Online Shopping with Endogenous PC and Mobile Channel Choice

Shuo Zhang

Washington University in St.Louis

Zhenling Jiang

Washington University in St.Louis

Hai Che

University of California, Riverside

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Abstract

Mobile phones have emerged as a major channel for online shopping as an alternative to PCs. Despite more consumers using mobile phones, the conversion rate on the mobile channel is lower than that on the PC channel. In this paper, we propose a structural consumer search-and-purchase model that endogenizes the channel choice to explain the observed data pattern. Results suggest starting a search session using mobile phones is less costly, but intensive search is costlier. Consequently, mobile phones attract consumers who tend to have lower overall purchase interests and will search less. Based on the results, we use counterfactuals to explore how online retailers can customize their marketing strategies for consumers on the two channels. We find the optimal price on mobile is 2.7% lower than on PC. When sellers retarget non-purchasers by offering channel-specific coupons, the optimal coupon value is 6% higher for consumers on mobile than on PC. Sellers' profit increase will be 5.1% higher when the retargeting coupons are channel specific.

Key words: channel choice, consumer search, conversion rate, retarget strategy

1. Introduction

In recent years, the online retail industry has seen a rapid increase in traffic from mobile devices compared to traditional PCs, including desktops and laptops. In the US, the average time adults spend using mobile devices to shop has surpassed that using PC since 2015.[1] Knowing the popularity of online shopping by smartphones, most major US retailers have been aggressively increasing their investment in both mobile application development and advertisement.[2]

Despite the more intensive usage of smartphones, consumers make fewer purchases from mobile devices than from PCs. A report from Business Insider Intelligence 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.[3] Such disproportionally low sales on mobile is consistent with the conversion-rate gap between the two channels. Based on data collected from over 1.9 billion shopping sessions in the US from 2015 Q4 to 2016 Q4, the conversion rate on PC is consistently much higher than that on mobile (e.g., the average conversion rate is 4.14% on PC and 1.55% on mobile in 2016 Q4).[4]

The systematic differences in browsing and purchase behaviors between PC and mobile channels offer online retailers an opportunity to differentiate and target consumers on the two channels. Traditional multi-channel retailers with online and offline channels have been engaging in channel-based price differentiation (Wolk and Ebling 2010, Cavallo 2017). With the emerging mobile channel,

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[1] Source:https://www.businessinsider.com/the-mobile-checkout-report-how-retailers-and-tech-giants-are-pushing-consumers-12-2015.

[2] 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.

[3] Source:https://www.businessinsider.com/the-mobile-checkout-report-how-retailers-and-tech-giants-are-pushing-consumers-12-2015.

[4] Souce:https://www.smartinsights.com/mobile-marketing/mobile-commerce/mobile-users-still-not-converting/.

some companies have offered lower prices for mobile users. For example, anecdotal evidence shows Kayak and Orbitz quote lower hotel prices for mobile users than for PC users.[5] Other companies do the opposite. Hannak et al. (2014) document that Home Depot provides more expensive products for mobile users than for desktop users. Many other companies do not engage in differential product offerings on the two channels. Clearly, what pricing strategy is more profitable depends on how consumers on the two channels differ from each other.

This paper has two main objectives. The first is to study how and, more importantly, why consumer search and purchase behaviors on PC and mobile channels differ. To achieve this goal, we develop a structural consumer search model with endogenous channel choice. The proposed model can explain how different types of consumers choose the shopping channel depending on the benefits and costs of using each channel. By modeling the consumer's channel choice, our model rationalizes the intriguing data pattern of a higher usage rate but a significantly lower conversion rate on mobile. Estimation results from our model can help firms predict which segments of consumers would shop on mobile and PC channels, which enables us to achieve the second objective of the paper, which is to design channel-specific marketing strategies targeting consumers on the two channels. Without the structural model, whether and how prices should differ on the two channels is not ex-ante clear.

We estimate the proposed model using a unique clickstream dataset from both PC and mobile channels from Taobao, the largest online shopping platform in China. Consumers can use PCs or smartphones to browse and make purchases. The data set contains information on which channel consumers use to browse and purchase. We observe each consumer's search activities (through

[5] https://www.bostonglobe.com/business/2014/10/22/online-shopping-yields-different-prices-results-says-northeastern-study/ZbSVnoBxPJtA8STeWbpQ9H/story.html

browsing different product options) and purchase decisions. We also collect some additional information, such as consumer demographics and their smartphone attributes that may influence consumer channel choice.

Based on the data, we find (1) a higher proportion of consumer usage, (2) a smaller number of searches per customer, and (3) a lower conversion rate for the mobile channel than for the PC channel, consistent with the industry reports of the US market.[6] Even after controlling for the difference in the number of searches on the two channels, the gap in the conversion rate remains unchanged. Estimation results show that, on average, the marginal search cost for an additional search is ¥1.55 (or US$0.23) higher on mobile than on PC. The average initial fixed search cost for starting a search session, however, is ¥1.66 (or US$0.25) higher on PC than on mobile. How does this difference influence consumers' channel choice and conversion rate on each channel? When deciding which channel to shop, consumers consider the search-cost differences and choose the channel that maximizes the expected utility after search. Given the lower marginal search cost on PC, consumers who want to conduct more extensive search are more likely to choose PC over mobile. Because consumers with higher overall valuation are willing to search more, they are more likely to self-select into using the PC channel. Consumers with a lower valuation of the category are more likely to conduct fewer searches and choose the mobile channel due to a lower initial fixed cost. This mechanism of consumer self-selection in our model therefore explains the observed conversion-rate gap between the two channels. We present evidence in the paper that several other alternative explanations, including the difference in transaction costs, cannot explain this difference.

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[6] Souce:https://www.smartinsights.com/mobile-marketing/mobile-commerce/mobile-users-still-not-converting/.

The estimation results also show the heterogeneity in search costs and channel choices across different types of consumers. For example, consumers with more prior purchases and a longer registration history on the platform are associated with a lower fixed search cost on PCs, likely because these consumers were more accustomed to shopping from PCs before the mobile phones became popular. In terms of demographics, younger consumers and women are more likely to choose the mobile channel. Different types of smartphones influence the marginal search cost on mobile. We find that smartphones with a higher screen resolution (typically associated with a larger screen size) and better operating systems are associated with a lower marginal search cost, which increases the likelihood of using the mobile channel.

To guide how sellers can better target consumers on the two channels, we conduct counterfactual analyses. We first investigate the optimal strategy if sellers set different prices on PC versus mobile channels. Optimal prices can be different because consumers drawn to shopping on the two channels are systematically different. Our proposed model accounts for both channel choice and search activity. We find the optimal price on mobile is 2.7% lower than on PC, because consumers on the PC channel tend to have higher overall valuation due to the self-selection in channel choice. Next, we investigate the retargeting strategy by providing a coupon for consumers who browsed but did not purchase. When sellers utilize the information of consumer channel choice, results suggest the optimal coupon value is about 6% higher for consumers on mobile than on PC. Although this analysis focuses on non-purchasers, the result is consistent with a lower optimal price on mobile suggested by the first counterfactual. Overall, sellers' profit increase is 5.1% higher when the retargeting strategy is channel specific than when it does not differentiate channels. The counterfactual results illustrate the importance of considering consumers' channel choice 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 counterfactual regarding optimal channel-specific pricing and retargeting strategies. We conclude the paper and suggest future research in section 8.

