Different but Equal? A Field Experiment on the Impact of Recommendation Systems on Mobile and PC Channels in Retail

Online Appendix

Appendix I. Related Literature

Table A1. Differences between Mobile and PC Channel

Study	Empirical Context	Theoretical Basis / Mechanism	Key Findings
Chae and Kim (2003)	Analysis of three consecutive online surveys in Korea	Resource availability, ubiquity, user identity, risk, information search cost,	Mobile customers prefer to purchase low-risk products than high-risk products. Mobile users prefer low-intensity contents and customized contents.
Ghose et al. (2013)	Analysis of user posting behavior of the microblogging service website in Korea	Ranking effect, information search cost, cognitive load, geographical proximity	Due to the higher search cost, ranking effects are higher on mobile channel than on PC channel. Mobile users have stroger local interest than PC users..
Bang et al. (2013)	Analysis of online and mobile transaction data of Korean e-commerce company	Ubiquity, usability, access capabilities, search capabilities	Mobile channel complemnts the PC channel. Performance impact of mobile channel depends on time criticality and information intensity of product.
Burtch and Hong (2014)	Analysis of random sample of TripAdvisor	Convenience, fading affect bias, typing and navigating difficulties, temporal distance,	Mobile based online reviews have lower and more varied star ratings, have more concrete and emotional text, and are perceived as more helpful.
Einav et al. (2014)	Analysis of eBay transaction data	Information search cost	Mobile commerce adoption lead to both immediate and sustained increase in total retailing website sales. Mobile purchases are skewed towards commodity products rather than idiosyncratic products that require careful inspection.
Maity and Dass (2014)	Analysis of three lab experiments about airline ticket reservation and food menu selection	Media richness theory, cognitive cost model, information search	Consumers prefer mobile channel for a simple decision-making task to for a complex one. Perceived media richness-task fit, satisfaction, and channel choice are the lowest in mobile channel.
Xu et al. (2014)	Analysis of Fox News websites visit regarding to their mobile app release by using comScore MobiLens data	Sampling effect, selective exposure	Mobile news app adoption increases the visiting of mobile website. Complementarity is stronger for consumers who favor concentrated news content.

Wang et al. (2015)	Analysis of customers' transactions of Internet based grocery retailer	Convenience, temporal and spatial flexibility, information search cost, habitual interaction	Mobile channel adoption lead to increase order rate. Mobile channel customers tend to purchase habitual products that they have purchased.
Huang et al. (2016)	Analysis of purchase data of Chinese e-commerce company that expanded its web service onto a mobile platfom	Ubiquity, ease of information, personalization, information search	While mobile channel cannibalizes the web channel, synergy effect between mobile and PC channel override the cannibalization effect.
Xu et al. (2017)	Analysis of purchase data regarding to tablet applications release of Taobao	Usability, ubiquity, channel interdependence	Tablet channel substitutes PC channel while tablet complements mobile channel. Use of tablet leads purchase of more impulse products and a wider diversity of products.
Jung et al. (2019)	Analaysis of about 50,000 users of online dating websites	Impulsivity, ubiquity, information search costs	Mobile application adoption lead users login more often across more hours in the day (i.e., ubiquity) and increase social engagement activities on online dating platform.

Table A2. Effects of Recommendation System on Consumer Decision Making

Study	**Empirical Context**	**Theoretical Basis / Mechanism**	**Key Findings**
Häubl and Trifts (2000)	Analysis of 249 students for shopping back-packing tents and compact stereo system in an online store by conducting lab experiment	Information search cost, quality of decision outcome, consumer information processing	Recommendation system reduces consumer search effort for product information. Recommendation system improves the quality of consideration set and quality of purchase decision.
Senecal and Nantel (2004)	Analysis of 487 subjects for shopping mouse, calculator, and red wine in an online store by conducting online experiment	Information search cost, information source, attribution theory,	Recommendation system is the most influential recommendation source than human experts and other consumers.
Häubl and Murray (2006)	Analysis of 265 consumers for shopping a notebook computer at an online store by conducting lab experiment	Information search cost, quality of decision outcome, consumer information processing	Recommendation system reduces consumer search effort for product information. Recommendation system improves decision quality.

