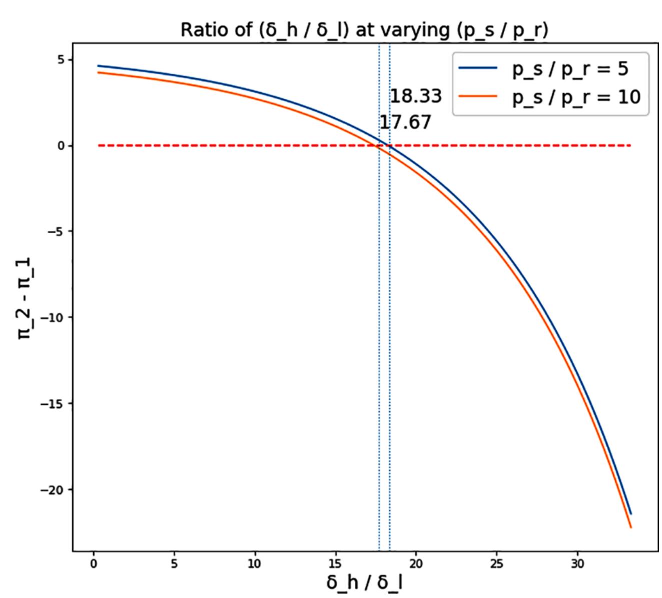

Fig. 4. Case 3b.

Fig. 5. Clickstream data example: The point of purchase is highlighted in red.

Fig. 6. Online recommendations example (source:amazon.co.uk): Top panel shows viewed book; bottom panels show relevant book recommendations.

enough to compensate for the lower current profit. Fig. 4 *depicts exactly this phenomenon. As* δ_H/δ_L *increases, it becomes more and more profitable for the firm to recommend. Similar to the other cases, we are able to derive computationally the optimal value of* $\bar{\delta}$ *that would make recommending profitable for the firm in state L. However, as* P_S/P_R *increases,* $\bar{\delta}$*, or the level at above which recommending is profitable in state L decreases gradually. This is not surprising, as the limiting case of this would lead us to Case 3a where it is always optimal to recommend.*

3. Data

Click stream data records complete search paths of online shoppers and is a powerful source of information on consumer behaviour in the internet markets. The dataset used for this study contains purchases made by shoppers, whose identity have been anonymized, between November 2015 and March 2016 on a leading Finnish multi-product electronic commerce platform. It is an "Amazon"-like platform for the Finnish market with a diverse assortment from several brands spanning across product categories such as electronics, home, clothing, cosmetics and stationary (Fig. 7 provides the revenue distributions across categories in states H and L). The individual brands determine product pricing, however, it is the platform that controls the algorithm designing relevant product recommendations for shoppers based on their search histories. In other words, if a high priced product is recommended more frequently over its low priced alternative, it is likely to be an outcome of the platform's recommendation strategy as opposed to the individual brand's.[3] As a result, the dataset contains associated search histories leading up to purchases of unique shoppers, duration of visit, number of brands and products, price of goods and related product descriptions of each good viewed. Fig. 5 looks at a typical example of the entire

Table 1
Descriptive statistics 1.

Data sample overview		
Number of H states in sample	14498	
Number of L states in sample	27853	
Total number of repeat buyers	11697	
% of repeat buyers	40.5%	
Number of unique products	68782	
Average search time	Mean	St. Dev.
Search time prior to purchase (in minutes)	11.31	19.69

[3] The data source cannot be revealed due to non-disclosure agreements.

Table 2
Descriptive statistics 2.

Distribution of repeat buyers in various states		
Number of repeat buyers exclusively in state H	977	
Number of repeat buyers exclusively in state L	4543	
Number of repeat buyers in both states H & L	6177	
% of repeat buyers who switch between states only once	65%	
% of repeat buyers who switch between states more than once	35%	
Average search times in various states	Mean	St. Dev.
Search time prior to purchase(in minutes) in state H	32.76	30.02
Search time prior to purchase(in minutes) in state L	23.32	20.43

Table 3
Descriptive statistics 3.

