

Online Shopping with Endogenous Channel Choice: PC vs. Mobile

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Abstract

Mobile phones have emerged as a major channel for online shopping as an alternative for using PCs. In this paper, we investigate how consumers choose the two channels to search for information and make purchase online. Our study is motivated by the empirical observation that, despite the high percentage of consumers who choose mobile phones for online shopping, the conversion rate from the mobile channel is significantly lower than that from PCs even with the same search intensity. After examining several candidate explanations, we use a structural search model that endogenizes the channel choice to explain this data pattern. Model estimation results show that, for an average consumer, it is easier to start search using mobile phones, but it is more difficult for intensive search, compared with using PCs. Consequently, mobile phones attract a systematically different pool of consumers who have lower purchase interests and will search less. We use counterfactual analyses to investigate the managerial implications of the price equilibrium if online sellers can set different prices and offer retargeting coupons on unique channels. The results show that by utilizing the preference information revealed by the consumer channel choice, online sellers could further improve the overall profit from channel-specific marketing decisions including pricing and retarget strategies.

Key words: Mobile shopping, Online Search, Channel Choice, Pricing, Retarget

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1. Introduction

In recent years, the online retail industry has seen rapid growth of traffic from mobile devices compared to the traditional PC channel. In the United States, the average time adults spend using mobile devices to shop has surpassed that using PC since 2015². Knowing the popularity of online shopping by smartphones, most major US retailers have been aggressively increasing their investment in both mobile application development and advertisement³.

Despite the more intensive usage of smartphones, industrial reports on online retailing suggest a potentially concerning pattern that consumers make fewer purchases from mobile devices compared to PC. A report from Business Insider Intelligence⁴ shows that although almost 60% of the time is allocated to the mobile device, only 15% of the total sales are generated from this channel. Such disproportionately low sales are consistent with the conversion rate gap between the PC and the mobile channels. Based on data collected from over 1.9 billion shopping sessions in the US over a one-year period from 2015 Q4 to 2016 Q4, the conversion rate on PC is consistently much higher than that on smartphone.⁵ For example, the average conversion rate is 4.14% on PC compared to only 1.55% on smartphone in 2016 Q4. Such data pattern motivates us to investigate how consumers browse and purchase on the mobile channel compared to the PC channel. This question is becoming increasingly important as more online retailers start to or continue to invest in the mobile shopping channel. Understanding consumer behavior on each channel will help retailers manage the multi-channel online environment.

This paper studies consumers' online browsing and purchasing behaviors on both the traditional PC channel and the fast-growing mobile channel. Consumers can choose between the two channels for their online shopping needs. Although the product offering is the same on both channels, PC and smartphones are essentially different search channel for consumers: it

² Source:<https://www.businessinsider.com/the-mobile-checkout-report-how-retailers-and-tech-giants-are-pushing-consumers-12-2015>

³ Source:<https://www.forbes.com/sites/johnkoetsier/2018/02/23/mobile-advertising-will-drive-75-of-all-digital-ad-spend-in-2018-heres-whats-changing/#69b95ed758be>

⁴ Source:<https://www.businessinsider.com/the-mobile-checkout-report-how-retailers-and-tech-giants-are-pushing-consumers-12-2015>

⁵ Souce:<https://www.smartinsights.com/mobile-marketing/mobile-commerce/mobile-users-still-not-converting/>

may be easier to browse more options on the PC channel due to the large screen size compared to the mobile channel. At the same time, smartphones provide ease of access for consumers so that it may be more convenient to start a search session on the mobile channel. For online sellers who face increasing traffic from the mobile site, it is important to understand how and why consumers behave differently on PC and mobile channels. Retailers can design marketing elements such as pricing and promotion by considering the consumer channel choice.

There are two main objectives for this paper. The first objective is to propose a model that can explain the observed consumer search and purchase decisions on both the PC and the mobile channels. By incorporating the consumer's channel choice, our proposed model can rationalize the intriguing data pattern that the conversion rate is significantly lower on the mobile channel even though the prices and other product attributes are the same on PC and mobile. The model estimation results can help firms better understand what drives consumers to which channel, and therefore which types of consumers would shop on mobile vs. PC channels. The second objective is to design better marketing strategies for sellers to better target consumers using the PC and mobile channels. It is not clear *ex ante* how consumer utility differs from each other: on one hand, consumers search less on their smartphones, which may make sellers tempting to increase the price on the mobile channel; on the other hand, the conversion rate is higher on PC, which suggests consumers may be willing to pay more on PC. Our structural model accounts for both channel choice and search activity, and thus provide a complete picture when making marketing recommendation to online retailers. More specifically, we study two aspects, pricing and promotion, by considering consumer channel choice as well as their search and purchase behaviors. First, we investigate the optimal channel specific pricing by allowing sellers to offer discounted prices on certain channel and quantify its impact on profit. Our structural model enables us to consider consumer's response to different prices for the same product on different shopping channels when designing such optimal pricing strategy. Second, we explore the optimal retargeting coupon value to consumers considering their channel choice, which enables sellers to utilize the information of consumer channel choice to send targeted offers.

To answer the research questions, we use a unique clickstream data set from Taobao,

the largest online shopping platform in China, on both PC and mobile channels. To browse and make a purchase on Taobao, consumers can use both the traditional online channel with computers and the mobile channel using their smartphones. The data set captures which channel, PC or mobile, the consumers use to browse and make a purchase. We observe each consumer's search activities (through browsing different product options) and purchase decisions. We also gather some additional information, such as consumer demographics and their smartphone attributes (even when they do not use their smartphones for online shopping during the data observation period), that may influence consumer channel choice.

With the data set on Taobao, we observe: i) a high proportion of consumers (49%) using the mobile channel to shop; and ii) higher search times per customer on PC compared to consumers on mobile iii) a lower conversion rate on mobile than on PC, consistent with the industry reports of the U.S. market. Moreover, we find that even after controlling for the number of searches on each channel, the gap in conversion rate between PC and mobile channels persists. We propose a structural model that incorporates consumers' channel choice in addition to their search and purchase decisions. The proposed model can explain the conversion rate difference between the two channels while several alternative explanations including difference in transaction cost fail to do so. We identify both a marginal search cost (for an addition search) as well as an initial fixed cost (for starting a search session) for the two channels. We find that on average, the marginal search cost is higher on mobile than on PC, with the average difference across consumers at \$0.23. The initial fixed cost, however, is \$0.24 higher on PC than on mobile on average.

How does this influence consumers' channel choice and the conversion rate on each channel? Given the lower marginal search cost on PC, it is more likely for consumers who want to conduct more extensive search to choose PC over mobile. Since consumers with higher category valuation are willing to search more to find a product with high match value, consumers with a higher initial category valuation are more likely to self-select into using the PC channel. For lower valuation consumers, they are more likely to conduct fewer searches and choose the mobile channel due to a lower initial fixed cost. This mechanism of consumer self-select channels based on their category valuation and search cost can explain the observed

conversion rate gap between the two channels. In addition, we find that consumer demographics, smartphone features, and prior usage behavior have significant impact on consumer search cost, and thus will influence channel choice. For example, younger consumers and women are more likely to choose the mobile channel.

Using the estimated model, we study the pricing and promotion strategies for sellers by considering consumer channel choice. First, we investigate the new price equilibrium if the sellers set different prices for the same product on PC and mobile channels. Although sellers may have incentive to lower price on the PC channel due to consumers searching more and thus are more likely to find a lower price from the competitors, it is still optimal for them to offer a slightly lower price on the mobile channel. This is because consumers on the PC channel tend to have higher valuation toward the products due to the self-selection in channel choice, and sellers can charge a higher price for these consumers. Second, we investigate the optimal coupon value to retarget consumers who have browsed but did not purchase while accounting for the consumers' channel choice. Our results show that on average, it is optimal to offer a coupon with slightly higher value on mobile than on PC, but the strategy also depends on the number of searches. By adopting the proposed individual retargeting strategy, sellers can get a 14% increase in profit. The results illustrate the importance of considering channel as an endogenous choice for consumers and the value of taking it into consideration when planning marketing activities.

The rest of the paper is organized as follows. We discuss related literature in Section 2 and present the data in Section 3. We develop the model in Section 4, followed by the estimation strategy and model identification in Section 5. The estimation results are discussed in Section 6. Section 7 presents the counterfactuals regarding optimal channel specific pricing and retargeting strategy. We conclude the paper and suggest future research in Section 8.