Tam and Ho (2006)	Analysis of 207 subjects for personalized banner lab experiment and 182 subjects for personalized music recommendation field experiment	social cognition, consumer information processing	Recommendation relevance and personalized offering significantly affect consumers' cognition and perceptions in decision making stages.
Kumar and Benbasat (2006)	Analysis of 60 subjects for shopping CD using Amazon.com's recommendation system and customer reviews by conducting lab experiment	Technology acceptance model, social presence, information search cost	Recommendations and consumer reviews increases the usefulness and social presence of the website.
Fleder and Hosanagar (2009)	N/A, Analytical modeling and simulation	Consumer utility maximization, information search cost	Recommendation systems increase sales.
De et al. (2010)	Analysis of medium-sized women's clothing company's Internet channel sales in April 2006	Information search cost	Recommendation systems increase sales of both promoted and non-promoted products by lowering search costs.
Lee and Benbasat (2010)	Analysis of 75 subjects printer shopping in an artificial store using mobile recommendation systems by conducting a lab experiment	Cognitive effort, quality of decision outcome, consumer information processing,	Mobile recommendation system use in a retail store reduces perceived effort and increases accuracy of the decisions.
Pathak et al. (2010)	Analysis of 156 books for 52 days from Amazon.com and B&N.com	Information quality, signaling and advertising, customer loyalty and switching cost	Recommendation systems increase sales. The recency of the product positively moderates the impact of recommendation systems on sales.
Zhang et al. (2011)	Analysis of a two-phase lab experiment with 253 subjects for online DVD shopping	Retailer learning, information search cost, consumer information processing, customer retention	Higher quality recommendation systems amplify customer retention by reducing product screening cost and improving consumer decision-making quality. Higher quality recommendation systems are associated with higher product evaluation cost.
Dellaert and Häubl (2012)	Analyses 438 panels stereo product preference survey, 60 subjects product search lab experiment, and 169 subjects product search online experiment	Consumer utility maximization, consumer product search process model, choice deferral	Recommendation systems lead customers to make broader comparisons among alternative products. Recommendation system causes customers to terminate product search sooner.

Oestreicher-Singer and Sundararajan (2012b)	Analysis of Amazon's recommendation networks for 250,000 books over a period of a year and B&N's co-purchase network.	Network of products, attention, observational learning	The visibility of the recommendation system increases the shared purchasing of complimentary products.
Adamopoulos and Tuzhilin (2015)	Analyses of the restaurants in the mobile urban guide app for the 15 most popular cities from December 2014 to March 2015 by using discrete-choice models	Consumer utility maximization, design of recommendation systems	Recommendation system has a positive impact on demand of restaurants. The effect of in-the-moment recommendations is stable across various levels of popularity.

Table A3. Effects of Recommendation Systems on Sales Diversity

Study	**Empirical Context**	**Theoretical Basis / Mechanism**	**Key Findings**
Fleder and Hosanagar (2009)	N/A, analytical modeling and simulation	Consumer utility maximization, information cascade, Internet balkanization	Recommendation systems decrease aggregate sales diversity.
Brynjolfsson et al. (2011)	Analysis of medium-sized women's clothing company's 734 products in Internet and catalog channels between Aug 16 to Sep 12 in 2006.	Information search cost	Recommendation systems increase sales diversity.
Hinz et al. (2011)	Analysis of 843,922 purchases from 143,939 customers from video-on-demand operator over 111 weeks	The long-tail of demand, information search cost	Recommendation systems shift demand from niches to blockbusters while search functionalities lead to a shift in demand from blockbusters to niches.
Oestreicher-Singer and Sundararajan (2012a)	Analysis of Amazon's recommendation networks for comprising over 250,000 books over 28 days in 2007.	The long-tail of demand	Recommendation system is associated with a more even or flatter distribution of both revenue and demand.
Hosanagar et al. (2014)	Analysis of online music services data between January and July 2007.	Fragmentation vs. homogenization, product-mix effect, volume effect	Recommendations systems are associated with an increase in commonality.
Lee and Hosanagar (2019)	Analysis of Blu-ray discs and DVDs sales from North America retailer website over two weeks by conducting field experiment	Design of recommendation systems	Collaborative filtering based recommendation algorithm increases individual consumption diversity while decreases overall aggregate sales diversity.