Product distribution in various states	
% of non-unique products purchased in state H	40%
% of non-unique products purchased in state L	60%
% Retailer revenue of non-unique products purchased in state H	32%
% Retailer revenue of non-unique products purchased in state L	68%
Average number of products purchased per session in state H	4.1
Average number of products purchased per session in state L	3.2

consumer journey in the data, from the point she clicks on the first good to the point of purchase (Basu, 2018). A key objective of this study is to investigate the reputation effects of platform generated recommendations, therefore shoppers with no visible purchase history are excluded from the analysis.

For the sake of relevance, browsing sessions of only those users who have made a purchase from the store have been considered. This is because consumers often engage in online search to obtain product prior to visiting the physical stores, where they eventually buy from. All purchases are observed along with the related browsing behaviour of the unique users, since their first arrival at the store. This means, that although all the non-purchase sessions were excluded from the sample, the entire search history was used for this study. So, the final sample including search histories mapped to purchases goes back to March 12, 2014. The richness of the data lies not only in that we are able to map unique agents' search behaviour to purchases, but also to derive insights on consumer preferences on brands, how that evolves over time, to what end they use information aids such as recommendations online, and their impact on buying behaviour. It allows us to examine search and purchase patterns of the representative agent across a diverse set of goods in a multi-product platform, while avoiding heterogeneity of preferences across stores offering substitutes. For each session that culminates into a successful purchase, the data shows if the purchase was via search or a platform generated product recommendation. Recommendation agents cluster consumers based on similar preferences, search behaviour, demographics and several such factors to show a set of relevant products to inform and persuade consumers to buy. Fig. 6 illustrates how recommendations typically appear on online platforms. For each product viewed, there are suggestions based on similar purchases:"Customers who viewed this item also viewed" or "What do customers buy after viewing this item" (see Table 1).

The goal of this study is to investigate firm incentives to deploy recommendations on their online platforms when a fraction of shoppers have a clear preference to buy via search (state L) and the other via recommendations (state H). As shown in Table 2, the sample contains 1000 shoppers that are strictly in state H, 4500 strictly in state L and 6000 in both H and L. Interestingly, on average shoppers spend 9 min less in the store when in state L. This is not surprising as one of the objectives of recommendation engines is to enlarge consideration sets by informing consumers of relevant options available, thereby increasing time spent in store and in turn, improving likelihood of purchase. As supported by theoretical findings in Section 2, when costs are below a certain threshold it is optimal to recommend a relevant good even in state L. Improving reputation of the recommendations may implicitly improve performance in the long run, so it is in the firm's interest to show recommendations of high enough relevance that consumers switch from state L to H. In this particular sample, 65% of repeat buyers have switched between states at least once (Table 2).

The data allows observing purchases made via clicks on recommendations. Table 3 summarizes the product distribution across states in the data sample and it can be observed that a higher percentage of the total revenue is generated from purchases via search (68%), however, purchases via recommendations on average are higher.[4] This implies although shoppers, may not follow recommendations as much but if a recommendation is highly relevant, they buy more on average. This clearly points to the challenge firms face today in realizing the value of allowing recommendations on online retail platforms.

Fig. 7 shows the revenue distribution across categories in both states. Generally speaking, reputation of platform generated recommendations do not have varying effects on revenue generated across product categories. As is observed from the data, electronic goods generate the highest revenue both via recommendations and search, followed by home goods. This is expected as these categories are likely to have higher prices on average compared to the rest. Interestingly, sport goods exhibit twice the revenue via recommendations than search, which is driven by volume, i.e., shoppers simply purchased more in this particular category via recommendations. Although, recommendations positively impact extent of search for search goods, (such as, electronics) and negatively experience goods (such as, beauty and health, there is no clear correlation with revenue generated (Basu, 2018).

4. Empirical analysis

In this section, several sources of empirical evidence on the effects of personalized recommendations on firm revenue are presented. Consider the following linear model in the population:

$$y = \alpha + \beta x + \gamma s + \epsilon \tag{10}$$

where, for each purchase, y represents firm revenue, s, a binary variable that takes the value 1 if consumer was in state H at the purchase event, 0 if in state L and x, a k-dimensional vector of covariates. Among the three population parameters (α, β and γ), we focus primarily on γ which can be interpreted as the effect of consumer state, as defined in the theoretical model, on firm revenue.

