How Recommendation Affects Customer Search: A Field Experiment

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Abstract

Product recommendation and search are two technology-mediated channels through which E-commerce platforms can help customers find products: Customers are passive in the former and proactive in the latter. However, the relationship between the two channels, and the underlying mechanisms and implications for platform design are not well understood. We leverage a randomized field experiment with 555,800 customers on a large E-commerce platform to investigate how product recommendation affects customer search. We vary the quality of the recommendation that users experience upon arriving at the homepage of the platform and find that a decrease in the recommendation relevance leads to a significant increase in consumers' use of the search channel, indicating a (partial) substitution effect between the two at the aggregate level. We find substantial heterogeneity across product categories. Customers' search activities are positively correlated with recommendation browsings in categories with increased recommendation browsings. In contrast, customer search activities are negatively correlated with recommendation browsings in the other categories. We propose a conceptual framework and theorize how different states of customer demand—demand fulfillment and demand formation—may drive such heterogeneity. The results are aligned with our framework and provide evidence that both demand formation and fulfillment are at work in the channel interactions between recommendation and search: demand formation is associated with channel complementarity, and demand fulfillment is associated with channel substitution. Specifically, when customers receive more product recommendations in a category, they search more in that category and search with generic query words, which indicates complementarity between recommendation and search. However, when customers receive fewer product recommendations in a category of their interest, they compensate for this reduction by searching more in that category and searching with long-tail query words, which indicates a substitution between recommendation and search. However, we do not find substitution or complementarity when customers receive fewer product recommendations in categories that are not of their interest. This experimental study is among the first to examine the causal relationship between the recommendation channel and search channel and offers implications for the design of E-commerce platforms.

Keywords: Recommendation, Search, Channel Substitution, Channel Complementarity, E-commerce, Field Experiment, Recommendation System, Personalization

1 Introduction

Digital platforms help customers discover products through two technology-mediated channels—*personalized recommendation* initiated by the platforms and *search engine* initiated by the customers.[1] Personalized recommendation and customer search are the top channels on these online platforms and account for a large portion of online sales (e.g., De et al. 2010, Lee and Hosanagar 2021). As such, recommendations have become increasingly important across all platforms around the world (Adomavicius et al. 2013, 2018, 2019, Lee and Hosanagar 2019, Li et al. 2021). For instance, both Amazon and Alibaba have "items you may like" types of personalized recommendations on their homepages. Customers can explore a wide range of products without typing in any search queries. In contrast, customers who initiate active search queries tend to have clear purchasing intent, unlike those who passively browse the recommendations (Bronnenberg et al. 2016). The searching customers have already formed a unit demand and are at a later stage in the conversion funnel (e.g., Bettman et al. 1998).

These two technology-mediated channels have become increasingly important for E-commerce platforms with vast product information. Customers may directly ***search*** for products in the search bar when they have a specific demand. At the same time, for customers with less-specific demands, online platforms optimize communications via ***personalized recommendations***, helping customers form demands and find products with less effort. Understanding the relationship between these two channels is crucial as it is a focal part of platform design. However, how product recommendations influence customer search on the platforms is unclear. On the one hand, customers may search less because platform recommendations can reduce customers' search efforts for target products (Fong 2017). On the other hand, customers may initiate a new search when platform recommendations inform and remind customers of their potential needs (Shin and Yu 2020). Ultimately, the relationship between the two is a question for empirical investigation.

Our study attempts to answer the following questions regarding the relationship between recommendation and search:

(1) (**Main Effect**) What is the causal effect of product recommendations on customers' search activities and subsequent purchase behaviors? Would search activities increase or diminish after recommendation becomes less relevant?

(2) (**Heterogeneity**) What is the causal effect for different types of customers and different kinds of customer preferences?

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[1] Online platforms with a combination of recommendation and search channels are abundant. We include some examples for illustration purposes: https://www.amazon.com/ (online marketplace), https://www.ebay.com/ (online marketplace), https://www.footlocker.com/ (specialized online marketplace), and https://www.youtube.com/ (online video platform).

(3) (**Potential Mechanism**) How does the channel interdependence vary across different scenarios regarding customer preferences? If so, why?

The answers to these questions have broad implications for digital platform design. Despite the central role of recommendation and search on digital platforms, there is a dearth of research investigating the relationship between these two technology-mediated channels. Testing such channel interdependence between recommendation and search is empirically challenging. On the one hand, a non-experimental approach based entirely on observational and archival data suffers from endogeneity problems, as the usage of both channels is correlated to users' underlying unobservable preferences and their previous interactions with the platform. On the other hand, most A/B tests in Computer Science literature on recommendation systems result in relatively small variations in recommendation quality, as documented in the literature (e.g., see a review by Jannach and Jugovac 2019, usually single digits over popularity-based RecSys). Regular A/B tests in recommendation systems that fine-tune the algorithm cannot lead to major changes in the quality of personalized recommendations. Thus, they cannot influence customer search and are not useful for revealing the channel dynamics between recommendation and search.

To address the endogeneity issue and the lack of variation challenge, we leverage a large and exogenous shock on the recommendation quality created by a large-scale field experiment on a world-leading E-commerce platform. We randomly vary the quality of the product recommendation on a random subset of 555,800 customers to identify the causal effect of recommendation on search. Specifically, we turn off personalization in the homepage recommendation algorithm, thereby creating an exogenous shock of recommendation quality. The exogenous variation in the recommendation system creates a heterogeneous shock on the exposure of different product categories. We take advantage of the category heterogeneity in the experimental shock to explore the interdependence of the two channels. We are able to collect highly granular user- and product-level data from the experiment, which we complement with detailed and rich archival information, including all past clicks and purchases of the customers and their characteristics.

Our experimental findings shed light on the effects of recommendation on search. First, we document the main effect: A substitution effect exists between the two channels at an aggregate level. Compared to the control group, the customers in the treatment group significantly increase their searches when the product recommendations become less relevant. Importantly, this channel substitution effect holds universally across all customer behaviors—that is, customers' browsing (Product Views, or PV hereafter)[2], clicks, and purchases

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[2] ***Product View (PV)*** measures the number of products that appear on the customers' screens—the customer may have some control over this by scrolling the recommendation interface or search results. PV is both a "feature" of the experiment and a decision made by the customer. On the one hand, the platform's algorithm determines the set of products and the product orderings displayed to the customers, which includes the portion of different category products determined by the algorithm.

(Gross Merchandise Value, or GMV thereafter) in search. The surge in search activities is driven by increases in both extensive and intensive margins, indicating that the increase in search is driven by both the inflows of new searchers and additional searches from existing searchers.

Second, we find substantial heterogeneity across product categories. Some categories receive more recommendation PVs, while others receive fewer recommendation PVs. Customers respond differently across categories. When customers are exposed to 300% more products in the grocery and furniture categories, they also search for 20% more products in these categories, which manifests a complementary relationship between recommendation and search. All other categories, except Grocery and Furniture, suffer from a reduction in recommendation PVs. When customers are exposed to 90% fewer products in categories such as clothing, they search for 9% more products, which manifests a substitution relationship between recommendation and search.

To unpack the black box of the channel relationship and explain the heterogeneity, we propose a conceptual framework to theorize the determinants of channel ***complementarity*** versus ***substitution*** between recommendation and search. Specifically, we introduce two states of customers in their decision-making processes on the digital platform: the demand fulfillment state and the demand formation state. On the one hand, prior research has demonstrated that recommendation systems can influence consumers' consideration sets (e.g., Häubl and Murray 2003, Fong 2017) and consumer preferences (Adomavicius et al. 2013, 2018, 2019), supporting the idea that customers may form new demands while browsing recommendations ("demand formation"). We expect that consumers will also search for more products that appear more frequently in the recommendation system, in which case we expect to observe a ***complementary effect*** between recommendation and search. On the other hand, customers may have ex-ante pre-existing demand intents for specific products before browsing recommendations. When fewer relevant products in those categories are presented, customers have no choice but to actively initiate a search to meet their needs ("demand fulfillment"), manifesting a ***substitution effect*** between the two channels.

The heterogeneous effects across product categories, as well as the granular evidence from customer search queries in the experiment, allow us to investigate the potential mechanisms and test the hypotheses derived from our conceptual framework. Our experimental shock affects both demand formation and fulfillment, and the effect may vary across specific customer preferences and product categories. On one hand, when more products are displayed to customers, these customers may search more for related products. In addition, using computational linguistic technologies on granular customer search queries, we provide direct evidence that

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On the other hand, customers decide whether to scroll down the recommendation interface or the search results and determine the number of products to browse.

customers search for products in new categories and expand their consideration sets (as evidenced by more generic query words in the customer search queries) when more products not related to customers' prior interests are recommended. This is consistent with the demand formation process. On the other hand, when fewer products *related* to customers' prior interests (as revealed from their past clicks on the platform) are recommended, they compensate for this reduction by searching for more products in these categories, which manifests a substitutive relationship between recommendation and search. We also show that consumers increase the length of their search queries (revealing the attempt to realize a more specific and well-defined demand), which is consistent with their intent to fulfill an ex-ante pre-existing demand. In summary, consistent with the posited framework, we provide empirical support that both complementarity and substitution are at work: channel complementarity in the categories that appear more in the recommendation (associated with demand formation) and channel substitution in the categories that appear less in the recommendation (associated with demand fulfillment).