2. Literature

Our paper is related to the multi-channel retailing literature. It has always been of interest for marketers to understand how to manage customers in a multi-channel environment. In the existing literature, researchers are primarily concerned about issues related to online shopping websites, physical stores, and catalogs (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, Forman et al. 2009). One of the questions of interest in this line of research is to understand the behavioral difference for consumers who use different channels. Hitt and Frei (2002) document the difference in consumer characteristics and behavior with PC and traditional banking. Degeratu et al. (2000) find that online and physical store environments can affect consumer choices in different ways. Our paper investigates the difference in behavioral patterns (e.g., the intensity of search, conversion rate, etc.) for consumers who use smartphones or PCs to shop, which is a relatively new and increasingly important multi-channel context. Different from de Hann et al. (2018), who focus on the conversion rate for consumers who switch devices between mobile and PC, we explain the conversion-rate difference for consumers who choose either channel. By treating channel as an endogenous choice in our model, we can not only explain the observed behavioral difference on mobile and PC channels, but can also provide guidance on how sellers can offer *channel-specific* pricing and promotional strategies to increase profit.

This paper is also related to the growing literature about consumers using mobile devices. Existing research has studied how consumers respond to firms' mobile marketing activities (Shankar and Balasubramanian 2009, Andrews et al. 2016), the impact of the mobile channel on consumer purchase (Einav et al. 2014, Wang et al. 2015, Xu et al. 2016) and news consumption (Xu et al. 2014), content generation and usage (Ghose and Han, 2011), and consumer search behaviors (Daurer et al. 2016). Using data from eBay, Einav et al. (2014) document that the mobile channel is more often used for strictly browsing, leading to a lower conversion rate than on PC. They also find the mobile channel is more often used for common products instead of idiosyncratic items that require more careful inspection. Ghose et al. (2012) find the search cost is higher on mobile than on PC, although local activities (distance) matter more. They do not explicitly model how consumers choose between the two channels. Different from the existing literature on the mobile channel, our paper studies the consumer channel choice using a structural model. Furthermore, our paper documents how channel choice differs across consumers with different demographics, purchase history, and mobile-device attributes.

Finally, the paper is related to the literature of consumer search. Because 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 how consumers make search and purchase decisions (e.g., Kim et al. 2010, Koulayev 2014, Honka 2014, Chen and Yao 2016, Kim et al. 2016, Honka and Chintagunta 2016). Understanding consumer search is important for firms when making marketing decisions, such as pricing (e.g., Hong and Shum 2006, Wildenbeest 2011, Zhang et al. 2018). 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 (e.g., Chen and Yao [2016] and Ursu [2018] 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 consumers' browsing and purchase data as well as which channel, PC or mobile, consumers use. Our search model endogenizes consumers' channel choice, which allows us to study the optimal channel-specific pricing and promotional strategies. A recent working paper by Jiang et al. (2019) uses a consumer search model to explore the effectiveness of retargeting strategies. We also study how to improve the effectiveness of retargeting strategies in one of the counterfactuals; however, our focus is on channel-specific strategies.

3. Data

Our dataset comes from Taobao, which is the largest online shopping platform in China and is owned by Alibaba. Taobao has both mobile and PC channels for consumers to browse and make purchases. The product offerings and their attributes, including prices, are the same on the two channels. From the dataset, we observe detailed individual-level browsing history and purchase decisions and, more importantly, through which channel, mobile or PC, a browsing activity happens. The dataset also contains additional consumer characteristics including demographic information, smartphone attributes (even for those who did not use the mobile channel to make purchases in our data), and prior shopping history on the platform. We collect data for consumers who had browsed the fishing pole category. We observe search and purchases of 133,896 unique consumers during the data-observation period from October 15, 2014, to November 15, 2014. Among those consumers, 51% had browsed at least one product option from the mobile channel and 49% from the PC channel. Moreover, only 6% of them had used both PC and mobile channels during the one-month data-observation period. Most purchasers (99.2%) bought only one product during the sample period. Thus, we assume consumers have a unit demand in the model.

The data show the browsing and purchase patterns are very different on mobile versus PC. First, the conversion rate, defined as the percentage of consumers who made a purchase out of those who browsed, is significantly lower on mobile (9.93%) than on PC (13.59%). Second, the search intensity, defined as the number of unique products browsed, is higher on PC than on mobile: 58% of consumers browse one product on PC, compared to 65% on mobile, and 28% of consumers browse at least three products on PC, compared to 20% on mobile. Figure 1 graphically compares the proportion of consumers shopping on the two channels conditional on the number of searches. More consumers choose the mobile channel if they only search one option; however, for those who search three options or more, the proportion who shop via PC is significantly larger.

<Insert Figure 1 about here>

Table 1 reports the average and the standard deviation of prices and number of searched options. We observe consumer demographics, gender and age, for 65% of the sample. We also collect consumers' smartphone-device information including the model, screen size, and the phone's operating system, for 82% of the sample. The rest of Table 1 reports the variable descriptions and summary statistics for consumer demographics and mobile-device characteristics.

<Insert Table 1 about here>

3.1 Channel Choice

The prices for fishing poles did not change over time during our sample observation period. Other product attributes are also identical on mobile and PC, and thus do not affect the channel choice. Consumer characteristics, on the other hand, may affect the choice. We use a reduced-form regression to test how consumers who choose to use PC or mobile 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 regression to study how the channel choice correlates with various observed consumer characteristics (described in Table 1).[7] Results are reported in Table 2.

<Insert Table 2 about here>

Considerable heterogeneity exists among consumers who choose PC or mobile. We find that younger consumers and consumers who use mobile phones with higher screen resolution and more advanced operating systems[8] are more likely to use the mobile channel. In addition, consumers with a higher buyer rating (based on a higher number of prior purchases) and higher prior spending are more likely to use the PC channel, both of which positively correlate with the consumer's past experience on Taobao. These consumers are likely more familiar with the PC channel than the mobile channel because Taobao only introduced the mobile channel in 2008.[9] The reduced-form evidence suggests the observed consumer characteristics significantly correlate with their channel choice. We incorporate these characteristics in the structural model to account for consumer heterogeneity.

[7] We multiply the screen resolution in pixels in length and width, and use the demeaned value to represent screen resolution in the model estimation.

[8] Apple and Android operating systems were considered advanced in China during 2014, when many other smartphones used operating systems developed by local manufacturers.

[9] Source: https://yq.aliyun.com/articles/583335.

3.2 Potential Explanations for the Conversion-Rate Difference

The underlying mechanism driving the observed data pattern in our model is that consumers endogenously choose which channel to browse. We identify and estimate 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. The channel choice depends on the level of overall valuation as well as the cost to search on the two channels. Before describing the full model, we discuss in this subsection several possible explanations for the lower conversion rate on mobile compared to PC to help justify our model setup. Note we assume consumers have a choice between using mobile or PC. The CNNIC (the Chinese administrative agency responsible for Internet affairs) reports that among Internet users, the smartphone penetration is 85.8%, and desktop and laptop penetrations are 70.8% and 43.2% during 2014.[10] Therefore, it is reasonable to assume that consumers have access to both types of devices.

The first potential explanation is that the lower conversion rate on mobile is driven by a higher marginal search cost. With a higher marginal search cost, consumers browse fewer options and are less likely to find a good match and make a purchase on mobile. To test the hypothesis that the difference in the marginal search costs is the only cause for the conversion-rate gap, we compare the conversion rates for consumers who browsed the same number of products. Figure 2 shows the conversion rate on PC is still consistently higher than that on mobile among consumers who browse the same number of products. Therefore, although the marginal search-cost difference between the two channels can lead to an overall conversion-rate gap, it cannot explain the gap after controlling for the number of products browsed.