Appendix II

Pilot Field Experiment: Mobility Index and Customer Heterogeneity

Introduction

In this appendix, we describe the second field experiment conducted to test the differential effects of recommendation systems between PC and mobile users, to complement the field experiment described in the main paper. In terms of chronology, the experiment described here was conducted first, i.e. over 120 days between February and May 2014. Based on the findings of this experiment and the potential limitations of the experimental design, we designed the experiment described in the main paper. Thus, it is possible to treat this experiment as a preliminary or pilot experiment – to enhance clarity, we refer to this experiment as the *pilot experiment* hereafter. We include a description of the pilot experiment here because it provides supportive evidence for the main results reported in the paper: (a) we see a significant moderating effect of channel on the efficacy of recommendation systems on product sales, in that the mobile channel leads to higher sales, (b) there is no direct effect of the recommendation system on sales diversity but mobile users show higher sales diversity relative to PC-based users.

There are some significant differences in the design of the pilot experiment, relative to the experiment in the main paper, which we describe here briefly. First, the pilot experiment was conducted over a period of 120 days post-treatment, relative to the three days that were possible in the experiment in the main paper. Therefore, we were able to study the effects of the recommendation system on customers for a longer time-period. Second, pre-treatment trends in the pilot experiment were only available for product views by customers, as opposed to complete pre-treatment trends on purchase and conversion behavior in the experiment in the paper. This reduces the extent to which we can identify pure-mobile and pure-PC users, or use a differences-in-differences model in estimating the treatment effects. Third, in the pilot experiment, we had data only on total sales for each customer, rather than the sales of recommended products specifically.

This also implied that we could adequately model alternative outcomes such as click-through and conversion rates, which we are able to do in the experiment in the paper. However, we had access to some demographic data in the pilot experiment, which allows us to consider the effects of customer characteristics in our analysis. Fourth, in the pilot experiment, the treatment group had a recommendation panel added to the interface while the control group did not see anything. Recall that in the experiment reported in the paper, the control group was provided with a similar panel showing a set of popular products in place of the recommendation panel. Thus, the interface in the pilot experiment was not exactly identical across the two groups – we rectified this in the main experiment. Finally, the issue of channel selection in the pilot experiment was handled differently since we did not have pre-treatment trends to identify pure-channel users or channel switchers. We describe the analyses conducted for the pilot experiment below in some detail.

Experimental Design and Data

As mentioned above, the pilot field experiment was conducted over 120 days between February to May 2014 on a fashion retailing website in South Korea and yielded a large sample of 145,098 transactions from 77,305 distinct customers [1]. As before, the randomized treatment was the availability of the item-to-item collaborative filtering-based recommendation panel. The treatment was applied using the PCID device identifier described in the main paper; users with even numbers were assigned to the treatment group while those with odd numbers were assigned to the control group. The data for the experiment comes from the actual purchase information (all orders) placed during the experimental period. Therefore, we focus only on those consumers who have made at least one purchase during the study period. This strategy is consistent with the sample selection approach in the existing literature (De et al. 2010). Since the treatment (presence of a recommendation system) is randomized across the full sample of consumers, not only those with purchases during the experimental period, we check to see if the treatment retains parity across the

[1] The overall sample was 86,242 customers, of whom 7,475 were multi-device users who could be potentially exposed to inconsistent treatment conditions across devices, and were therefore dropped from the analysis. In addition, 1,462 customers were excluded for missing customer-level variables. Thus, the final sample was 77,305 customers.

treated and control groups in the final purchase-based sample.

