How Do Personalized Recommendations Affect Consumer Exploration: A Field Experiment

Michelle Song

June, 2021

Abstract

Personalized recommendations are known for their ability to navigate shoppers to the most relevant products first, saving their time. However, the hidden cost is that shoppers are less likely to find other desirable products along the search process serendipitously. Such a potential cost casts doubts on whether websites should adopt personalized recommendations. I suggest a positive spillover effect of gained efficiency from personalized recommendations: consumers explore more because increased search efficiency countervails an increasing opportunity cost of time. In addition, the total shopping time is likely to decrease if efficiency gains prevail over enhanced exploration expectations. I examine these hypotheses empirically using field experiment data from Missfresh, one of China’s biggest grocery delivery platforms. Personalized recommendations enable consumers to reduce the search for essential items, spend more time exploring other categories, and make more purchases while decreasing their total shopping time. These findings are important because they show consumers’ active exploration under time pressure and they demonstrate a demand-increasing mechanism of increasing search efficiency through personalized recommendations.

1 Introduction

E-commerce websites sell millions of products to consumers every day. To help consumers find their desired products, e-commerce websites offer personalized recommendations that cater to their individual preferences. By navigating consumers to their favored products, personalized recommendations save consumers’ time. As a potential benefit of saving time, consumers may be able to engage in more directed exploration. However, the downside is that E-commerce websites might lose some profits from other products that consumers encountered during their online travels. For instance, a consumer may only purchase products from the recommended list and then leave the E-commerce website within a short period of time. Alternatively, without recommendations, she had to search the website for the items she required. The search process might lead her to other desirable products which she might
not have found if she had not spent extra time looking for the essentials. Such serendipities provide consumers a pleasant shopping experience while generating revenue for the website. Therefore, the trade-off between giving consumers personalized recommendations and allowing them to explore extensively becomes a practical problem for E-commerce websites to consider before adopting recommendations.

In this paper, I investigate how personalized recommendations affect consumer exploration on e-commerce websites. My research focuses on 1) whether personalized recommendations lead to a reduction in consumer searches of their favored products, and 2) whether improved search efficiency leads to greater consumer exploration. I study the question in an online grocery setting where consumers shop for multiple products across various categories. This setting is typical because many large E-commerce websites such as Amazon, Walmart, and Taobao have consumers who return frequently and purchase multiple items from different categories within one visit.

In the context of online shopping, I hypothesize that personalized recommendations reduce the need to search for favored products in online shopping because these products are displayed at the top of the page based on the user’s shopping history. Consumers have an increasing opportunity cost of time when they are under time pressure. In turn, the increased shopping efficiency will offset the increasing opportunity cost of time. Therefore, consumers will spend more time exploring less-frequently visited categories that they do not normally browse due to time constraints. As a result, the new equilibrium marginal benefit of exploration will be lower as consumers spend more time engaging with it. It follows that the total shopping time will be shorter if efficiency gains prevail over enhanced exploration expectations.

In my study, I employ a first dataset containing an experimental variation on whether or not consumers observe personalized recommendations. The exogenous variation allows me to study the causal impact of recommendations on consumer shopping behavior. I find that the personalized recommendation generally reduces the number of clicks while increasing the number of purchased products. To analyze the changes, I separate the effect of recommendations on shopping behavior in the following categories: frequently visited categories and less frequently visited categories. By studying consumer shopping patterns across categories that are not affected by particular recommendation algorithms, I am able to examine the impact on consumer self-exploration that occurs independently of algorithm effects. According to my findings, consumers spend a relatively greater amount of time exploring less frequently visited categories, and as a result, make more purchases from them. Additionally, the effect is economically significant: treated consumers spend 24 percent more time in the less frequently visited categories and order 35 percent more products from those categories. The results are consistent with my first hypothesis, which predicts that recommendations will lead to more consumer exploration. Meanwhile, personalized recommendations reduce total shopping time, indicating that the efficiency improvement effect outweighs any other potential learning effects. Moreover, consumers are increasing their frequency of shopping on the website due to personalized recommendations, suggesting a more pleasant shopping experience. Additionally, I examine the long-term effects of personalized recommendations by analyzing consumers’ shopping behavior one month following the experiment.
Treated consumers tend to return more frequently in the following months. They have continued browsing and purchasing from the infrequently visited categories explored during the experimental period. The economic impact of the experiment is persistent: following the end of the experiment, treatment users spent approximately 7 percent more time in the explored categories and purchased approximately 5 percent more items. This long-term impact of recommendations suggests that users benefit from the additional exploration enabled by more efficient searching.

This paper makes the following two contributions. First, I demonstrate a demand increasing mechanism of increasing search efficiency through personalized recommendations. My research shows that personalized recommendations increase search efficiency in the frequently visited categories, which in turn encourages browsing and purchasing in less frequently visited categories. Personalized recommendations free up consumers’ time for more exploration, which is a significant factor for generating more revenue for a business website. These findings relieve concerns about losing additional profits from consumers' unplanned purchases. In recent years, there have been concerns that recommendations' proliferation can lead to the creation of "filter bubbles" (Pariser 2011[1]). However, consumers' active exploration contradict the "filter bubble" phenomenon, informing us that recommending familiar items will not always lead to stagnant consumption if exploration is a normal good. It is therefore imperative that E-commerce sites develop their recommendations for improving efficiency.

Furthermore, I show that personalized recommendations have a brand new effect on consumer engagement. Unlike the point that recommendations can increase consumer engagement (Holtz et al. 2020 [2]), I find that personalized recommendations decrease shopping time on E-commerce websites by increasing shopping efficiencies, but then yield more revenue owing to increased consumer demand. The main difference is that in shopping circumstances consumers not only spend time searching for inexperienced products that require learning, but also look for products that have already proven to be successful. Thus, recommendations play a key role in navigation for experienced products and save customers time. The contrast highlights the need for further research on the impacts of recommendations in various business contexts.

The rest of the paper is organized as follows. In the next session, I will review related work. Section 3 describes the empirical context and the experiment. In section 4 I will present theoretical hypotheses based on my context, followed by an analysis of and discussion of the data. Section 5 concludes the paper and points out the direction for future research.

2 Related Literature

The paper is related to the literature on recommendation, especially to research that examines how recommendation affects user behavior. It is well documented in the literature that recommendations often lead to enhanced consumer engagement online (Freyne et al. 2009 [3], De et al.2010 [4]). In contrast, I find that better recommendations lead to less time spent on E-commerce websites due to the increased search efficiency. Another stream of papers explore the effect of recommendation on consumption diversity (Fleder and Hosanagar 2009 [5], Oestreicher-Singer and
In particular, Holtz et al. (2020) [2] suggest that personalized recommendations may lead to higher consumer engagement but may also result in less diversity consumed. It is intriguing to observe the contrasts in the context of E-commerce. As a result of personalized recommendations, consumers are more likely to purchase more and spend more time looking for diverse categories without increasing their shopping time. This contrast is primarily determined by the differences between online shopping recommendations and content-related recommendations, such as news, music, and movies. By investigating the impact of recommendations in a prevalent but relatively understudied industry in the recommendation literature, I add to the understanding of recommendations’ influence in our daily life.