2. Literature

Our study is related to the literature of consumer search, multi-channel retailing and consumer behavior on mobile devices. First, the paper is related to the literature of consumer search. Since information gathering is costly (i.e., requiring time and effort), consumers cannot review

all possible options when making a purchase. Recent empirical studies have estimated consumer search models to describe the consumers search and purchase behaviors (e.g., Kim et al. 2010, Koulayev 2014, Honka 2014, Chen and Yao 2016, Kim et al. 2016, Honka and Chintagunta 2016, Jiang et al. 2018). Understanding consumer search is important for firms when making marketing decisions, such as pricing (e.g., Hong and Shum 2006, Wildenbeest 2011). Most of the existing literature considers consumer search behavior on one channel, which is likely driven by the availability of browsing data only from one channel (for example, Chen and Yao 2016, Ursu 2018, Jiang et al. 2018 all study consumer search behaviors using online browsing data). Honka (2014) considers different channels by allowing the search cost to differ when obtaining an insurance quote through the insurer website, online quote service or call center. In this paper, we obtain consumer browsing and purchase data as well as which channel, PC or mobile, the consumers choose to use. Motivated by the different browsing and purchase patterns from the two channels, we contribute to the search literature by incorporating consumer channel choice in the search model. Considering channel choice allows us to study the optimal pricing policy across channels when sellers have the products available on both platforms and can potentially set different prices. Consumers choose either PC or mobile devices by considering their level of preference for the product as well as search costs on both channels. We are able to identify a different fixed search cost (when starting a search session) on PC relative to mobile as well as different marginal search costs (for each additional search), both of which contributes to consumers channel choice. Although we assume simultaneous search in our search model, the proposed framework of channel choice can be applied to scenarios where consumers search sequentially (e.g., Weitzman 1979).

Second, our paper contributes to the multi-channel retailing literature. There has been long interest for marketers to understand multi-channel customer management. Historically, researchers are primarily concerned about issues with the online channel and the traditional physical store and catalog (e.g., Neslin et al. 2006, Verhoef et al. 2007, Ansari et al. 2008, Neslin and Shankar 2009, Venkatesan et al. 2007, Wang and Goldfarb 2017). One of the questions of interest in this line of research is to understand the behavioral difference for consumers who use different channels. For example, Hitt and Frei (2002) document difference

in consumer characteristics and behavior with PC and traditional banking, and Degeratu et al. (2000) find the importance of consumer choice attributes to differ in online and offline channels. Our paper investigates the difference in behavioral patterns (e.g., the intensity of search, conversion rate, etc.) for consumers who use smartphones and those who use PCs to shop. We propose a structural model of consumers' channel choice between mobile and PC and their search and purchase decisions. The model is able to explain the observed behavioral differences due to consumers *self-selecting* into using either mobile or PC. Different from Hann et al. (2018), who focuses on conversion rate for consumers that switch devices, we explain the conversion rate difference for consumers that choose either channel. Given the difference in customer base on the two channels, we further provide managerial guidance for sellers to find the channel-specific optimal prices.

Third, this paper contributes to the growing literature related to consumers using mobile devices. Examples include mobile marketing (Shankar and Balasubramanian 2009, Andrews et al. 2016), impact of the mobile channel on consumer purchase (Wang et al. 2015, Huang et al. 2016, Xu et al. 2016) and news consumption (Xu et al. 2014), content generation and usage behavior on mobile devices (Ghose and Han, 2011), and consumer search behavior on the mobile Internet (Daurer et al. 2016). Ghose et al. (2012) find the search cost to be higher on the mobile channel compared to the PC channel, although local activities (distance) matter more. Different from the existing literature, our paper studies the consumer choice of the mobile vs. PC channel when shopping online. We model both a marginal and a fixed search cost when consumers choose between mobile and PC channels. By treating channel as an endogenous choice, we are able to understand the difference in consumer search and purchase behavior on mobile and PC channels. Furthermore, by incorporating individual observed heterogeneity such as demographics, purchase history, and device attributes, our paper documents how channel choice differs across consumers.

3. Data

Our data set comes from one of the largest online shopping platform in China, Taobao, which is owned by Alibaba. Taobao has both mobile and PC channels for consumers to browse and

make a purchase. The product offerings and their attributes, including the prices, are the same from the two channels. From the data set, we observe detailed individual level browsing history and purchase decision on the Taobao platform. In addition, this data set captures whether a browsing activity happens on mobile or PC. This unique data feature allows us to study the consumers' choice of channels. The data set also contains additional consumer characteristics including smartphone models, demographic information and prior shopping history on the platform. We collect data for consumers who have browsed the fishing pole category. We observe the search and purchase behavior for 133,896 consumers during the data observation period from October 15, 2014 to November 15, 2014. 51 percent of these consumers have browsed at least one fishing pole from the mobile channel, and 49 percent, have browsed on the PC channel. Among these consumers, we observe 6 percent of consumers have used both PC and mobile channel during the data sample period.

Using this data set, we observe that the browsing and purchase patterns are very different on the mobile and PC channels. First, the conversion rate, defined as the percentage of consumers who made a purchase out of those who browsed, is much lower on the mobile channel than on the PC channel. The overall conversion rate is 13.59% on the PC channel, which is significantly higher than the 9.93% on the mobile channel. Second, we find that the search intensity, defined as the number of unique products browsed, is higher on the PC channel than on mobile. On the PC channel, the percentage of consumers who browse only one product is 58%, which is significantly lower than the 65% on the mobile channel. On the other hand, the percentage of consumers who conduct more intensive search is higher on the PC channel. 28% of consumers browse at least three products on PC, compared to 20% on mobile. Most consumers (99.2%) who decide to purchase the product buy only one product during the sample period. It supports the unit demand assumption we make in the model, which simplifies the estimation procedure.

We observe consumer demographics, gender and age, for 65% of the sample. In addition, we collect consumers' smartphone device information including the model, screen size and the phone's operation system, for 82% of the sample. Table 1 reports the variable description and summary statistics for consumer demographics and mobile device

characteristics.

<Insert Table 1 about here>

The prices for fishing pole do not change over time during our sample observation period. The average price in our data is 263.7 RMB, and the price ranges from 5.4 to 379.5 RMB. Weighted by sales volume, the average price paid by consumers for a fishing pole is 141.1 RMB. The product attributes such as price do not affect consumers' channel choice because they are identical on the mobile and PC channels. In other words, consumers face the same selection of products with the same attributes on either channel. Consumer characteristics (shown in Table 1), on the other hand, may impact their choice of channels.

3.1 Channel Choice

Before introducing the proposed model of consumer channel choice, we first show reduced form evidence that consumers who choose to use the PC and mobile channels are systematically different. Using channel choice as the dependent variable, which equals 1 if the consumer chooses PC, and 0 if he chooses mobile, we run a probit model to study how consumers' channel choice correlates with various observed consumer characteristics (described in Table 1).⁶ Results are reported in Table 2.

<Insert Table 2 about here>

There is considerable heterogeneity among consumers who choose the PC and mobile channels in terms of their observed characteristics. We find that younger consumers and consumers who use mobile phones with higher screen resolution and more advanced operation system⁷ are more likely to use the mobile channel for online shopping. In addition, consumers with a higher buyer rating and a higher number of prior purchases are more likely to use the PC channel. Both buyer rating and the number of prior purchases positively correlate with the consumer's past experience on Taobao.com. Early adopters of the online shopping platform

⁶ We multiply the screen resolution in pixels in length and width and use the demeaned value to represent screen resolution in model estimation.

⁷ Apple and Android operating systems were considered advanced in China during 2014, where many other smartphones were using operating systems developed by local manufacturers.

are more likely to have more transactions and a higher buyer rating. It is likely that these consumers are more familiar with the PC channel than the mobile channel because Taobao only introduced the mobile channel in 2008⁸. The reduced form evidence suggests that the observed consumers characteristics significantly correlate with their channel choice. We incorporate these characteristics in the structural model to account for consumer heterogeneity.

3.2. Alternative Explanations for the Difference between the Two Channels

The conversion rate pattern from our data sample, as well as reported in numerous industrial reports, suggests that the mobile channel performs rather poorly compared to the traditional PC channel to convert shoppers into purchasers, even though it attracts a large proportion of consumers to browse on the channel. We discuss several possible explanations that could drive such data pattern. This helps guide us in developing an empirical model in consumers' channel choice. Note that the alternative explanations discussed here and our proposed model both assume that consumers have a choice between the mobile and PC channel, which we believe is the case during the data observation period (Oct-Nov 2014). The CNNIC (a Chinese Internet government agency) reports that among Internet users, the penetration rate of smartphone is 85.8% during 2014⁹. Therefore, it is safe to assume that consumers can have access to both types of devices.