As a first step in understanding the relationship between consumer states and firm revenue, we study the OLS estimates of a set of regressors $x = [R, T, Q, I]$, where R = relevance of a recommendation, T = time spent on search, Q = number of searches and I = prior product knowledge. These variables are constructed from the browsing and purchase data described in Section 3. At each purchase session, T is expressed in seconds spent on the platform prior to purchase, while Q is the total number of unique page views during the session that leads to a successful purchase. R and I are derived from the data for the empirical model. In order to calculate I or prior product information from the data, we observe search paths of each shopper from their first arrival to the store till the penultimate session. At each search (product page view) there is transfer of information, only some of which is relevant to the buyer. So, in order to understand how information search influences purchase decisions, search events that do not potentially inform consumers must be filtered out. The idea is to collect only search events that help shoppers make the final choice. To this end, a measure of similarity is defined between products that have been viewed prior to the session of purchase and the purchased good, based on product descriptions

[4] Retailer revenue is calculated as price multiplied by quantity of each product

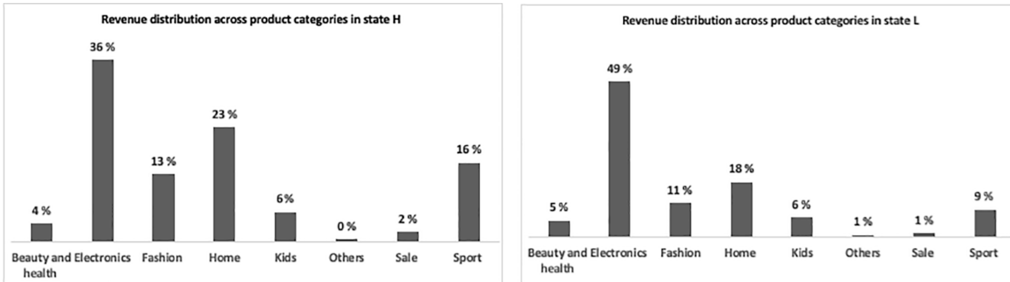

Fig. 7. Revenue distribution by product categories.

(Basu, 2018).

4.1. Calculating measures for Relevance and Prior product knowledge

Each product has a description based on associated attributes or features. Entity-related search on web data is non-trivial, in the sense that the attributes are described in different ways for different products. The objective is to find similar products based on such attributes, hence its essential to find commonality between every word of the attribute vectors (combination of several keywords). A common method in the field of information retrieval, namely Tf-idf (term frequency-inverse document frequency) model is used here to mine relevant words from a large body of text or information set. It is often used as a weighting factor such that importance of a word increases proportionally to the number of times it appears in the document, but is offset by the frequency of the word in the entire collection. Let t_d be the frequency of the term t in a document d, and $d_t^{'}$ be the document frequency or the number of documents in which term t appears. The inverse document frequency means how important a term is in a collection, that is, how common it is across all the documents. Finally, let n be the total number of documents (product descriptions) in the data. Then the term frequency inverse document frequency weight, ω is calculated by,

$$\omega = t_d \times \left(d_t^{'}\right)^{-1}$$

where,

$$\left(d_t^{'}\right)^{-1} = log\frac{n}{d_t^{'}}$$

Once the relevant words from the descriptions have been retrieved, a measure of similarity between the attributes is derived. The *cosine similarity* between two vectors or documents in the vector space is a measure that calculates the cosine of the angle between them. This is a comparison metric between two documents or product descriptions on a normalised space as it not only takes the magnitude of each word count into consideration, but also the angle between the documents. Let us consider vectors x and y, then the cosine of these two vectors is given by the Euclidean dot product:

$$x \cdot y = ||x||||y||cos\ \theta$$

$$S\left(x, y\right) = \frac{x \cdot y}{||x||||y||}$$

Cosine similarity, (S(x,y)) gives how similar goods are based on their product descriptions. Observing similarity scores between products in several random samples of goods, only those products are collected from the browsing history that have a similarity coefficient of 0.4 or above (Basu, 2018). For each purchase session, the entire search history is observed in order to construct similarity scores for each sampled good with respect to the final purchase. Summing over all the similarity scores greater than 0.4 until the final purchase session gives a measure of prior product information, I. R or relevance of recommended products to a shopper is calculated with the same principle, but only restricted to the purchase session (not search history leading up to the session). Summing pairwise comparisons of each recommendation with the purchased item (s) during this session gives a measure of product relevance to shopper's preferences.

Table 4
OLS estimates.

	Dependent variable: Firm revenue	
	(1)	(2)
State (H = 1)	0.228***	0.295***
	(0.020)	(0.011)
Relevance	0.195	0.227***
	(0.026)	(0.018)
Search time	0.139***	0.191***
	(0.061)	(0.056)
Number of searches	−0.067***	−0.069***
	(0.008)	(0.009)
Prior information	0.081	0.079
	(0.011)	(0.012)
Relevance-State		0.305***
		(0.023)
Search time-State		−0.198***
		(0.066)
Number of searches-State		0.042***
		(0.010)
Prior information-State		−0.088
		(0.015)
Constant	0.065***	0.073***
	(0.028)	(0.031)
Observations	40,544	40,544
R^2	0.335	0.378
Adjusted R^2	0.283	0.362
Residual Std. Error	0.017	0.015
Method	OLS	OLS with interaction terms
Time period (search and purchases)	2 years	2 years

*p<0.1; **p<0.05; ***p<0.01.

4.2. Consumer state and firm revenue: OLS estimates

The OLS estimates of firm revenue are reported in Table 4 Columns (1) and (2), along with heteroskedasticity robust standard errors. Column (2) includes the interaction terms of all control variables with the consumer state in order to study their combined effects on firm revenue. Evidently, this improves accuracy of the model. All coefficients except for prior product knowledge, I, are statistically significant at 1% or 5% level.

Recommendations play a critical role in the world of digital commerce and remains a key lever for firms to boost their revenue. The variable of interest in this study is, therefore, the consumer state, where state H indicates purchase via recommendations and L indicates purchase via search. As observed, consumer state being H or purchases via personalized recommendations is associated with a 29% increase in firm revenue. The positive relationship between revenue and personalized recommendations on the retail platform appears to be fairly robust. This effect on revenue clearly points to the incentives of the firm to show personalized recommendations to online shoppers.

Furthermore, as the theoretical model in Section 2 shows, net revenue from recommendations are dependent on the value shoppers derive from them and their willingness to pay a premium (purchasing a recommended good that is high priced). This is reflected in the OLS estimates, as relevance has a high positive impact on revenue when shoppers are in state H (30%). These results clearly indicate the importance of personalization in recommendations, which is rather intuitive, as the likelihood of purchase depends on the shopper's match quality with the recommended product. Therefore, recommendations are profitable provided they are above a certain relevance threshold. As firms invest more in improving the relevance of recommendations, it implicitly increases perceived value, therefore consumers' willingness to pay for the right offering. This allows platforms to optimize cross-sell and upsell opportunities as well as highlight products with higher margins.

Additionally, a positive association between time spent on search and firm revenue is observed. More time spent on search likely affects purchase probability positively, hence online platforms implement several strategies to keep shoppers engaged with the goal of improving conversion rate. Surprisingly, the number of searches or pages (urls) viewed have the exact opposite relationship with revenue. With every additional product page viewed, revenue is likely to go down by approximately 7% in this model. As potential shoppers sift through product pages without spending much time on any page, it signals either recreational browsing or low buying intent. This implies that simply increasing consumer search time online does not necessarily imply higher firm revenue. The quality of search matters. Firms have to design user interfaces and provide relevant information in ways that engage potential buyers truly, it is not sufficient to simply increase traffic.