Of the 77,305 unique customers who made at least one purchase, 37,811 appeared in the control group (48.9%) while 39,494 customers are in the treatment group (51.1%), suggesting that the treatment appears well-distributed in the sample. Further, Table A4 provides variable descriptions of our data and descriptive statistics between the control group and the treatment group. The average sales per customer during the experiment period was $172.64[2], and is higher in the treatment group ($180.72) compared to the control group ($164.19). Beyond total sales per customer, we also consider sales quantity, i.e. the number of products purchased during the experimental period. The average number of products purchased (sales quantity) by a customer during the experiment period is 1.94. Since our interest is in differentiating between PC and mobile users, we use a dichotomous measure to distinguish those customers who only use the PC versus those who also use a mobile device. Accordingly, we code the variable *Mobile*=0 for all customers who exclusively use the PC channel to make purchases across the experiment period. The remaining customers therefore have at least one purchase in the experiment period on the mobile channel – we code these as 1. In certain cases, we observe users with inconsistent treatment exposure, i.e., in some cases, customers may change devices or use browser settings that resets their PCID. In other cases, we observe users across both channels that are assigned the treatment group on one channel but the control group on the other. We exclude these customers from the analysis. We also have access to some customer demographic data here, specifically customer gender, age, and tenure on the retail platform. We also ensure that the sample is well balanced across customer-level variables, i.e., *Female*, *Age*, and *Tenure*, indicating that the randomization is successful and has not led to a skewed distribution. Table A5 provides the correlation table for the pilot field experiment.

Table A4. Variable Definition and Descriptive Statistics for the Pilot Field Experiment

Variable	**Definition**	**Treatment Group**	**Control Group**	**Total**
		n=39,494	n=37,811	n=77,305
Sales	Total dollar amount spent by a customer during	180.72	164.19	172.64

[2] We use mean forex exchange rate between Feb 1st and May 31, 2014 (www.federalreserve.gov/releases/h10/hist/.)

	Experiment 1 period	(329.96)	(234.34)	(287.31)
SalesQty	Total sales quantify by a customer during Experiment 1 Period	2.00 (2.64)	1.87 (2.20)	1.94 (2.43)
Recommendation	0: without recommendation (control group) 1: with recommendation (treatment group)	1.00 (0.00)	0.00 (0.00)	0.51 (0.50)
Mobile	0: purchase through PC channel only 1: purchase through mobile channel at least once	0.26 (0.44)	0.22 (0.42)	0.24 (0.43)
Female	0: Male, 1: Female	0.71 (0.45)	0.71 (0.46)	0.71 (0.45)
Age	Customer age in 2014	31.55 (7.98)	31.42 (7.86)	31.48 (7.92)
Tenure	Number of months from a customer's first signed up date to May 31, 2014	59.93 (54.34)	58.66 (54.35)	59.31 (54.35)

Table A5. Correlations for the Pilot Field Experiment

	Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
(1)	ln(Sales)	1.000						
(2)	SalesQty	0.390	1.000					
(3)	Recommendation	0.027	0.028	1.000				
(4)	Mobile	0.066	0.069	0.043	1.000			
(5)	Female	0.047	0.024	0.007	0.116	1.000		
(6)	Age	0.099	0.103	0.008	-0.053	0.046	1.000	
(7)	Tenure	0.121	0.093	0.012	0.044	0.174	0.292	1.000

Empirical Analysis

We use regression models to examine the contingent effects of recommendation systems usage on product sales for the pilot experiment. The unit of analysis is the individual customer, since the treatment is applied at the level of the individual customer through the PCID. The baseline model includes recommendation system treatment, access channel (mobile/PC), and customer-specific variables:

$$\ln(Sales_i) = \beta_0 + \beta_1 Recommendation_i + \beta_2 Mobile_i + \beta_3 Female_i + \beta_4 Age_i + \beta_5 Tenure_i + \varepsilon_i \quad \text{(A1)}$$

$Sales_i$ indicates customer *i*'s total purchases during the experiment period. The dummy variable $Recommendation_i$ indicates whether customer *i* is assigned to the treatment group. The dummy variable $Mobile_i$ indicates whether customer *i* is categorized as a mobile user or a PC user. As discussed above, channel use is potentially endogenous; in tests reported later, we further classify mobile users into levels of mobile device use through the use of customer-level browsing behavior from pre-treatment periods. In baseline analyses, we retain the dummy variable defined here, acknowledging the relative coarseness of the variable. The variables $Female_i$, Age_i, and $Tenure_i$ captures customer *i*'s gender, age, and tenure on the website for the pilot field experiment.