By examining the influence of recommendations on consumer search across a wide range of categories, this study complements research on the impact of rankings on consumer choices. Ursu 2018 [10] shows that on Expedia, a hotel booking website, ordered rankings decrease consumer search costs and increase the probability of a match with a seller, ultimately improving consumer welfare. Similarly, Ghose et al. (2014)[11], and De Los Santos and Koulayev (2017) [12] all examine the effect of ranking within one specific category. In my study, I discover that a multi-category search can display some qualitative differences when compared with a single-product search under the influence of ranking. Specifically, I have demonstrated that a better ranking algorithm enabled by personalized recommendations causes shoppers to discover desirable products in less frequently visited categories due to the time they have saved in those familiar categories. Therefore, my research contributes to our understanding of how a personalized algorithm may benefit consumers in alternative ways.

Furthermore, this paper also relates to research that discusses the impact of search frictions on consumers’ online shopping behavior. Ngwe et al. 2019 [13] show that placing discounted items lower in the list may result in higher average sales prices and more purchases by encouraging consumers to search for additional products. According to this study, removing search frictions by providing better recommendations can also create a similar effect, as the increased search efficiency provides the consumer with more time for exploration.

Additionally, this study is related to current research on improving online ranking algorithms. For example, Yoganarasimhan 2020[14] develops an algorithm to score the likely relevance of a search result to a consumer and rank according to the score. Ghose et al. 2014 [11] compare the effects of two ranking mechanisms in the lab and show that personalized ranking leads to more clicks but fewer purchases, probably due to information overload. De Los Santos and Koulayev (2017) [12] construct a model and demonstrate that personalized ranking increases click-through rates. This study shows that personalized ranking affects shopping efficiency more than consumer expected utilities. As a result, personalized ranking leads to lower click-through rates and saves consumer time for more exploration and more purchases.

Lastly, since I examine the impact of different online product sorting strategies on consumer behavior, this project contributes to previous research on product assortment strategies that aim to trigger unplanned purchases.
among consumers. For instance, Granbois 1968 [15] proposes placing popular product categories at various points throughout the store, similar to the conventional wisdom of "hiding the milk at the back of the store" among practitioners. A more recent paper by Hui et al. 2013 [16] empirically finds a positive impact of more distance traveled in-store on unplanned spending. However, the papers ignore the importance of consumer search costs and time pressure. In an offline environment, there is a fixed cost associated with physically entering a store. Despite this, the marginal cost of search is relatively low when compared with the online environment since people cannot switch freely between shopping and other activities in the brick and mortar context. In light of the fact that a consumer has entered the store, our model predicts that the consumer will stay longer in the store and explore more than the online setting. In this regard, hiding the milk at the back of the store may not be the only strategy to increase unplanned purchases for the traditional practitioners. The reverse might also be true: if retailers can increase shopping efficiencies, consumers are likely to spend the extra time exploring other sections of the store on their own. Future research could examine specific product assortment strategies that are effective for various contexts.

3 Background and Data

3.1 Online Grocery Industry

The online grocery industry has proliferated over the past ten years as online shopping becomes increasingly popular. In the United States, firms such as Amazon, Instacart, and Walmart are accelerating the shift from offline to online grocery shopping. Despite the extensive literature on studying consumer packaged goods and consumer shopping behavior at local grocery stores, research on online grocery shopping is sparse. The world of online grocery presents a variety of challenges as well as opportunities. For instance, while offline grocery assortments vary little between customers walking into the store within a day, online grocery stores can predict preferences and change their product assortments based on customer tastes instantly. Yet, we have limited understanding of the impact of varying product listings according to consumer tastes, which is crucial to determining how the grocery business operates today.

3.2 The Company and Empirical Background

I collect data from Missfresh, a Chinese e-commerce platform that offers online sales and delivery of fresh produce. The company ran an experiment at the end of 2019 on its category page where consumers arrive to buy groceries by categories. The typical consumer accesses the category page from the front page by selecting the specific category, just like walking down each aisle after entering a grocery store. A user can also reach the category page by searching

1https://www.ibisworld.com/united-states/market-research-reports/online-grocery-sales-industry/
2Missfresh, founded in 2014, has more than 1,500 mini-warehouses that promise deliveries as fast as within an hour. Missfresh had nearly 25 million monthly active users as of May, 2019.https://www.bloomberg.com/news/articles/2020-07-23/cicc-leads-495-million-funding-for-tencent-backed-missfresh
for specific keywords associated with a product name or a category name. The category pages display multiple brands or types of products within a category. In E-commerce, categories are usually classified into three levels. Take blueberry as an example; it belongs to category level one: fruit, category level two: berries, and category three: blueberry. I choose to focus on the highest category level, but my results are robust to the selection of category levels.

Figure 1: Empirical Background: Online Grocery Shopping by Categories

Figure 1 provides an example of shopping by categories on this website. For illustration purposes, I have taken screen shots of four different category pages, including fruit, housewares, snacks, and beverages on this website. There are 46 such categories in total. The number of categories did not change over the course of the experiment. Consumers can click on each item on the page to go to the product detail pages or directly add the item to their cart. They collect their shopping cart items and make purchases at the checkout page.

3.3 Experiment

The field experiment happened from December 10 to December 16, a week at the end of 2019. Consumers are randomly selected into the treatment group once they open this website’s App. The total number of participants in the experiments is 1,114,823 who arrive at the category page from Dec 10th to Dec 16th, 2019. 83% of users are randomly assigned to the control group, and 17% of users are in the treatment group. The experiment happens at the consumer level so these consumers stay in the same group during the entire experimental period. As of December 16, the personalized ranking algorithm has been made available to all consumers who access the website’s category pages. The experiment aimed to compare personalized ranking versus non-personalized ranking.

Figure 2 illustrates how the control and treatment groups’ category pages rank items differently. In particular,
treatment group users observe products ranked by predicted click through rate (CTRs) that use consumer-specific viewing and purchase history features. Examples of these features include user_sku_click_number that signifies the number of items this user has clicked on the product (SKU), user_sku_exposure_number that means how many times the user has been exposed to this product, user_cid3_buy_count that indicates how many products the user has bought from the specific category level three. Based on these features, the ranking algorithm can recommend products based on a user’s preference for a particular product. The taste is predicted from the machine learning model that the company adopts, which is not publishable. However, it would seem logical that products previously browsed, clicked, or purchased by consumers would appear at the top of a personalized ranking. In terms of new products, if a new product shares some features with the favored products in history, it will be ranked higher than other new products. For instance, a price-sensitive consumer is more likely to see a low price new wine ranked higher than other expensive new wine. For new users, the personalized ranking algorithm takes real-time data into account. The real-time data is any history (browse, click, add-to-cart, and purchase) a consumer has with the product before arriving at the category page. As the category page is not the first site consumers encounter upon opening the App, this type of history is highly likely to exist for new users. For control group users, they see products ranked by product popularity and availability. In other E-commerce websites, the difference in ranking between the treated and control group would be the equivalent of sorting by "Most Popular" and "Most Relevant". Nevertheless, random assignment enables us to avoid the problem of selection.