[10] Source: http://www.cac.gov.cn/files/pdf/hlwtjbg/hlwlfzzktjbg035.pdf.

<Insert Figure 2 about here>

The second potential explanation is the difference in transaction cost for completing a purchase on mobile versus PC. For example, consumers may have difficulty typing in the shipping address or the payment information when using a smartphone without a keyboard. In that case, consumers might be more likely to abandon the shopping session on mobile without purchase. To test this explanation, we focus on a small group of consumers (6%) who use both channels to browse the products. If the transaction cost is higher on mobile, we would expect a higher conversion rate on PC among these consumers as well. Figure 3 shows that among the consumers who browse both channels, the conversion rates on the two channels are almost the same (12.9% on PC, 12.2% on mobile). The interpretation for the equal conversion rates is that either the transaction cost is the same on both channels or the transaction cost is trivial, so it does not play an important role in determining where to purchase. In reality, once a debit or credit card is linked to the account, consumers on Taobao only need to type in a six-digit password for payment using mobile devices. Therefore, the time and effort required for payment on mobile is not distinctively higher than that on PC.

<Insert Figure 3 about here>

4. Model

We propose a consumer search-and-purchase model that incorporates endogenous channel choice. Before starting the search, consumers first choose through which channel (mobile or PC) to browse the products. We assume consumers can only choose one channel, due to the empirical observation that only 6% of consumers ever switch devices in our data. We exclude this small group of consumers in our empirical analysis to keep the model tractable.

Conditional on the channel choice, consumers then decide how many product options to search. In the literature, both simultaneous and sequential search models have been applied to study consumer search behavior. We do not observe the order of search from data. This data limitation makes estimating a sequential search very difficult. Prior empirical studies (e.g., De Los Santos et al. 2012 and Honka 2013) have tested the two search models and found evidence to support the simultaneous-search model. Therefore, we follow these studies by assuming consumers conduct simultaneous search. We note that if the data on the search order are available, our proposed framework of channel choice can be easily carried through to scenarios where consumers search sequentially.

Finally, given the channel choice and the number of product options to search, consumers will search on the retail platform. After the search, they will decide whether to purchase from the searched options and, if they do, which option they should buy.

4.1 Consumer Utility and Search

We first describe consumers' search and purchase decisions *after* they have selected a channel to browse. Suppose there are I consumers and J products. The utility of product j for consumer i is specified as

$$u_{ij} = a_i - \lambda \cdot P_j + e_{ij,} \tag{1}$$

where a_i is consumer $i's$ valuation for the product category. We allow a_i to be heterogeneous across consumers with a normal distribution $a_i \sim N(\mu_\alpha, \sigma_\alpha^2)$. P_j is the price of product j and e_{ij} is the individual match value. We assume e_{ij} follows i.i.d. extreme-value 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 consumers know their own outside option before conducting the search activities. e_{i0} is assumed to follow i.i.d. extreme-value type-I distribution across consumers.

Denote channel choice as $s_i \in \{1,0\}$, where $s_i = 1$ if consumer i chooses the PC channel, and $s_i = 0$ if choosing mobile. We first describe how consumers decide the number of product options to search, conditional on choosing channel *s*. Before the search, consumer i knows his initial utility level a_i. We assume the consumer knows the overall distribution of p_j and e_{ij}, but he has no information on p_j and e_{ij} for a specific retailer j, which are only revealed if he clicks into the product detail page. Therefore, the expected u_{ij} conditional on purchase for all product options are the same to the consumer before the search, but the overall expected utility from search will be different due to individuals having different levels of a_i and thus different purchase probabilities. The justification of this assumption is that many small sellers are on Taobao, and none of them belong to well-known branded manufacturers. Consumers are unlikely to have *a priori* information on the quality of any specific seller. Furthermore, each seller sells multiple brands and models of fishing poles; without searching for detailed information on the product page, consumers are unlikely to know anything about the price or other product and service attributes.

Under this assumption, our simultaneous search model focuses on how many product options the consumer chooses to search, denoted by b_i. Consumer i incurs a marginal search cost c_i^s for each product he browses. We allow the marginal search cost to vary across the two channels and individuals. Furthermore, as is common in the search literature, our data do not include consumers who do not search at all. Thus, we require that consumers search at least once in the model. A consumer chooses b_i to maximize the expected utility taking account of the search cost. Following Chade and Smith (2010), the consumer maximizes the following indirect utility by choosing the number of searches:

$$IU_i(b) = E\left[\max_{j \in C_{ib}}\{u_{ij}\}\right] - b_i \cdot c_i^s, \tag{2}$$

where C_{ib} is the set of the searched options (the outside option e_{i0} is always an element in C_{ib}).

The probability that consumer i chooses to search b_i times is

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

After the 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

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

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

Note that various factors, including the ranking of product options (e.g., Ursu 2018), may affect the final outcome. We do not observe those factors from data. The impact of these factors on the purchase decision is captured by e_{ij}, which is unknown to the consumer when he decides the optimal b_i. Conditional on b_i, these factors may affect which product options the consumer will search, as well as the order of the search. Our model is agnostic about what options are searched and how they are searched. Importantly, these unobserved factors do not affect our main focus on consumer channel choice.

4.2 Consumer Channel Choice

Before starting the search process, consumers choose whether to use a smartphone or a PC to shop. 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 use a PC or a smartphone to initialize the search process, whereas the marginal search cost is associated with the time and effort required to gather information from the product page. Prior literature (Ghose et al. 2012) and the data pattern of a higher number of searches on PCs suggests the marginal search cost on mobile should be higher than that on PCs, likely because of the 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, because the portability of a smartphone allows consumers to access it from anywhere.[11]

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 operating systems could make the search process more effortless and thus are associated with a lower marginal search cost. Because 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

[11] We assume consumers have access to both channels. If a consumer cannot access a channel (e.g., cannot use PC to shop while in transit), the model interprets such cases as the consumers having a very high fixed search cost to start a shopping session on PC.

$$fc_i = \mu_{fc} + \beta Z_i + v_{ifc}, \tag{5}$$

where μ_{fc} is a 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 mobile. The estimated parameters determine 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 ($s_i = 1$) is

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

where v_{ic} follows a standard normal distribution. The marginal search cost is guaranteed to be positive in this specification (e.g., Hortaçsu and Syverson 2004).

The marginal search for consumer i on the mobile channel ($s_i = 0$) can be systematically different from his marginal search cost on PC. We specify the marginal search cost as

$$c_i^0 = c_i^1 + sc_0 + \gamma X_i, \tag{7}$$

where sc_0 represents the average difference in marginal search cost between mobile and PC, X_i is a list of consumer $i's$ smartphone characteristics and his past mobile shopping experience that may affect his marginal search cost on mobile, and γ 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, $sc_0 + \gamma X_i$, to be negative or positive. The estimated parameters determine the marginal search cost for different consumers.

