Does Position Matter More on Mobile? Ranking Effects across Devices

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Abstract

Achieving a better rank online is often costly. Is the effect of ranking different for mobile devices and traditional PC? This study empirically examines the ranking effect across different device types in an ecommerce environment. With over 4 million observations from Tweaker.net, the largest shopbot in Netherlands, we estimated the ranking effect between mobile and PC. Surprisingly, and contrary to prior findings, our results across different model specifications consistently show that ranking effect is smaller on mobile devices. This study extends the understanding about the effect of position in e-commerce context by empirically examining the ranking effect across devices. This study has important managerial implications for retailers and e-commerce platforms. As the ranking effect is smaller on mobile devices, retailers should take account of the source of traffic (mobile or PC) while bidding for a particular position. And platforms should consider the different ranking effects on different channels.

Keywords: Ranking effect, Mobile devices, Position

1. Introduction

"Being first or early in a sequence would often increase the chances to be selected."

----Becker (1954)

Position matters, especially in an online retailing context. And achieving a higher rank or better position is often very costly. For instance, advertisers need to pay to appear in top positions as sponsored search results, and retailers have to pay for being displayed in a higher rank in consumers' search results pages. The search advertising in United States has kept growing at a 37% growth rate, and the total market revenue of search advertising reached almost 30 billion dollars.[1] Despite the important effect of position, the economic effect of position is not straightforward as it appears to be. Researchers (e.g., Agarwal et al. 2011, Ghose and Yang 2009, Yang and Ghose 2010) have found that the top positions are often *not* the optimal profit point. Therefore, understanding the "ranking effect" is particularly important to several entities, such as retailers, advertisers, marketing managers, and platform managers.

With the growing popularity of mobile devices like smartphones and tablets, mobile shopping is no longer an innovative fashion among young consumers, thus mobile has become an increasingly important channel for online retailing that differs from PC channels. According to the most recent survey by eMarketer 2015, online retailers receive more than 50% of online traffic from mobile devices, and for the first time in history, Americans used mobile devices to browse and shop more than they used PCs on Thanksgiving Day, 2014 (Wang et al. 2015). In spite of the important role of mobile channels, integrating mobile channels into existing strategies, such as identifying the optimal ranking position is a major challenge for companies (Hoehle and Venkatesh 2015) due to a lack of theoretical understanding and empirical evidence about how the mobile channel differ from the traditional PC channel.

Previous literature (e.g., Jones et al. 1999, Kourouthanassis and Giaglis 2012) on mobile channels focused mainly on how mobile devices differ from PCs (e.g., smaller screen, slower mobile Internet, convenient access to information anytime anywhere), how the adoption of mobile devices affects online learning (Maniar et al. 2008), and shopping behavior such as shopping frequency (Wang et al. 2015). Little is known about how the "ranking effect" works on mobile devices, and as a distinct channel for retailing, how the mobile channel would differ from PCs. Ghose et al.'s (2013), to the best of our knowledge, is among the first studies to examine the ranking effect (termed search cost) across devices in the context of microblog reading. This study seeks to theorize and empirically examine how the ranking effect differs between mobile devices (smartphones and tablets) versus traditional PCs in an online retailing context.

We collected the data in collaboration with the largest price comparison website (also known as shopping robot or shopbot in short) in Netherlands Tweakers. The data set contains over 4 million observations from about 50 of the most popular products in the electronics category in two months from March to May 2015. Using a conditional logit and a linear probability model with session fixed effects, we estimated the effect of position on a product's probability to be clicked by taking advantage of within-session variation. Results across different model specifications consistently show that position has a *negative* effect on a product's probability to be clicked on both mobile devices and PCs, namely the ranking effect exists on both devices. Surprisingly, our results show that ranking effect is smaller on mobile devices, which is contrary to the finding of Ghose et al. (2013) that the ranking effect is stronger on mobile devices in microblog reading.