3.4 Data

I have data on consumer conversion on the website, product id, product category information, and an identifier of which group this consumer belongs to (Treatment versus Control). Conversion data includes browsing, click,
add to cart, and purchase. A consumer browsing a product refers to the exposure of that product to a consumer. Whenever the product appears on the consumer’s visiting page, it is counted as one exposure. Browsing history is a more precise measure for consumer attention on the website. When a consumer is not paying attention when logging on to the website, the exposure will stay the same, whereas the time count will increase. A consumer click is counted when she clicks on the product, which leads her to the product detail page where she will see detailed descriptions of the product. A consumer can add the product directly to her cart from the category page without going into the detail page; this behavior is recorded as a direct add to cart. If she adds the product to her shopping cart from the detail page, it will be documented as an add cart on the detail page. In my analysis, an add cart means the consumer adds the item into her cart from the category page. Lastly, a purchase happens at the checkout page after the product is added to the cart.

Table 1 provides summary statistics of the key outcome measures in the sample. The outcome variables are scaled to protect data privacy. The key takeaway from this table is that some outcome variables are skewed, like purchases and revenue. This phenomenon is common in E-commerce data. Hence, I use log transformation to resolve this issue in the later data analysis. However, the zero-inflation problem is less severe in the data because the 75th percentile of purchase and revenue variables are already bigger than zero. The boxplots of these variables are shown in Appendix 7.3. The plots are more direct ways to witness that zero-inflation is less of a concern in this data.

In addition to the experiment week data, I also observe consumer conversion data from a week before and a month after the experiment ends. The previous week’s data is used for identifying consumer’s browsing history. I refer to repeat-browse products as those products that have been exposed to a specific consumer within the past week. Similar definitions apply to repeat-add-to-cart and repeat purchase items. The post-experiment data is used to study how likely consumers will continue to purchase from those explored categories.

Table 1: Summary Stats Table

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Pctl(25)</th>
<th>Median</th>
<th>Pctl(75)</th>
</tr>
</thead>
<tbody>
<tr>
<td>browse</td>
<td>2,266.759</td>
<td>3,890.596</td>
<td>3.700</td>
<td>281.200</td>
<td>943.500</td>
<td>2,641.800</td>
</tr>
<tr>
<td>click</td>
<td>11.380</td>
<td>23.274</td>
<td>0.000</td>
<td>0.000</td>
<td>3.700</td>
<td>11.100</td>
</tr>
<tr>
<td>add_cart</td>
<td>14.289</td>
<td>24.244</td>
<td>0.000</td>
<td>0.000</td>
<td>3.700</td>
<td>18.500</td>
</tr>
<tr>
<td>purchase</td>
<td>7.742</td>
<td>16.050</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>11.100</td>
</tr>
<tr>
<td>revenue</td>
<td>74.512</td>
<td>165.594</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>94.128</td>
</tr>
</tbody>
</table>

Variables are scaled by an unrevealed number to preserve data privacy.

---

4Browse data is also widely used for measuring consumer attention rather than the actual timestamp in the industry according to my data source.
4 Result

4.1 Hypothesis

As a starting point for the empirical data analysis, I present two hypotheses regarding the impact of recommendations on consumers. Appendix 7.1 includes a theoretical model that fits my empirical setting and mathematically derives two hypotheses. I will address the intuition of the model mainly in this section. First, I hypothesize that personalized recommendations reduce consumer search. The increased shopping efficiency counteracts the increasing opportunity cost of time. Therefore, consumers will explore more in the less frequently visited categories that they do not usually spend time browsing or purchasing. Intuitively, this makes sense because the marginal cost of time is still lower than the continuation value of search when consumers stop earlier after shopping more efficiently from the recommended list. To give a concrete example, suppose on a given shopping trip, a consumer planned for an hour for that trip. With personalized recommendations, she can finish within 20 minutes compared to the usual 30 minutes spent on shopping for essential items. At the 20 minute cutoff, her continuation value, which is the expected benefit from further exploration, is likely to be higher than her opportunity cost of time. She will continue the exploration that leads to some unplanned spending as a result of the increased shopping efficiency for her essential needs.

In addition, I expect that the total shopping time will decrease if the improved efficiency effect dominates the enhanced expectation effect. To be specific, on the one hand, increased search efficiency enabled by personalized recommendations might lead to a decrease in total shopping time. As consumers allocate proportionally more time on exploration, the new equilibrium marginal benefit/cost is going to end at a lower point. As a result, the new equilibrium time will decrease as a result of the law of demand. On the other hand, personalized recommendations may also enhance the expectation of a consumer to explore the website, which may have a positive impact on the total amount of time spent shopping. The net effect of these two forces can be seen in the total amount of time consumers spend shopping on the website after the introduction of personalized recommendations.

4.2 Empirical Analysis

Given the above two hypotheses, I conduct data analysis to estimate the impact of recommendations on consumer search. I quantify the effect of personalized recommendations by estimating the following log-linear regression.

\[
\log(1 + y_i) = \beta_0 + \beta_1 T_i + \epsilon_i
\]

I use \(\log(1 + y)\) because of the skewed distribution of outcome variables. \((1 + y)\) transformation allows me to take care of zero issues in the outcome variables. Appendix 7.2 displays 1000 bootstraps of mean distributions of outcome measures for each group, Treatment and Control. I multiply the data by an unrevealed number to protect data privacy. So the absolute values of outcome measures do not matter as long as the mean distribution is normal. Though these variables are skewed, their means are confirmed to distribute normally. Also, the mean difference between the two groups is distributed normally. These histograms justify the mean comparison between treatment and control groups.
\( T_i \) is an indicator of whether the individual \( i \) is a member of the treatment group. The primary focus is on the magnitude and sign of the coefficient. \( \beta_1 \) informs us about the average treatment effect of personalized ranking on various outcome variables. Moreover, \( \beta_1 \) is interpreted as the relative increase/decrease compared to the control group users who do not see the intervention. \(^7\) The outcome measures are aggregated over the week of the experiment for each individual, so it is a cross-sectional regression. \(^8\)