We assume that before the search, consumer i is aware of the distribution for prices and individual match values. He knows his level of interest in the product category a_i and his outside option e_{i0}. He also knows his marginal and fixed search costs for both channels. Based on the information, the consumer forms expectations on the utility for each channel. Let F_{ib}^s be the cumulative distribution function of the expected maximum utility among b products searched by consumer i on channel s, and f_{ib}^s is the corresponding *pdf* function. The calculation of F_{ib}^s is shown in detail in the next section. The consumer's expected utility for channel s is

$$ECU_i^s = \max_b [F_{ib}^s(e_{i0}) \cdot e_{i0} + \int_{e_{i0}}^{+\infty} f_{ib}^s(u) u du - fc_i \cdot s_i - b_i \cdot c_i^s]. \quad (8)$$

When the maximum utility from the b browsed products is lower than the outside option, the consumer chooses the outside option. Otherwise, he will choose the maximum of the searched options. The consumer chooses the channel that offers a higher expected utility. The channel choice probability thus is

$$P_{is|a} = P\left(ECU_i^s \geq ECU_i^{s'} \middle| a_i\right), s' \in \{0,1\}. \quad (9)$$

To summarize, the channel choice depends on their overall valuation, outside option value, and the fixed and marginal search costs on the two channels. 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 understanding the observed conversion rate and search patterns between the two channels.

5. Model Estimation and Identification

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

5.1 Estimation Procedure

The likelihood function comprises the three parts of consumer decisions: 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 ν_{ifc} and marginal search cost ν_{ic}, and the valuation of the product category a_i:

$$LL = \sum_{i=1}^{I} \log\left(\int\int\int\int \prod_{s=0}^{1} \prod_{b=1}^{N} \prod_{k=i_1}^{i_b} P_{ik|e,b,a,s}\, P_{i,b|a,s} P_{is|a}\, dF(e) dF(\nu_{fc}) dH(\nu_c) dG(\alpha)\right). \quad (10)$$

The probability functions in the equation do 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. Consumer $i's$ match value for product j e_{ij}^{q} and the outside option e_{i0}^{q} are drawn independently from extreme-value type-I distribution. The error terms for fixed search cost and marginal search cost, ν_{ic}^{q} and ν_{ifc}^{q}, are drawn i.i.d. from a standard normal distribution. Consumers' utility constant term is parameterized as $a_i = \mu_\alpha + \sigma_\alpha \cdot e_{ia}^{q}$, where e_{ia}^{q} is drawn from a standard normal distribution.

We assume 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 prices follow an extreme-value type-I distribution and estimate the price-distribution parameters. We use the estimated price-distribution parameters in the model estimation.

Consumers form expectations 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. To calculate the distribution of the 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 $V_b = \max\{-\lambda p_1 + e_1, \dots, -\lambda p_b + e_b\}$. The process is repeated Q times. We get a Q-length vector of V_b for b number of searches, which represents the distribution of the 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_i times on channel s_i is

$$\widehat{ECU}_i^s = \max_b [u_{ib}^s] - fc_i \cdot s_i, \tag{11}$$

where u_{ib}^s is the maximum utility from the searched products and the outside option minus the corresponding marginal search cost. To calculate u_{ib}^s through simulation, we draw Q times from the distributions for overall product valuation, outside option, and marginal search cost. We calculate the utility with each set of random draws, and u_{ib}^s is evaluated as the average from the Q values:

$$u_{ib}^s = \frac{1}{Q}\sum_q \{[I(a_i^q + V_b^q > e_{i0}^q) \cdot (a_i^q + V_b^q) + I(a_i^q + V_b^q < e_{i0}^q) \cdot e_{i0}^q] - b_i \cdot c_i^{s,q}\}.$$

We draw the fixed-search-cost random-error term Q times to calculate fc_i as specified in equation 5. The expected utility for channel s $\widehat{ECU}_i^s$ is the maximum of u_{ib}^s by selecting the optimal number of searches b_i minus the corresponding fixed search cost.

Consumers choose the channel that gives them higher expected utility $\widehat{ECU}_i^{\,s}, s \in (0,1)$. The channel-choice probability calculated from the simulations is not a smooth function. Following prior literature (McFadden 1989, Honka 2014), we apply a kernel-smoothing method where the choice probability is represented by a scaled multivariate logistic CDF. The probability of consumer *i* choosing channel s_i is

$$P_{is} = \frac{1}{1 + exp\left(-\omega_1 \cdot \left(\widehat{ECU}_i^s - \widehat{ECU}_i^{1-s}\right)\right)},$$

where ω_1 is a scaling parameter.

Next, we evaluate the probability of searching b_i times. Consumers choose the number of searches by maximizing the expected utility (equation 3). Applying the kernel-smoothing method, the probability of consumer i choosing to search b_i times conditional on choosing channel s_i is

$$P_{ib|s} = \frac{1}{1 + exp(-\omega_2 \cdot \left(IU_{i,b} - \max\left(IU_{i,-b}\right)\right)},$$

where ω_2 is a scaling parameter, and -b denotes search times other than b.

Finally, we evaluate the purchase probability for consumers after they have chosen a channel and have selected the number of products to browse. The prices and individual match values are realized for options in the consumers' consideration set C_{ib} (the b_i products consumer i browses). The probability that consumer i chooses option k from the consideration set C_{ib} on channel s_i is

$$P_{ik|C_{ib}s} = \frac{1}{1 + exp(-\omega_3 \cdot (u_{ik} - \max(u_{ik'}))},$$

where k' denotes choices other than option k, including the outside option $k = 0$ when consumers do not make a purchase, and ω_3 is a scaling parameter.

Combining the three sets of probabilities together, we obtain the overall probability of observing consumer i choosing channel s_i, searching b_i 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 ν_{ifc}, ν_{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 $P_{ik|C_{ib}s}^{q}$:

$$p_{ij} = \frac{1}{Q}\sum_q P_{is}^{q}\, P_{ib|s}^{q}\, P_{ik|C_{ib}s}^{q}. \tag{12}$$

5.2 Identification

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

For the marginal search-cost parameters, we identify the constant term and the standard deviation of the error terms from the distribution of search times on both PC and mobile channels. sc_0 captures the average difference in marginal search cost on PC and mobile. It is identified from the difference in the mean of the number of searches for consumers on the PC and mobile channels. The systematic difference in the number of searches for consumers with different mobile attributes identifies 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 who choose the PC channel, after accounting for the difference in marginal search cost. If the fixed cost on the PC channel is higher, 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.

The mean of the product-category valuation μ_α is identified from the overall level of the conversion rate after search, and price sensitivity λ is identified from the purchase data. The variation of the overall product valuation among consumers, σ_α, leads to the systematic difference in consumers who select a certain channel for browsing. Consumers with a higher level of overall product valuation may systematically choose a channel given its search-cost structure. For example, when the average fixed cost on PC is higher than on mobile and the marginal search cost is lower, consumers with a high value of a_i will be more likely to choose PC. In general, if σ_α is greater, the average utility difference of consumers who use PC will be greater than for those who use mobile, which will lead to a larger difference in conversion rates across the two channels. Thus, the value of σ_α is identified by the systematic conversion-rate gap observed in our data. [12]

We run a Monte Carlo study to test the model identification. We simulate data for 10,000 consumers and set the maximum number of searches at 5. The simulation procedure is as follows. We draw the error terms of marginal search cost ν_{ic} and fixed search cost ν_{ifc} i.i.d. from a standard normal

[12] When $\sigma_\alpha = 0$, the systematic conversion-rate gap between PC and mobile will no longer exist.

distribution. The outside option e_{i0} is drawn from extreme-value type-I distribution. The expected channel utility and the optimal search times are calculated as in equations 7 and 8. With the chosen channel s and search times b, consumers sample b products. After search, consumers see b prices (drawn i.i.d. from the price distribution) and the match values for each product e_{ij} (drawn i.i.d. from extreme-value type-I distribution). Consumer i makes purchase decisions depending on the realized utility.