Since the recommendation system is randomized across customers, the coefficient β_1 is estimated without bias. In addition, we observe that the sales quantity per consumer is low (mean=1.94), suggesting that while consumers may browse many products, their purchases are not as frequent. Therefore, we treat the data as cross-sectional across the four months of observation for the analysis and use an OLS model to estimate equation (A1) for sales (in dollars), shown in column (1) of Table A6. The treatment, i.e. presence of a recommendation system, has a significantly positive effect on customer-level sales (β=0.046, p<0.01). On average, recommendation system usage increases sales by 4.6%. The results also show that mobile users spend more on the site, all else being equal, providing baseline evidence for the positive effects of ubiquity and convenience (β=0.145, p<0.01. In addition to total sales per customer, we also consider the effects of the treatment on sales quantity per customer. Since sales quantity is a nonnegative count variable, with a lower bound of 1, we cannot use OLS (Greene 2011). The variance of the sales quantity exceeds its mean (mean = 1.94, variance = 2.43, see Table A4). Therefore, the Poisson model is also not appropriate as it assumes that mean and variance of the counts are equal (Cameron and Trivedi 1990). We use the negative binomial regression, which corrects for over-dispersion and accounts for omitted variable bias, with robust standard errors to estimate the following model (Greene 2011)[3]:

$$SalesQuantity_i = \exp[\beta_0 + \beta_1 Recommendation_i + \beta_2 Mobile_i + \beta_3 Female_i + \beta_4 Age_i + \beta_5 Tenure_i + \varepsilon_i] \quad \text{(A2)}$$

$SalesQuantity_i$ indicates customer *i*'s total sales quantity during experiment period while other covariates remain the same. Column (5) of Table A6 show the estimates of the equation (A2). The direct effects of recommendation system usage (β=0.056, p<0.01) and mobile use (β=0.194, p<0.01)

[3] We also estimate a zero-inflated negative binomial model for sales quantity, with fully consistent results. These results are available upon request from the authors.

have a significantly positive effect on sales quantity, consistent with results from total sales.

As a baseline, the results from the estimates of equations (A1) and (A2) are consistent with prior research showing the direct influence of recommendation systems on sales and sales quantity (De et al. 2010; Lee and Hosanagar 2019; Pathak et al. 2010). In addition, these results also show that mobile-based customers tend to be active buyers, driven by the convenience and ubiquity of mobile retail channels, in contrast to pure PC-based customers (Einav et al. 2014; Wang et al. 2015).

Table A6. Effects of Recommendation System Across Mobile and PC – Pilot Field Experiment

DV	**Sales**				**Sales Quantity**			
	(1) Total	**(2) Mobile**	**(3) PC**	**(4) Total**	**(5) Total**	**(6) Mobile**	**(7) PC**	**(8) Total**
Recommendation	0.046*** (0.007)	0.195*** (0.015)	-0.002 (0.008)	-0.002 (0.008)	0.056*** (0.009)	0.203*** (0.019)	0.003 (0.010)	0.003 (0.010)
Mobile	0.145*** (0.009)			0.039*** (0.012)	0.194*** (0.011)			0.082*** (0.015)
Recommendation x Mobile				0.197*** (0.017)				0.201*** (0.021)
Female	0.045*** (0.008)	0.041** (0.018)	0.045*** (0.008)	0.045*** (0.008)	0.001 (0.010)	0.007 (0.023)	-0.001 (0.011)	0.001 (0.010)
Age	0.009*** (0.000)	0.011*** (0.001)	0.009*** (0.001)	0.009*** (0.000)	0.014*** (0.001)	0.015*** (0.001)	0.013*** (0.001)	0.014*** (0.001)
Tenure	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Constant	4.161*** (0.016)	4.174*** (0.036)	4.198*** (0.017)	4.185*** (0.016)	0.048*** (0.019)	0.093** (0.043)	0.095*** (0.020)	0.075*** (0.019)
Observations	77305	18799	58506	77305	77305	18799	58506	77305
R-squared	0.024	0.026	0.020	0.026				

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$

Having established the baseline results, we now shift to testing for the differential (moderating) effects across the two channels. We estimate this effect in two ways. First, we conduct subsample analyses by splitting the sample into mobile and PC-based subsamples and estimating equations (1) and (2) for each subsample, consistent with prior work in marketing (Sharma et al. 1981). We use the Chow's test (Chow 1960) to test for the inequality of the treatment effect across the two subsamples. Second, we interact the treatment dummy with the mobile dummy to evaluate moderation (Carte and Russell 2003). Table A6 shows the results of both forms of analyses on overall sales and sales quantity across mobile and PC channel.