The OLS estimate of key variable as discussed above, measures the magnitude of association between consumer state and firm revenue, however not necessarily causation (Cameron and Trivedi, 2005). The goal is to estimate revenue impact to any exogenous changes in consumer state. However, whether consumers purchase via recommendations or only search is typically dependent on the reputation of firm-generated recommendations. As discussed extensively in both academic literature and media, firms often invest heavily into improving relevance of recommendations in order to show more and more relevant products to potential buyers. Over time it is likely that they develop a reputation on the relevance of their recommendations. Consumers' willingness to follow such recommendations will be influenced by their past experiences. If recommendations on a platform have a high reputation and trust, it will stimulate a higher conversion rate. As consumer engagement increases, likelihood of purchase also rises, in turn boosting firm revenue. As correlation between a firm's reputation and revenue is expected to be positive, so the estimate would likely be biased upwards. Therefore, the OLS estimate of consumer state alone will overstate the effect of showing recommendations, on firm revenue.

Table 5
Probit model.

	Dependent variable: Consumer state
Preferred state	3.376**
	(0.027)
Relevance	1.931***
	(0.125)
Search time	2.016***
	(0.098)
Number of searches	−0.117
	(0.066)
Prior information	−0.298
	(0.115)
Constant	1.223***
	(0.021)
Observations	40,544
Method	Probit(Step 1 of 3-step IV)
Time period (search and purchases)	2 years

*p<0.1; **p<0.05; ***p<0.01.

Let $Cov(x_i, \epsilon) = 0, \forall i = 1 \ldots k$ and $Cov(s, \epsilon) \neq 0$, such that we have an endogenous dummy variable model (Heckman, 1978). As the state variable is endogenous, OLS will inconsistently estimate parameter of interest, γ. There is both a direct effect via γ and an indirect effect via ϵ, which in turn impacts y. Instead of estimating the first effect only, in this case the OLS estimate combines both effects such that, $\widehat{\gamma} > \gamma$, when both effects are positive. The estimate will be biased upwards if consumers in high state are generating higher revenue and $Cov(s, \epsilon) > 0$. To gain further insight into the nature of the relationship between recommendations and firm performance, we use instrumental variables to isolate the effects of consumer state on firm revenue from other sources of variation.

4.3. *Consumer state and firm revenue: Three-step IV estimates*

The possible endogeneity of consumer state is dealt by means of the instrumental variables method. If there exists a valid set of instruments **z** for consumer state, it will ensure consistent estimation of γ by following the steps below (Renee Adams and Ferreira, 2009; Wooldridge, 2001):

1. Estimate a probit of the determinants of consumer state and obtain the fitted values $\widehat{s_{i,t}}$
2. Regress $s_{i,t}$ on $\widehat{s_{i,t}}$ and $x_{i,t}$, but not $z_{i,t}$ and $x_{i,t}$
3. Regress $y_{i,t}$ on $x_{i,t}$ and the fitted values of the second step

The above is a three step procedure which enables treating a binary endogenous variable with IV regression (Renee Adams and Ferreira, 2009). This procedure is applied to avoid any possibility of a *forbidden regression* which involves direct application of 2SLS to a non-linear model (Angrist and Pischke, 2009). Furthermore, it does not require the binary response model to be correctly specified in step one of the three step procedure (Renee Adams and Ferreira, 2009; Wooldridge, 2001).

Next, we discuss the economic arguments supporting validity of the instrument used, namely, *preferred state*. This variable is derived from historical transactional data of each unique shopper to the penultimate purchase session. It represents the ratio of the total number of purchases via recommendations and the number of purchases via search. This is believed to satisfy the conditions necessary for a valid instrument. The state of the representative agent in the current period is quite significantly influenced by her reputation of the firm's recommendation engine. So, if she has received a number of relevant product recommendations in the past that lead to successful purchases, then the likelihood of her being in state H at time t is higher than being in state L. Higher the reputation of firm generated recommendations, higher is the likelihood that consumers purchase via recommendations at the current time period. The motivation of choosing such a variable is twofold: firstly, the probability that a consumer is going to be in state H at time t increases as the value of the variable, preferred state keeps increasing. The theoretical findings in Section 2 show that the price threshold for a firm to recommend, with the aim of switching potential buyers from L to H is significantly lower. In other words, it is easier, hence more attractive for firms to incentivize high state shoppers to remain in that state every period. Secondly, the instrument should be exogenous in the current framework as consumer's preferred state is unlikely to have a direct impact on revenue.[5] Given that, first step of the IV estimation of the endogenous dummy variable model is as follows:

[5] Correlation between revenue and preferred state $= 0.00046$. Furthermore, this variable was included in the list of control variables for the OLS estimation and was found to be statistically insignificant.