In the estimation, we set all scaling factors $(\omega_1, \omega_2, \omega_3)$ in the kernel-smoothing logit functions to be 20. The number of simulations Q is 50. Results from the Monte Carlo study are reported in Table 3. Column (1) shows the true value of the parameters, and columns (2) and (3) show the estimated value and standard error. Thus, the proposed estimation procedure can successfully recover the true parameters.

<Insert Table 3 about here>

6. Results

We apply and estimate the proposed model using the Taobao data. In this section, we report and discuss the model-estimation results. In particular, we highlight how the model of channel choice can explain the lower conversion rate on mobile compared to PC. We show the estimated model can reproduce the conversion rates and the number of searches very well across both channels.

The estimation results are shown in Table 4. The estimated parameters are presented in four panels. Starting from the first panel, the price coefficient is negative at -5.16 for ¥1 (or -\$0.77 for US\$1). We transform the utility parameters into dollar value by dividing the estimated parameters by the price coefficient. The mean valuation for the product category μ_α is ¥148 (or US$21.7) and the standard deviation across consumers σ_α is ¥53 (or US$7.9).

<Insert Table 4 about here>

The second panel shows the search-cost parameter estimates. Note the marginal search cost is assumed to follow a log-normal distribution. We calculate the mean marginal search cost for using PCs as $\exp(5.09+0.82^2/2)=227.3$. Divided by the price coefficient, the mean cost is ¥44.05 (or US$6.61). Using the same procedure, the mean marginal search cost for using mobiles is ¥45.60 (or US$6.84). Thus, the average marginal search cost is 3.5% (¥1.55 or US$0.23) higher on mobile than on PC. The difference is statistically significant but not very large in magnitude. The marginal search cost determines the number of searches. This result is consistent with the data pattern showing the average number of searches on mobile is lower than on PC.

The fixed search cost on mobile is normalized to 0. Dividing the fixed search-cost parameter by the price coefficient, the cost for using PCs is higher by ¥1.66 (or US$0.25). Compared to the average difference in marginal search cost ¥1.55 ($0.23), the one-time fixed cost is higher (by about 6.8%) than the difference in marginal search cost between the two channels. Therefore, an average consumer who searches only one time would prefer using the mobile channel to PC because of the lower fixed search cost. When the optimal search times increases, PC becomes increasingly appealing to consumers because of its lower marginal search cost. The results are consistent with the data pattern showing that a larger proportion of consumers who search less tend to shop on mobile phones, whereas those who search more are more likely to choose PCs.

In addition to explaining the difference in the number of searches for consumers on the two channels, the marginal and fixed search-cost difference contributes to the observed gap in conversion rates between the two channels. When deciding which channel to search, consumers consider the search-cost differences and choose the channel that maximizes the expected utility after search. For consumers with higher overall valuation for the product category, the probability of making a purchase after search is high. Consumers who are likely to buy have a higher expected number of searches, because one additional search can have a higher marginal benefit in terms of a lower price and/or a higher individual match value. With a higher expected number of searches, these consumers are more likely to choose the PC channel with a lower marginal search cost. Therefore, PC is more likely to attract consumers with a higher overall valuation, who are expected to have a higher number of searches. Such self-selection of consumers leads to a higher conversion rate on the PC channel.

The third panel reports the observed heterogeneity of fixed search cost across consumers. Because Taobao started with the website optimized for PC and only introduced the mobile interface later, long-time consumers may have started shopping on Taobao before the introduction of the mobile-shopping option, and therefore become used to the PC shopping channel. We include measures that positively correlate with long-time usage history on the platform. Results support our hypothesis. Consumers with a higher buyer rating, more purchases in the past, and a longer buyer history on the platform are associated with a lower fixed search cost on the PC channel, which leads to a higher likelihood of using the PC channel compared to other consumers. This finding is also consistent with the probit regression results (Table 2).

In addition to length of usage history, consumer demographics may also play a role in explaining the choice of PC or mobile. We find age is negatively correlated with the fixed search cost for the PC channel. In other words, older consumers are more likely to have a lower fixed search cost on PC and are therefore more likely to use the PC channel for shopping. Male consumers have a lower fixed search cost for PC, which means they are more likely than women to use the PC channel for shopping. These estimates are again consistent with the reduced form in Table 2.

In the fourth panel, we explore how the marginal search cost varies with different types of mobile devices. Because the marginal search cost is influenced by the effort in gathering information from an additional search, such a process should be less costly if gathering information on some mobile devices is easier. For example, consumers may find shopping using smartphones with a higher screen resolution (typically associated with a larger screen size) and a more robust operating system is easier. We find the parameter estimates for screen resolution, IOS, and Android operating systems are all negative and statistically significant. For smartphones with higher screen resolution and better operating systems, the marginal search cost becomes lower on the mobile channel. The results are consistent with reduced-form analysis showing that consumers with the more advanced smartphones are more likely to choose the mobile channel. Our results suggest that as the smartphone technology continues to improve, the marginal search cost on the mobile channel will decrease, leading to a higher number of consumers using the mobile channel for shopping.

Lastly, we examine the model fit by simulating consumer actions (channel choice, number of searches, and purchase decision) with the model estimates, and compare simulation results with the actual data. We run the simulation 100 times and take the average. We compare the conversion rate by search times on mobile (Figure 4A) and PC (Figure 4B), and the proportion of consumers who search one to five times on mobile (Figure 4C) and PC (Figure 4D). Both the conversion rates and the search times match well between simulated and actual data on both channels. The proposed model can predict the key empirical patterns. First, the conversion rate is higher with a higher number of searches on both channels. Second, the conversion rate is higher on PC than on mobile for the same number of searches. Third, consumers with more intensive searches (who search at least three times) are more likely to choose the PC channel, which matches well between the simulated and actual data.

<Insert Figure 4 about here>

To summarize, our results suggest the self-selection of consumers can explain the gap in conversion rates between the two channels. The PC channel has a higher fixed search cost and a lower marginal search cost, and it attracts consumers with higher valuation toward the product category who are more likely to make a purchase. The mobile channel has the advantage of a lower fixed search cost, because of the channel's great portability and ease of access anywhere. It attracts consumers who may not find searching on PC to be worthwhile. Therefore, the pool of consumers the two channels attract can be systematically different before the start of any search activity.

7. Counterfactual

Consumers who choose PC and mobile channels are systematically different. Taking the different pools of consumers into account, we study how sellers can improve profits by utilizing channel-specific pricing and promotion strategies. Whether sellers are better off charging a lower price or offering a larger promotion deal on mobile is not obvious. On the one hand, consumers have a smaller consideration set (lower search intensity) on mobile, which reduces price competition and allows sellers to set a higher price. On the other hand, the conversion rate is lower on mobile, which suggests consumers are less inclined to make a purchase and sellers could be better off lowering prices. The proposed structural model accounts for both effects. With the estimated model, we can provide a more complete picture for sellers about consumer preferences using channel-choice information in addition to the search and purchase activities.