Understanding the relationship between product recommendation and customer search has immediate managerial implications for platform design. First, our study highlights the importance of considering the impact of channel interactions on platform design. We provide detailed evidence for platform managers on how recommender systems and search engines are interconnected. Previous studies tend to treat recommendation and search as stand-alone systems, while we attempt to fill the gap by understanding recommendation and search as an overall interactive online ecosystem. The platform may benefit from a more organic and coordinated integration of the two traffic channels—specifically, from the complementarity effect, though not the substitution effect. If the recommendation system better exposes customers to product varieties, customers may be encouraged to search more and complete their respective purchases in the search channel (demand formation). However, if the recommendation system focuses only on maximizing purchase transactions within the recommendation channel, it can cannibalize the GMV in the search channel (demand fulfillment). Our results could provide valuable guidelines for better platform design. A related implication of our study is how activities in one technology channel can dynamically inform the potential improvements of another. Second, we propose a conceptual framework to understand how customer demands and consideration sets can be affected by the design of a recommendation system. When more products are recommended to customers, they may become aware of and interested in new product categories. Platforms may want to recommend new products and give customers the best aid to explore their options, ultimately increasing customer welfare. Third, customers search proactively when they cannot find products of interest in the recommendation system. Reducing the quality of the recommendation system may induce customers to more explicitly express their demand intents in the search channel, which indicates that the design of the recommendation platform can also benefit from consumer input in the search channel. Customer search queries can reveal customer demands and are a tremendously informative data asset for platform designs. Finally, our study reveals that platform planners should optimally allocate their limited resources to helping customer groups that are more vulnerable to recommendation quality and data regulation changes. For example, we demonstrate that experienced customers adapt better to recommendation variations. Disparate types of customers may rely on recommendation and search in heterogeneous ways. Platform managers may wish to tailor their platform design to different customer groups and should pay attention to customers who are more affected by the recommendation quality.

The rapidly changing landscape of data regulation and privacy concerns directly influences both the quality of the recommendation channel and search channel (Sun et al. 2021, Jin 2018). Compared to search engines, recommendation systems require more personal data as input.[3] Therefore, as recent high-profile data regulations in China, Europe, and the U.S. have restricted platforms' ability to collect and use personal data for personalized recommendations, the ecosystem of Internet Commerce may be fundamentally impacted, especially the platforms relying on recommendation systems. Variations in recommendation quality can significantly affect customers' platform experience, thereby reshuffling customer–demand formation and the usage of search channels. Sun et al. (2021) find that data privacy regulations can significantly affect product recommendations. This current study provides important insights that the customers would most likely turn to the search channel in such a regulatory environment. Moreover, from an industrial organization perspective, each digital platform used to have its unique positioning in the online platform ecosystem (McKinsey 2019). If data regulations and customer privacy concerns continue to scale up, our study posits that search functions should play an increasingly significant role in online platforms, which could shift the competitive landscape. Our findings can inform policymakers and online platform developers about the potential impact of data regulations, including their potential long-term implications. As such, the platforms may strategically restructure their platform designs, which may eventually cause them to move closer to a more search-focused model and a better integration of recommendation and search.

2 Literature Review and Contributions

[3] When customers use a search engine, they type in query words that work as information inputs. The search engine algorithm then explores the customer inputs, identifies the customer demand intent from the query words, and displays the products. In contrast, customers using recommendations do not have any direct input. Therefore, when an extremely stringent data regulation exists, the recommendation system would have zero data input; however, the search engine still has customer queries as input. Therefore, recommender systems demand more data input. Our other research of data regulations also empirically confirm our theory. Sun et al. (2021) study the effect of data regulations on recommendation. We find that, when there is no data input for both recommendation and search, the reduction in the click-through rate and GMV are substantially higher in the recommendation.

Our study is closely related to four streams of research that span information systems, marketing, and economics, among other disciplines. Previous research has largely studied recommendation systems and consumer searches separately, without investigating the channel substitution or complementarity among them. However, recommendation and search are intrinsically related on E-commerce platforms, and both influence the consumer decision-making process. Empirically testing the channel interdependence presents a non-trivial challenge. To the best of our knowledge, no studies in information systems, marketing, economics, or computer science have directly tested the causal relationship between recommendation and search channels. We address this challenge using a large-scale field experiment, and we complement this field experiment with detailed data on consumers, products and merchants, as well as unpack the intermediate processes and potential mechanisms. We demonstrate a nuanced channel relationship between recommendation and search at the aggregate level and in more granularity.

Channel Substitution and Complementarity: The first and most relevant stream of literature has focused on channel interdependence. The earlier literature has studied channel interdependence mostly in the contexts of online vs. offline (Brynjolfsson et al. 2009, Forman et al. 2009), mobile vs. desktop (Xu et al. 2014, 2016, Sun et al. 2019), and mobile vs. fixed lines (Xu et al. 2019). The researchers find both substitution and complementarity across channels. For instance, Xu et al. (2016) discover that the tablet channel acts as a substitute for the PC channel, while it functions as a complement for the smartphone channel. To explore the underlying mechanisms of interdependence, De Haan et al. (2015) reveal that customers use different devices at different stages of their purchase journeys and hypothesize that mobile and alternative channels fulfill different flows of demand (e.g., information vs. transaction) for a customer. The previous literature has studied the channels of different firms or one customer's two devices. Our study complements this stream of literature by examining the interdependence of two important modules—the recommender system and the search engine—on the E-commerce platform. Fong (2017) and Fong et al. (2019) demonstrate that targeted offers promoting customers' previously purchased categories generate more purchases in the same category, but reduce customer searches. Our paper diverges from these two studies because they focus on targeted advertising instead of product recommendation. We also document both substitution and complementarity across these two channels and hypothesize that customers may be in diverse states of demand. Correspondingly, Fong (2017) discerns that targeted offers result in decreased search activity. However, our study demonstrates that less-relevant product recommendations can drive up search activity in the demand-fulfillment mechanism. In addition, our work extends previous research by designing a new identification strategy—a randomized field experiment—to cleanly identify the causal relationship between recommendation and search. Our analysis also supplies novel insights that such channel complementarity and substitution may be closely related to how customers use online platforms in their decision-making processes.

Consumer Search Literature: Second, our paper contributes directly to the understanding of online customer search, a recurring and important topic in the literature. Tam and Ho (2006) find that personalized song recommendations reduce search activity on an MP3 download site. Häubl and Trifts (2000) propose a two-step process for customers to make purchase decisions: Customers first identify a subset of the most promising alternatives from screened products (facilitated by a recommendation system), after which they compare the product attributes, and make purchase decisions. They find that using interactive decision aids affects customer search. Dellaert and Häubl (2012) investigate how product recommendation in the form of rank-ordered lists affects customer search. They find that, with recommendations, customers focus on a comparison of already-inspected items rather than inspecting additional alternatives. Mayzlin and Shin (2011) show that high-quality sellers produce uninformative advertising to invite consumers to engage in searches, which is likely to reveal positive information about the products. Hong and Pavlou (2014) demonstrate the importance of product fit. Our study extends this stream of search research in three ways. First, we study the relationship between two channels: recommendation and search, while other papers study the effects of using aids on searches. We also document rich heterogeneity in customer search activities. Second, most research has examined cases in which product recommendation or customer targeting becomes more relevant to customers. Our experiment exploits a reverse process and asks the following question: How would customer search change when recommendations become less relevant? This is particularly significant in the current privacy regulatory landscape. Finally, this paper uses a field experiment to estimate the causal effects of recommendation on search, which avoids potential selection biases in non-experimental settings. The large scale of our experiment, conducted on one of the world's largest e-commerce platforms, also increases the external validity of the findings.

Recommender System Literature: In addition, our study is also closely related to the literature on recommendation systems (e.g., Diehl 2005, Diehl et al. 2003, Fitzsimons and Lehmann 2004, Häubl and Murray 2003, Häubl and Trifts 2000, Adomavicius et al. 2013, 2018, 2019, Li et al. 2021, Hosanagar et al. 2014). Adomavicius et al. (2013) provide evidence that users' preference ratings can be significantly influenced by the recommendations received, indicating that the ratings presented by a recommender system serve to anchor the consumer's constructed preference (Li 2018). This is consistent with our findings that recommendation systems can help customers form new demands and preference construction while browsing products. Our findings are also related to Sun et al. (2021). The two papers study the same context but with an entirely different research focus and present very different sets of empirical findings. The identification strategy in the two papers exploits a large-scale experiment on homepage recommender systems to examine the impact of personal data regulation on E-commerce. Sun et al. (2021) find that restricting the use of personal data can result in a significant reduction in customer browsing and GMV in homepage recommendations. However, the current paper examines the relationship between recommendation and search. The restriction of personal data usage generates an exogenous shock of recommendation, and we study the follow-up changes in customer searches.

Data Regulation Policy: Finally, our study relates to another recent stream of research on data privacy and the impact of data regulation policy. Jin (2018) notes that AI and big data are reshaping consumer privacy and data security risks—a topic that deserves the attention of researchers and regulators (e.g., Pu et al. 2020, Liang et al. 2022, Chen et al. 2022). A stream of studies has discussed the consequences of data regulation policy, with a focus on the GDPR and CCPA (Acquisti et al. 2015, 2016, Campbell et al. 2015). Ealier research on data regulation policy has examined the effect of privacy regulations on target advertising and its impact on websites. Goldfarb and Tucker (2011) demonstrate that advertising becomes far less effective after the EU's privacy regulation. Goldberg et al. (2019) reveal that the GDPR may result in an approximate 10% fall in the recorded page views and revenues of online sites for EU users. In addition, Jia et al. (2020, 2021) depict that the GDPR may have affected investors' appetite to invest in European technology ventures. Adjerid et al. (2016) find that, when coupled with incentives, privacy regulation with requirements for patient consent can actually positively affect technological innovation in health information exchanges. Our study complements the ongoing literature and focuses on the effect of regulations through the lens of two technology-mediated channels in online platforms. In E-commerce, customers have various channels through which they can obtain information and make purchase decisions (i.e., recommender systems and search engines). Data regulations have a heterogeneous impact on these channels: Compared to the search channel, data regulations have a larger impact on the recommendation channel because recommender systems demand more personal data to effectively match customers with products. As our experiment resembles the most stringent policy (*no* personal data for recommendation systems), it can be viewed as a benchmark that evaluates the impact of types of data regulation policies on the channel relationship. It is crucial for platforms to understand how such regulations affect customers' use of technology channels for information acquisition and product purchases. Our results imply that platforms should balance recommendation and search and strategically enhance their search channels when facing increasingly stringent data regulations.