Table 6
Three step IV estimates.

	Dependent variable: Revenue
State	0.122***
	(0.010)
Relevance	0.202***
	(0.023)
Search time	0.258***
	(0.022)
Number of searches	−0.117***
	(0.037)
Prior information	0.139
	(0.034)
Constant	0.046**
	(0.029)
Observations	40,544
Weak instruments	57.87***
Wu-Hausman	2.44**
R^2	0.346
Adjusted R^2	0.319
Residual Std. Error	0.015 (df = 40538)
Method	Three-step IV regression
Time period (search and purchases)	2 years

*p<0.1; **p<0.05; ***p<0.01.

$$Pr(f = 1|x, z) = F(\sigma + \sigma' z + \sigma'' x) \tag{11}$$

where F is the CDF for a standardized normal random variable, $\mathbf{z}$ is the instrument and $\mathbf{x}$ the vector of exogenous regressors. As discussed, the three-step IV procedure does not necessarily require this specification to be correct, however the instrument must be correlated to the probability of the consumer being in a certain state.

From the probit estimates in Table 5 it is evident that the proposed instrument is highly significant and correlated with consumer state. Also, sign of the coefficient is consistent with our intuition, preferred state of a shopper which is the measure of reputation of firm generated recommendations, is positively related to current state of the consumer.

Table 6 reports the results of the instrumental variables regression. The exact same sample is used here as in the OLS specification. The model uses data on purchases between November 2015 and March 2016. Associated browsing or transaction history of unique shoppers go back to 2014 and the resultant sample has approximately 40,544 observations. As the main first step coefficients are statistically significant at 1% and 5% level and the F-statistic is 12 (p-value = 0.0005) we conclude that the instrument is strong (Stock et al., 2002). The coefficient for state is directionally comparable with the corresponding OLS estimate, however, it is much smaller in magnitude. This may suggest that there exists an upward bias in OLS estimates stemming from endogeneity of the consumer state. Intuitively, if the reputation of a platform's recommendations is improving, shoppers are more likely to purchase recommended products, as it reduces search cost of time. With more relevant recommendations, there is an increase in likelihood of shoppers switching from low state to high state. Consistent with Proposition 2 in Section 2, when recommendations are valued sufficiently by potential buyers, it is always optimal for a firm to recommend above a certain price threshold. Therefore, as reputation of recommendations improve, it has a positive impact of firm revenue.

Summarizing the results of the empirical analysis in sub-Sections 4.2 and 4.3 as follows. Firstly, we find clear evidence that recommendations are significantly positively associated with firm revenue, as improving relevance of recommendations increases buyer's willingness to pay, thereby allowing firms to position high margin products as recommendations. This finding is consistent with the second key result that improving relevance of recommendations will have a positive impact on firm revenue. As consumers face alternatives recommended by the platform with improved match quality, additional utility derived over the functional value of the product is twofold: one through reduced search cost of time and two higher salience effect which impacts purchase decisions. Thirdly, we find evidence on a positive relationship between search time and revenue which explains why firms use several tools in order to enhance shopper engagement online. The impact of search time on revenue can be explained via increase in aggregated conversion rates. We also find strong evidence that consumer state is endogenous in firm revenue regressions, and once the direct effect of consumer state on firm revenue is factored out, the remaining correlation between revenue and reputation of firm generated recommendations is significantly positive.