7.1 The Optimal Pricing Policy on Two Channels

In the first counterfactual, we study how sellers can utilize the information revealed by the consumer channel choice by offering different prices across channels. In practice, sellers can offer mobile-only prices for consumers using their smartphones to shop. With different prices on mobile and PC, in equilibrium, consumers will consider the price distribution on both channels and select channels accordingly. Therefore, channel-specific prices will also lead to changes in the pool of customers on both channels. Using our estimated model, we calculate the new equilibrium situation where sellers set different prices on PC and mobile and consumers have rational expectations of the price distribution, which influences their channel-choice decisions.

To find the optimal channel-specific prices, we need to estimate the marginal cost of sellers and the consumer demand function. This approach allows us to find the equilibrium condition, in which sellers set prices accounting for the customer base on both channels and, additionally, consumers choose a channel considering the channel-specific price distribution. Our dataset contains more than 100 different products. Recovering the marginal cost for each one is computationally infeasible. We focus on the top 10 products, which account for more than 60% of the total sales during the data period. The prices of these products range from ¥117 to ¥208 (US$17.6 to $31.2).

To estimate the marginal cost of each seller, we assume the observed prices are the equilibrium prices when sellers can only choose the same price level for both channels. We first estimate the consumer demand function. The demand of product j with price p_j in channel s is

$$D^s(p_j) = \pi^s \cdot \left(\sum_{b=1}^{5} \pi_b^s \cdot \frac{b}{N} \cdot P\left[U_b^s(p_j) > \max\left(U_b^s(p_{-j}^b), 0\right)\right]\right), \tag{13}$$

where π^s is the proportion of consumers who choose channel s. π_b^s is the proportion of consumers searching b products on channel s. They search product j with probability $\frac{b}{N}$, where N is the number of all available products. $U_b^s(p_j)$ denotes the utility of product j for consumers who search b times on channel s minus the outside option value. A consumer chooses to purchase j if and only if the utility is higher than the utility of all other products browsed $U_b^s(p_{-j}^b)$, and is larger than 0 (i.e., buying product j is more appealing than leaving without a purchase).

To evaluate $D^s(p_j)$, we draw the error terms in the model and simulate consumer search and purchase decisions using the model parameters. With the simulation results, we estimate π^s and π_b^s by the corresponding average values. For consumers who search b times on channel s, we evaluate the probability that product j offers the highest utility. For each product j, we obtain price draws for the other $b - 1$ products, as well as their individual match values. [13] With 1,000 sets of draws, we approximate the probability $P\left[U_b^s(p_j) > \max\left(U_b^s(p_{-j}^b), 0\right)\right]$ by its corresponding sample average.

[13] Note the individual match value e_{ij} is only realized after consumer i searches product j. This is different from search models (e.g., Honka 2014) where consumers know all the individual match values prior to search. In our model setting, the distribution of e_{ij} is not subject to selection. Similarly, prices are also realized after search. Therefore, we can take unconditional draws from the price distribution and extreme-value type-I distribution in the model simulation.

We calculate the demand function by changing p_j from 0 to ¥1000, which covers all observed prices in our dataset. Figure 5 plots the demand functions for PC (black dashed line) and mobile (grey solid line). The demand on PC is higher than on mobile at any given price, due to the self-selection by which consumers on PC are likely to have higher valuation of the product category than those on mobile. On both channels, price elasticity of demand is larger for moderate prices. When price is very low, demand is bounded above by the probability of the product being browsed. When price is very high, demand converges to 0 because the utility is likely to be lower than that of the other products or the outside option.

<Insert Figure 5 about here>

With the demand function, we then infer the marginal cost for product j assuming that, given the prices of other sellers, the observed price maximizes the seller profit when the seller sets a single price for both channels. The marginal cost for seller j mc_j satisfies the condition

$$\hat{p}_j = argmax_{p_j} R(p_j, mc_j) = argmax_{p_j} \sum_s (p_j - mc_j) D^s(p_j),$$

where $R(p_j, mc_j)$ is the profit function for product j with price p_j and marginal cost mc_j. With the profit-maximizing assumption that observed price $\hat{p}_j$ maximizes the seller's profit, we estimate the marginal costs for the top 10 sellers.[14]

[14] We assume the remaining sellers keep their original uniform pricing on both channels in the counterfactual exercise.

Instead of a single price on both channels, sellers can charge channel-specific prices to maximize profits. Seller j chooses prices p_j^0 on mobile and p_j^1 on PC to maximize his expected profit as a function of the two prices and marginal cost:

$$Max_{p_j^0, p_j^1} R\left(p_j^0, p_j^1, mc_j\right) = \sum_s \left(p_j^s - mc_j\right) D^s(p_j),$$

where $D^s(p_j)$ is the channel-specific demand function under the new counterfactual prices. Consumers form rational expectations of the new price distributions on both channels, which will affect consumers' channel choice. For example, if prices on mobile are lower than on PC, more consumers will choose the mobile channel, which will further influence the seller's optimal prices on both channels. To find the equilibrium, we iterate between sellers choosing channel-specific prices given consumer channel choice, and consumers choosing a channel given channel-specific prices. The process converges when the changes in channel-specific prices are less than 0.1 between iterations.

We find that when sellers charge channel-specific prices, the optimal price on mobile is lower than that on PC. Across the top 10 sellers, the average optimal price on mobile is ¥163.94, which is lower than the original uniform price at ¥165.74, whereas the optimal price on PC is ¥168.43, which is higher than the original price. On average, the price on mobile is lower by ¥4.49 (95% confidence interval: ¥3.73 – ¥5.11) or 2.7%. For the top 10 sellers, the optimal price on mobile is always lower than that on PC, with the magnitude of difference ranging from 1% to 4% across the sellers. With prices becoming lower on mobile under channel-specific prices, the conversion rate on mobile increases from 12.51% to 12.85% (or 2.7% in relative terms). We see the opposite story on PC where the prices become higher under channel-specific prices, and the overall conversion rate decreases from 16.35% to 16.10% (or 1.5% in relative terms). The overall pattern of a higher conversion rate on PC than on mobile continues, although the gap becomes slightly smaller. With channel-specific prices, sellers are able to make higher profits than under uniform pricing on both channels. Overall, the average profit increases by 0.55% (95% confidence interval: 0.06% – 0.70%) for the top 10 sellers.

To summarize, we find the optimal prices on mobile is 2.7% lower than that on PC. The proposed model considers the differences in search pattern and conversion rate on PC and mobile and shows that prices should be lower on the mobile channel, because of the lower valuation for consumers shopping on the channel. Ignoring consumer self-selection between the two channels can lead to incorrect channel-specific prices.

7.2 Optimal Retargeting Strategy for Sellers

In the second counterfactual, we investigate a retargeting strategy by offering coupons to consumers who have browsed but have not purchased. Similar to the first counterfactual, we consider the different pools of consumers on mobile and PC. However, consumers who abandon the search without purchase are systematically different from the total consumer population targeted in the first counterfactual (see Jiang et al. 2019). We focus on how sellers can use the channel choice information to offer optimal channel-specific coupons to attract consumers who have browsed without purchase. Such a retargeting strategy can be economically impactful because as many as 85% of consumers browse without making a purchase.