### 4.3 Effect on Search and Demand

Table 2: Main Experiment Effect

<table>
<thead>
<tr>
<th></th>
<th>(1) click</th>
<th>(2) add_cart</th>
<th>(3) purchase</th>
<th>(4) revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>( T )</td>
<td>-0.00977***</td>
<td>0.0643***</td>
<td>0.0402***</td>
<td>0.0537***</td>
</tr>
<tr>
<td>( % \text{ change} )</td>
<td>-1.29%</td>
<td>8.12%</td>
<td>5.97%</td>
<td>5.64%</td>
</tr>
<tr>
<td>( N )</td>
<td>1114823</td>
<td>1114823</td>
<td>1114823</td>
<td>1114823</td>
</tr>
</tbody>
</table>

\( t \) statistics in parentheses

* \( p<0.10 \), ** \( p<0.05 \), *** \( p<0.01 \)
Dependent variables are log(1+Y) transformed

First of all, I examine the main effect on the number of items that consumers click, add cart, purchase, and the website’s total revenue. Table 2 shows the regression results of the main experiment effect. From left to right, each column reports regression results on outcome measures, including the number of items clicked, the number of add cart items, the number of items purchased by each individual, and the total revenue generated from an individual consumer. The first row shows the regression coefficients estimates \( \beta_1 \), and the second row displays the percentage changes at the average level of \( y \) in the Control group.

In summary, I find that personalization reduces search, but it also leads to an increase in demands. Treatment group users make fewer clicks than control group users. On average, they click on 1.29% fewer items than the control group users who do not have personalized ranking. Nevertheless, they add 8.12% more things into their cart directly from the category page. From their expanded shopping carts, treated consumers purchase 5.97% more items. In turn, the website generates, on average, 5.64% more revenue from the treatment group than the control group.

The fact that consumers purchase more and the revenue increases without more clicks can be driven by either the reminder effect or the exploration effect. To be specific, on the one hand, it is possible that personalized recommendations remind consumers to buy things that they would have forgotten. Alternatively, personalized recommendations might enable consumers to find desirable products through exploration, which generates extra revenue. In the next sections, I will examine the impact of personalized recommendations on exploration by focusing

---

\(^7\) Due to confidentiality concerns, I am only allowed to display relative changes instead of absolute measures. The upside of relative changes is that they are straightforward numbers to tell the economic significance.

\(^8\) In this way, I avoid the complication from time variations. Given that the experiment happens at the individual level, it makes sense to aggregate the analysis at the individual level.
on the ratio of explored items in consumers’ basket. In the robustness check section 5.2, I differentiate between the reminder and exploration effects in greater detail. I investigate the effect of changes in the absolute number of goods in consumers’ baskets of goods that can be classified into frequently visited and less frequently visited categories. Indeed, both reminder and exploration effect contribute to the growth of consumer baskets, with the exploration plays a larger role in terms of the magnitude of the effect.

4.4 Effect on Exploration

First of all, I define exploration as time spent on those less frequently visited categories instead of products. So I am studying consumers’ consumption expansion into other categories, not just products. The reason is that the experiment happens on the category page, where consumers shop by categories. Generally, items are more likely to be substitutes within a certain category, ⁹. The way that personalized ranking tends to rank relevant products on the top will create negative externality to lower-ranked substitutes. ¹⁰ For example, if a consumer sees her favorite milk listed on the top of the dairy section, she will probably add the top ones into her cart without paying extra effort searching for other brands of milk. To avoid such externalities between products, I decide to examine shopping behavior across more categories that are not influenced by the recommendation algorithm. ¹¹ In this way, I can examine the effect on consumer’s self-exploration behavior that is independent of the recommendation algorithm choice.

Table 3 presents evidence of consumer exploration in the less frequently visited categories. Firstly, infrequently visited categories in my data context mean that consumers have not browsed them a week before the experiment period. ¹² These infrequently visited categories are heterogeneous among consumers in that consumers have different shopping patterns. Columns in Table 3 report the proportion of the items in the infrequently visited categories out of the total number of items that consumers spend time browsing, click, add cart, or purchase. ¹³ In general, I find that consumers spend only a small fraction of time exploring. The third row in Table 3 reports the average baseline level of exploration among the control users. For example, control group consumers only spend 1.66% of total time on exploring new category items. They only distribute 0.7% of clicks on new category items and add 0.6% into their carts. Overall they only purchase 0.5% of things from newly explored categories. For treatment users, I find an economically significant marginal effect of personalized recommendations on their exploration behaviors defined by these four measures. They spend more time in those infrequently visited

---

⁹In Robustness Check section 5.3, I also examine exploration within categories that tend to exhibit variety-seeking features
¹⁰Previous paper has found that such a ranking leads to inadequate screening in that consumers are less likely to consider low-position items. (Derakhshan et al 2018 [17])
¹¹Similarly, Ursu and Dayabura 2019 [18] examines consumers’ search costs of shopping across multiple independent categories to study retailers’ strategy to allocate these categories optimally given consumers’ search costs.
¹²I remove new consumers from both groups as they do not have prior history on the website. Therefore, the number of observations is smaller.
¹³I construct a proxy for total shopping time, which is the total number of items browsed on the entire website during the experiment period. As discussed before, I do not observe the exact timestamp of consumers’ footprints on the website. But the number of items browsed is a good proxy for time measure as consumers get exposure to all sorts of objects when they spend time actively browsing on the website.
¹⁴I assign zero values for this measure if a user makes zero-click/add to cart/order on the items that she browsed
categories as they browse 23.75% (on top of a baseline level of 1.66%) more items. Meanwhile, treated consumers tend to distribute a larger proportion (19.3% more on top of the baseline average) of clicks on these categories. They also add 34.83% more things into their carts than control users from these new categories and make 34.80% more new purchases in the end. In aggregate, I can conclude from this evidence that I find the economically and statistically significant effect of exploration in the infrequently visited categories.