Modeling Consumer Decision-Making: More broadly, our study relates to streams of research on modeling consumer decision-making and the formation of consideration sets. Previous research has shown that consumers often use a two-stage "consider-then-choose" decision process when facing a large number of products. That is, consumers choose products by first forming a consideration set from alternative products and then picking from among the products considered (e.g., Hauser and Wernerfelt 1990, Shocker et al. 1991, Hauser 2014, Li et al. 2022). Hauser (2014) reviews theories and measurements of consumers' heuristic consideration-set rules. Häubl and Murray (2003) illustrate that electronic recommendation agents can influence customers' purchase decisions in a systematic manner that leads customers to search in "choice mode" and to change product comparisons and stopping decisions (Dellaert and Häubl 2012). Diehl (2005) finds that the temptation to search more deeply reduces choice quality by reducing the average quality of the consideration set. Sun et al. (2019) find a complementary effect between the mobile app and the desktop channel for information-induced app adopters: The mobile app serves as a discovery tool and helps them find a greater variety of deals. To the best of our knowledge, the literature has not yet explored the roles of preference formation and consideration sets in the relationship between recommender systems and search engines. Our paper extends the literature by exploring how customers form their demand and finds that the customer decision-making process could vary depending on whether the customer is in the demand formation vs. the demand fulfillment state.

3 Research Context and Field Experiment

3.1 Research Context

We partner with a world-leading E-commerce platform and conduct a large-scale randomized experiment to identify the causal effect of recommendation on search by varying the quality of the product recommendation. Our collaborating platform offers a great setting for our experiment, with two billion product listings across differentiated categories, tens of millions of sellers, and hundreds of millions of buyers. This platform has two main technology channels—*product recommendation* and *customer search*—in which customers can gather product information and make purchase decisions; therefore, it provides an ideal setting for investigating the relationship between the two channels.[4] As such, we can also examine the rich heterogeneity at the highly granular product, customer, and merchant levels.

Our experiment focuses on the **homepage recommendation** in online marketplaces, as this is the main personalized recommendation channel designed to facilitate better matching between buyers and sellers. Personalized recommendation makes it easier for customers to navigate products and to reduce search costs when arriving at the platform. In general, the recommender system has become a key engine for platform revenues. Customers can click, purchase, or continue browsing the recommended products by scrolling down

[4] Both recommendation and search channels are key integral parts of the business models of platforms and provide decision aids (Adomavicius et al. 2013, 2018, Yoganarasimhan 2020). Thus, it is vital for digital platforms to optimize the integration of the two channels to facilitate the matching between customers and merchants.

the endless product feed on the mobile interface. We include a screenshot of the homepage recommendation and search engine from the collaborating platform in Appendix A.

Our cooperating platform deploys the collaborative filtering (CF) algorithm in the recommendation systems (see, e.g., Wang et al. 2018, Zhao et al. 2019, Lv et al. 2019). Collaborative filtering (CF) algorithm is a mainstream personalized recommender system widely implemented in business practice (Adamopoulos and Tuzhilin 2005) and is deployed in most recommender systems in E-commerce and other industries (Linden et al. 2003, Sarwar et al. 2001). Previous IS literature on recommender systems has thoroughly discussed CF (e.g., Fleder and Hosanagar 2009, Adamopoulos and Tuzhilin 2013, Hosanagar et al. 2014, Lee and Hosanagar 2019, 2021, Li et al. 2022).[5]

3.2 Field Experiment

We implement the experiment on a regular day in Summer 2019. The experiment day has no major promotions or campaigns. A random subset of users who open the app and visit the homepage recommendations are selected for our experiment during the experiment's hours. These subjects are randomly split into a control group (C) and a treatment group (T). Whereas recommendations to the subjects in both the control and treatment groups are generated from the same algorithm, the use of personal data as input in the algorithm varies.[6] Specifically, the personal data includes customer characteristics, such as demographics, and behavior information, such as past browsing, clicks, and purchases on the platform. The input in the algorithm for the control group includes the merchant data, product data, and personal data. In contrast, personal data usage is prohibited in the treatment group—the algorithm input includes only product and merchant data.[7] The randomized experiment creates a large and exogenous shock in the recommended matching between

[5] Additional details and discussions on the recommender system and experimental setting can be found in Appendix B.

[6] For both groups, the goal of the algorithm is the same as the mission of the platform: to maximize the matching probability between customers and products, regardless of the data input. The algorithm behind homepage recommendation utilizes product data, merchant data, and personal data only when it is feasible. The exogenous variations of recommendations create heterogeneous effects on product categories in the homepage recommendation. This helps us study how product recommendations would influence customer search on E-commerce platforms.

[7] Not all customers in the treatment group see the same set of products. When the recommendation algorithm does not use personal data, it uses only the product's popularity to recommend products. The product popularity and ratings vary across time: even within a day, customer searches and purchases fluctuate, which changes the product's popularity. Accordingly, customers who enter the platform at different times may see different sets of products. In addition, the algorithm may have included some randomness and customers who enter simultaneously may have seen separate products. Comparing products in the treatment and control groups, we find the products displayed in the treatment group are more concentrated than those displayed in the control group. In the treatment group, the most recommended items receive over 30,000 exposures, and the top 1,000 items account for almost 90% of all product views in the homepage recommendation (with a Gini index of ~0.97).

customers and merchants.[8] Variations in recommendation quality allow us to further study customer behavior in the search channel afterward.[9]

In the experiment, customers could access product information and make purchases on the online platform through different channels. Platform recommendation and proactive customer search are likely the two most prominent ways for customers to identify products on platforms. We examine the main effects of the channel relationships between product recommendation and customer search, using the experiment in which the use of personal data in treatment group customers is banned. Although the experiment introduces an exogenous shock to the recommendation channel for the treatment group's customers, the quality of the search channel remains the same. Comparing customers whose personal data usage is allowed (Control group) and banned (Treated group) enables us to evaluate interdependence across these two channels. We collect the customers' detailed recommendations and search activities in our experiment and examine the channel relationship between the two.

Our experiment covers a total of 555,800 customers exposed to the homepage recommendations. For every customer, we record information including the customers' assigned test group, all the products and merchants they have browsed, their clicks, and purchases during the experiments in both the recommendation and search channels. For each click or purchase, we record the timestamp, the purchased product(s), the merchant, and the revenue from the purchase. We complement the data with customer demographics and previous interactions with the platform. The resulting dataset enables us to analyze customer responses in recommendation and search at an aggregate and highly granular levels.

Besides the exogenous variations created by randomization, our data has several advantages. First, we record the product recommendations that each customer has browsed. Thus, we can characterize how customers respond differently in search when they browse different products in the recommendation system. Second, we infer the interests and preferences of customers from their historical clicks on the platform and characterize the match between product recommendations and their interests. Third, we collect customers' behaviors beyond the homepage and, therefore, could understand customers' information gathering through

[8] The platform matches the product offerings with customers using personalized recommendations (Adomavicius and Tuzhilin 2005). The homepage recommendation on our collaborating platform is controlled purely by algorithm and does not have any sponsored product listings.

[9] *Recommendation quality* is defined as "the matching quality between customer interest and recommendation product listings." A high recommendation quality means that customers like the products from the recommendation system. In contrast, a low recommendation quality means that customers dislike the products from the recommendation system. One measure is to assess product sales, as our referee kindly discussed. The average GMV for a control group customer is 1.363, while the average GMV for a treatment group customer is 0.257. An alternative measure of recommendation quality is that the CTR (click-through rate, the number of clicks over the number of PV) is substantially lower in the treatment group. The average CTR in the control group is 4.5%, while the average CTR in the treatment group is 1.1%. Both measures imply a substantially lower recommendation quality. Hence, we can conclude that the recommender systems have low recommendation quality.

active searches.[10] We also conduct a randomization check on customer demographics and past behaviors and find no significant distinctions across customers in the control and treatment groups (Appendix D), indicating that the experiment's randomization is at work.

4 Overall Evaluation of How Recommendation Channel Affects Search Channel

Without personal data, online platforms cannot predict products that match customers' preferences, as revealed by their demographics or past activities. The best the platforms can do is to recommend popular products that match the preference of an average customer with the maximum likelihood (Sun et al. 2021, Bakos 1997). The non-personalized recommendation algorithm has a lower matching probability between customers and products. Thus, customers are less likely to be exposed to products that they appreciate, and may find the product recommendations less attractive. They might start to search through the search engine.[11] We first evaluate the main effect and then explore heterogeneous effects.

4.1 Main Effect of Recommendation Channel on Search Channel

Here, we report the main effect of recommendation quality on customers' active use of search channels in Table 1.[12] We find that when customers in the treatment group ("no personal data") receive less relevant recommendations, they search significantly more in the search bar. The results are robust for all dependent variables of interest—that is, customers' browsing (PV), clicks, orders, and purchases (GMV) in search—which strongly supports the substitution effect between the two channels at the aggregate level. Specifically, customers in the treatment group perform 7% more browsing (PV) in the search engine during the experiment period. Moreover, customers, on average, click on 6.3% more products in search and make 6.4% more purchases from search. In summary, the search engine compensates for 22% of the reduction in PVs, 7% of the Clicks, and 52.8% of the reduction from the homepage recommendations.[13] As such, when the quality of product recommendations is reduced, customers on average can adapt and search more actively, which partially compensates for the reduced use of the platform recommendation.

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[10] We provide the variable definitions in Appendix C.

[11] Sun et al. (2021) discuss in detail the experimental impact on the outcomes related to the recommender systems. However, they do not explore the channel interactions between recommendation and search.

[12] We employ a classic experiment regression model: $\mathrm{PV}_{Rec,i} = \alpha + \beta * 1[\mathrm{Treat}_i] + \varepsilon_i$. We obtains the same finding as Sun et. al. (2021); however, we focus on different aspects. Sun et. al. (2021) study the impact of data regulation on the recommender system, while the current paper focuses on the channel relationship between recommendation and search using the ban of data on the recommendation system as a shock. We go further and explore how this effect varies across customer characteristics and across product categories.

[13] According to Table 1, the average reductions in recommendation PV/Click/GMV are 39.03/4.416/1.106, respectively. The increments in search PV/Click/GMV are 8.532/0.310/0.584, respectively. Therefore, the search channel compensates 21.8%/7%/52.8% of the reduction in the recommendation channel.