We propose two possible explanations. First, consumers overcome the limitations of mobile devices, such as the smaller screen sizes because of the increasingly intensive usage of mobile devices (learning effect). Second, information on mobile devices is often shrunk or tailored to adapt to the smaller screen. Therefore, a consumer has to click a product to see some information that would otherwise display on larger-screen PCs. The tailored information on mobile devices and convenient scrolling facilitated by touch screens makes it easier and less effortful for a user to search for products (decreasing search cost).

Our study is among the first to empirically examine the ranking effect across devices (mobile versus PC), which extends the understanding about the effect of the ranking position in e-commerce context. This study has managerial implications for retailers and platforms. As the ranking effect is smaller on mobile devices, retailers should take account of the source of traffic (mobile or PC) while bidding for a particular position. Platforms can also optimize their revenue by pricing differently across mobile and PC channels.

2. Related Literature

In this section, we review the literature on the ranking effect in ecommerce in a PC environment and explain why the ranking effect may differ on mobile devices. We also introduce the IS literature related to shopbots.

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[1] http://www.statista.com/statistics/190275/us-online-display-and-search-advertising-forecast-2010-to-2015/ accessed on May 2016.

2.1 The Ranking Effect

Just as a good location helps attract traffic and sales to an offline vendor's store, appearing on the first screen or in the first position of an online catalog offers online retailers a significant advantage in being chosen by a consumer (Smith and Brynjolfsson, 2001). A product's probability to be viewed and clicked varies by its position on the screen, which is termed as the *ranking effect* in this study.

The ranking effect has been shown to play an important role in click-through rates and conversion in the context of search engine advertising and online retailing. Agarwal et al. (2011) showed that click-through rates of ads on search engines decrease with positions, the conversion rates increase with positions, and top positions are not necessarily associated with the highest profit of advertisers. Similarly, Ghose and Yang (2009) showed that conversion rates are highest at the top and decrease with rank as one goes down the search engine results page. Similar findings indicated that higher ranked hyperlinks are more likely to be clicked in desktop environments (e.g., Ansari and Mela 2003; Drèze and Zufryden 2004; Baye et al. 2009; Yang and Ghose 2010). Although findings about the relationship between position and conversation rate and profit are inconsistent, the finding that the position is negatively associated with the click-through rate (or probability to be clicked) seems to be a consensus in the literature.

Why does the ranking effect exist? There are three main reasons. First, most consumers start browsing the search results from the top of the list (Ghose et al. 2013), thus higher ranked products are more likely to receive more attention, and they are more likely to be clicked. Second, scrolling down a list of products requires effort, which includes not only the effort to scroll down the list using a mouse, control board or touch screen, but also the waiting time for the device to process the scrolling action. A higher ranking effect suggests a higher degree of effort required. Finally, the total number of products that a consumer needs to evaluate before making a purchase decision is limited. Thus, ceteris paribus, she will be less likely to click on lower-ranked products.

2.2 Mobile Devices

With the increasing use of mobile devices, mobile has become an important channel for online retailing that differs from PC channels. Mobile devices in this study include smartphones, tablets or other personal decision assistants (PDAs) that are often smaller in screen size, easier to carry, and usually lack of physical input accessories, such as a keyboard (Hoehle and Venkatesh 2015).

The ranking effect on mobile devices could be higher for several reasons. First, in comparison to PCs that often have a larger screen, mobile devices have relatively smaller screens, which limits their capacity to display information (Sweeney and Crestani 2006). Second, most existing Web sites are designed and optimized for PCs only. They are poorly suited for mobile devices, making the Web content look aesthetically unpleasant and difficult to navigate (Sweeney and Crestani 2006, Hoehle and Venkatesh 2015). Therefore, consumers often need to scroll up/down and left/right continuously within a page, making it difficult to gather information to make a purchase decision (Ghose et al. 2013). Meanwhile, some Web browsers on mobile devices adapt to smaller screens (Sweeney and Crestani 2006, Zhang and Lai 2011) by increasing the length of the information for one item. This means more scrolling effort is needed on mobile devices to view one additional item compared with the effort needed on PCs.