Table 3: Explorations in Less Frequently Visited Categories

<table>
<thead>
<tr>
<th></th>
<th>(1) %browsed_items</th>
<th>(2) %clicked_items</th>
<th>(3) %add_cart_items</th>
<th>(4) %purchased_items</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline Average</td>
<td>0.0166</td>
<td>0.0071</td>
<td>0.0065</td>
<td>0.0049</td>
</tr>
<tr>
<td>N</td>
<td>984489</td>
<td>984489</td>
<td>984489</td>
<td>984489</td>
</tr>
<tr>
<td>T</td>
<td>0.00387***</td>
<td>0.00137***</td>
<td>0.00226***</td>
<td>0.00168***</td>
</tr>
<tr>
<td>% change</td>
<td>23.75%</td>
<td>19.30%</td>
<td>34.83%</td>
<td>34.80%</td>
</tr>
</tbody>
</table>

Dependent variables are log(1+Y) transformed

The average level of exploration in the baseline group is shown in the third row

I remove new users without history, so the number of observation is fewer than the total population

The first column outcome measure %browsed_items is computed as the following (similarly for other three columns):

\[
\frac{\# \text{ of browsed products that come from the less frequently visited categories}}{\text{total \# of browsed items}}
\]

There are two main mechanisms that could possibly drive the increase in consumer exploration: enhanced search efficiency for essential items versus improved impression about the website. I first investigate if the first mechanism is at work, i.e. if consumer reduce clicks and browsing behaviors in the familiar categories which they often visit after the introduction of personalized recommendations. Based on Table 4, the first two columns reflect that treated consumers tend to browse fewer products and click on fewer products with which they have previously interacted. Meanwhile, they purchase more of these products. Thus, personalized recommendations save them from having to search for these familiar products. As they gain extra time, they use it to explore less frequently visited categories as shown in Table 3. In the Robustness Check section 5.1.2, I further examine the second mechanism by checking whether the explored categories tend to be less popular categories on this website. In the case where consumers are able to improve their perception after using personalized recommendations, I expect them to discover other less well known categories on this website. However, I do not observe any such pattern of exploration. Indeed, consumer behavior tended to overlap heavily with popular choices, suggesting that little belief update occurs following the intervention.

4.5 Effect on Total Shopping Time

This section investigates the effect of personalized recommendations on the total shopping time consumers spend on the website. If we expect that personalization will primarily change how time is allocated between frequently
visited categories and infrequently visited categories, total shopping time will decrease. Alternatively, if the learning effect dominates in that consumers develop a different perception of the website because of the personalized recommendation, I will observe an increase in the total shopping time spent on the website. Based on the results reported in Table 5, personalized recommendations reduce total shopping time in each visit by 10\textsuperscript{15}, which is equivalent to 0.66\% change in the average level pre-treatment period. This effect is statistically significant at the 5\% level, but the economic magnitude is minimal, implying that consumers’ spending of time online does not vary drastically as a result of personalization.

As consumers spend less time per visit on the website, I would like to know if they are increasing the frequency of visits as a result of recommendations. I analyze revisits as a measure of how often consumers return to the website after personalization has been applied. Regarding the effect on revisits, the treated group revisits the website more often, at a rate of 0.34\% more than the average level in the pre-treatment period. There is a statistically significant effect here, but the magnitude is not large since the absolute average value of this measure is in the range of 1 to 7, i.e. consumers only visit 1 to 7 times to the website within a week. The slight increase in visit rate in the treated group implies that personalized recommendations have a positive effect on consumer satisfaction and impression.

Overall, the regression results in Table 5 confirm that personalized recommendations work mainly through the channel of increasing search efficiencies, while increasing consumer revisits and their demands per visit. Generally, the adverse effect on shopping times is not too significant if websites are more focused on increasing revenue per minute spent on their sites.

Table 5: Effect on Total Shopping Time and Visits

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>time_per_visit</td>
<td>-9.997**</td>
<td>0.00523**</td>
</tr>
<tr>
<td>T</td>
<td>(-2.20)</td>
<td>(2.37)</td>
</tr>
<tr>
<td>N</td>
<td>1114203</td>
<td>1114203</td>
</tr>
</tbody>
</table>

\textit{t} statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

As mentioned before, time per visit is proxied by the number of products consumers browse on the website after logging in.

4.6 Long Term Effect

In this section, I want to examine if the effect of personalized recommendation persists over a more extended time than just a week. The website rolled out the personalized ranking to all consumers who arrive at the category page after the experiment ends. Therefore, the estimates in the following regressions are lower-bounds estimates. I chose a month after the experiment ended to investigate the long-run effect because the pandemic hit the Chinese market after Jan 16th, 2020, when the data about online grocery shopping became less credible because large amounts of stockpiling behavior happened.

Table 6: Long-run Effect on Churn and Revisits

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>churn</td>
<td>revisit_next_month</td>
</tr>
<tr>
<td>T</td>
<td>-0.00893</td>
<td>0.00665***</td>
</tr>
<tr>
<td></td>
<td>(-1.63)</td>
<td>(3.14)</td>
</tr>
<tr>
<td>N</td>
<td>1114849</td>
<td>1114849</td>
</tr>
</tbody>
</table>

* t statistics in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

The first column show the logistic regression of the churn indicator on the treatment indicator. The second column outcome measure is log(1+Y) transformed.

First of all, I want to examine if consumers continue to shop frequently on the website in the next month. I construct two measures to examine the revisits reported in Table 6. I first look at the churn rate for the two groups of people. If a user stops coming to the website in the next month, then churn will be equal to 1 for that user and vice versa. In terms of churn rate, I do not find any significant difference between the two groups. In other words, I do not find that personalized recommendation leads to fewer or more churns. Next, I examine how many days a user visits the website within the next month. I find that treated consumers continue to shop more frequently on the website than the control users who did not see personalized ranking before. The magnitude of difference between the two groups is 0.83% percent more, which is a lower bound effect. In the counterfactual world where the experiment did not end, I expect a larger revisit rate difference.

Next, I would like to analyze if those newly explored categories continue to draw attention from consumers. One alternative scenario could be that those discoveries are just one-time serendipities in that consumers find them unattractive after exploration and thus stop wasting time or money on them. If that is the case, exploration does not seem beneficial for consumers or the website in the long run. Nevertheless, I find that consumers continue to explore and purchase from these newly explored categories. Table 7 reflects this pattern. I investigate whether or not consumers continue to spend time, click, and buy from these newly explored categories. Treated users spend 7.28% more time browsing in the newly explored category afterward. They also click on 6.49% more items from these categories. Moreover, they add 6.42% more items into the cart and purchase 5.14% more items from these categories in the month after. These results suggest that using the extra time saved by recommendations,
consumers are more likely to discover desirable products that they tend to purchase in the long term. 16

Table 7: Long Run Exploration in Newly Discovered Categories

<table>
<thead>
<tr>
<th></th>
<th>(1) %browsed_items</th>
<th>(2) %clicked_items</th>
<th>(3) %add_cart_items</th>
<th>(4) %purchased_items</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td>0.00814***</td>
<td>0.00662***</td>
<td>0.00803***</td>
<td>0.00610***</td>
</tr>
<tr>
<td></td>
<td>(17.13)</td>
<td>(13.93)</td>
<td>(16.80)</td>
<td>(14.00)</td>
</tr>
<tr>
<td>% change</td>
<td>7.28%</td>
<td>6.49%</td>
<td>6.42%</td>
<td>5.14%</td>
</tr>
<tr>
<td>N</td>
<td>755379</td>
<td>755379</td>
<td>755379</td>
<td>755379</td>
</tr>
</tbody>
</table>

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01
Dependent variables are log(1+Y) transformed
The first column outcome measure %browsed_items is computed as the following (similarly for other three columns):
# of browsed products that come from explored categories during experiment
/ total # of browsed items

5 Robustness Check

5.1 Alternative Mechanisms

5.1.1 Potential Retention Effect

Section 4.5 shows that treated consumers pay slightly more visits to the websites than control group consumers. An alternative explanation for the exploration effect found in section 4.4 could be that treated consumers disproportionately purchase more new items in their extra visits to the websites. If that is the case, the mechanism that recommendations increase shop efficiencies and induce more explorations does not hold anymore.