The first alternative explanation is that the lower conversion rate on the mobile channel can be the result of a higher marginal search cost. For example, Ghose and Han (2011) found that the larger screen size of a computer enables consumers to browse more products at one time compared to a smartphone. Consumers are less likely to find a good match, and thus less likely to make a purchase, after browsing fewer product options on the mobile channel. To test whether the conversion rate difference is only driven by the difference in marginal search cost, we compare the conversion rates for consumers who browsed the same number of product options on the mobile and PC channels. The observed data pattern contradicts this hypothesis. The conversion rate on the PC channel is consistently higher than that on the mobile channel

⁸ Source: <https://yq.aliyun.com/articles/583335>

⁹ Source: <http://www.cac.gov.cn/files/pdf/hlwjtjbg/hlwlfzktjbg035.pdf>

for consumers who browse the same number of product options (Figure 1). The gap is larger when the total number of product browsed increases. When the size of consideration set is the same across the two channels, the gap in conversion rate cannot be explained by the potential marginal search cost differences.

<Insert Figure 1 about here>

The second potential explanation is the difference in transaction cost for completing a purchase on each channel. For example, consumers may find it difficult to type in the shipping address or the credit card information when using a smartphone without a keyboard. In that case, consumers may be more likely to abandon the shopping session on smartphones without making a purchase. To test this explanation, we focus on the group of consumers who use both channels to browse the products, which accounts for a small percentage out of all sampled individuals (6%)¹⁰. If the transaction cost is higher on the mobile channel, we would expect a higher conversion rate on the PC channel among these consumers as well. We find evidence inconsistent with this hypothesis. Figure 2 shows that among the consumers who browse both channels, the conversion rate is almost the same (12.9% on PC vs. 12.2% on mobile) on the two channels.

<Insert Figure 2 about here>

Given these consumers have browsed both channels, the interpretation for the equal conversion rates is that either the transaction cost is the same across both channels or transaction cost is trivial so that it does not play an important role in determining where to purchase. In fact, Taobao enables users to type in a six-digit password for payment once one links a debit or credit card with his Taobao account during the period of our data observation. Therefore, the time and effort required for payment on the mobile channel is not distinctively higher than that on PC.

In this paper, we propose that consumers *endogenously* choose which channel to browse. As will be described in more detail in the model section, we identify and estimate both a

¹⁰ Consumers typically do not switch devices within a shopping session.

marginal search cost (for an addition search) as well as an initial fixed cost (for starting a search session) for the two channels. The channel choice depends on the level of consumer valuation for the product category, as well as the cost to search on the two channels. Higher valuation consumers are willing to search more to find a product with high match value, and thus are more likely to self-select into using the PC channel because of its lower marginal search cost. On the other hand, lower valuation consumers are more likely to conduct fewer searches and choose the mobile channel due to a lower initial fixed cost. The consumer self-selection into difference channels contributes to the observed difference in browsing and purchase behavior on the two channels.

4. Model

We propose a consumer's search and purchase model that incorporates channel choice. Consumers first choose which channel (mobile or PC) to browse the products. On the chosen channel, consumers decide what products to browse and whether to make a purchase. We assume that consumers choose one channel and do not switch devices. This is due to the empirical observation that only 6% of consumers have ever switched devices during the one-month data observation period. This small group of consumers are excluded in our empirical analysis to keep the model tractable. The proposed model is presented in two parts. First, we describe the consumer search and purchase decisions after choosing a channel. Second, we show how consumers make the channel choice based on their expected utility on each channel.

4.1. Consumer Search and Purchase

We first describe consumer search and purchase decisions *after* he has selected a channel to browse. The channel choice decisions are laid out in details in Section 4.2. Regarding consumer search behavior, both simultaneous and sequential search models have been applied to study consumer search behavior. Prior literature (e.g., De Los Santos et al. 2012 and Honka 2013) test between the two search models and find that the empirical evidence better supports the simultaneous search model over the sequential search model. Following prior literature, we assume that consumers conduct simultaneous search in this paper. Our proposed framework of channel choice can easily carry through to scenarios where consumers search

sequentially.

Suppose there are I consumers and J products. After consumers choose the channel to browse, denoted by s , they arrive at a page that lists available product options. On this page, consumers can observe all the product attributes except for the price. This model assumption fits our empirical context. During the data observation period, when consumers search for fishing poles on Taobao.com, the search results page display most of the important product attributes such as the material, model and available length, but in order to find out the price of a fishing pole, consumers need to click into the specific product page¹¹. After clicking into the product page, consumers observe the price as well as more detailed description of the product, such as more pictures, consumer reviews, etc. We capture the consumer's valuation of the more detailed product description by an idiosyncratic individual match value for the product. After each search, consumers know the price and the individual match value for the searched product. The utility of product j for consumer i is

$$u_{ij} = \alpha_i - \lambda \cdot P_j + e_{ij} \quad (1)$$

where α_i is consumer i 's valuation for the product category, P_j is the price of product j and e_{ij} is the individual match value.¹² We assume that e_{ij} follows i.i.d Extreme type I distribution across consumers and products. If the consumer decides not to purchase any product after search, he chooses the outside option denoted by e_{i0} . The outside option e_{i0} represents consumer i 's valuation of purchasing from other websites or purchasing other products. We assume that consumers know their own outside option before conducting the search activities. e_{i0} is assumed to follow i.i.d Extreme type I distribution across consumers.

At this point, consumer choose which product to purchase or the outside option of no purchase.

¹¹ A price range is displayed with the minimum and maximum prices for a pool of different products (e.g., different length or color options). The price range is typically very large. To find out the exact price for a particular product, consumers need to click into the product page which we count as a search activity.

¹² We do not observe product or seller attributes in the data. To the extent that those attributes may impact consumer's utility, our estimated price coefficient may be biased.

In simultaneous search model, we model how many product options a consumer chooses to search, denoted by b . Consumer i incurs a marginal search cost c_i for each product he browses. A consumer chooses how many products to search to maximize the expected utility by considering the benefit from searching as well as the marginal search cost. We allow marginal search cost to vary across the two channels. For simplicity, we omit the channel subscript s in the search model. Following Chade and Smith (2010), consumer i maximizes his indirect utility by choosing the number of searches b ,

$$IU_i(b) = E[\max_{j \in C_{ib}} \{u_{ij}\}] - bc_i \quad (2)$$

C_{ib} is the consideration set for consumer i who searches b times (the outside option e_{i0} is always an element in C_{ib}). Consumer i maximizes the expected utility of the consideration set minus the marginal search cost incurred. As is common in consumer search literature (e.g., Ursu 2018), our data does not include consumers who do not search at all. Thus, we require that consumers search at least once in the model. Before the search, consumer i knows his initial preference for the product α_i and has chosen a channel to browse s_i . The probability that consumer i chooses to search b times is

$$P_{ib|a,s} = P\{IU_i(b) \geq IU_i(b') | a_i, s_i\} \quad (3)$$

Consumer i clicks into the product detail pages for each of the b products and observes the price and the individual match value e_{ij} . We abstract away from modeling the content of the choice set and instead focus on the size of the choice set because of the lack of data on the product attributes that consumers may observe on the product search page. In addition, our focus in the paper is to explain how different consumers self-select into the two channels. Modeling search order or content is not necessary to understand our research questions. Instead, we assume that consumers randomly choose b products. After search, consumers make their purchase decisions by comparing the realized utilities among the choice set (knowing the price and individual match value) and the outside option. Consumer i 's conditional purchase

probability for product k is

$$P_{ik|e,b,a,s} = P\{u_{ik} > u_{ik'}, \forall k' \in C_{ib} | e_{ij}, P_j, a_i, s_i\} \quad (4)$$

In other words, the consumer will choose option k if the realized utility is larger than any other options k' in the choice set.

4.2. Consumer Channel Choice

Before starting the search process, consumers choose between mobile and PC channels. In other words, they decide whether to use a smartphone or a PC to shop. Denote channel choice as $s \in \{1,0\}$, where $s = 1$ if the consumer chooses the PC channel, and $s = 0$ if choosing mobile.

In order to understand consumers' channel choice, we introduce a fixed search cost in addition to the marginal search cost for both channels. Different from the marginal search cost, which depends on how many products a consumer browses, the fixed search cost is a one-time upfront cost to start a search session. The fixed cost can come from the time and effort required to start up the PC or smartphone and initialize the search process, while the marginal search cost is associated with the time and effort to gather information from the product page.

Prior literature (Ghose et al. 2012) and the data pattern of higher number of searches on PC suggests that the marginal search cost on the mobile channel should be higher than that on the PC channel. This is likely due to smaller screen and lack of keyboard on a smartphone. On the other hand, we expect the PC channel to have a higher fixed cost than the mobile channel. This is because the portability of a smartphone allows consumers to access it from anywhere. It can be less effortful to start a search session using a smartphone than a PC due to the ease of access for smartphones.