Given that the treatment status directly affects only customer activities in the recommendation system and that customer searching activities happen after browsing in the recommendation system, our finding reveals a causal relationship. We conduct a causal analysis with IV regression below to formally establish this causal relationship. We also run additional regressions in which we regress customers' search PV on their recommendation PV, with treatment status as an instrument,

$$\mathrm{PV}_{Search,i} = \alpha + \beta * \mathrm{PV}_{Rec,i} + \varepsilon_i$$

Table 2 reports the IV results. We find a negative relationship between recommendation activities and search activities in all measures. One unit reduction in recommendation PV results in a 0.22 unit increase in search PV. Similar results are obtained for all the above variables. All results are consistent with our main findings in Table 1.

There are two main managerial implications. First, we demonstrate that recommendation and search are interconnected, and the platform manager should be careful when designing them in the ecosystem. Second, our experiment reveals that the search channel can be deployed in a substitutive fashion with the recommendation channel when the platform faces more stringent data regulations. Overall, customers have a strong incentive to rely on search when the recommendation quality drops. However, the increase in customer browsing and purchases in the search channel cannot fully compensate for the total loss in the recommendation channel.

4.2 Heterogeneity in the Treatment Effect Across Product Categories

An important feature of this experiment is that the change in the distribution of the displayed recommendation products is *not uniform* across product categories.[14] Figure 1 summarizes the PV changes in the recommendation channels for the top 10 categories.[15] There are two groups of categories: (a) categories with an increase in Recommendation PV (only two product categories: Furniture and Grocery) and (b) categories with a decrease in Recommendation PV (other product categories). Comparing categories in Group (a) with categories in Group (b), we conjecture that the two categories in Group (a) are less sensitive to the use of personal data and are, therefore, less affected once personal data are turned off compared to products in other categories. The Furniture category includes products such as pillows and tableware, while the Grocery category includes products such as fruit bowls, garbage bags, and cushions. We believe that customers on the

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[14] We focus on heterogeneity in the treatment effect across product categories in the main body of this paper and leave heterogeneity in customer characteristics in Appendix E.

[15] In the heterogeneous analysis, we focus on only one dependent variable, PV, to simplify the analysis and presentation of the empirical results. We focus on PV for the following reasons. First, PV is the most responsive metric in the customer browsing journey. PV is much more responsive compared to sparse purchase decisions. Second, the platform cares about both PV and sales. PV is the intermediate metric, while sales are the final outcome. Usually, changes in PV and sales are proportional to each other. Third, when we explore the mechanism of how recommendations affect searches and study potential demand formation, PV is a mechanism instead of an outcome because we are interested in whether "display products in some category result in more searches in the other categories".

platform are likely to purchase these products with a broader market appeal regardless of their demographics or prior interests.[16] In contrast, other categories have a narrower market appeal and are purchased only by a specific group of customers. For instance, female customers purchase most women's apparel. Therefore, the recommender system promotes more products in Grocery and Furniture to an average customer if it has no customer characteristics after banning personal data.

The category-heterogeneity finding provides important insights. Specific categories might receive greater attention after implementing the data regulation policy. In contrast, other categories suffer from less exposure to customers on the homepage recommendation, potentially affecting product category competition and firm/platform strategies. It is important to understand how transactions in the recommendation channel evolve and the resulting impacts on transactions in the search channel when the recommender system embraces less personalization. As we observe a more stringent data regulatory environment, search platforms and functions on digital platforms may play an even more critical role.[17]

The heterogeneous effect across categories provides a unique opportunity to study the relationship between recommendation and search. For categories with *increased* recommendation PVs, we illustrate that recommendation and search manifest a complementary relationship in scenarios where customers search more. Conversely, for categories with *decreased* recommendation PVs, we show that recommendation and search manifest a substitutive relationship in scenarios where customers search more.

4.2.1 Complementary Channel Relationship

We first present the complementary effect between platform recommendation and customer search using product categories with an increase in recommendation PVs once the personal data are turned off.

Table 3 reports the recommendation and search PV changes in the Furniture and Grocery categories.[18] Columns (1) and (3) report the change in recommendation PVs in the Furniture and Grocery categories,

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[16] The recommender algorithm specifics may play a role here and promote more of these two categories. Usually, the recommender systems under no information default back to site-level historical data, merchant data, and customer product rating data. During the experiment, we find that these two categories: Furniture and Grocery, perform differently from the other categories. There is a PV increase in the recommendation for these two categories but a PV reduction in the other categories. This is an empirical finding. Given that the algorithm is a black box, what we can do is conjecture what happened in this black box. We do not rule out other explainations and exploit this variation to help us identify the relationship between recommendation and search. In addition, regarding the recommendation algorithm, we provide extensive details in both Section 3.1 and Appendix B (as well as a visualization in Appendix A). The detailed machinery of the homepage recommender systems in our setting has also been documented in previous research in Computer Science (graph embedding CF, Wang et al. 2018, Zhao et al. 2019, Lv et al. 2019).

[17] According to our study and our interviews with the staff of the collaborating platform, the recommender system relies more on personal data than the search engine. In the more stringent data regulation environment, the platform recommendation system will be affected more than the search engine, and many customers may turn to the search engine to make purchases, according to our main results.

[18] The regression equation is $\mathrm{PV}_{Rec,ij} = \alpha + \beta * 1[\mathrm{Treat}_i] + \varepsilon_{ij}$, where *i* indexes the customers, *j* represents a category. The unit of observation is at the customer-category level and each column measures the performance of one customer in one category. Column (1) and (2) in Table F1 (Appendix F) report the IV regression results. We have similar findings in the IV regression: in categories with PV increase, more recommendation PVs result in more search PVs and Orders.

respectively. Columns (2) and (4) report the changes in search PVs in these two categories. Columns (1) and (3) show that Furniture/Grocery categories receive an over 320% increase in recommendation PVs (328% for Furniture and 320% for Grocery). Columns (2) and (4) demonstrate that both categories receive a 26% increase in search PVs. Thus, the two channels are complementary, indicating that customers search significantly more for related products when more products are recommended. This is consistent with the channel complementarity hypothesis: When customers are exposed to more products in specific categories, they may be encouraged to explore more products in these categories. This finding provides evidence for the demand formation mechanism we will discuss later in the theoretical framework. Platforms' pushing more products in a category to the customers would likely influence customers' demand formation and preference construction. Customers may form new demands and expand their consideration sets while browsing product recommendations on the platform.

4.2.2 Substitutive Channel Relationship

When customers visit online platforms with a specific demand to fulfill but fail to find the desired products on the product recommendation page, they turn to the search engine to find the target products. Therefore, in the demand fulfillment process, product recommendation can play a substitutive role to customer search. We supply robust evidence supporting this mechanism.

As discussed, we document that there are fewer recommendation PVs in all categories except for Grocery/Furniture. Nevertheless, customers only increase their search in some such categories, providing evidence that the two channels are substitutes only in *specific* types of conditions. Table 4 compares recommendation and search PVs across categories.[19] We report the results for the three largest categories out of the 26 categories (excluding Furniture and Grocery): Clothes, Shoe/Luggage/Bag, and Baby Clothes. The results for the other categories are consistent and available upon request. Columns (1) and (2) report that the Clothes category receives a 91% reduction in recommendation PVs, yet its search PVs significantly increase by 9%. This corroborates the substitution effect: When customers find fewer targeted items (such as clothes) in the recommendation system, they turn to the search engine right away to fulfill their demand for the desired products. Columns (3) to (6) show that when the recommendation PVs decrease, the search PVs do not always increase significantly. Below, we further explore why we observe such an intriguing empirical pattern.

5 Conceptual Framework and Underlying Mechanism

[19] Column (3) and (4) in Table F1 (Appendix F) report the IV regression results. We have similar findings in the IV regression: in categories with PV decrease, fewer recommendation PVs lead to more search PVs and Orders.

In Section 4, we have examined the overall impact of the recommendation channel on the search channel and also identified a range of heterogeneous treatment effects at the user and product category levels. In this section, we further explore the underlying process and the role of recommendation and search channels in influencing consumer decision-making. We first propose a conceptual framework to illustrate the potential mechanism, generate conditions for channel complementarity and substitution, and then propose testable hypotheses. Our empirical analysis supports these hypotheses and aligns with the conceptual framework.

5.1 Conceptual Framework for Consumer Decision Making and the Role of Recommendation Channels and Search Channels

We propose a conceptual framework of customer decision-making (Figure 2) to theorize how changes in recommendation quality and category composition affect customer search at an aggregate and a more granular level.[20] The framework can help us understand the role of the recommendation channel and the search channel in the consumer decision-making process, and ultimately, the relationship between the two channels. Our framework hypothesizes that the customer shopping mode can be broadly divided into two states: *demand formation* (left-side panel of Figure 2) vs. *demand fulfillment* (right-side panel of Figure 2). We argue that the interaction between recommendation and search is contingent on the state of demand of the customer in each category-search instance.

Customers who arrive at the E-commerce platform are in one of the two states. On the one hand, customers in the **demand fulfillment state** have well-defined pre-existing preferences, or specific "demand intents". Before arriving at the platform, they have already formed their final consideration sets and only desire to fulfill their demands at the online marketplace (Hauser and Wernerfelt 1990, Hauser 2014, Shocker 1991).[21] They only need to decide whether to make a purchase via the recommendation or search channels, or not purchase at all if they do not find the desired products (right-side panel of Figure 2). As customers encounter the platform recommendations first on the front page, they can find the desired products easily and quickly if the recommender is able to predict customers' preferences (Adomavicius and Tuzhilin 2005). In this case, customers may not use the search engine at all.

On the other hand, customers in the **demand formation state** arrive at the online platform without well-defined pre-existing demand intents (left-side panel of Figure 2). Recommendations can influence consumer preferences through the context in which product choices are made (Xiao and Benbasat 2007). Specifically, after being exposed to the homepage recommendation provided by the online platform, customers can update

[20] Our conceptual framework is motivated by previous literature on consumer decision-making such as user engagement stages (Engel et al. 1990, Zhang et al. 2019) and the consumer decision-making and consideration sets (e.g., Hauser 2014, Häubl and Murray 2003, Dellaert and Häubl 2012, Häubl and Trifts 2000, Tsekouras et al. 2019).