To check whether the above explanation exists, I examine the fraction of new items only in the first order that consumers placed on the website since the experiment started. What’s more, I check the interaction term between indicator T and the order occasion within the experiment’s week. The interaction term’s coefficient tells us whether the fraction of new items per order increases with the order occasions within a week.

\[
fr\_new\_purchase\_per\_order_i = \beta_0 + \beta_1 T_i + \beta_2 T_i \ast order\_occasion + \epsilon_i
\]

Table 8 reports the regression results. The first column shows the fraction of new items in the first order that the consumers placed on the website after the experiment. Even in the first order, consumers are already showing exploration patterns as they purchase more new items.

The second column shows the exploration effect across different order occasions. The coefficient of interest \(\beta_2\) before the interaction term \(T_i \ast order\_occasion\) is not significant, implying that treated consumers do not...
systematically vary their explorations across multiple orders placed on the website.

Table 8: Robustness Check: Exploration Effect Across Multiple Orders

<table>
<thead>
<tr>
<th></th>
<th>(1) fr_new_purchase_first_order</th>
<th>(2) fr_new_purchase_per_order</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td>0.00173***</td>
<td>0.000852</td>
</tr>
<tr>
<td></td>
<td>(8.95)</td>
<td>(1.46)</td>
</tr>
<tr>
<td>n_order</td>
<td>0.00497***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(24.18)</td>
<td></td>
</tr>
<tr>
<td>t#n_order</td>
<td>0.000830*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.72)</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>397930</td>
<td>488673</td>
</tr>
</tbody>
</table>

* t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01
Dependent variables are log(1+Y) transformed
The first column shows the first order new purchase fraction and the second columns shows the interaction effect model

5.1.2 Potential Learning Effect

Another plausible effect from better recommendations could be that consumers change their overall perceptions of the website and explore categories that the website is less famous for. For instance, before recommendations, this website may be renowned for its fresh produce. After observing the recommended lists, a consumer might change her prior belief about this website only selling good fresh produce. She might spend some time exploring other less popular categories, like household supplies on the same website, instead of visiting different places for household supplies. To investigate if this phenomenon exists, I compared the most popular ten categories on the website with the most popular ten explored categories by treated users to see if there is any difference. If the explored categories are significantly different from what consumers usually purchase on Missfresh, then it might reflect that consumers have updated their perception about the website.

The top 10 most popular categories are presented on the right-hand side of Figure 3. The popularity of categories is measured by how many users visit a category within the experiment week. The website is most well-known for its fresh produce selections, and it is also reflected in the data. The most popular categories are fruit, hotpot, veggies, meat, pantry goods, prepared food, premium fresh food, snacks, and raw meat and dairy. In terms of explorations, consumers mostly explore fresh produce categories, including fruits and veggies. The top 10 most popular explored categories overlap heavily with the most popular categories, suggesting that consumers did not change perceptions of the website due to better recommendations. Otherwise, I would observe consumers tend to visit less well-known categories of the website.
Figure 3: Most Popular Categories vs. Explored Categories
5.2 Exploration vs. Reminder

In this subsection, I examine the reminder versus exploration impact of personalized recommendations on consumers by focusing on the absolute change in the number of frequently visited and infrequently visited items. Table 9 shows the recommendation effect on the number of frequently visited items. Consumers spend less effort in searching these frequently visited items since they reduce browse and clicks on these items. However, they do increase their demands for these products, possibly because the algorithm tends to recommend these products on the top which attracts their attention. Since they are already familiar with these experienced products, they do not search but directly purchase them. Table 10 reflects the impact of recommendations on the items that are coming from the less frequently visited categories. The absolute changes are all positive, implying that treated consumers spend more time search, click, and thus purchase from these categories that they did not have extra time for without recommendations. Moreover, the magnitude of the effect is larger in the new categories than the old categories, suggesting that the exploration effect mainly drives the increase in demands.

Table 9: Shopping in Frequently-visited Categories

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>no_browsed_items</td>
<td>no_clicked_items</td>
<td>no_add_cart_items</td>
<td>no_purchased_items</td>
</tr>
<tr>
<td>from_frequently_visited_categories</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t</td>
<td>-0.0113***</td>
<td>-0.0150***</td>
<td>0.0806***</td>
</tr>
<tr>
<td>(-2.50)</td>
<td>(-4.46)</td>
<td>(22.02)</td>
<td>(14.72)</td>
</tr>
<tr>
<td>N</td>
<td>984489</td>
<td>984489</td>
<td>984489</td>
</tr>
</tbody>
</table>

The first column outcome measure no_browsed_items is (the rest columns follow the same manner)

# of browsed products that come from the frequently visited categories

Table 10: Exploration in Less Frequently Visited Categories

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>no_browsed_items</td>
<td>no_clicked_items</td>
<td>no_add_cart_items</td>
<td>no_purchased_items</td>
</tr>
<tr>
<td>from_less_frequently_visited_categories</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T</td>
<td>0.0721***</td>
<td>0.00556***</td>
<td>0.0139***</td>
</tr>
<tr>
<td>(16.20)</td>
<td>(7.98)</td>
<td>(18.16)</td>
<td>(14.98)</td>
</tr>
<tr>
<td>N</td>
<td>984489</td>
<td>984489</td>
<td>984489</td>
</tr>
</tbody>
</table>

The first column outcome measure no_browsed_items is (the rest columns follow the same manner)

# of browsed products that come from the frequently visited categories

* p<0.10, ** p<0.05, *** p<0.01
5.3 Within Category Exploration

Other than exploration in less-frequently visit categories, I expect to see exploration happens in the category where consumers tend to seek varieties. Among the 46 first-level categories, I summarize the average number of different purchased products by each individual within a category. I define variety-seeking categories in terms of how many different products consumers purchase. According to the definition, I found the following categories that contain the largest variety of products purchased: fruits, snacks, hotpot, and snacks.

Table 11-14 presents the regression of the fraction of new items consumers click, add cart, and purchase within a specific category. Overall, I find that consumers purchase more new items within the category that they commonly seek variety. However, I find that more purchases of new things do not come together with more search for new items. Instead, consumers directly add new items to their carts and experiment with them. Therefore, I find that consumers tend to seek variety by directly ordering new things within the fruit, snack, hotpot, and snack sections.