The ranking effect on mobile devices could also be lower. First, consumers may overcome the limitation of smaller screen size of mobile devices as they get used to using mobile devices because of the learning effect. According to a recent BBC News, in most developed countries, mobile phone penetration rates have reached over 100% per capita, with individuals often owning more than one mobile phone (Wang et al. 2015) and mobile devices have become an integral part of consumers' daily routines. Second, over the last few years, mobile devices have improved computing power, resolution, touch screen, and speed of mobile Internet like LTE or 4G, which have significantly narrowed down the difference in information processing between mobile and PCs for consumer browsing. Especially, the touch screen of mobile devices makes it much easier to scroll and navigate to acquire information. Furthermore, information displayed on mobile devices is often abbreviated (see Figure 1 for an example) compared with the information on PC for the same product. Therefore, mobile customers have to click the item for detailed information, which is readily available to see on PC. The learning effect due to extensive use of mobile devices and the effortless scrolling enabled by touch screen together with the necessity to click for detailed information on mobile may make the position on mobile devices less important than that on PCs.

Ghose et al. (2013) was among the first to compare ranking effect between mobile devices and PCs in the context of microblog reading. They found that position of microblog posts negatively associated with probability to be clicked and this negative effect is much stronger for mobile users than for PC users. Our study builds on the work by Ghose et al. (2013) and extends ranking effect to the context of online shopping.

2.3 Shopbot

Shopbots, short term for shopping robots, are Internet services that allow consumers to search and compare prices and product offerings among competing retailers (Montgomery et al. 2004, Brynjolfsson et al. 2004). At a shopbot site, a consumer places a product search for a unique product and obtains a list of retailers' offers displayed in a tabular format with price and other attributes such as shipping time, shipping fee and product availability. The consumer evaluates these offers and makes a selection by "clicking" on a particular item (Brynjolfsson et al. 2004 and Brynjolfsson et al. 2010). Shopbot (e.g., Yahoo European-based Kelkoo site) platforms charge retailers fees ranging from 40 cents to $1.90 per click and attract over 10 million consumers per month in the UK alone (Baye et al. 2009).