[21] "Final consideration set" is also referred to as the "choice set" ready for purchase decisions (e.g., Shocker 1991).

their original demands and form an updated ex-post demand intent (middle box of Figure 2). The increased product views of specific recommendations can facilitate new demand formation and prompt customers to build their consideration sets via information search, using the search engine. Ultimately, the customers finalize their consideration sets, arrive at the demand fulfillment state (right-side panel of Figure 2), and purchase the desired products in either recommendation or search channels. Thus, in the demand formation stage, recommender systems can influence customers' preferences on the spot (Haübl and Murray 2003) and prompt customers to revise or recall their demands, which facilitates further information collection activities via the search engine.

The conceptual framework predicts both complementarity and substitution relationships between recommendation and search but under different conditions:

Complementary Channel Relationship: For customers in the **demand formation state**, homepage recommendations may influence customers' preference formation, expand their consideration sets, and affect their demands (Hauser 2014, Häubl and Murray 2003, Dellaert and Häubl 2012). The presence of recommender systems affects the set of available products that customers encounter. The cueing of specific recommended products also affects retrieval from memory and, hence, the formation of consideration sets. The consideration sets may evolve until the consumer decides to make a final choice. In the demand formation state, customers can form consideration sets on the spot after having updated their demands from product recommendations (especially the homepage recommender system can expose the customers to a variety of product categories). For instance, a customer who initially wants to buy clothes may eventually become interested in groceries after browsing attractive grocery products in the recommendation system. Through engagement with recommendations, this customer may start to search for "grocery" in the search engine. Accordingly, we would observe increases in grocery PV in both recommendation and search. In this case, recommendations can facilitate further information-collection activities via the search engine, thereby manifesting a complementary relationship between recommendation and search channels.

Substitutive Channel Relationship: Customers in the **demand fulfillment state** have already formed a well-defined pre-existing demand intention. Their demand can be fulfilled by either the recommendation or the search channels. For instance, for a customer who visits the homepage recommendation, her demand can likely be immediately fulfilled if the recommendation system successfully predicts her purchase intent using her personal data (Adomavicius and Tuzhilin 2005). Consequently, in the demand fulfillment state, we expect customers' exposure to the relevant recommended products to reduce customers' information search for the targeted products (Haübl and Trifts 2000). If the customer can find the desired products on the product recommendation page, she may not use the search engine at all. Otherwise, she could instead purchase in the search engine to satisfy her needs. In this case, recommendation and search manifest a substitutive channel relationship.

Our conceptual framework is connected to the previous literature in at least four dimensions. First, previous research has shown that, in a shopping environment, consumers often use a two-stage "consider-then-choose" decision-making process when facing a great many products. That is, consumers choose products by first forming a consideration set from alternative products and then picking from among the products considered (Payne 1982, Hauser and Wernerfelt 1990, Nedungadi 1990, Shocker et al. 1991, Shapiro et al. 1997, Haübl and Trifts 2000, Hauser 2014, Caplin et al. 2019). Our framework for understanding the relationship between recommendation and search has deep roots in the literature on the two-stage process in consumer decision-making. Second, our framework closely relates to how recommender systems affect consumer decision-making and preference-construction processes (see Haübl and Murray 2003, Xiao and Benbasat 2007 for example). Previous research has documented that recommender systems can affect the size of consideration sets (Haübl and Trifts 2000, Haübl and Murray 2003, Xiao and Benbasat 2007, Zhang et al. 2011, Dellaert and Haübl 2012, Li et al. 2022). It has also been documented that recommender systems can reduce search costs and increase customer's incentives to generate sales (Adomavicius and Tuzhilin 2005, De et al. 2010, Brynjolfsson et al. 2011, Adomavicius et al. 2018).[22] Third, we expect the presence of recommendations to transform the demand formation process by activating customers' awareness of a product category, or their potential demand. Customers can discover demand by browsing the products.[23] This is related to the literature on how customers form their consideration sets using heuristic decision rules (e.g., Hauser 2014). For example, research has illustrated that consumers use a recognition heuristic to form their consideration sets (e.g., Marewski et al. 2010 ab). Haübl and Murray (2003) demonstrate an "inclusion effect" that the mere inclusion of a particular attribute in a recommender system will affect the subjective importance of the attribute in consumer decision-making. In addition, they depict that this inclusion effect would persist into subsequent scenarios with no recommender system. Consumers are bounded by limited cognitive capacities, such as memory, inattention, and motivation (e.g., Payne et al. 1993). Moreover, consumers have limited resources for information processing. Through reciprocity in the exchange of information between the recommender system and the customers, they may update their original demand. Fourth, the way in which customers acquire product information and make purchase decisions is a function of the particular interactive decision tools available on the digital platform (Haübl and Trifts 2000). Earlier studies tend to treat

[22] In addition, Tsekouras et al. (2019) reveal that the granularity of the product recommendation sets can promote customer responses.

[23] Especially the homepage recommender system can expose the customers to a variety of product categories. Empirically, we find that an average customer spends a good amount of time browsing recommended products on the homepage (over 100 products), which will have a material impact on customers' demand formation.

recommendation and search as stand-alone systems, while we attempt to fill the gap by understanding the recommendation and search as an overall interactive online ecosystem.[24]

5.2 Testable Hypotheses Based on the Conceptual Framework for Consumer Decision Making with Recommendation and Search Channels

According to the conceptual framework, we first discuss how the experiment shock may affect the customers in the ***Demand Formation*** and ***Demand Fulfillment states***. Subsequently, we propose several testable hypotheses regarding how such shocks influence customer searches, generating conditions in which recommendation and search are complements or substitutes. We also present and explain some of the hypotheses in Figure 3.

5.2.1 Recommendation Affects Demand Formation

We observe a recommendation PV increase in the grocery and furniture categories in the experiment. The conceptual framework implies that these products may enter into customer demand intents in the demand formation state. Consequently, these customers may search more for similar or related products and compare detailed prices and styles in the search engine, which manifests a ***complementary*** dynamic between recommendation and search **(Figure 3, Quadrants 2 and 3)**. For instance, the recommendation system displays more groceries to the customer, and the customer would search for more groceries in the search engine.

H1a (Complementarity)*: When customers are displayed more products in certain categories in the recommendation, they engage in more searches for products in these categories.*

The searches are likely to reflect the newly-formed demand after browsing the recommendation, as evidenced by more generic query words.

H1b*: When customers are displayed more products in specific categories, they search for more generic query words if they engage in search queries in these categories.*

5.2.2 Recommendation Affects Demand Fulfillment

In our experiment, we observe product recommendation PV decrease in all other product categories (i.e., clothing, food, etc.). Given that customers have varying pre-existing preferences, we separately study two different scenarios: **Scenario I (Figure 3, Quadrant 1),** where the product recommendation PV decreases in the product categories of customers’ interests, and **Scenario II (Figure 3, Quadrant 4),** where the product

[24] A wealth of information may not necessarily be beneficial for attention allocation with the overabundance of product information. We show that recommendations can help form demand by making certain product information more salient.

recommendation PV decreases in the product categories in which customers are less interested in. Below, we show that the recommendation PV reduction has a different impact in these two scenarios.

In **Scenario I (Figure 3, Quadrant 1),** customers are interested in these categories but their demands are now less likely to be satisfied by the recommendation system. The conceptual framework predicts that customers will turn to the search engine for their desired products. For instance, a customer visits the platform with the intent of purchasing women's apparel, yet she does not find any women's apparel in the recommendation system. She may opt out of the recommendation system and instead search in the search bar. Therefore, in this demand-fulfillment process, product recommendations can play a ***substitutive*** role to customer search.

H2a (Substitution)*: When customers are shown fewer products in the category they are interested in, they will search more for products in this category.*

Moreover, given that the recommendation system does not satisfy customer demand, we expect customers to search for the specific products in these categories related to their prior interests. These searches are likely to reflect their unsatisfied demand, as evidenced by more long-tail (specific) query words.

H2b*: When customers are shown fewer products they are interested in, they will search for more long-tail query words.*

In **Scenario II (Figure 3, Quadrant 4)**, the customers are *not* interested in these categories with a PV decrease in the homepage recommendation. A reduction in recommendation PV should not affect customer search decisions. Therefore, the demand fulfillment effect is therefore expected to be negligible.

H2c*: When customers are shown fewer products in a category they are not interested in, they will* ***<u>not</u>*** *search more for products in this category.*

We use Figure 3 to illustrate these hypotheses and empirical tests. **Figure 3** shows the 2 x 2 coordinate system based on consumer interest in a category (Y-axis) and change in Recommendation PV in a category (X-axis). For each customer, we define her "consumer interested category" as the category with the most customer clicks in the past 30 days (recommendation channel and search channel combined) without purchasing in this category.[25] In this framework, the second and third quadrants illustrate H1a, the first quadrant illustrates H2a, and the fourth quadrant illustrates H2c. Please see Figure 3 for a more detailed elaboration and explanation.

[25] This rules out the possibility that the demand has already been satisfied. We also tried to deploy alternative definitions, for instance, defining "interested category" as "the category with the most customer clicks in the past 30 days regardless of purchasing decision in this category in the past 30 days" or "the category with the most customer clicks in the past 7 days without purchasing in this category in the past 7 days". The results are robust to various definitions.

In summary, whether the two channels are substitutive or complementary depends on the customer's demand states. Consumers under a demand formation state manifest a complementary relationship between recommendation and search. In addition, the complementary effect is likely to be observed as irrelevant to customers' previous interests, as recommended products can inform a customer of products with which she is not usually familiar. On the other hand, in the demand fulfillment state, product recommendations can reduce search costs and function as a substitute for customer search (Adomavicius and Tuzhilin 2005, De et al. 2010, Brynjolfsson et al. 2011, Adomavicius et al. 2018). We expect that the substitution effect will appear only when customers see fewer products of interest in the recommendation system. In this context, they must search significantly further to fulfill their demands. Shocker (1991) also states that an individual's final consideration set reflects subjective characteristics related to her attitudes and perceptions, emphasizing the important role of customers' prior interests in the shopping process.