Table 11: Within Category Exploration Effect - Fruit

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>%new_clicked_items</td>
<td>-0.00965***</td>
<td>0.0114***</td>
<td>0.00556***</td>
</tr>
<tr>
<td>% Change</td>
<td>-3.59%</td>
<td>4.31%</td>
<td>3.23%</td>
</tr>
<tr>
<td>T</td>
<td>(-10.52)</td>
<td>(12.48)</td>
<td>(7.12)</td>
</tr>
<tr>
<td>N</td>
<td>931728</td>
<td>931728</td>
<td>931728</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 12: Within Category Exploration Effect - Veggie

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>%new_clicked_items</td>
<td>-0.00536***</td>
<td>0.0148***</td>
<td>0.0102***</td>
</tr>
<tr>
<td>% Change</td>
<td>-2.18%</td>
<td>4.88%</td>
<td>4.55%</td>
</tr>
<tr>
<td>T</td>
<td>(-4.88)</td>
<td>(12.78)</td>
<td>(9.52)</td>
</tr>
<tr>
<td>N</td>
<td>615072</td>
<td>615072</td>
<td>615072</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 13: Within Category Exploration Effect - Hot Pot

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>%new_clicked_items</td>
<td>0.00102</td>
<td>0.0169***</td>
<td>0.0112***</td>
</tr>
<tr>
<td>% Change</td>
<td>0.50%</td>
<td>6.98%</td>
<td>6.56%</td>
</tr>
<tr>
<td>T</td>
<td>(0.99)</td>
<td>(15.36)</td>
<td>(11.69)</td>
</tr>
<tr>
<td>N</td>
<td>624448</td>
<td>624448</td>
<td>624448</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.01
Table 14: Within Category Exploration Effect - Snack

<table>
<thead>
<tr>
<th></th>
<th>(1) %new_clicked_items</th>
<th>(2) %new_add_cart_items</th>
<th>(3) %new_purchased_items</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td>0.00339**</td>
<td>0.0196***</td>
<td>0.0146***</td>
</tr>
<tr>
<td>% Change</td>
<td>1.50%</td>
<td>(12.83)</td>
<td>(11.02)</td>
</tr>
<tr>
<td>N</td>
<td>314062</td>
<td>314062</td>
<td>314062</td>
</tr>
</tbody>
</table>

*p<0.10, ** p<0.05, *** p<0.01

5.4 Randomization Check

I want to examine if users are similar on pre-experiment observable characteristics, specifically conversion behaviors. I compare the conversion behavior between Treatment users and Control users a month before the experiment happened. I test that the experiment groups are balanced on these pre-experiment conversion variables. Table 15 shows the result of these tests, and I find that I cannot reject the hypothesis that these groups are balanced.

Table 15: Randomization Checks for Balance on Outcome Measures

<table>
<thead>
<tr>
<th></th>
<th>Browse</th>
<th>Add_cart</th>
<th>Click</th>
<th>Purchase</th>
<th>Revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg</td>
<td>0.30</td>
<td>0.03</td>
<td>0.03</td>
<td>0.04</td>
<td>0.61</td>
</tr>
<tr>
<td>Std.dev</td>
<td>0.31</td>
<td>-0.13</td>
<td>-0.24</td>
<td>-0.13</td>
<td>0.64</td>
</tr>
<tr>
<td>Avg</td>
<td>0.30</td>
<td>0.03</td>
<td>0.03</td>
<td>0.04</td>
<td>0.61</td>
</tr>
<tr>
<td>Std.dev</td>
<td>0.30</td>
<td>-0.12</td>
<td>-0.24</td>
<td>-0.13</td>
<td>0.65</td>
</tr>
<tr>
<td>p-value</td>
<td>0.65</td>
<td>0.41</td>
<td>0.77</td>
<td>0.14</td>
<td>0.24</td>
</tr>
</tbody>
</table>

*Averages and Standard Deviations are log transformed by an unrevealed base to preserve the confidentiality of the data
*N = 106,901 for Treatment and 536,745 for Control
*For each variable, p-values are from a two-sided t-test for equality of means between Treatment and Control groups.

6 Conclusion

In this paper, I study how personalized recommendations affect consumer exploration. I explore this question in the online shopping context where multi-category shopping and repeat purchases are frequent. I construct a theoretical model to motivate my empirical analysis. Then I employ a first data set with an experimental variation on personalized recommendations to causally evaluate its impact. I find that personalized recommendations reduce consumer search but increase consumer demand and the website’s revenue. Moreover, I find evidence consistent with my hypothesis, which predicts that increased search efficiency will spillover to more consumer exploration. Specifically, consumers who have personalized recommendations spend more time in less frequently visited categories and purchase more products from them. The increase in exploration time does not fully compensate for the saved time in the frequently visited categories; hence, consumers’ total shopping time decreases slightly. Regarding consumer satisfaction, I find that personalized recommendations cause consumers to revisit more often to the
website. Lastly, consumers enjoy their discoveries in that they continue to browse and purchase from these explored categories afterward. These results suggest that personalized recommendations mainly increase consumer shopping efficiency in addition to varying the expected benefit of searching.

In general, this paper’s findings demonstrate a new demand increasing mechanism of increasing search efficiency through personalized recommendations. This study’s results inform us that by leveraging recommendations’ navigational roles, E-commerce websites can achieve higher revenue from consumers’ exploration that expand their demands. The “filter bubble” effect of recommendations is less of a concern given that consumers are actively discovering outside of the recommended options.

Besides, our research suggests that saving shopping time for essential goods is another way to increase unplanned spending in the grocery setting. The finding contrasts with the traditional belief of "hiding the milk at the back of the store" among offline grocery store practitioners. In the offline environment, there is a fixed cost of physically entering the store. Still, the marginal search cost is relatively low compared to the online setting because people cannot switch between shopping and other activities as freely as possible. Given that a consumer has entered the store, based on our model prediction, the consumer will stay longer in the store and explore more than the online setting. In that sense, hiding the milk at the back of the store may not be the only solution that leads to more exploration. I propose that if offline grocery stores can provide a more efficient way of shopping, consumers will have extra time for exploration that leads to additional purchases in the store.

This research points to fruitful directions for further research. First, I have focused on the influence of recommendations on one E-commerce website. Due to data limitations, I cannot examine whether a retailer’s increased demand cannibalizes that of another retailer. From the retailer’s perspective, an increase in demands per visit is advantageous as it protects the retailer from losing the sale to a competitor. Further research should examine the effects of recommendations on store choice decisions and competition between stores.