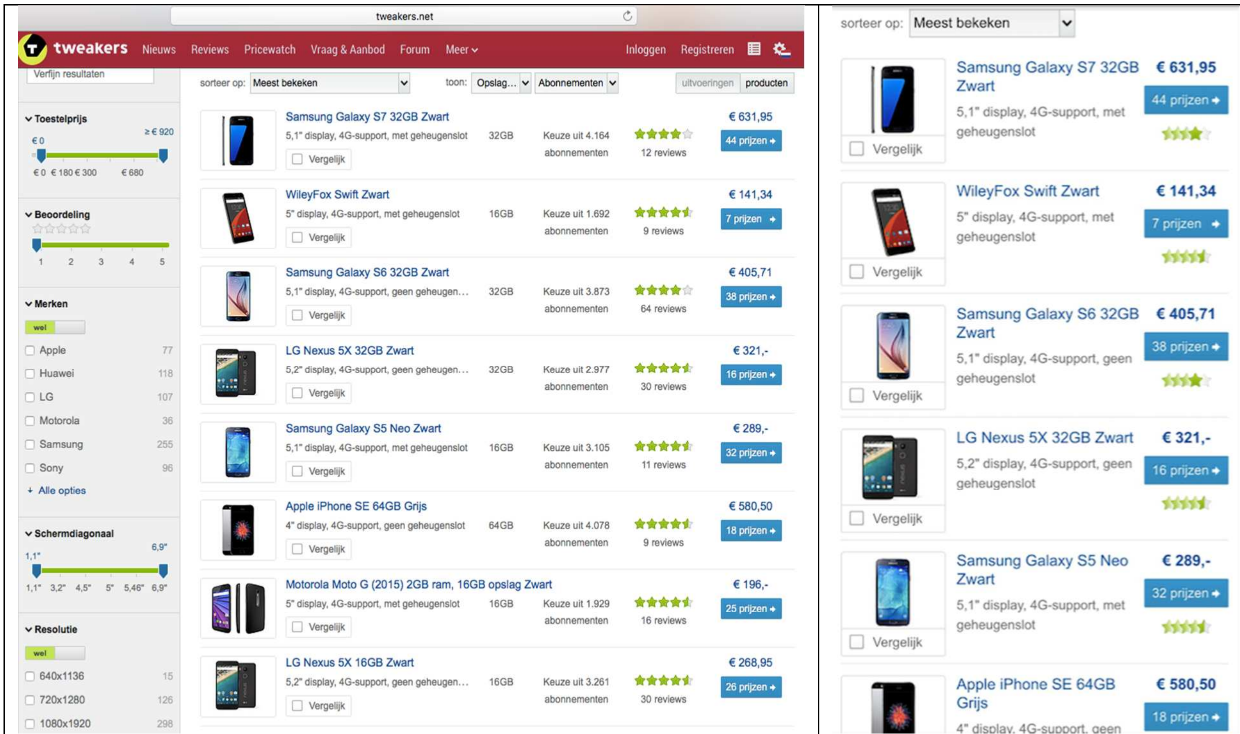
By gathering price information from all online retailers, shopbot is often used as a context to study search cost (e.g., Brynjolfsson et al. 2004 and Brynjolfsson et al. 2010). For instance, Tang et al. (2010) find that 1% increase in shopbot use is correlated with a $0.41 decrease in price levels and a 1.1% decrease in price dispersion. Baye et al. (2009) studied the effect of price on the probability to be clicked and found that a retailer offering the best price gains 60% more clicks than if it had not charged the lowest price. By surveying 52 students who had shopbot experience, Xu and Kim (2008) is among the first to study the ranking effect in shopbot and find that position is negatively correlated with an item's probability to be clicked, moderated by consumer's attention.

3. Data and Methods

In this section, we first introduce the data set, then define all variables and finally explain in details about the identification strategy we use to estimate ranking effects.

3.1 Data

Our data are provided by the largest shopbot in Netherlands: *Tweakers.net*. *Tweakers.net* currently has 156 product categories with over a million products. Instead of sampling from all product categories, we choose the most popular category "smartphones" to make sure we can observe enough clicks to test a statistical correlation between position and the probability to be clicked. The popularity is determined by the amount of click through performed by consumers of Tweakers.net. Following Brynjolfsson et al. (2010), we specially choose 50 most popular smartphone products (e.g., iPhone 5s, Samsung galaxy s6 etc.) to eliminate product heterogeneity and focus only on heterogeneity across retailer service characteristics such as reputation, shipping services, etc. Consumers visit *Tweakers.net* via PCs or mobile devices (smartphones or tablets). Regardless of the devices (mobile or PCs), *Tweakers.net* return the exact same results for the same search. Figure 1 left is the screenshot of the returned results for keyword "smartphone" search on PCs and Figure 1 right is the screenshot of the returned results for the same keyword search on mobile. As shown in Figure 1, mobile devices return the exact same results for the same keyword by display fewer (5 vs. 8) number of items than PC. Meanwhile, information displayed on mobile is also tailored to adapt to the smaller screens size: number of reviews, capacity of the smartphone and number of subscriptions are not displayed on mobile and therefore a consumer has to click on the item to view such information.



PC	Mobile

Figure 1. Screen shot of returned results on PC and mobile for the same keyword search

When a consumer visited *Tweakers.net*, a new session ID is created in the data sponsor's information system. Then the system recorded product ID that is clicked within 30 minutes. If a consumer doesn't finish searching within 30 minutes, a new session ID will be created. Therefore, each session ID corresponds to only one consumer but not necessarily a unique one. We collected search session data for the top 50 smartphone products from 30 March 2015 until 22 May 2015. For each search session, we recorded the returned results for each keyword search. The returned results for each keyword search is a list of products (smartphones) provided by different retailers based on the relevance to the keyword including position of each product, whether the product is clicked or not, retailer information, including retailer ID, name, rating, shipping time and fees. We also obtained detailed product information, including product ID, name, and price.