We allow individual heterogeneity in both the fixed and marginal search costs given the consumer's demographic information, mobile device features and past usage patterns. For example, younger consumers may be more proficient in using their smartphones for online shopping. In addition, smartphones with larger screen sizes or advanced operation systems could make the search process more effortless and thus are associated with a lower marginal

search cost. Since consumers choose one of the channels to search, for model identification, the fixed cost of the mobile channel is normalized to 0. We specify the fixed cost of the PC channel as

$$f c_i = \mu_{fc} + \beta Z_i + v_{ifc} \quad (5)$$

Where μ_{fc} is the constant term, Z_i is a list of relevant consumer characteristics and device attributes, and v_{ifc} captures the unobservable heterogeneity and is assumed to follow a standard normal distribution. We do not impose the fixed cost on PC to be higher or lower than that on the mobile channel (normalized to 0). The estimated parameters will decide the sign and magnitude of the fixed cost on PC for different consumers.

Consumers pay a marginal search cost for an additional search. The marginal search cost for consumer i on the PC channel ($s = 1$) is

$$c_i^1 = \exp(\mu_c^1 + \sigma_c v_{ic}) \quad (6)$$

where v_{ic} follows a standard normal distribution. The marginal search cost on PC c_i^1 follows a log-normal distribution with $\log(c_i^1) \sim N(\mu_c^1, \sigma_c^2)$, so that the marginal search cost remains positive (e.g., Hortaçsu and Syverson 2004). The marginal search for consumer i on the mobile channel ($s = 0$) is

$$c_i^0 = c_i^1 + s c_0 + \alpha X_i$$

Where $s c_0$ represents the average difference in marginal search cost between mobile and PC, and X_i is a list of relevant individual i 's smartphone attributes (screen size, operation system, etc.) that may impact the search cost on the mobile channel. α captures the heterogeneity in marginal search cost with observed characteristics X_i . We do not impose the difference in marginal search cost between mobile and PC, $s c_0 + \alpha X_i$, to be negative or positive. The estimated parameters will determine the marginal search cost for different consumers.

With the specifications for marginal and fixed search costs, we describe how consumers choose a channel to search. We assume that consumer i is aware of the distribution for price and individual match value (actual values are realized after search). He knows his level of

interest in the product category a_i and his outside option e_{i0} prior to making the channel choice. He also knows his marginal and fixed search costs for both channels. Base on this information, the consumer forms expectation on the utility for each channel. Therefore, consumers know the expected utility distribution for each channel, and make the channel choice accordingly.

Let F_{isb} be the cumulative distribution function of the expected maximum utility among b products searched by consumer i on channel s . In other words, F_{isb} captures all possible realizations of utility and the associated probabilities when consumer i searches b times on channel s . The calculation of F_{isb} is shown in detail in the next section. Consumer i 's expected utility for channel s is

$$ECU_i^s = \max_b [F_{isb}(e_{i0}) \cdot e_{i0} + \int_{e_{i0}}^{+\infty} F'_{isb}(u) u du - f c_i \cdot s_i - b \cdot c_i^s] \quad (7)$$

When the maximum utility from the b browsed products is lower than the outside option, consumers choose the outside option . Otherwise, consumers choose to browse the b products and pay the corresponding fixed and marginal search costs. Consumer i chooses the channel s that offers higher expected utility between the two channels. The channel choice probability is

$$P_{is|a} = P(ECU_i^s \geq ECU_i^{s'} | a_i), s' \in \{0,1\} \quad (8)$$

To summarize, in this section, we propose a consumer's search and purchase model that incorporates channel choice. First, consumers decide which channel to use, mobile or PC. The channel choice depends on their overall product valuation, outside option value, and the fixed and marginal search costs on the two channels. Second, conditional on the channel choice (consumers pay the corresponding fixed search cost), consumers choose how many products to search on the channel (consumers pay the corresponding marginal search cost). At this point, the product prices and individual match values for the searched products are realized. Lastly, consumers choose the product that maximizes their utility, including the outside option.

The proposed model is able to capture the difference in channel choices among consumers with different observed characteristics by incorporating heterogeneous fixed and marginal search costs. Moreover, it provides a mechanism of how consumers with different product valuation and search costs tend to select certain channel. This endogenous channel choice is key to understand the observed conversion rate and search patterns between the two channels. The model allows us to investigate marketing strategies to better target consumers on either channel, which we describe in detail in Section 7.

5. Model Estimation and Identification

In this section, we lay out detailed model estimation procedure, present results from a Monte Carlo simulation study and discuss model identification.

5.1. Estimation Procedure

The likelihood function captures the three parts of consumer decisions: the probability of choosing a channel (channel choice probability $P_{i,s|a}$), searching b product options (optimal search time probability, $P_{i,b|a,s}$), and purchase decisions (purchase probability $P_{ik|e,b,a,s}$). The likelihood function integrates over the distribution of the outside option e_{i0} , the individual shock for fixed search cost, v_{ic} , and marginal search cost v_{fc} , and the valuation of the product category a_i .

$$LL = \sum_{i=1}^I \log \left(\int \int \prod_{s=0}^1 \prod_{b=1}^N \prod_{k=i_1}^{i_b} P_{ik|e,b,a,s} P_{i,b|a,s} P_{is|a} dF(e) dF(v_{fc}) dH(v_c) dG(a) \right) \quad (9)$$

The likelihood function does not have a closed-form solution. We use simulated maximum likelihood to estimate the model by drawing from the corresponding distributions for numerical integration. More specifically, we draw the following variables Q times. Within simulation q , consumer i 's match value for product j e_{ij}^q and the outside option e_{i0}^q are drawn independently from Extreme Type I distribution. The error terms for fixed search cost and marginal search cost, v_{ic}^q and v_{fc}^q , are drawn i.i.d. from a standard normal distribution. Consumers' utility constant term is parameterized as $a_i = \mu_a + \sigma_a e_{ia}^q$ where the error term of

the consumers' valuation for the product category, e_{ia}^q is drawn from a standard normal distribution.

We assume that consumers know the distribution of prices prior to search but the actual values are only realized after they browse the product detail pages and pay the corresponding search cost. Before the main model estimation, we first estimate the price distribution, which determines the benefit from an additional price search. Following prior literature on price search models (e.g., Hong and Shum 2006, Moraga-González and Wildenbeest 2008, Honka 2014), we assume that prices follow an Extreme Type I distribution and estimate the price distribution parameters. We use the estimated price distribution parameters in the model estimation.

Consumers form expectation of the benefit they receive under a specific number of searches. We evaluate the distribution of the benefit consumers receive from drawing the price and individual match value b times. We assume that there is no heterogeneity in consumers' price sensitivity or expectation for the distributions of price or individual match values. Thus, consumers have the same expected benefit from an additional search. To calculate the distribution of expected benefit from search given one set of parameters, we draw from the price and individual match value distributions b times and calculate the expected maximum value as $w_b = \max\{-\lambda p_1 + e_1, \dots, -\lambda p_b + e_b\}$. The process is repeated Q times. We get a Q -length vector of w_b for b number of searches, which represents the distribution of expected benefit from searching b times.

To calculate channel choice probability (Equation 8), we evaluate the expected utility from choosing channel s (Equation 7). For consumer i , the expected utility from searching b times on channel s is

$$\widehat{ECU}_i = \max_b [u_{ib}] - fc_i * s$$

where u_{ib} is the maximum utility from the searched products and the outside option minus the corresponding marginal search cost. To calculate u_{ib} through simulation, we draw Q times

from the distributions for overall product valuation, outside option, fixed and marginal search costs. We calculate the utility with each set of random draws, and u_{ib} is evaluated as the average from the Q values.

$$u_{ib} = \frac{1}{Q} \sum_q [I(a_i^q + w_b^q > e_{i0}^q) \cdot (a_i^q + w_b^q) + I(a_i^q + w_b^q < e_{i0}^q) \cdot e_{i0}^q] - b \cdot c_i^q$$

We also draw Q draws from the fixed search cost random error term to calculate $f c_i$ specified in equation 5. The expected utility for channel s \widehat{ECU}_i is the maximum of u_{ib} by selecting the optimal number of searches b minus the corresponding fixed search cost.

Consumers choose the channel that gives them higher expected utility $\widehat{ECU}_s, s \in (0,1)$. The channel choice probability does not have a closed form solution and is not smooth. Following prior literature (McFadden 1989, Honka 2014), we apply a kernel smooth method where the choice probability is represented by a scaled multivariate logistic CDF. The probability of consumer i choosing channel s is

$$P_{is} = \frac{1}{1 + \exp(-s_1(\widehat{ECU}_{i,s} - \widehat{ECU}_{i,1-s}))} \quad (9)$$

where s_1 is a scaling parameter.