From columns (2) and (3) of Table A6, we see that the treatment (i.e. recommendation system usage) has a significantly positive effect on sales for mobile-based customers (β=0.195, p<0.01), whereas this effect is not significant for PC-based customers (β=-0.002, ns). The Chow's test provides further evidence for this strong moderation effect; the coefficients are significantly different for mobile and PC customers (F=90.07, p<0.01). The interaction approach also shows a positive moderation effect, as seen in column (4) (β=0.197, p<0.01), indicating that the recommendation system effect is significantly stronger in the case of mobile channel, compared to pure-PC customers. All else equal, providing access to a recommendation system leads to 19.7% higher sales for mobile-based customers.

The results for sales quantity in columns (6), (7), and (8) of Table A6 shows fully consistent results. Recommendation system usage has a positive effect on sales quantity for mobile customers (β=0.203, p<0.01) but no effect for PC-based customers (β=0.003, ns). The Chow's test shows that these coefficients are statistically different (F=405.84, p<0.01). The interaction coefficient in column (8) is positive and significant as well (β=0.201, p<0.01). In summary, we see evidence of the interaction effect between the mobile channel and recommendation system for sales and sales quantity.

Channel Selection and the Mobility Index

We now address the issue of channel selection, since we cannot randomize channel use in our experiments. In comparison to the experiment reported in the main paper, we do not possess a full set of pre-treatment trends data here for each consumer. However, we were able to gain access to data on pre-treatment views of products by consumers, i.e. we had access to the products that consumers viewed and the channel they used to view these products prior to the treatment. This allows us to approximate pre-treatment behavior in terms of whether the consumers were predominantly PC or mobile users, which then allowed us to account for the extent to which they may switch channels.

We use this information in the construction of the *Mobility Index* variable, which captures the extent to which a consumer was primarily PC-based, mobile-based, or multi-channel in their viewing activity. Using such a variable also allows us to relax the relatively coarse measurement of a mobile user in the analyses shown thus far, where consumers with even one mobile purchase were categorized as mobile users. Such a measurement scheme can mask differences between customers in terms of their actual mobile use. Users who use the mobile device only occasionally to complete their purchase may not experience significant search costs and may be less engaged with their device, thereby being less influenced by the recommendation system in their purchase behavior. We therefore require a measure of the user's level of mobile use that is first, ideally measured *before* the period of the experiment so as to avoid confounding effects from users who may have changed channels, and second, provides a granular measure of how mobile-intensive the consumer's online behavior is in order to differentiate frequent mobile users from occasional users.

We develop the Mobility Index through the customers' pre-treatment browsing history. We use browsing data on the retail platform (mobile and PC-based) for the periods of November and December 2013, selecting a period a month before the start of the experiment. The browsing data for customers from this period was matched with data from the experimental period on customers with at least one purchase. The intersection of these two sets provided 21,204 customers with pre-treatment browsing history and at least one purchase during the experimental period. These customers made an average of 2.61 purchases during the experimental period while they viewed 69.18 individual pages in the pre-treatment period. Using this information, we calculate each consumer's Mobility Index (*MI*) as the ratio of the customer's browsing behavior using the mobile channel as a percentage of total browsing behavior. Thus, the mobility index for customer i is calculated as follows:

$$Mobility\ Index_i = \frac{Mobile\ Browsing_i}{Total\ Browsing_i} \times Population\ Quintile\ of\ Total\ Browsing_i \qquad \text{(A3)}$$

To differentiate between heavy and light users, we weight the mobile browsing percentage appropriately. We consider the total browsing behavior of all users and divide the distribution of browsing into quintiles. We use the quintile score (from one to five over five) to weight the ratio of mobile to total browsing. Effectively, the MI ranges in value from zero to one. For customers using the PC channel exclusively for browsing, the MI score is zero. Alternatively, a customer that also uses mobile to browse will obtain MI values ranging from 0.2 to 1.0. We use the MI in lieu of the mobile dummy to evaluate the robustness of our results. [4]