In total, we have 126,343 unique search sessions, which in total returned 4,832,277. 62.1% of the sessions (searches) come from PCs and the remaining 37.9% come from mobile. The overall click-through-rate for is 3.31% (PC) and 3.15% (mobile).

3.2 Variable Definition

Position is the rank of each returned product in one session. In each different session, position starts from 1 and ends with a positive scalar conditional on how much returned results in one session. The smaller the number of *Position*, the higher is the rank. In our dataset, the largest number of returned results for a session is 59. *Click* is a binary variable indicates whether a product is clicked or not. Table 1 summarizes the definitions of all variables and Table 2 presents the summary statistics for each variable.

Table 1. Variable Definition	
Variables	Definition
Click	Whether an item among the returned results is clicked or not
Position	Position in the returned results in each search for a product
Session ID	ID of a consumer search in 30 minutes. One session corresponds with one consumer but (probably) multiple searches
Popular	The average position in one week, which is an index of popularity
Screen	Whether an item is on the default screen that can be seen without any scrolling
Price Total	Total price of the item
Rating	User generated rating of the retailer
1Big Three	Whether the retailer is among the three most popular smartphone retailers
Ads	Whether the retailer has an advertisement besides its online icon in the search results
Shipping Fee	Shipping fee of the item
Shipping Time	Delivery time
Sunday Shipping	Whether the retailer ship during Sundays
First Page	Whether the retailer is on the first page of the search results
Second Page	Whether the retailer is on the second page of the search results (max page 3)

Table 2. Summary Statistics					
Variable	Obs.	Mean	Std. Dev.	Min	Max
Click	4,832,277	0.032	0.177	0	1
Position	4,832,277	20.419	13.189	1	59
Popular	4,832,277	20.419	12.990	1	58.398
Price Total	4,832,277	478.701	184.420	88.48	999.270
Rating	4,832,277	3.635	1.020	0	5
Big Three	4,832,277	0.055	0.230	0	1
Ads	4,832,277	0.223	0.416	0	1
Shipping Fee	4,832,277	1.505	2.688	0	9.990
Shipping Time	4,832,277	1.947	1.722	0	7
Sunday Shipping	4,832,277	0.060	0.238	0	1
Screen	4,832,277	0.244	0.430	0	1
First Page	4,832,277	0.6657	0.472	0	1
Second Page	4,832,277	0.3196	0.466	0	1

3.3 Identification Strategy

The dependent variable (click) is a binary variable, we will estimate a conditional logit model with robust standard errors (Equation 1). U_{ijk} is the latent utility a shopper infers in session i from product k sold by retailer j. β_1 captures the effect of position on click and β_2 captures the moderating effect of mobile on the effect of position on click.

For each session, *Tweakers.net* returns the results based on product popularity, calculated based on the total number of clicks during the past week. Therefore, conditional on popularity, price, advertisements, shipping fee and shipping time, position of product k provided by retailer j is exogenous. This is an important assumption we rely on to estimate the effect of position on click.

$$U_{ijk} = \beta_0 + \beta_1 Position_{ijk} + \beta_2 Position \times Mobile_{ijk} + \beta_3 Popular_{ijk} + \beta_4 Price_{ijk} + \beta_5 Rating_{ij} + \beta_6 BigThree_j + \beta_7 Ads_j + \beta_8 ShippingFee_{jk} + \beta_9 ShippingTime_{jk} + \beta_{10} ShippingSun_{jk} + \beta_{11} Page_{ij} + \alpha_i + \gamma_k + \varepsilon_{ijk} \quad \mathbf{(1)}$$