Next, we evaluate the probability of searching b number of times. Consumers choose the number of searches by maximizing the expected utility (Equation 3). Applying the kernel smooth method, the probability of consumer i choosing to search b times conditional on choosing channel s is

$$P_{ib|s} = \frac{1}{1 + \exp(-s_2(IU_{i,b} - \max(IU_{i,-b})))} \quad (10)$$

where s_2 is a scaling parameter, and $-b$ denotes all search times other than b .

Finally, we evaluate the purchase probability for consumers after they have chosen a channel s and have selected the number of products to browse b . The prices and individual

match values are realized for options in the consumers' consideration set C_{ib} (the b products consumer i browses). The probability that consumer i chooses option k from the consideration set C_{ib} on channel s is

$$P_{ik|C_{ib}s} = \frac{1}{1 + \exp(-s_3(u_{ik} - \max(u_{ik'})))} \quad (11)$$

where k' denotes all choices other than option k , including the outside option when $k = 0$ without consumers do not make a purchase.

Combining the three sets of probabilities in equation 9~11 together, we obtain the overall probability of observing consumer i choosing channel s , searching b times and choosing option k . We evaluate this probability through simulation by drawing the error terms for overall product valuation α_i , fixed and marginal search costs v_{ifc}, v_{ic} , individual match value for each product searched e_{ij} , and outside option e_{i0} Q times. The overall likelihood considers channel choice probability P_{is}^q , number of searches probability $P_{ib|s}^q$ and purchase probability $P_{ik|C_{ib}s}^q$.

$$p_{ij} = \frac{1}{Q} \sum_q P_{is}^q P_{ib|s}^q P_{ik|C_{ib}s}^q \quad (12)$$

5.2. Identification

We discuss the identification of the model parameters. The parameters can be divided into three categories: the utility parameters $\{\mu_\alpha, \sigma_\alpha, \lambda\}$, the marginal search cost parameters $\{\mu_c, \sigma_c, sc_0, \alpha\}$, and the fixed search cost parameters $\{\mu_{fc}, \beta\}$.

The mean of the product category valuation μ_α is identified from the overall level of conversion rate after search, and price sensitivity λ is identified from the purchase data. The variation of the overall product valuation among consumers leads to the systematic difference in consumers who select certain channel to browse. Consumers with higher level of overall product valuation may systematically choose a channel given its search cost structure. The identification of the standard deviation of the product category valuation σ_α comes from the difference in conversion rates between consumers who search the same number of times on the two channels. If σ_α is 0, given the same searches, we would not expect to see the conversion

rate on mobile to be systematically different from that on PC. When the conditional conversion rate on mobile becomes lower than that on PC, it implies a higher σ_α .

For the marginal search cost parameters, we identify the constant term and the standard deviation of the error terms from the search times distribution on both the PC and the mobile channels. sc_0 captures the average difference in marginal search cost on PC and mobile. Such difference is identified from the difference in average number of searches per person on the PC and mobile channels. The systematic difference in the number of searches among consumers with different mobile attributes identify the observed heterogeneity in marginal search cost across consumers on the mobile channel.

The identification of the fixed search cost on the PC channel comes from consumers' channel choice for browsing. Recall that the fixed search cost on the mobile channel is normalized to 0. The constant in the fixed cost μ_{fc} is identified from the proportion of the consumers that choose the PC channel, after accounting for the difference in marginal search cost. With a higher fixed cost in the PC channel, more consumers will choose the mobile channel. The systematic difference in channel choice among consumers with different demographics, user behaviors and device features identifies the observed heterogeneity in fixed cost across consumers.

We run a Monte Carlo study and find that the proposed estimation method can successfully recover the true parameters in the model. We simulate data for 10,000 consumers and set the maximum of number of searches at 5. The simulation procedure is as follows. We generate each individual's marginal search cost from random draws of the normal distribution and their outside option out of Extreme Type I distribution. The expected channel utility and optimal search time is calculated for each individual as described in Equations 7 and 8. With the search channel s and search times b , consumers draw of b prices and the match values for each product are also realized. Consumer i makes purchase decision depending on the realized utility. In the estimation, we set all scaling factors to be 20. The number of simulations Q is 50. Results from the Monte Carlo study is reported in Table 3. Column (1) shows the true value of

the parameters, and Column (2) and (3) show the estimated value and standard error. All parameter estimates are within two standard error from the true value.

<Insert Table 3 about here>

6. Results and Discussion

We apply the proposed model on the data set of 133,896 consumers' search and purchase activities on both the mobile and PC channels. In this section, we discuss the model estimation results. In particular, we highlight how the model of channel choice can explain the lower conversion rate on the mobile channel compared to that on the PC channel. We show that the estimated model can reproduce the conversion rate and number of searches very well across both channels. Table 4 shows the estimation results. For ease of organization, they are broken into four sections: utility parameters, search cost distribution parameters, heterogeneity in fixed search cost parameters, and heterogeneity in marginal search cost parameters.

In the first section, the utility parameters include the overall valuation for the product category μ_a as well as its standard deviation across consumers σ_a . The price coefficient is negative of -5.16 as expected. This put the average category valuation into 21.39 dollars with standard error of 7.9 dollars.

The second section shows the origin parameter estimates for search costs. For illustration purpose, here we transfer these terms into dollar terms. Since we assume log normal distribution for marginal search cost on PC and mobile, the mean of the marginal search cost on PC equals 227.28 which is worth \$6.61 for consumers. For mobile, the average marginal search cost is 6.84 dollars, which is about 3.6 % higher than the marginal search on PC. The difference in marginal search cost is statistically significant but not large in magnitude. This fits our empirical data pattern where the average search time on mobile is slightly lower than on PC. For the fixed cost, our model estimation implies that the fixed cost to start a shopping session on PC compared to on mobile is worth 0.25 dollar to consumers. Compared to the average marginal search cost difference between mobile and PC, the fixed search is about 6.8% higher. This implies that for an average consumer who search 1 time, he/she will prefer the

mobile channel. When the optimal search time increases, the channel utility for PC will become increasingly appealing to consumers. All search parameter and their difference are statistically significant. The results support our previous hypothesis – although the marginal search cost is lower on the PC channel, the initial fixed search cost is higher for consumers to start a shopping session on PC than on a smartphone.

The difference in marginal and fixed search costs, together with consumer utility heterogeneity can explain the gap in conversion rate between the two channels. Consumers take the search cost differences into account and choose the channel to maximize the expected utility after search. For consumers with higher overall valuation for the product category, the probability of ending up with a purchase is high. For these consumers, one additional search could lead to higher marginal benefit in terms of a better price and/or a higher individual match value (the utility error term). With a higher number of expected number of searches, these consumers are more likely to choose the PC channel with a lower marginal search cost. On the other hand, consumers with lower overall valuation have a smaller number of expected number of searches. Since these consumers have lower probability of purchase, they are less likely to search a large number of product options by paying additional marginal search cost, given that they are likely to walk away without making a purchase. The lower number of searches makes it more likely for these consumers to choose the mobile channel with a lower fixed search cost. When the heterogeneity of the overall valuation is high enough, consumers who choose the mobile channel have a lower conversion rate because of their lower initial valuation. And this holds true for consumers with the same size of consideration set across the two channels.

<Insert Table 4 about here>

Consumers can have different fixed search cost for the two channels, which influences their channel choice decisions. In the third section, we explore the heterogeneity of fixed search cost across consumers with different buyer rating, purchase history, site registration history and demographics. A higher fixed search cost on the PC channel leads to higher probability of using the mobile channel compared to the PC channel. Note that our model assumes that all consumers have access to both channels. If a consumer cannot choose a channel, for example

they cannot use PC for shopping when in transit, such cases would be interpreted as these consumers having a high fixed search cost to start a shopping session on PC. Consistent with the probit regression results (Table 2), we find that higher buyer rating, more purchase in the past and longer user history are associated with a lower fixed search cost on the PC channel. These three measures are all positively correlated with the length of time a consumer uses the website for purchase. For long-time users of the website, they could have started shopping on Taobao.com before the mobile shopping option was introduced and become used to the PC shopping channel. In addition, we find that age is negatively correlated with the fixed search cost for PC channel, which means that younger consumers are more likely to use mobile channel for shopping than older consumers. Male have lower fixed search cost for PC, which means that men are more likely to use the PC channel than women. Those with missing rating are slightly more likely to use the mobile channel. The magnitude of the parameter estimates for missing gender or age information are very small.

In the fourth section, we explore how the marginal search cost varies with different types of mobile devices. Consumers may find it easier to shop on the mobile channel using advanced smartphones with larger screens and more robust operation system. The features of the smartphone could significantly affect the user's time and effort when browsing product options on the mobile channel. We find that the parameters for screen size, Apple and Samsung brands are all negative and statistically significant. Larger screen size and premium brand can moderate the high marginal cost on the mobile channel compared to the PC channel. With rapid development of the smartphones, the marginal search cost on the mobile channel goes down, and more consumers will use the mobile channel for shopping.