We calculate the optimal coupon values offered to retargeted consumers on mobile and PC. To focus on how the channel choice provides valuable information for sellers, we assume sellers know which channel consumers chose but not which products they have browsed. Seller j chooses the coupon value x on each channel to maximize the expected profit $r_j(x)$:

$$Max_x r_j(x) = \sum_s \left(p_j - mc_j - x\right) B_j^s(x) I^s, \tag{14}$$

where $p_j - mc_j - x$ represents the profit for seller j considering the marginal cost (estimated in the first counterfactual) and coupon value x. $B_j^s(x)$ denotes the purchase probability on channel s for seller j when he offers a coupon value x (the estimation procedure is described later). I^s represents the number of consumers who browsed without purchase.[15]

We calculate the purchase probability $B_j^s(x)$ using simulation. We assume that when sending the coupons, sellers also provide detailed product information including price. Therefore, retargeted consumers do not need to search for the information and pay the search costs again. Using the estimated model, we simulate consumer channel-choice, search, and purchase decisions by drawing $Q = 50$ times from the error-term distributions and price distribution for each consumer. Let $I^{s,q}$ be the number of consumers who do not make a purchase on channel s at simulation q, and $a_{I^{s,q}}$ is the overall category valuation for these non-purchasers, whose outside option value is $e_{0I^{s,q}}$ and the individual match value toward seller j is $e_{jI^{s,q}}$.

The purchase probability for seller j on channel s when the seller offers a coupon value x is

$$B_j^s(x) = \frac{1}{Q} \sum_q \frac{1\left[a_{I^{s,q}} - \lambda \cdot \left(p_j - x\right) + e_{jI^{s,q}} > e_{0I^{s,q}}\right]}{I^{s,q}},$$

where the numerator calculates the number of non-purchasers who will make a purchase after receiving coupon x. Dividing it by the total number of non-purchasers, we get the purchase probability for the

[15] We assume consumers do not anticipate the retargeting coupon (i.e., they will not choose to search and abandon in order to get a retargeting coupon). Therefore, the percentage of non-purchasers I^s does not change when the coupon value x varies.

retargeting coupon x. $B_j^s(x)$ represents the expected purchase probability when seller j sends a coupon worth value x to retarget consumers on channel s.

With estimated $B_j^s(x)$, we calculate the optimal coupon value x for seller j on PC and mobile given its original price and marginal cost. Similar to the first counterfactual, we focus on the top 10 sellers. We find the optimal retargeting coupon value is higher for consumers on mobile than on PC. The optimal coupon value for mobile consumers is ¥5.11 (about 3% of the original price) and ¥4.81 for PC consumers. The difference in the coupon values is about ¥0.3 (or 6%) between the two channels with a 95% confidence interval from ¥0.0076 to ¥0.6057.

With the retargeting coupon, sellers can improve profits by 9.97% on the mobile channel, and by 10.05% on PC. The overall expected profit increases by 10.01%. We compare it with a scenario where sellers do not know the consumers' channel choice. Sellers can only set one retargeting coupon value for all non-purchasers, regardless of their chosen channel. The optimal coupon value in this case is ¥4.92. The overall expected profit is lower by 5.1% than the profit under channel-specific coupons. This finding demonstrates how online sellers can utilize the channel-choice information for a more effective promotional strategy such as sending out retargeting coupons.

To summarize, we find sellers' profit increase is higher when they offer channel-specific retargeting coupons than when channel choice is not considered. The optimal coupon value is higher for consumers on mobile than on PC. The result is consistent with that in the first counterfactual, which suggests a lower optimal price on mobile than on PC. Both results are driven by the difference in what types of consumers will self-select to browse on mobile phones or PCs.

8. Conclusions and Limitations

In this paper, we develop a model of consumer channel choice in addition to search and purchase. The proposed model can explain an intriguing phenomenon whereby, although more consumers use mobile phones to shop, the conversion rate is significantly lower than that on PCs. We find the PC channel has a lower marginal search cost but a higher fixed search cost than the mobile channel. Consumers with higher product valuation are more likely to use the PC channel because they have a higher search intensity and will benefit from the lower marginal search cost. Consumers with lower product valuation, on the other hand, are more likely to choose the mobile channel because of its lower fixed cost to start a shopping session.

The estimated model allows us to study channel-specific marketing strategies for sellers. We find the optimal price on mobile is 2.7% lower than on PC. For non-purchasers, the optimal retargeting coupon value is 6% higher for consumers on mobile than on PC. Overall, sellers' profit will increase if their marketing strategies are channel specific. Both counterfactual analyses demonstrate how the proposed model can provide sellers with important managerial insights. Ignoring consumer self-selection between the two channels can lead to incorrect channel-specific marketing strategies.

The contributions of this paper are two-fold. From a methodological prospective, we propose a flexible framework that incorporates endogenous consumer channel choice in addition to the search and purchase decisions. The proposed model can capture the observed search activities and purchase decisions on both channels. From a managerial perspective, our results offer guidance to sellers on the optimal channel-specific marketing strategies. We consider channel-specific prices and retargeting coupons and show how they should be different on the two channels.

Like all research, our study has limitations. First, the optimal channel-specific prices and marketing strategies are from counterfactual analysis using one product category on Taobao. We call for future research to further test these recommendations with actual field experiments. They should also be tested with a broader range of product categories and in different countries for generalizability. Second, our proposed model makes several strong assumptions on consumer search and purchase behaviors. In particular, we assume consumers use simultaneous search strategy. Future research with richer datasets should further explore consumers' channel choice in other scenarios, such as when consumers use sequential search and when they have prior knowledge on the differentiated quality of sellers. Results on how consumers who choose to shop on the two channels are systematically different will help test the robustness of our findings.

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Tables and Figures

Table 1. Variable Description and Summary Statistics

Variable	Description	Mean	Std. Dev.
Price	Unit price for fishing poles	263.7	63.69
Search times	Number of products browsed by consumers	1.89	1.27
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 ¥ 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 operating system	0.34	–
Android	Indicator variable; equals 1 for Android operating 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	Indictor variable; equals 1 if gender information is missing	0.09	–
Age missing	Indictor 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 Consumer Characteristics

	Estimate	Std. Error	p-value
(Intercept)	-1.12	0.08	***
Buyer rating	0.12	4.06E-03	***
Buyer rating missing	-0.32	0.03	***
Buyer spending	8.38E-05	2.11E-05	***
Buyer history	7.89E-05	6.66E-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	***
Mobile missing	1.82E-03	1.22E-02	
Male	0.40	0.08	***
Age	0.01	5.97E-04	***
Gender missing	-0.04	0.08	
Age missing	0.23	0.08	**
Note:	*:p<0.1; **:p<0.05; ***:p<0.01		

Table 3. Results from Monte Carlo Simulation

	Variable	True Value (1)	Estimated Value (2)	Standard Error (3)
Utility parameters	μ_a: Mean of valuation	-45.0	-43.47	0.770
	σ_a: Std. dev. of valuation	110.0	125.71	13.48
	λ: Price coefficient	-1.5	-1.45	0.005
Search-cost parameters	μ_c: Mean of marginal search cost	4.0	4.09	0.006
	σ_c: Std. dev. of marginal search cost	0.4	0.42	0.01
	sc_0: Difference in marginal search cost on PC from mobile	10.0	9.34	0.372
	μ_{fc}: Fixed search cost on PC (normalized to 0 on mobile)	0.3	0.27	0.007

Table 4. Estimation Results

	Variable	Estimated Value	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_c: Mean of marginal search cost	5.09	1.35E-03	***
	σ_c: Std. dev. of marginal search cost	0.82	3.91E-04	***
	sc_0: Difference in marginal search cost on PC from mobile	8.02	0.04	***
	μ_{fc}: Fixed search cost on PC (normalized to 0 on mobile)	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	***
	Gender missing	-7.85E-06	0.02	
	Age	-0.02	6.46E-04	***
	Age missing	3.51E-05	0.02	
Marginal-cost heterogeneity (Mobile)	Screen resolution	-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	***
	Mobile missing	-9.57E-08	0.01	