$$ClickProbability_{ijk} = \frac{Exp(U_{ijk})}{1 + Exp(U_{ijk})}$$

It is possible that the error term is correlated with position thus inducing an endogeneity issues. Thus we control all other observable confounding factors that may affect both position and the probability to click. Following Brynjolfsson et al. (2010), $BigThree$ is set to 1 if the retailer is one of the three most popular retailers in the Netherlands. $BigThree$ is correlated with position since the best retailers often have competitive prices and shipping services, and can affect a shopper's click probability due to the brand effect. $ShippingSun$ indicates whether a retailer delivers goods on Sundays. Most shipping services on Sunday in Netherlands is closed, therefore Sunday delivery becomes an advantage that may increases' shopper's click likelihood. Sunday delivery can also be correlated with the position of an item via the effect of popularity. $Page$ indicates which page the item is displayed. Although, $Page$ is correlated with position[2], accounting for the effect of pages. Table 3 reports the correlation matrix between those variables.

Finally, we only use within session variation to estimate our coefficients by applying a session fixed effects. Meanwhile, product fixed effects are also included to capture the unobserved attributes of the product that could potentially affect both the position of an item and shoppers' likelihood to click. ε_{ijk} is the error term.

Table 3. Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Click	1												
2. Position	-0.21	1											
3. Popular	-0.21	0.48	1										
4. Price Total	-0.06	0.30	0.30	1									
5. Rating	0.06	-0.27	-0.28	-0.03	1								
6. Big Three	0.08	-0.24	-0.25	-0.06	0.21	1							
7. Ads	0.12	-0.13	-0.14	0.00	0.08	-0.13	1						
8. Shipping Fee	-0.08	0.05	0.05	-0.03	-0.25	-0.09	-0.12	1					
9. Shipping Time	-0.07	0.06	0.06	0.11	-0.15	-0.16	-0.13	0.30	1				
10. Sunday Shipping	0.08	-0.14	-0.15	-0.03	0.21	0.40	0.22	-0.14	-0.29	1			
11. Screen	0.25	-0.66	-0.65	-0.18	0.17	0.26	0.08	-0.11	-0.07	0.14	1		
12.First Page	0.11	-0.84	-0.83	-0.26	0.22	0.17	0.10	-0.01	-0.03	0.10	0.40	1	
13. Second Page	-0.11	0.77	0.76	0.25	-0.18	-0.16	-0.09	0.02	0.02	-0.10	-0.39	-0.97	1

[2] On both mobile and PCs, *Tweakers.net* displays 25 items on each page. Position 1~25 is on the first page, position 26~50 is on the second page and position 51~75 will be on the third page. Since the marginal effect of position on click is not necessarily linear, $Page$ helps capture the effect that couldn't be captured by the linear specification. We use third page as the reference group and only include two dummies to indicate the page effect to avoid dummy trap.

4. Results

4.1 Main Results

We present our estimation results in Table 4. The result shows a negative and significant association between position and the probability to be clicked for an item. Position is centered, therefore, the coefficient of position represents the main effect of position on click. Specifically, Columns (1) shows the results of the conditional logit estimation with session fixed effects for the full sample. The coefficient of position is negative, indicating that the probability to be clicked is smaller for lower ranked items. This finding is consistent with the findings in literature (e.g., Agarwal et al. 2011, Ghose and Yang 2009, Baye et al. 2009). The significant positive coefficient of the interaction term means that the negative effect of position on click is smaller on mobile devices. Namely, the ranking effect is smaller on mobile devices.

Table 4. The Role of Position on Click: Mobile vs. PCs.