5.3 Mechanism and Hypothesis Testing

Section 5.3.1 tests the complementarity hypotheses (H1a and H1b in Section 5.2.1). Customers search more in product categories with increased recommendation PV, demonstrating a complementary relationship between recommendation and search. Section 5.3.2 tests the substitution hypotheses (H2a, H2b, and H2c in Section 5.2.2). Suppose customers fail to find their products of interest in the recommendation system, they will search for these specific products as compensation, revealing a substitutive relationship between recommendation and search. In contrast, customers will not search for products in which they are not interested, even though these products appear less in the recommendation system.

5.3.1 Test Channel Complementarity in Demand Formation (H1a and H1b)

A significant feature of our experiment is that the changes in the distribution of the displayed recommendation PVs are *not* uniform across product categories. The first consequence of category heterogeneity is a surge in the recommendations of the Grocery/Furniture categories. This subsection studies how customers respond when shown more products in the Grocery and Furniture categories. Our H1 hypothesizes that the recommendation system affects the demand formation state and that customers form a new demand. Consequently, customers will search for more products in these two categories (Grocery/Furniture) after they are shown more products therein. This analysis is intended to provide evidence for the complementary relationship between recommendation and search.

We further explore whether the complementarity effect is driven by categories that interest customers, or by categories that do not. A customer's *high-interest category* is defined as the one with the highest clicks in the past 30 days, and each customer has a unique high-interest category. All customer-category pairs can be divided into two groups: (1) Customer category of high interest—that is, there is one and only one category that matches each customer's interest, which is defined as the customer's most-clicked category, and (2) customer categories of low interest—that is, all other categories except for the customer's category of interest.

Table 5 reports changes in consumer recommendations and searches in Furniture and Grocery by customer interest.[26] In the regressions, the unit of observation in this analysis is the customer-category pair. Columns (1) and (3) report the changes in recommendation PVs, and Columns (2) and (4) convey the results for search PVs. Columns (1) and (2) in Table 5 report customers' high-interest categories. Columns (3) and (4) report customers' low-interest categories. We find that both recommendation and search PVs increase regardless of customer interest. Comparing Columns (2) and (4), we find that customers who are less interested in Grocery/Furniture also search more. All of these are consistent with the demand formation hypothesis. Customers uninterested in Grocery or Furniture are also shown more of these products. After having browsed the products in these categories, they start to search for products in these two categories.

To further investigate the mechanism behind customer intents, we turn to Natural Language Processing (NLP) technologies to examine users' search queries. *Search queries* are direct communications from customers, providing an excellent setting to understand customers' demand intents. We study the first query word of customers and apply NLP technologies to decompose a customer's query-word structure to reveal her or his intents. We emphasize the customer's first search query for the following two reasons. First, the first search query accurately describes the customer's demand intent compared to the following queries and better captures the comparison between demand formation and fulfillment. Customers may refine their search queries afterward (Bronnenberg et al. 2016) The following queries are not direct or clean measures of customer intent. Second, when we focus our analysis on the first query, we can obtain a balanced sample that enables a more robust empirical test. By construction, all customers have at most one first query.

We construct two indices from our NLP analysis for each query word: (1) the generic dummy and (2) the query length. The *generic dummy* measures whether the query word is a generic word. When the query word is a generic query, customers only have the type of product they want in mind, but no clear idea of the specific product. For instance, customers may want to buy a T-shirt but have not determined the decorations on the T-shirt. The second index—*query length*—measures the specificity of demand. Customers who type in a longer query word have more specific demands in mind. For instance, "Red T-shirt with Flowers" is a longer query word than "Red T-shirt" and is more specific. The details regarding how we use NLP to construct these two indexes are reported in Appendix G.

[26] Table F2 (Appendix F) reports the IV regression results. We have similar findings in the IV regression: More recommendation PVs result in more search PVs and Orders, regardless of customer interest.

Table 6 reports the NLP results for consumers who search for products in the Grocery/Furniture categories. Regardless of customers' previous interests, customers search for more generic queries in these two categories. Columns (1) and (2) summarize the findings for customers interested in Grocery/Furniture. We find that these customers *do not* search with longer query words (i.e., indicating long-tail and more specific demand) but search for 19% more generic queries (i.e., indicating generic demand). Columns (3) and (4) summarize the findings for customers who were *less* interested in Grocery/Furniture. We have a similar finding, with customers searching with 13% more generic queries. This novel finding supports the demand formation hypothesis. Customers form a new demand for products in a category when they are recommended more products from that category. The increase in generic queries indicates that these customers are exploring new categories when the recommendation system affects their preference formation and expands their consideration sets. However, notably, customer demand does not become more specific, as the query length does not change significantly.

5.3.2 Test Channel Substitution in Demand Fulfillment (H2a, H2b and H2c)

The second consequence of category heterogeneity is a PV decrease in categories, except for Grocery and Furniture. According to our H2, customers search more in their category of interest as compensation, because (1) they cannot find products of interest in the recommendation, and (2) the quality of their products of interest in the recommendation has reduced. We further study the mechanism behind the substitution effect and discuss how this mechanism diverges from the complementary effect mentioned above.

We provide direct evidence that the substitution between recommendation and search is more pronounced in the product categories customers are interested in. Table 7 reports changes in the recommendation and search PVs by customer interest.[27] Columns (1) and (2) depict changes in the recommendation PVs in the customers' high-interest categories. Columns (3) and (4) reveal changes in recommendation PVs in customers' low-interest categories.

In both subsample tests, the recommendation PVs were reduced by about the same percentage (91%–92%), regardless of customer interest. However, the search compensation varies in an expected way: Customers only increase their searches (10% increase) in categories of their interest. However, their search in the other categories in which they are less interested is *not* affected (insignificant). This novel finding provides strong support for our demand fulfillment mechanism: Customers search more when their categories of interest are not recommended, assuming these categories reflect customers' typical demand.

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[27] Table F3 (Appendix F) reports the IV regression results. We have similar findings in the IV regression: In categories in which they are interested, customers increase their search (in both PVs and Orders) when they browse fewer recommendation PVs in these categories. In contrast, their search in the other categories in which they are less interested is not affected (insignificant).

Our NLP analysis of the search queries also provides further evidence for demand fulfillment in channel substitution. Table 8 demonstrates that the proportion of generic queries remains the same for customers searching for products aligned with their prior interests, providing evidence that their demand intents do not change significantly. In contrast, we find the query length becomes significantly longer. This reveals that customers express more specific demands in search engines. This is consistent with the demand fulfillment hypothesis: Customers turn to searching when the homepage recommendation cannot fulfill their pre-existing well-defined demand. These findings are the opposite of our findings in Subsection 5.3.1 (i.e., customers who search Grocery/Furniture increase their portion of generic queries, although the length of the query word remains unchanged). Customers searching for products in categories of previous interest express a more specific demand because the recommendation system does not display niche product categories after their personal data are turned off. However, when customers search for categories of no previous interest, both the share of generic keywords and the length of keywords increase.

6. Discussion and Conclusion

Our paper is among the first to examine the causal relationship between product recommendation and customer search. Using a large-scale experiment of 555,800 customers on a large E-commerce platform, we find that customers would search more when the product recommendation becomes less relevant, indicating a (partial) substitution between the recommendation channel and the search channel at an aggregate level. Furthermore, we find substantial heterogeneity in the use of search channels across product categories.

To understand the potential mechanisms underlying the experimental findings, we propose a conceptual framework for the consumer decision-making process with recommendation and search channels, and theorize how different states of customer demand—demand fulfillment and demand formation—may drive the channel relationship. On the one hand, recommendation systems may affect customer demand formation and preference construction. Customers may form new demand after receiving more recommendations in a product category and would search more in that category for related products. As a result, demand formation leads to a complementary relationship between recommendation and search channels. On the other hand, if customers have already formed a well-defined demand a priori before arriving at the platform, they may actively use the search channel when their specific demand cannot be fulfilled by the recommendation channel. In other words, when customers cannot find products that match their prior interests in recommendation systems, they compensate for this reduction by searching for more of these products. Correspondingly, demand fulfillment leads to a substitutive relationship between recommendation and search channels.

The empirical results reveal that both demand formation and demand fulfillment are at work in channel interactions between recommendation and search: Demand formation is associated with channel complementarity, and demand fulfillment is associated with channel substitution. Specifically, when customers receive more product recommendations in a category, they search more in that category with generic query words (channel complementarity). However, when customers receive fewer product recommendations in a category of their interest, they search more in that category with long-tail query words (channel substitution). Nevertheless, we do not find substitution or complementarity when customers receive fewer product recommendations in categories that they are less interested in.

The findings of this study provide relevant managerial implications for designers, managers, and regulators of digital platforms. First, the large-scale field experiment supplies a causal understanding and sheds light on the nuanced relationship between product recommendation and consumer search in various scenarios. We show that the channel relationship critically hinges on the consumer demand state (demand formation and demand fulfillment) and varies based on whether the recommendation matches customers' previous interests. Digital platforms may leverage our conceptual framework (Figures 2 and 3) and use our empirical findings in different ways: They can customize the relevance of product recommendation at an individual customer level and take advantage of the channel relationship between recommendation and search across different scenarios. For instance, the platform may cultivate more customer exploration by facilitating channel complementarity between recommendation and search with a broader set of product recommendations. They may also improve the recommender systems by incorporating the interests that new customers reveal when they fulfill their demands through active searches (e.g., integrating the click data and search query data).

Second, our results also highlight the importance of considering channel spillovers between recommendation and channel when enhancing recommender systems. A wide range of research in IS, Marketing, and Computer Science has examined ways to optimize recommender systems. However, the augmentation of recommender systems may be suboptimal if one ignores the impact of channel interactions with search engines. The platform may benefit from a more coordinated integration of recommendation and search channels. Our conceptual framework also provides a qualitative understanding to the platform designers of how customers in different demand states can be influenced and served by the recommendation system and search channel, together.