5. Discussion

5.1. Summary of findings

This paper sheds light on several factors that influence the firm's optimal choice to invest in personalized product recommendations, with the aim of higher sales or increased performance. Additionally, as the relevance of personalized recommendations improve, it is shown to have a positive impact on revenue. One of the key findings of this study is the unobserved reputation effects of firm-generated recommendations on consumers' willingness to pay. A three-step IV treatment allows isolating this effect from the set of control variables, which shows a significantly positive relationship between the firm's reputation and revenue. Furthermore, both OLS and the IV regressions show that if consumers prefer to purchase via recommendations (state H), it increases the firm's revenue at a higher rate than purchases via search alone (state L). This result explicitly points to the firm incentives not only to convert potential buyers from low to high state, but also to keep them in the high state.

The empirical results are supported by theoretical findings, where in state H it is always optimal for firms to recommend goods above a price threshold. Even if the recommended good is low-priced, is optimal to recommend this, as long as the consumer derives certain value from such a recommendation. Identifying this value or relevance threshold enables firms to maximize their long-term revenue, as increased relevance of the recommended good is shown to have a significant positive impact on revenue. It may seem unnecessary for firms to recommend when a potential buyer is in state L, as it generates lower per-period profits. However, the model shows that for a sufficiently high salience effect, it is always optimal to show recommendations. Based on the assumption that high state consumers experience a higher salience effect, it allows for the expected stream of future revenue to be high enough to compensate for the lower current period profits.

Finally, it is shown that the quality of online search has a notable impact on the firm's revenue. On the one hand, increased search time positively affects revenue, but, on the other hand, as the number of pages viewed increases, revenue diminishes. These findings clearly imply the type of traffic firms aim to generate on their retail platforms. Having a large number of page views does not necessarily boost revenue; however, improving the quality of information available for consumers, to accurately sample their match quality at every search, will improve the likelihood of a purchase and, in turn, increase the firm's revenue.

5.2. Future research directions

This paper presents a theoretical framework pinning down optimal price and value thresholds that allow firms to profitably show personalized recommendations. Furthermore, the empirical relationships between these variables and firm performance are studied in detail, accounting for unobserved heterogeneity via reputation effects. The aim is to provide a baseline study for future research to derive optimal price and relevance thresholds, empirically, which should be valuable for e-commerce platforms in designing long-term recommendation algorithms. It is of further interest to characterize these thresholds while controlling for the consumer state, which make recommending the optimal choice for the firm especially when reputation effects are as significant.

Additionally, consumers may exhibit contrasting behaviour when exposed to personalized recommendations for different product categories. Controlling for product groups such as, experience versus search goods and studying the varying impact of reputation effects would enable a deeper understanding of consumer motivations and how firms may differentiate strategies across different product groups.

5.3. Managerial implications

As retailing has moved towards digital commerce, persuasive advertising via recommendation agents has become rather commonplace. Online platforms with large and diverse assortments additionally invest in long-run recommendation policy designs to maximize their revenue. The key considerations in that have been studied here. Firstly, is there a trade-off between the relevance of a recommendation and the price of the recommended good? Online retailers must determine if personalized recommendations are of sufficiently high value to the consumer to justify the associated price point.

Secondly, the trade-off between short-term profitability and the discounted stream of future revenue is studied in detail. This is especially relevant for platforms that have a low reputation in the current period. Their objective is twofold: first, to build a reputation with consumers by showing high value or relevant product recommendations. Second, to recommend following a long-run profit maximizing strategy which, as shown in this paper, may lead to a seemingly sub-optimal outcome in the short run. The empirical findings point to the positive impact of reputation effects on the firm's performance, which is likely driven by a higher willingness to pay.

Thirdly, it can be observed from the theoretical model that the price thresholds in state L are much lower as compared to state H. This is because in state L firms have the additional task of building a reputation with shoppers, as it is positively related to revenue. However, improving the reputation of recommendations will improve the firm's performance to a degree, beyond which it may not yield sufficiently high marginal value to compensate for the low price. It is this threshold that firms must consider in order to effectively guide consumer search and choice, that maximizes profitability in the long-run.

CRediT authorship contribution statement

Shreya Basu: Conceptualization, Methodology, Data curation, Writing - original draft, Visualization, Investigation, Validation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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