Finally, future research could explore the extent to which the model and findings of this paper can be applied to offline grocery stores as well as other retail environments. As I predicted above, it is plausible that consumers will explore further in the offline setting even though they have what they need in their basket soon after they walk into the store. The impact of displaying essential products at the front of the offline store rather than hiding them at the back can be studied and consumers’ shopping paths around the store can be tracked to determine whether they continue to explore. Researchers could also examine data from other retail contexts where repeat purchases are less frequent than in the online grocery context, such as Amazon and Taobao, to investigate the impact of recommendations on consumer exploration. These studies will contribute to a better understanding of recommendations’ effects, which will allow retailers to optimize their decision making processes in diverse business situations.
7 Appendix

7.1 A Theoretical Model and Hypotheses

In this paper, I propose a simple theoretical model that conceptually fits my empirical context. The model provides several empirically testable implications that are helpful for guiding and interpreting the findings of my empirical analysis. This model fits into the context of consumers visiting an E-commerce site to purchase multiple products from various categories within one transaction. These E-commerce websites include Amazon, Taobao, JD.com and many other large online retailers. There are two main types of categories of goods in the consumer’s basket: frequently visited and less frequently visited. In my analysis, a frequently visited category is defined as one that has been browsed at least once in the past week, whereas an infrequently browsed category is one that has not been browsed by a certain consumer in the last week.

7.1.1 Model

The utility of searching for each consumer $i$ is

$$U_i = B_i - C_i = f(x_i) - g(x_i + y_i)$$

where

$$B_i = f(x_i)$$

and

$$C_i = g(x_i + y_i)$$

Here, I define $x_i$ as time spent on exploring in less frequently visited categories on the website, $y_i$ as time spent on frequently visited categories on the website.

$f(.)$ is a strictly concave function because we assume the marginal benefit of searching is decreasing as consumers spend more time exploring. $(f''(.) < 0)$ This insight comes from the seminal paper in sequential search literature: Weitzman 1979[19]. His sequential search model suggests that as one searches more, the possibility that the next item will exceed the current reservation value is lower. Furthermore, I assume that time spent on shopping for consumers’ favored items does not bring additional exploration utility because consumers know the match value with these experienced items.

Then I model the total opportunity cost of searching as a convex function due to increasing marginal cost of searching. Marginal search costs increase because consumers have to leave at some point as opposed to spending an unlimited amount of time online. Hence, $g(.)$ is a strictly convex function, which implies $g''(.) > 0$. The opportunity cost of time is a function of both time spent on exploration $x_i$ and time spent on purchasing essential items $y_i$. 


Since $U_i$ is a concave function of $(x_i, y_i)$, there exists a pair of $(x_i, y_i)$ that maximizes $U_i$. The equilibrium pair of $(x_0, y_0)$ that maximizes $U_i$ satisfies the condition that

$$F(x_0, y_0) = f'(x_0) - g'(x_0 + y_0) = 0$$

(1)

Theoretically, my first objective is to determine if time spent exploring increases when time spent purchasing familiar items is reduced by personalized recommendations. Mathematically, it transfers to the first difference of $x_i$ on $y_i$.

**Hypothesis 1:** If time spent on buying familiar products reduces, exploration time will increase.

**Proof:**

By implicit function theorem, we can differentiate both sides of equation (5) with respect to $y$, which gives us

$$0 = \frac{\partial F(x_0, y_0)}{\partial y} + \frac{\partial F(x_0, y_0)}{\partial x} \frac{dx}{dy}$$

(2)

$$= -g''(x_0 + y_0) + (f''(x_0) - g''(x_0 + y_0)) \frac{dx}{dy}$$

(3)

Rearranging equation (2) gives us

$$\frac{dx}{dy} = \frac{g''(x_0 + y_0) > 0}{(f''(x_0) - g''(x_0 + y_0)) < 0} < 0$$

(4)

Therefore, $x$ is a decreasing function of $y$, which implies that as time spent on buying from familiar categories $y$ decreases, time spent on exploration $x$ will increase.

This occurs because the comparative static: $\frac{dx}{dy}$ is less than zero, which implies that time spent on exploration is a decreasing function of time spent on shopping for familiar products.

Intuitively, this makes sense because the marginal cost of time is still lower than the continuation value of search when consumers stop earlier after shopping more efficiently from the recommended list. To give a concrete example, suppose on a given shopping trip, a consumer planned for an hour for that trip. With personalized recommendations, she is able to finish within 20 minutes compared to the usual 30 minutes spent on shopping for frequently purchased grocery items. At the 20 minute cutoff, her continuation value, which is the expected benefit from further exploration, is likely to be higher than her marginal cost of time. So she will have more time left for exploration.

Furthermore, I would like to know if total shopping time varies with the reduction in shopping time for familiar items as a result of personalized recommendations. Mathematically, that question is transferred to how does change in $y_i$ affect change in $y_i + x_i$. It’s difficult to decide intuitively, since if $y_i$ drops, $x_i$ increases, but the net change in $y_i + x_i$ is unclear, since one term goes up and the other drops.

**Hypothesis 2:** Overall shopping time will decrease as a result of increased efficiency for purchasing familiar
Proof:

Rewrite (5) as a function of time spent on exploration $x$ and total time spent online $u = x + y$

$$F(x_0, u_0) = f'(x_0) - g'(u_0) = 0$$  \hspace{1cm} (5)

By implicit function theorem, we can differentiate both sides of equation (5) with respect to $y$, which gives us

$$0 = \frac{\partial F(x_0, u_0)}{\partial y} + \frac{\partial F(x_0, u_0)}{\partial x} \frac{dx}{dy} + \frac{\partial F(x_0, u_0)}{\partial u} \frac{du}{dy}$$  \hspace{1cm} (6)

$$= f''(x_0) \frac{dx}{dy} - g''(u_0) \frac{du}{dy}$$  \hspace{1cm} (7)

Rearranging equation (6) gives us

$$\frac{du}{dy} = \frac{f''(x_0) \frac{dx}{dy}}{g''(u_0)} > 0$$  \hspace{1cm} (8)

Therefore, $u$ is an increasing function of $y$, which implies that as time spent on buying from familiar categories $y$ decreases, time spent on the website $u$ will increase.

An intuitive explanation is that as consumers allocate proportionately more time to exploration, they are likely to find that the new equilibrium marginal benefit/cost will end at a lower level. As a result, the new equilibrium time will decrease due to the law of demand. In short, the effect of recommendations is mainly saving the time on buying necessities, leaving more time for exploration. Consequently, the increase in exploration time will not exceed the decrease in the shopping time for favored items.

7.2 Mean Distributions of Outcome Measures

These histograms justify the mean comparison between treatment and control groups. Appendix 7.2 displays 1000 bootstraps of mean distributions of outcome measures for each group, Treatment and Control$^{17}$. Though these variables are skewed, their means are distributed normally, as it is shown in the bootstrap distributions below. Meanwhile, the mean differences between the two groups are also distributed normally.

$^{17}$The true mean of outcome variables cannot be revealed here. All outcome variables are multiplied by an unrevealed number to protect the data privacy.
7.3 Boxplots of Outcome Measures
References