Third, our findings can inform policymakers and platform designers about the potential impact of data regulations on E-commerce platforms. Our study demonstrates that data regulations have a heterogeneous impact on technology-mediated channels: Compared to the search channel, data regulations have a larger impact on the recommendation channel because the recommender system demands more personal data input to effectively match customers with their desired products. As our experiment resembles the most stringent policy (no personal data for recommendation systems), it can be viewed as a benchmark for evaluating the impact of various types of data regulation policy on the consumer decision-making process and the channel relationship between recommendation and search. It is crucial for platforms to understand how such regulations affect customers' use of various technology channels for information acquisition and product purchases. Our results imply that platforms should balance recommendation and search when facing increasingly stringent data regulations. Platforms may strategically restructure their platform design toward the search channel (e.g., highlight the search bar) to solicit revealed interests from customers, which may eventually lead to a more search-focused platform model and a deeper integration of recommendation and search channels.

Finally, there are two caveats regarding the generalization of our findings. First, it is well known that it is hard for the field experiment approach to address the general equilibrium effect (Duflo et al. 2007). Thus, our field experiment focuses on the short-term impact of algorithm quality change (mimicking a data regulation) and sheds light on the qualitative pattern of the relationship between recommendation and search. In the long term, platforms may strategically redesign the recommendation interface and re-optimize the matching algorithms taking into account the relationship between recommendation and search. Customers may adapt to changes in recommender systems or find alternative shopping channels. Additionally, the way E-commerce platforms compete with each other and with offline retailers may change. It might be interesting to explore observational studies to obtain general equilibrium conclusions. Again, any generalization of our findings to a longer time horizon must be made cautiously. The second caveat is that the lack of variation in the experimental treatment may limit the generalizability of our study. Given the high stake and large scale, we only conduct one experiment with one treatment for all customers. Therefore, there are some treatments that we cannot study, which limits the generalizability of our study. First, we have only one quality-level variation in the experiment. We compare matching quality between customers with a non-personalization algorithm and customers with a personalization algorithm. This experiment cannot capture possible non-monotone effects. Second, our experiment observes a recommendation PV increase in Grocery and Furniture and a decrease in other categories. We do not have a counterfactual scenario: a recommendation PV decrease in Grocery and Furniture and an increase in other categories. Therefore, we cannot claim beyond the scope of our paper the generality of our framework.

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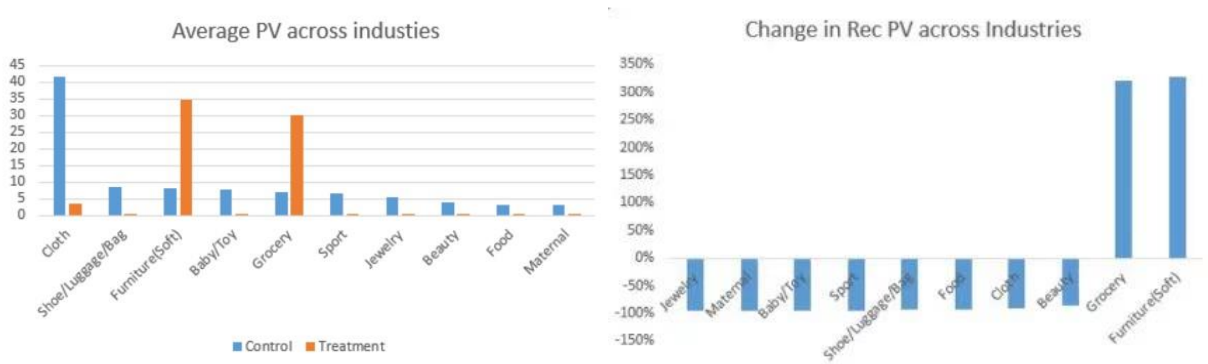
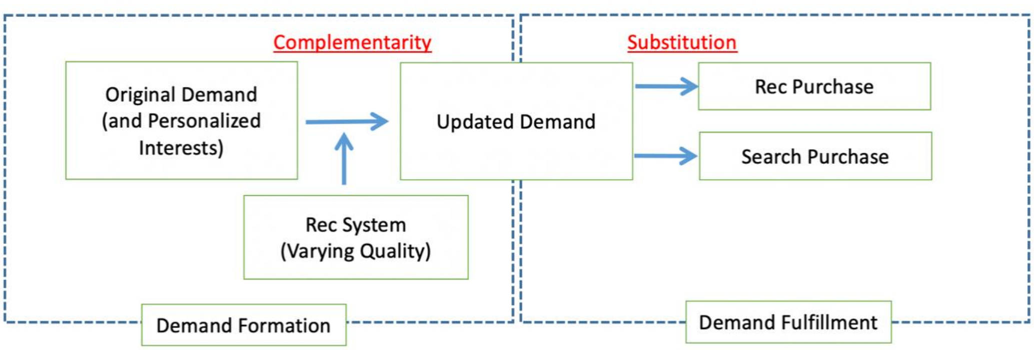
Figure 1: Product Recommendations Across Product Categories in the Control/Treatment (Visualization of the Heterogeneous Shock of Product Recommendations Across Categories)



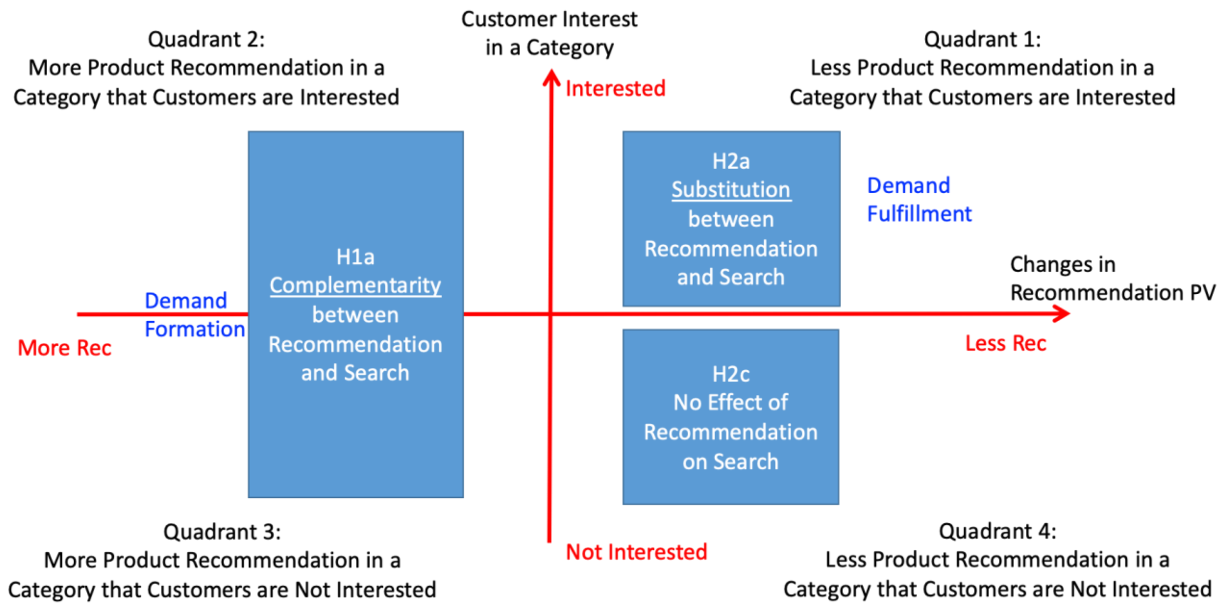
Note: Figure 1 summarizes the PV changes in the recommendation channels for the top 10 categories. The left panel presents the average PVs across the product categories. The right panel presents the changes in recommendation PVs across the product categories. We observe that there are two groups of categories: (a) categories with a Recommendation PV increase (only two categories: Furniture and Grocery) and (b) categories with a Recommendation PV decrease (other categories). Comparing the categories in (a) with the categories in (b), we conjecture that the two categories in (a)—Furniture and Grocery—are less sensitive to the use of personal data and are, therefore, less affected once the personal data are turned off in our large-scale experiment compared to products in the other categories. All customers on the platform are likely to purchase these products with a broader market appeal regardless of their demographics or previous interests. In contrast, other categories have a narrower market appeal and are purchased by only a specific group of consumers. For instance, most women's apparel is purchased by female customers. Therefore, the recommender system promotes more products in Grocery and Furniture to an average customer if it has no customer characteristics after the banning of personal data. The heterogeneous effect across categories provides a unique opportunity to study the relationship between recommendation and search in different product markets.

Figure 2: Conceptual Framework for Consumer Decision Making and Proposed Mechanisms on the Relationship Between Recommendation and Search Channels



Note: We visualize our conceptual framework for consumer decision-making with recommendation and search in Figure 2. Specifically, we theorize that there are two states of customers when they are shopping on the platform— "demand formation" and "demand fulfillment" —and discuss how these states drive the channel relationship between recommendation and search. In the framework, we hypothesize that customers can be broadly divided into two states of shopping: demand formation (left-side panel) vs. demand fulfillment (right-side panel). **Customers with a certain demand state encounter the recommendation system, update their demand, and eventually fulfill their demands with the recommendation and search channels**. In the demand formation state (left side panel), customers arrive at the online platform without a well-defined pre-existing demand intent. After receiving product recommendations from the homepage recommender system, customers update their demands (middle part). In the demand fulfillment state (right-side panel), customers satisfy their very specific demands through various channels on the online platform (via recommendation or search channels). Channel complementarity between recommendation and search channels is associated with the demand formation process, while channel substitution is associated with the demand fulfillment process.

Figure 3: Visualization of Hypotheses 1 and 2 on Channel Substitution and Channel Complementarity



Note:
(X-axis) Change in Recommendation PV: Changes in the Product Recommendation in a category.
(Y-axis) Customer Interest: Whether customers are interested in a product category, as revealed from past clicks.