Model Fit

To examine the model fit, we use the model estimates to simulate consumer actions, including their channel choice, number of searches and purchase decisions, and compare the simulation results and actual data. We run the simulation 100 times and take the average. The results are reported in Figure 3. In Figure 3, the two diagrams in the left panel report results on the mobile channel and the two in the right report results on the PC channel. The conversion

rate and number of searches match well between simulated and actual data for both channels. The estimated model is able to predict the key empirical patterns – 1) higher conversion rate with higher number of searches within a given channel, and 2) higher conversion rate on PC than mobile for the same number of searches. The channel choice decisions also match well between the simulated and actual data. From the two diagrams showing search time distribution in the bottom of Figure 3, we see that for consumers who search only once, they are more likely to choose the mobile channel than the PC channel. On the other hand, for consumers who search more than three times, the proportion to choose the PC channel is higher.

<Insert Figure 3 about here>

Our results suggest that the gap in conversion rates between the two channels can be explained by the self-selection of consumers. The PC channel has higher fixed search cost and lower marginal search cost. Consumers with higher valuation toward the product category are more likely to choose the PC channel, which leads to a higher overall conversion rate on the PC channel. The lower conversion rate on the mobile channel may not be a concerning trend for online retailers. The mobile channel has the advantage of a lower fixed search cost, because of its great portability and ease of access anywhere. The mobile channel can attract a large group of consumers who may not find it worthwhile to start a shopping session on the PC channel. Hence, the mobile channel could potentially enable market expansion by drawing in consumers with a lower probability to purchase.

7. Counterfactual

By modelling consumers' channel choice, we find that consumers who choose the PC and the mobile channels are systematically different. Taking the different pool of consumers into account, we study sellers' optimal pricing policy by allowing channel-specific pricing. In the first counterfactual analysis, we illustrate how sellers can use the consumer channel choice information to optimize pricing decisions.

Furthermore, sellers can retarget consumers who have browsed the products but did not make a purchase using coupon promotions. Consumers' channel choices provide additional

information about their overall valuation and search cost. In the second counterfactual analysis, we illustrate how sellers can use consumer channel choice information to optimize the retargeting strategy.

7.1. The Optimal Pricing Policy on Different Channels

Our model estimates suggest that consumers who choose to browse on the PC channel have higher purchase probability than those on the mobile channel. We study how sellers can utilize the utility information revealed by the consumer search channel choice by offering different prices across both channels. In reality, sellers can achieve such goal by offering coupon for consumers who search and purchase on their smartphones. When the sellers' pricing policy changes, consumers will also adjust their price expectation and change their search and purchase decisions accordingly. The customer base at each channel will change compared to under the current pricing scheme. Our structural model approach allows us to account for such consumer reaction by calculating the new equilibrium where sellers set different price on PC and mobile and consumer adjust their decisions accordingly.

In the first step, we recover the marginal cost of sellers. To estimate the marginal cost, we assume that the observed prices are the equilibrium prices when sellers can only choose the same price level for both channels. There are over 100 different products in our dataset, it would be computationally difficult to recover the marginal cost for each product. Instead, we focus on the top 10 sellers whose sales together account for over 60% of the total sales during the data observation period. The prices of these products range from 117 to 208 RMB (17.55 to 31.2 dollars).

To recover the marginal cost, we first estimate the consumer demand function. The demand of product j with price p_j is

$$D_s(p_j) = \pi_s \left(\sum_{b=1}^5 \pi_{sb} \cdot \frac{b}{N} \cdot P[U_{sb}(p_j) > 0] \cdot P[U_{sb}(p_j) < U_{sb}(p_{-j}^b)] \right)$$

For consumers who search b number of times on channel s , they will purchase product j if the following three conditions are satisfied. 1) It appears in the consumer consideration set. Since

we assume random draw in our model, the probability of product j being browsed during b searches is simply $\frac{b}{N}$, where N is the number of all available products. 2) The utility of purchasing product j $U_{sb}(p_j)$ is larger than the outside option. 3) The utility of product j is higher than the maximum utility of all the other products browsed $U_{sb}(p_{-j}^b)$.

We use the estimated parameters and run model simulations 50 times. Using the simulation results, we estimate the proportion of consumers on each channel, π_s , as well as the proportion of consumers conducting b number of searches on channel s , π_{sb} . Since the sellers do not know the true utility for each consumer who visited the store, we need to further estimate the distribution of $U_{sb}(p_j)$. There are three two source of uncertainty when it comes to form the expectation value of $U_{sb}(p_j)$: the individual initial willingness to buy, α_i , and the individual matching value toward seller j 's product, e_{ij} . Since channel choice and search time are affected by α_i , sellers could use such information to update the expected utility distribution for every consumer who visit their stores. During the simulation, we record all the values of α_i for every consumer, and calculate the simulated distribution of $U_{sb}(p_j) = \alpha_i + \lambda p_j + e_{ij}$ for all consumers who search s times on channel b . Finally, we run a separate simulation to calculate the probability that product j offers the highest utility. For each number of searches b , we draw $b - 1$ times from the price distribution and b times from the extreme type I distribution. We get 1000 sets of draws and approximate the probability $P[U_{sb}(p_j) < U_{sb}(p_{-j}^b)]$ by the average of the probability $P[\lambda p_j + e_{ij} > \lambda p_{-j}^b + e_{i,-j}]$ using the 1000 sets of draws. Notice that different from previous search models such as Honka (2014), the term e_{ij} is not realized until the consideration set is determined by consumers, so the distribution e_{ij} still remains intact without going through the selection process. We can simply take random draws from the price distribution for p_j and extreme type distributions for e_{ij} to calculate the $P[\lambda p_j + e_{ij} > \lambda p_{-j}^b + e_{i,-j}]$.

We calculate the demand function for prices ranging from 0 to 1000 RMB, which covers

all observed prices in our data set. Figure 4 plots the demand functions for the PC (black dashed line) and the mobile channel (grey solid line) separately. Since consumers on the PC channel are likely to have higher valuation of the product category, we observe a higher demand on PC than on mobile at any given price. In addition, demand is most sensitive to changes in price when price is in the medium range. When price is very low, total demand is bounded upward by the probability of the product being browsed. When price is very high, it is less likely to be the best option compared to the other products and the outside option. Therefore, the demand converges to 0 when price is too high.

<Insert Figure 4 about here>

With the estimated demand function, we can infer the marginal cost for each product j . The profit function for product j with price p_j and marginal cost mc_j is

$$R(p_j, mc_j) = \sum_s (p_j - mc_j) D_s(p_j)$$

With the assumption that the observed price p_j maximizes total profit, the marginal cost for seller j mc_j^* should satisfy the condition

$$\hat{p}_j = \operatorname{argmax}_{p_j} R(p_j, mc_j^*)$$

We recover the marginal costs for each of the top 10 sellers.

The second step is to calculate the optimal channel pricing for each of the top 10 sellers by allowing them to have channel specific pricing. Each seller j chooses its price on the mobile channel p_{j0} and on the PC channel p_{j1} to maximize its expected profit across both channels.

$$\operatorname{Max}_{p_{j0}, p_{j1}} R(p_{j0}, p_{j1}, mc_j) = \sum_s (p_{js} - mc_j) D_s(p_j)$$

The change in price distribution in the two channels will affect consumer channel choice. In the third step, we get an updated price distribution in both the mobile and the PC

channels from the second step. To account for the impact of the price distribution on consumer channel choice, we repeat the first step by plugging in the updated price distribution to get an updated demand function. This process is repeated until the optimal pricing decisions converge for each seller, when the changes in optimal prices are less than 0.1 between iterations.

<Insert Table 5 about here>

Table 5 reports the results in estimated marginal cost and the equilibrium channel specific prices, aggregated from the top 10 sellers. The optimal prices on the mobile and PC channels are reported in Column (3) and (4). Under the new equilibrium with channel specific pricing, we find the top 10 sellers will set the price on mobile 1~4% lower than the price on PC. In average, price difference between mobile and PC among these sellers is about 4.49 RMB with a 95% confidence interval of 3.73 to 5.11 RMB. This result suggests that, taking consumer channel choice into consideration, sellers should offer lower mobile specific prices to maximize profit. With the channel specific pricing, the weighted average increases for the top 10 sellers by 0.55% (95% CI: 0.06%~0.70%).