	(1)	(2)	(3)	(4)
VARIABLES	CLOGIT	LPM	CLOGIT	LPM
	Full Sample	Full Sample	First Page	First Page
Position	**-0.117*****	**-0.00439*****	**-0.252*****	**-0.0194*****
	(0.000902)	(5.03e-05)	(0.00239)	(0.000281)
Position × MT	**0.00382*****	**0.000208*****	**0.000129*****	**0.00100*****
	(0.000849)	(1.64e-05)	(0.00316)	(0.000255)
Price Total	-0.0421***	-1.98e-05	-0.0411***	1.28e-05
	(0.000220)	(4.80e-05)	(0.000397)	(0.000173)
Rating	-0.0572***	-0.000510***	-0.106***	-0.00489***
	(0.00428)	(3.34e-06)	(0.00586)	(4.04e-05)
Big Three	0.242***	0.00111***	0.306***	0.000666
	(0.0112)	(7.45e-05)	(0.0134)	(0.000452)
Ads	0.642***	0.0223***	0.616***	0.0243***
	(0.00702)	(0.000615)	(0.00878)	(0.000964)
Shipping Fee	-0.0826***	-0.0420***	-0.0556***	-0.0852***
	(0.00188)	(0.000277)	(0.00241)	(0.000795)
Shipping Time	-0.138***	-0.00241***	-0.176***	-0.000686***
	(0.00301)	(2.51e-05)	(0.00409)	(0.000130)
Sunday Shipping	0.539***	0.00285***	0.536***	0.00859***
	(0.0110)	(4.56e-05)	(0.0138)	(0.000202)
First Page	-4.130***	0.00806***		
	(0.110)	(0.000641)		
Second Page	-1.805***	-0.184***		
	(0.106)	(0.000585)		
Constant		0.381***		1.055***
		(0.00340)		(0.0105)
Observations	4,264,890	4,264,896	1,062,103	1,065,685
Number of id session	110,252	110,257	98,402	110,219
R-Square	--	0.083	--	0.181
Session FE	YES	YES	YES	YES
Product FE	YES	YES	YES	YES
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Given that the fixed effects estimators of nonlinear panel models can be severely biased and the marginal effect of the logit model always depends on other covariates, we also used a Linear Probability Model (LPM) to check the average effect of position on click (see Column (2)). Although LPM allows for a straightforward and meaningful interpretation of coefficients, it may introduce heteroscedasticity into the estimates (Greenwood and Agarwal 2015) and generate predicted probabilities outside the [0, 1] bound. Following the approach used by Greenwood and Agarwal (2015), besides estimating cluster-robust standard errors, we further performed a post-estimation inspection, which shows that 98.71% (99.54% for Column (4)) predicted probabilities remain within the interval. According to Column (2), if the position of an item is lower by 1 (say from position 5 to position 6), the probability that item to be clicked on average will decrease by 0.44%. Considering the overall click through rate is 3.24%, this ranking effect is almost 14% of the click through rate. The ranking effect on mobile is 4.73% smaller (ranking effect on mobile is 0.418%) than the ranking effect on PCs.

In terms of other control variables, the higher the price of an item, the less likely it will be clicked. Similarly, the higher the shipping fee and the longer the shipping time, the less likely an item will be clicked. Meanwhile, providing Sunday delivery will increase the probability to be clicked. Besides, displaying an advertisement also increases the probability to be clicked.

4.2 The Heterogeneity of Ranking Effect

In Table 4 Column (1) and (2), we report the average effect of position on an item's probability to be clicked with an implicit assumption that the marginal effect of position click probability is constant at different positions. In Table (4), we notice that the effect of page on the probability to be clicked is inconsistent between conditional logit model and linear probability model. Practically, the marginal effect of position on the probability to be clicked can be different between from position 1 to position 2 (first page) versus from position 26 to position 27 (second page). We therefore conduct another sub-sample analysis to explore the heterogeneity of ranking effect.

Table 4 Column (3) and (4) report the results of both conditional logit model and linear probability model with session fixed effects for first page observations. Position has a negative effect on an item's probability to be clicked. However, the ranking effect (the coefficients) on the first page is qualitatively much larger than the average ranking effect. Specifically, the marginal effect reported in Table 4 Column (4) is almost 4.4 times larger than that marginal effect reported in Column (2).