Table A7 shows the results using MI scores on both sales and sales quantity. As reported in column (1), the direct effects of recommendation system usage and MI score on sales are positive and significant (β=0.095, p<0.01; β=0.315, p<0.01 respectively), consistent with the results shown earlier. Column (3) shows that the direct effects of recommendation system and MI score on sales quantity are also significant (β=0.097, p<0.01; β=0.345, p<0.01 respectively). In column (2), we note the moderating effect of MI score on the relationship between recommendation system and sales is positive and significant (β=0.134, p<0.05), consistent with the results in Table A6. Heavy mobile users (regardless of whether they purchase on mobile or PC channels) are more likely to be influenced by the recommendation system in terms of their purchases on the platform. Similarly, the interaction effect between MI and recommendation system on sales quantity, as presented in column (4), is also positive and significant (β=0.213, p<0.05). In summary, using a more fine-grained measure of mobile use, albeit with a smaller sample, the results show that the efficacy of a recommendation system is higher in the context of mobile-based customers compared to PC users.

As a final robustness test for channel selection, we use the Heckman two-stage procedure to explicitly model channel choice (Heckman 1979) using the pre-treatment views data. The Heckman sample selection procedure allows us to estimate, as a first step, the probability of the consumer being a mobile or PC-based user using a probit regression model. In the second stage, the effects of the recommendation system are estimated only on the mobile (PC-based) sample, with the appropriate addition of the Inverse Mills Ratio to account for bias from sample selection. We use the exogenous variables identified thus far – Gender, Age, Tenure, and the Mobility Index, as independent variables (instruments) for the first stage, while in the second stage, we include the Recommendation treatment, Gender, Age, and Tenure as exploratory variable. [5] The dependent

[4] To complement the earlier use of a mobile dummy, we also dichotomize the MI variable (PC only = 0, at least one observed use of mobile device for browsing = 1). The results using this variable alongside a control variable for browsing volume are fully consistent and are available upon request.

[5] We are grateful to an anonymous reviewer and the Associate Editor for suggesting this analysis.

variable in the second stage is Sales. The Heckman procedure is run separately for the PC and mobile subsamples and the results are shown in columns (5) to (7) of Table A7. The bias-corrected coefficient for the recommendation system treatment is statistically significant for the mobile customers but is not so for the pure-PC customers. Additionally, the exogenous variables are significant in the first stage, with the exception of Tenure. The MI variable is highly significant in determining the type of customer, as expected. In summary, we see strong support for differential effects of the recommendation system across channels.

Table A7. Mobility Index as a Moderator – Pilot Field Experiment

DV	**Sales**		**Sales Quantity**		**Heckman Correction**		
	(1) Total	**(2) Total**	**(3) Total**	**(4) Total**	**(5) Selection Equation**	**(6) 2nd Stage: Mobile**	**(7) 2nd Stage: PC**
Recommendation	0.095*** (0.014)	0.078*** (0.016)	0.097*** (0.017)	0.068*** (0.018)		0.260*** (0.027)	0.011 (0.016)
Mobility Index (MI)	0.315*** (0.031)	0.242*** (0.044)	0.345*** (0.043)	0.225*** (0.057)	0.453*** (0.008)		
Recommendation x Mobility Index		0.134** (0.061)		0.213** (0.083)			
Female	0.113*** (0.017)	0.113*** (0.017)	0.002 (0.021)	0.003 (0.021)	0.299*** (0.025)	0.077** (0.039)	0.085*** (0.020)
Age	0.013*** (0.001)	0.013*** (0.001)	0.018*** (0.001)	0.018*** (0.001)	-0.014*** (0.001)	0.014*** (0.002)	0.014*** (0.001)
Tenure	0.001*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	-0.000 (0.000)	0.001*** (0.000)	0.000** (0.000)
Inverse Mills Ratio						-0.158*** (0.032)	0.062* (0.037)
Constant	4.349*** (0.036)	4.358*** (0.036)	0.204*** (0.042)	0.219*** (0.042)	-0.635*** (0.050)	4.580*** (0.079)	4.325*** (0.046)
Observations	21204	21204	21204	21204	21204	6283	14921
R-squared	0.019	0.020					

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$

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