To understand the changes in consumer behavior under the new channel specific pricing, we compare the consumer browsing and purchase patterns under the current and the new channel specific pricing policies. Results are reported in Table 6. The search intensity and conversion rate both increase on the mobile channel. This is driven by the lower equilibrium prices on the mobile channel with channel specific pricing. On the PC channel, the conversion rate slightly decreases and so does the search intensity.

<Insert Table 6 about here>

The counterfactual analysis highlights the necessity for our structural model when considering the channel optimal pricing. There are two effects predicting the difference in pricing with the opposite direction. Without treating channel choice as consumer endogenous choice, researchers who observe the less intensive search on the mobile channel may suggest the sellers to set higher prices on mobile. This is because less search will shrink the consumer's consideration set and may reduce the price competition sellers face on the mobile channel,

which provides incentive for them to increase the price on mobile. On the other hand, if we only look at the higher conversion rate, one may reach to the conclusion that consumers are more inclined to make a purchase on PC and sellers should increase the prices on PC rather than the ones on mobile. By explicitly modeling both channel choice and search decisions, our structural model account for both effect. With parameters estimated from the field data, our approach enables us to provide a complete picture of channel pricing for sellers. In this case, the empirical result suggest that the second effect dominates, and the optimal prices are lower on the mobile channel. Ignoring the consumer self-selection between the two channels could lead to wrong channel specific pricing policy.

7.2. Optimal Retargeting Strategy for Sellers

Sellers can retarget a consumer by sending him a promotion coupon after he browses similar products but leaves without purchase. In this section, we study the channel specific optimal retargeting strategy for sellers. The consumers who abandon the search can be different from the general entire population in terms of realized utility toward the products. We study in the first counterfactual in terms of their utility distribution. Sellers can use the channel choice to infer consumer's overall category valuation and offer channel specific promotion to consumers.

We assume that sellers know the selected channel for consumers who have searched their products but do not know what or how many products the consumers have browsed. Although we know consumers in average have higher category utility on PC channel, it is not clear *ex-ante* whether such pattern still holds among consumers who do not make a purchase.

We empirically solve the optimal value for the retargeting coupon. We assume consumers will not exhibit strategic behavior toward the retarget policy, which means consumers will not try to search and stop at first in order to get retarget coupon before they make purchases. We also assume sellers know the overall distribution of consumer utility, but they do not observe the individual level decision including search time and consideration set. Seller j decides the optimal value of the coupon x on each channel s to maximize the expected profit $r_j(x)$.

$$Max_x r_j(x) = \sum_s (p_j - c_j - x) B_j^s(x) I_s$$

Where the first bracket represents the new marginal profit for seller j after the coupon value is deducted, and the second term denotes the purchase probability on channel s for seller j given the coupon value. Notice that the third term, I_s , will not change when x varies due to the non-strategical consumers assumption. Now we need to use simulation to calculate the purchase probability $B_j^s(x)$. Similarly, with the first counterfactual experiment, we achieve this goal by simulations:

- a) With our estimation result, we run $Q=50$ times of simulation of our model with random draws of category preference and prices for each consumer.
- b) Denote I_{qs} as the number of consumers who do not convert into buyers on channel s at simulation q. In each simulation q on channel s, record the $a_{I_{qs}}$ as the category utility for consumers who do not make a purchase, as well as their outside option value $e_{0I_{qs}}$ and individual match value toward seller j, $e_{jI_{qs}}$.
- c) Now given any x, we can calculate the purchase probability for channel s as:

$$B_j^s(x) = \frac{1}{Q} \sum_q \frac{1[(a_{I_{qs}} - \lambda(p_j - x) + e_{jI_{qs}}) > e_{0I_{qs}}]}{I_{qs}^s}$$

In the equation above, the numerator is the number of consumers who did not make a purchase but now are willing to buy seller j's product given the coupon value x. Divided by the total number of consumers who quit without purchase on channel s, we calculate the purchase probability for any value of retarget coupon x. Averaged by the simulation time Q, $B_j^s(x)$ represents the expected purchase probability when seller j sent a coupon with value x to retarget consumers on channel s.

With the expression of $B_j^s(x)$, now we calculate the optimal coupon value for x on PC and mobile channel given seller j's original price, marginal cost .

We calculate the optimal coupon value for the top 10 sellers with the highest market shares ranked in retailing price and report the average value in Table 7, whose marginal costs are recovered in the previous section.

<Insert Table 7 about here>

We find that the optimal retarget coupon value for mobile consumers is 5.11 RMB, which is roughly 3% of the average original price. And the coupon for PC consumers is 4.81 RMB. The difference of the optimal retarget coupon value between PC and mobile is small though statistically significant (95% CI is 0.0076~0.6057). With the retarget strategy, the sellers can improve the overall expected profit by 9%. The result suggests that conditional on consumers without purchase, it is still optimal for sellers to offer more discount for consumers who search on the mobile channel. The results are consistent with the optimal pricing results we get from the first counterfactual analysis.

8. Conclusion

In this paper, we develop a search model allowing for consumers' endogenous channel choice. This model is motivated by a potentially concerning phenomenon – despite the rapid growth of the mobile shopping option, the conversion rate on the mobile channel is significantly lower than that on the PC channel. After considering several alternative explanations including search cost and transaction cost difference between the two channels, we find that consumer endogenous channel choice can explain the data pattern. Consumers with higher product valuation, thus higher initial purchase intention, are more likely to choose the PC channel than the mobile channel. Model estimation results suggest that the PC channel has a lower marginal search cost but a higher fixed search cost than the mobile channel. The different search cost structure makes it more likely for consumers with a higher product valuation, who tend to have larger benefit from more intensive search, to choose the PC channel.

With the estimated model with endogenous channel choice, we conduct counterfactual analysis on optimal channel specific pricing for sellers. We find that the optimal price on the PC channel are higher than that on the mobile channel. This contradicts the traditional intuition

that sellers should offer discounts on the PC channel due to the higher search intensity hence more intense competition among different sellers. For the second counterfactual analysis, we investigate the optimal retargeting coupon value considering the endogenous channel choice. We find that it is optimal for sellers to offer higher discount to consumers who only search once on either channel, and to offer lower discounts for consumers with higher search intensity in general. This result also shows that the difference in category valuation from channel choice dominates the competition effect from search intensity. Both counterfactual analyses demonstrate how the proposed model can provide sellers with important managerial insights. We quantify the increase in profit from channel specific pricing and retargeting strategy. The results illustrate the importance of considering channel as an endogenous choice for consumers.

This paper has several important implications. From a methodological prospective, we propose a flexible framework that incorporates consumer channel decisions in addition to the search and purchase decisions. Consumers endogenously choose a channel to browse depending on their heterogeneous search cost and product category valuation. The proposed model can adequately capture the observed search activities and purchase decisions on both channels. From a managerial prospective, we investigate the optimal channel specific pricing for sellers and quantify the change in profit. We find that the optimal prices on the mobile channel are lower by about 1~2% than prices on the PC channel. In addition to channel specific pricing, we also explore the retargeting coupon value for consumers who have browsed some product options but did not make a purchase on both channels. We find that the retargeting coupon value is not necessarily higher for consumers on the mobile channel.

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Tables

Table 1. Variable Description and Summary Statistics

Variable	Description	Mean	Std. Dev.
Buyer rating	Based on buyer's prior purchase history	3.8	1.96
Buyer rating missing	Indicator variable; equals 1 if buyer rating is missing	0.005	–
Buyer spending	Buyer total spending in RMB before data observation period	183.2	575.81
Buyer history	Number of days passed since the buyer registered on the website	1099	831.47
Screen resolution (length)	Smartphone screen resolution in pixels (width)	1184	392.86
Screen resolution (width)	Smartphone screen resolution in pixels (height)	782.3	299.42
IOS	Indicator variable; equals 1 for IOS operation system	0.34	–
Android	Indicator variable; equals 1 for Android operation system	0.15	–
Mobile browsing	Total number of products browsed on a smartphone before data observation period	173.9	295.90
Male	Indicator variable; equals 1 for male	0.56	–
Age	Buyer's age	30.6	8.47
Male missing	Indicator variable; equals 1 if gender information is missing	0.09	–
Age missing	Indicator variable; equals 1 if age information is missing	0.13	–
Mobile missing	Indicator variable; equals 1 if there is no smartphone information	0.34	–

Table 2. Channel Choice with Observed Consumer Characteristics

	Estimate	Std.	Pr(> z)
(Intercept)	-0.74	0.03	***
Buyer rating	0.12	4.06E-03	***
Buyer rating missing	-0.32	0.03	***
Buyer spending	8.31E-05	2.11E-05	***
Buyer history	8.04E-05	6.67E-06	***
Screen resolution	-1.12E-07	6.52E-09	***
IOS	-0.03	0.01	*
Android	-0.05	0.01	***
Mobile browsing	-2.03E-03	2.84E-05	***
Male	0.44	0.01	***
Age	0.01	6.19E-04	***
Gender missing	-0.66	0.04	***
Age missing	0.51	0.05	***