"Quadrant 1" situation: Fewer Recommendation PV in product categories that customers are interested in.
"Quadrant 2" situation: More Recommendation PV in product categories that customers are interested in.
"Quadrant 3" situation: More Recommendation PV in product categories that customers are not interested in.
"Quadrant 4" situation: Fewer Recommendation PV in product categories that customers are not interested in

Explanation of the Figure: The experiment shock (change in the recommendation across product categories) affects both Demand Formation and Demand Fulfillment. We provide a conceptual framework (customer interest crossed with recommendation PV changes) to explore how changes in recommendation affect customer search. Figure 3 shows the 2 x 2 coordinate system based on "Consumer Interest in a Category" (Y-axis) and "Changes in Recommendation PV" (X-axis). We define the "consumer interested category" as the category with the most customer clicks in the past 30 days (recommendation channel and search channel combined). There are four quadrants in the coordinate system of Figure 3, which include all customer-category pairs. The detailed definition of the quadrants is described above under the figure. "Quadrant 2" and "Quadrant 3" jointly visualize the complementarity relationship between recommendation and search (Hypothesis 1a). "Quadrant 1" visualizes the substitution relationship between recommendation and search (Hypothesis 2a). "Quadrant 4" visualizes Hypothesis 2c.

Table 1: Effect of Turning Off Personalized Recommendation on Customers' Active Search

Outcome	(1) PV Rec	(2) PV Search	(3) Click Rec	(4) Click Search	(5) Order Rec	(6) Order Search	(7) GMV Rec	(8) GMV Search
No Data	-39.03***	8.532***	-4.416***	0.310***	-0.019***	0.0075***	-1.106***	0.584*
	(0.462)	(0.793)	(0.019)	(0.0314)	(0.0004)	(0.00123)	(0.050)	(0.321)
Constant	116.9***	120.1***	5.284***	4.935***	0.0221***	0.106***	1.363***	9.109***
	(0.325)	(0.558)	(0.0133)	(0.0221)	(0.00003)	(0.0008)	(0.035)	(0.226)
% Change	-33.4%	7.1%	-83.6%	6.3%	-85.9%	7.1%	-81.1%	6.4%
Control	N	N	N	N	N	N	N	N
R-squared	0.013	0.000	0.090	0.000	0.005	0.000	0.001	0.000
Obs	555,800	555,800	555,800	555,800	555,800	555,800	555,800	555,800

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: The sample includes 555,800 customers who have been exposed to the homepage recommendations in the experiment. The table reports the main effect of turning off personal data on customers' active searches. Generally, we find that after customers in the treatment group receive fewer relevant recommendations, they search significantly more in the search bar. The results are robust for all dependent variables of interest: customers' browsing (PV) for Columns (1) and (2), clicks for Column (3) and (4), order in Column (5) and (6) and sales volume (GMV) for Columns (7) and (8). The percentage of change (% Change) is also displayed for ease of interpretation.

Table 2: Customer Recommendation Substitute Search (IV results)

VARIABLES	(1) Search PV	(2) Search IPV	(3) Search Orders	(4) Search GMV
Rec PV	-0.219***			
	(0.0209)			
Rec IPV		-0.0701***		
		(0.00715)		
Rec Orders			-0.395***	
			(0.0657)	
Rec GMV				-0.529*
				(0.292)
Constant	145.6***	5.306***	0.115***	9.829***
	(2.083)	(0.0272)	(0.00104)	(0.288)
Observations	555,800	555,800	555,800	555,800
R-squared	0.023	0.021	0.003	0.002

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: The sample includes 555,800 customers who have been exposed to the homepage recommendations in the experiment. The table reports the IV results. We find a negative relationship between recommendation activities and search activities in all measures. One unit reduction in recommendation PV results in a 0.22 unit increase in search PV. Similar results are obtained for all the above variables. All results are consistent with our main findings in Table 1.

Table 3: Recommendation and Search PV Changes in Product Categories with PV Increases

	(1)	(2)	(3)	(4)
	Furniture		Grocery	
VARIABLES	Rec PV	Search PV	Rec PV	Search PV
No Data	26.79***	2.040***	22.88***	1.758***
	(0.127)	(0.176)	(0.109)	(0.140)
Constant	8.168***	7.717***	7.161***	6.821***
	(0.0894)	(0.124)	(0.0768)	(0.0985)
%Change	328%	26%	320%	26%
Observations	555,800	555,800	555,800	555,800
R-squared	0.074	0.000	0.073	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports the complementary effects between platform recommendation and customer search using categories with an increase in recommendation PV once the personal data are turned off. The table presents the changes in recommendation and search PVs in the Furniture and Grocery categories. Columns (1) and (3) report the changes in recommendation PVs in the Furniture and Grocery categories, respectively. Columns (2) and (4) report the changes in search PVs in these two categories. Percentage of change (% Change) is also displayed for ease of interpretation.

Table 4: Recommendation and Search PV Changes in Product Categories with PV Decreases

	(1)	(2)	(3)	(4)	(5)	(6)
	Clothes		Shoe/Luggage/Bag		Baby Clothes	
VARIABLES	Rec PV	Search PV	Rec PV	Search PV	Rec PV	Search PV
No Data	-38.04***	4.032***	-8.209***	0.0243	-7.275***	0.0281
	(0.190)	(0.520)	(0.0433)	(0.254)	(0.0500)	(0.167)
Constant	41.79***	42.63***	8.749***	13.71***	7.669***	7.213***
	(0.134)	(0.366)	(0.0305)	(0.179)	(0.0352)	(0.117)
%Change	-91%	9%	-94%	0%	-95%	0%
Observations	555,800	555,800	555,800	555,800	555,800	555,800
R-squared	0.067	0.000	0.061	0.000	0.037	0.000

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: The table reports the substitutive effect between platform recommendation and customer search using categories with a decrease in recommendation PVs once the personal data are turned off. As discussed, we document that there are fewer recommendation PVs in all categories except Grocery/Furniture. Yet, customers only increase their search in some of these categories, providing evidence that the two channels are substitutes only in specific types of conditions. This table compares recommendation and search PVs across categories. We report the results for the three-largest categories out of the 26 categories (the Furniture and Grocery categories are excluded): Clothes (Columns 1 and 2), Shoe/Luggage/Bag (Columns 3 and 4), Baby Clothes (Columns 5 and 6). The results for the other categories are consistent and available upon request. The percentage of change (% Change) is also displayed for ease of interpretation.

Table 5: Complementarity in Demand Formation (Product Categories by Customer Interest)

	(1)	(2)	(3)	(4)
	High-interest Categories		Low-interest Categories	
VARIABLES	Rec PV	Search PV	Rec PV	Search PV
No Data	10.67***	3.285***	25.57***	1.842***
	(0.495)	(1.142)	(0.0842)	(0.102)
Constant	22.02***	28.28***	6.924***	6.185***
	(0.347)	(0.801)	(0.0593)	(0.0720)
%Change	48%	12%	369%	30%
Observations	54,204	54,204	1,057,396	1,057,396
R-squared	0.009	0.000	0.080	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table examines whether the complementarity effect is driven by categories that interest customers or categories that do not. A customer's *high-interest category* is defined as a category with the highest clicks in the past 30 days, and each customer has a unique high-interest category. The table presents changes in consumer recommendations and searches in Furniture and Grocery by customer interest. Columns (1) and (3) report the changes in recommendation PVs, and Columns (2) and (4) report the results for search PVs.

Table 6: Complementarity in Demand Formation: Increase in Generic Demand

	(1)	(2)	(3)	(4)
	High-interest Categories		Low-interest Categories	
VARIABLES	Generic Dummy	Query Length	Generic Dummy	Query Length
No Data	0.0337***	0.0413	0.0238***	-0.00668
	(0.00993)	(0.0364)	(0.00431)	(0.0164)
Constant	0.175***	2.324***	0.188***	2.328***
	(0.00707)	(0.0259)	(0.00326)	(0.0124)
%Change	19%	2%	13%	0%
Observations	6,290	6,290	35,421	35,421
R-squared	0.002	0.000	0.001	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports the NLP results for consumers who search for products in the Grocery/Furniture category. Regardless of the customer's previous interests, customers search for more generic queries in these two categories. Columns (1) and (2) summarize the findings for customers interested in Grocery/Furniture. Columns (3) and (4) summarize the findings for customers who are less interested in Grocery/Furniture. Percentage of change (% Change) is also displayed for ease of interpretation.

Table 7: Substitution in Demand Fulfillment (Product Categories by Customer Interest)

	(1)	(2)	(3)	(4)
	High-interest Categories		Low-Interest Categories	
VARIABLES	Rec PV	Search PV	Rec PV	Search PV
No Data	-41.96***	4.736***	-2.028***	-0.00510
	(0.204)	(0.567)	(0.00515)	(0.0194)
Constant	45.54***	47.84***	2.226***	2.634***
	(0.144)	(0.399)	(0.00362)	(0.0136)
%Change	-92%	10%	-91%	0%
Observations	501,596	501,596	12,837,604	12,837,604
R-squared	0.078	0.000	0.012	0.000

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: This table reports changes in the recommendation and search PVs by customer interest. Columns (1) and (3) report the changes in the recommendation PVs, and Columns (2) and (4) report the results for the search PVs. Columns (1) and (2) show changes in recommendation PVs in customers' high-interest categories. Columns (3) and (4) depict changes in recommendation PVs in customers' low-interest categories. Percentage of change (% Change) is also displayed for ease of interpretation.

Table 8: Substitution in Demand Fulfillment: Increase in Query Length

	(1)	(2)	(3)	(4)
	High-interest Categories		Low-interest Categories	
VARIABLES	Generic Dummy	Query Length	Generic Dummy	Query Length
No Data	0.00239	0.115***	0.00991***	0.0215***
	(0.00181)	(0.0115)	(0.00164)	(0.00767)
Constant	0.0690***	2.813***	0.123***	2.476***
	(0.00128)	(0.00813)	(0.00114)	(0.00534)
%Change	3%	4%	8%	1%
Observations	79,247	79,247	165,980	165,980
R-squared	0.000	0.001	0.000	0.000

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports the NLP results for customers' search queries. The results demonstrate that the proportion of generic queries remains the same for customers who search for categories that are more aligned with their prior interests. In contrast, we find that the query length becomes significantly longer. Columns (1) and (2) summarize the findings for categories that are aligned with customer interests. Columns (3) and (4) summarize the findings for categories that are different from customer interests. Percentage of change (% Change) is also displayed for ease of interpretation.