Note: *:p<0.1; **:p<0.05; ***:p<0.01

Figure 1. Proportion of Consumers on Each Channel by Number of Products Searched

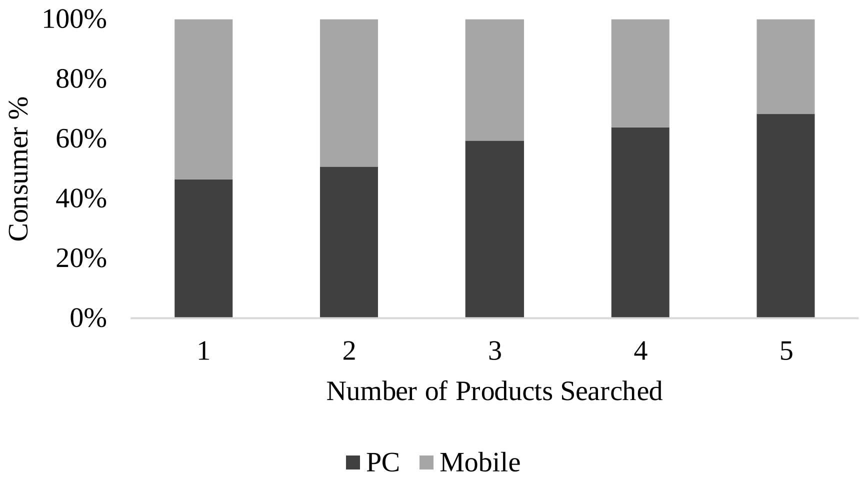

Figure 2. Conversion Rate with Number of Products Searched

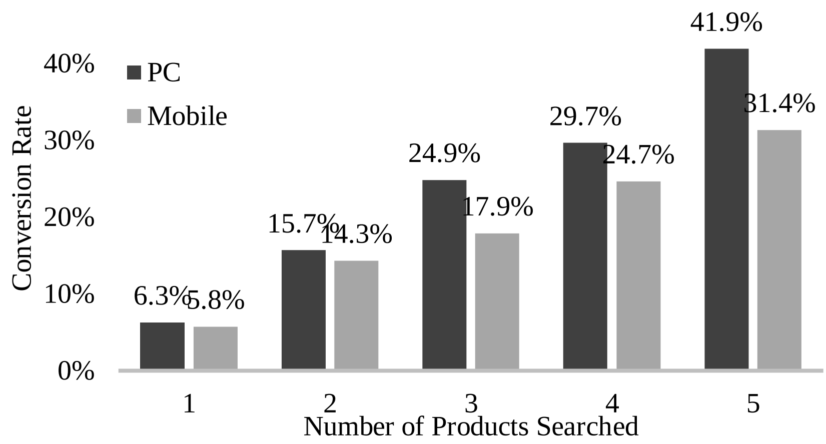

Figure 3. Conversion Rate on Mobile and PC for Consumers Who Used *Both* Channels

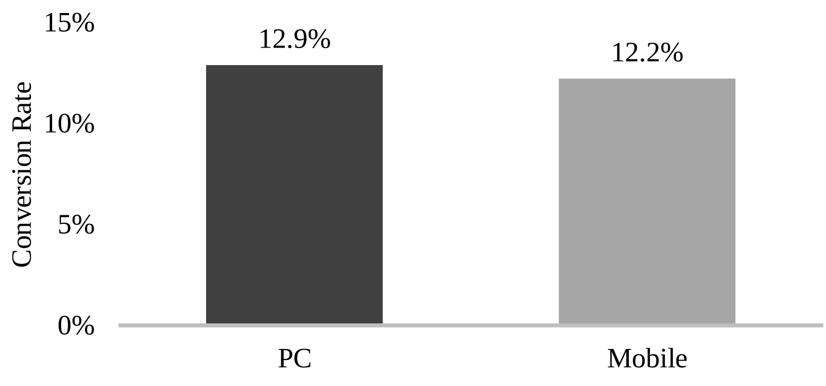

Figure 4. Model Fit by Comparing Actual and Model Simulated Data

Figure 4A. Conversion Rate on Mobile

Figure 4B. Conversion Rate on PC

Figure 4C. Search Times on Mobile

Figure 4D. Search Times on PC

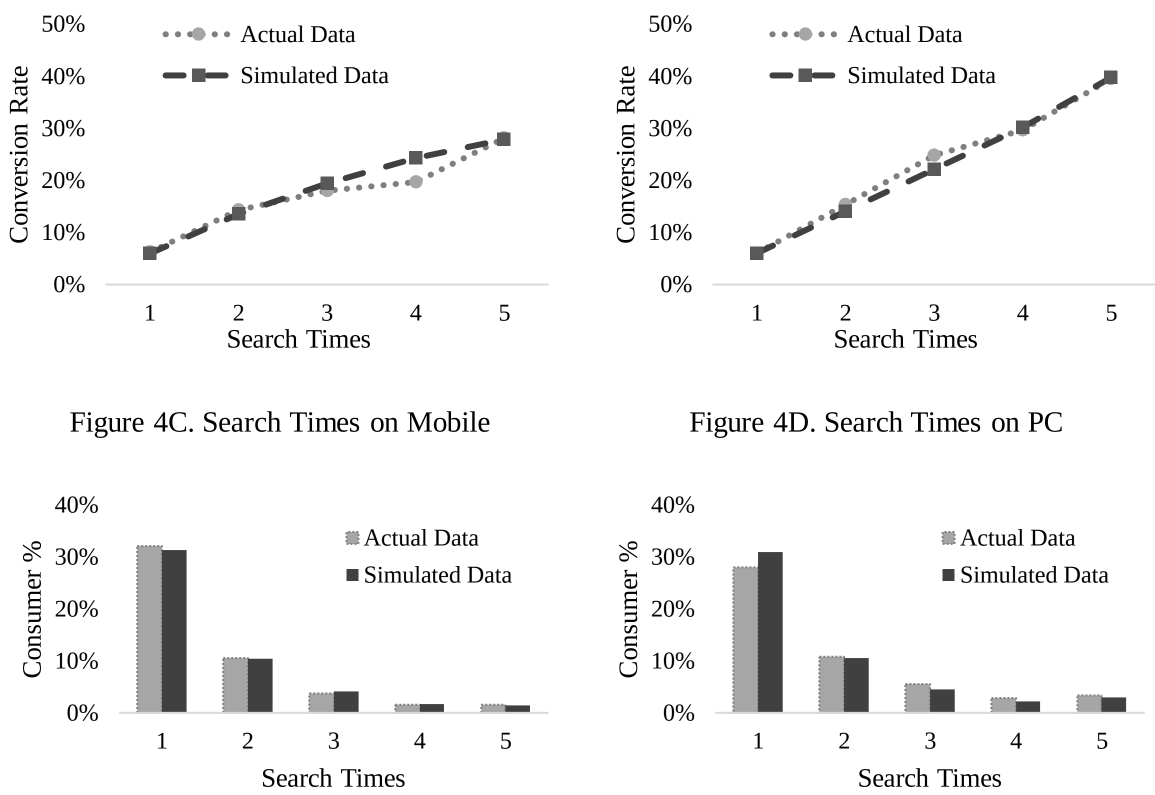

Figure 5. The Estimated Demand Function on PC and Mobile