Table 3. Results from Monte Carlo Simulation

Variable	True Value (1)	Estimated Value (2)	Standard Error (3)
μ_a	-45.0	-43.47	0.770
σ_a	110.0	125.71	13.48
λ	-1.5	-1.45	0.005
μ_{sc}	4.0	4.09	0.006
σ_{sc}	0.4	0.42	0.001
sc_0	10.0	9.34	0.372
fc	0.3	0.27	0.007

Table 4. Estimation results¹³

	Variable	Estimation	Standard Error	P value
Utility parameters	μ_a : Mean of valuation	763	10.55	***
	σ_a : Std. dev. of valuation	272	5.20	***
	λ : Price coefficient	-5.16	0.01	***
Search cost parameters	μ_{sc}	5.09	1.35E-03	***
	σ_{sc}	0.82	3.91E-04	***
	sc_0	8.02	0.04	***
	fc	8.57	0.05	***
Fixed cost heterogeneity	Buyer rating	-0.03	2.43E-03	***
	Buyer rating missing	0.01	0.02	
	Buyer spending	-1.10E-04	1.94E-05	***
	Buyer history	-9.47E-05	5.95E-05	*
	Male	-0.06	0.01	***
	Missing male	-7.85E-06	0.02	
	Age	-0.02	6.46E-04	***
	Missing age	3.51E-05	0.02	
Marginal Cost heterogeneity (Mobile)	Screen size	-1.32E-02	4.87E-04	***
	IOS	-1.95E-04	1.08E-04	*
	Android	-3.49E-05	1.44E-05	**
	Mobile browsing	-3.61E-02	3.14E-03	***
	Missing mobile device information	-9.57E-08	0.01	

¹³ In table 4, * for p<0.1; ** for p<0.05; *** for p <0.01

Table 5. Optimal Average Price on Mobile and PC¹⁴

Original price	Marginal Cost	Optimal Price on Mobile	Optimal Price on PC	Weighted Profit Increase
165.737	108.201	163.942	168.429	0.55%

¹⁴ The results in Table 5 are for the top 10 sellers who change their price on mobile and PC, we assume the rest of sellers will remain their original price across PC and mobile when calculating the new price equilibrium.

Table 6. Consumer Decisions under New Price Equilibrium

Channel Choice	Number of Searches	Current Pricing		Channel Specific Pricing	
		Conversion	Proportion of Consumers	Conversion	Proportion of Consumers
Mobile	1	6.88%	24.58%	7.05%	24.53%
Mobile	2	13.93%	12.35%	14.36%	12.33%
Mobile	3	18.17%	6.00%	18.74%	6.03%
Mobile	4	24.56%	2.81%	24.30%	2.84%
Mobile	5	31.37%	2.81%	32.39%	2.84%
PC	1	6.47%	24.12%	6.40%	24.23%
PC	2	15.80%	11.77%	15.80%	11.77%
PC	3	24.53%	6.36%	23.85%	6.29%
PC	4	29.41%	3.40%	28.57%	3.36%
PC	5	41.90%	5.80%	41.70%	5.78%

Table 7. Optimal Retarget Coupon Value

Search Channel	Optimal Coupon value (RMB)	Expected profit increase
PC	4.81	9.06%
Mobile	5.11	9.13%

Figures

Figure 1. Conversion Rate with Number of Products Browsed

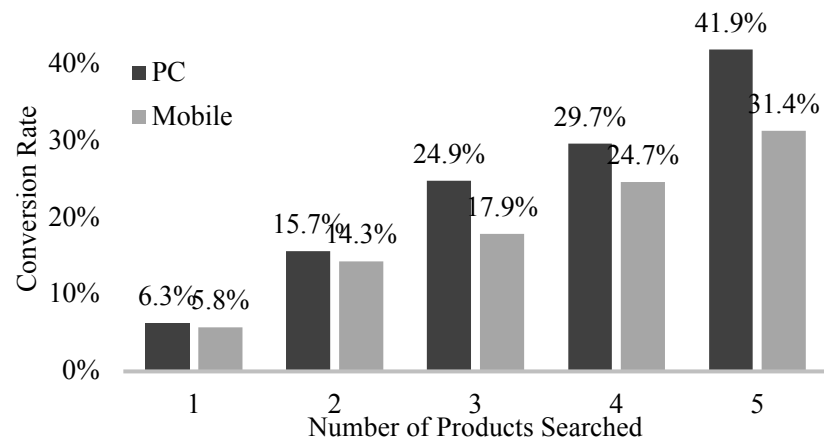
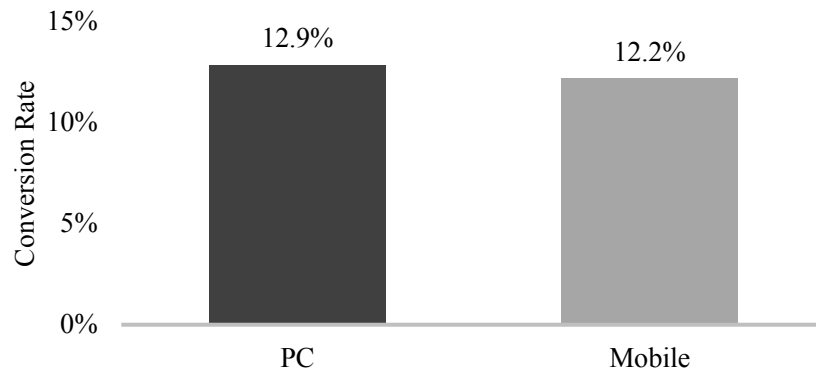


Figure 2. Conversion Rate on Mobile and PC for Consumers Who Used *Both* Channels



|

Figure 3. Model Fit

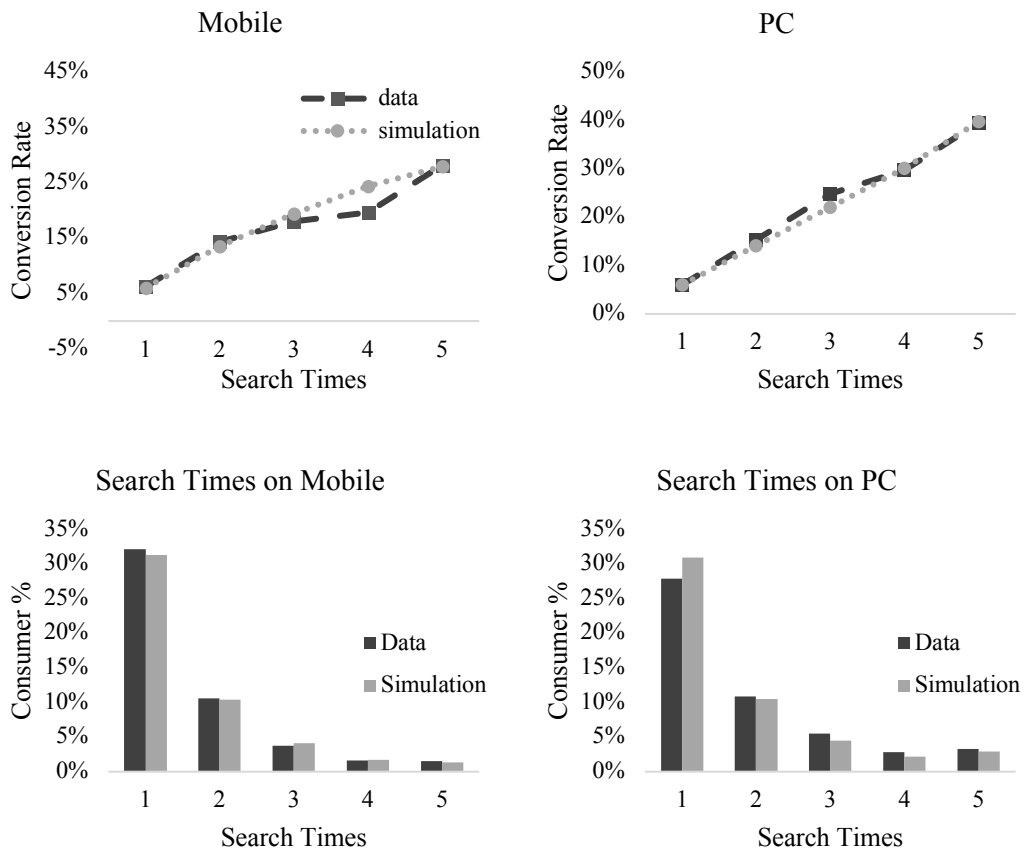


Figure 4. The Estimated Demand Function on PC and Mobile