4.3 Shoppers Using Mobile versus Shoppers Using PCs

The next concern goes to whether this smaller ranking effect on mobile driven by devices or by the differences in shoppers. Namely, the choice of shopping channels (mobile vs. PCs) is self-selected. It's possible that shoppers that use mobile are different from shoppers who use PC channels. Meanwhile, shoppers who use mobile may be in different shopping stage compared with shoppers who use PCs. Unfortunately, we don't have demographic information to account for the variation in shoppers. We try to address this concern in the following two ways.

First, even though shoppers using mobile devices are different from shoppers who use PCs, this difference is expected to remain the same. That is, the shopper-device combination is not supposed to change dramatically. Especially, our data come from real practice. The finding that smaller ranking effect on mobile (mobile-shopper combination) is still insightful for both retailers and ecommerce platforms.

Second, following Brynjolfsson et al. (2010), we try to provide evidence about shoppers' click behavior on mobile (smartphones and tablet) and PCs. Table 5 reports the average number of searches that a shopper had between smartphones, tablets and PCs. First of all, the mean value of the average number of searches that a shopper had between smartphone and tables is both qualitatively and statistically the same (P-value of the mean test is 0.54). The mean value of the average number of searches that a shopper had between PCs and mobile (smartphones and tablet) is qualitatively the same but statistically different. It's often easier to achieve a statistical significance when we have a large sample size. Therefore, it's also useful to look at the T-value, which is relative small. Taking into account of the absolute value of the average number of searches that a shopper conducted, the difference between mobile and PC is trivial from a perspective of economic effect. Therefore, qualitative comparison between the PCs and mobile is more meaningful.

Table 5. Number of searches a shopper has in each session across devices									
Variable	Freq.	Obs.	Mean	Std. Dev.	Min	Max	P-value	T-value	Between
Smartphone	38%	30004	1.0533	0.2644	1	8	0.54	-0.61	S-T
Tablet	14%	17888	1.0548	0.2525	1	5	0	7.94	T-P
PC	62%	78451	1.0752	0.3216	1	19	0	-10.5	P-S
Total	1	126343	1.0671	0.3000	1	19			

In Table 6, we report the average number of items a shopper clicked in each session. Qualitatively, the mean value of the average number of items that a shopper clicked between tablets and PCs is both qualitatively and statistically the same (P-value of the mean test is 0.28). However, the mean value of the average number of items that a shopper clicked between mobile and PCs is qualitatively the same but and statistically different. Again, we try to interpret this difference in terms of effect size. And thus the shoppers using mobile and PCs are not dramatically different from each other.

Table 6. Number of items a shopper clicked in each session									
Variable	Freq.	Obs.	Mean	Std. Dev.	Min	Max	P-value	T-value	Between
Mobile	0.237	30004	1.168	0.880	0	19	0.00	-11.8	M-T
Tablet	0.142	17888	1.269	0.957	0	14	0.28	-1.07	T-P
PC	0.621	78451	1.260	1.040	0	32	0.00	-13.62	P-M
Total	1	126343	1.240	0.993	0	32			

5. Discussion

5.1 Conclusion

Given the increasingly important role of mobile shopping and ranking in retailing, this study empirically texts the ranking effect across mobile and PC. Results consistently show that ranking effect is smaller on mobile. By providing descriptive evidence about shopper's behavior, we qualitatively show that shoppers from mobile and PC are similar. Therefore, the smaller ranking effect on mobile may be driven by device rather than the self-selection of shoppers.

5.2 Limitations and Future Research

This study has a few limitations that open opportunities for future research. First, in our dataset, we could not identify shoppers that use the shopbot more than 30 minutes as the same shopper. Therefore, a session is a conservative estimate of the searchers for a shopper.

Second, we couldn't perfectly disentangle the device effect and shopper effect. Therefore, it's unclear whether the smaller ranking effect on mobile is driven by differences in devices or shoppers.

Third, despite the fact we model the confounding factors that affect both position and probability to be clicked, unobserved factors may still exist hence we can only state the effect as correlation rather causal effect. Future research could introduce randomization of positions to better establish the causal link between position and probability to be clicked.

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