Exploitation and Exploration: The Value of Improving Search Precision on E-commerce Platforms

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Abstract

E-commerce platforms match online buyers and sellers using their search technologies. A more precise search algorithm may improve search targetability at the cost of preventing consumers from exploring not directly related products. In collaboration with Alibaba, we take advantage of a 2019 quasi-experiment on Taobao.com, in which the platform refined some product categories into finer subgroups in order to return more targeted search results to online shoppers. Using granular panel data on consumer search and purchase behaviors, we find that the improvement in search precision results in a 37.3% increase in consumers' click-through rates and a 64.4% increase in gross merchandise volume. This increase in matching is especially pronounced for consumers with specific products as search keywords. Also, small and niche sellers gain more market shares and are more likely to enter the market as the probability of matching increases. The improvement in matching outcomes in the short run, however, is accompanied with a substantial decrease in consumer engagement with the platform in the long run, especially for consumers with vague search keywords. On average, consumers conduct 1.2% fewer searches and spend 3.4% less time on the platform in the following week after the search precision increases. Overall, our findings illustrate the tradeoff between exploitation and exploration in e-commerce search design.

1. Introduction

One of the fundamental distinctions between online retailing and conventional retailing is the widespread use of recommendation systems and search tools that assist buyers and sellers in searching for trading partners (Bakos 2001, Brynjolfsson et al. 2011). Growing research interests in marketing, economics, and computer science have been directed toward the design of ranking and recommendation algorithms to increase search targetability and make the search results more customized to consumers' preferences (Ghose et al. 2012, De los Santos and Koulayev 2017, Yoganarasimhan 2018, Zhang et al. 2019). Specifically, researchers have shown that grouping similar web pages into categories can improve the precision in the retrieved results and enhance user search experience (Xing et al. 2008, Bilal 2012). However, more targeted search results may discourage consumers from exploring new products and result in missed opportunities of cross-selling (Fong 2017, Hagiu and Wright 2020). The design of search algorithms on e-commerce platforms thus parallels the exploitation-exploration dilemma across literature as diverse as organizational innovation, depression treatment, and reinforcement learning (March 1991, Currie and MacLeod 2020, Sutton and Barto 1998). Exploitation of familiar knowledge provides adequate solutions to current problems but at the expense of exploration of new knowledge.[1]

In this paper, we seek to understand the tradeoff between exploration and exploitation in e-commerce search design and measure the value of improving search precision on e-commerce platforms to two types of consumers.[2] Some consumers have an exact product in mind such as the newly released iPhone 11 Pro 64GB Gold. These consumers have specific shopping needs and the purpose of search is to actively learn about price or fit information about targeted products on the platforms and eventually land a deal. In contrast, other

[1] In the context of search design, e-commerce platforms should balance the short-term gains from increasing the search precision with the long-term benefits from encouraging consumer exploration. In section 2.3, we show the similarity of these two problems.

[2] Previous studies have documented two shopping motives in consumer search behaviors: goal-directed and exploratory search (Janiszewski 1998, Chiou and Ting 2011, Pfeiffer et al 2020). In goal-direct search, consumers are guided by specific goals and are motivated to gather information efficiently to achieve their goals. Exploratory search refers to consumers who are scanning and browsing in a search environment without predefined goals (Wolfinbarger and Gilly 2001).

consumers may be at the very early stage of shopping and only have a category of products in mind. For example, a consumer may want to buy a rice cooker but does not know which particular product has the features she needs. After browsing some listings and trying different search queries, she may realize, instead of a rice cooker, what she needs is actually a steamer. These consumers have general shopping needs and submit imprecise search queries to passively convey information to the search engines, relying on the "broad-match" function of the e-commerce platforms (Eliaz and Spiegler 2016).

Measuring the value of improving search precision using observational data is, however, challenging. First, the precision of search results is endogenously determined by consumers' unobserved preferences and their search actions such as sorting and filtering (Chen and Yao 2016, De los Santos and Koulayer 2017). Second, randomized experiments of consumers exposing to various search design may be insufficient if sellers are responsive to the changes of search algorithms and adjust competition strategies accordingly (Dinerstein et al., 2018).[3] Third and more importantly, it is rare to have access to individual-level search panel data that track each consumer across search sessions over time. Existing datasets mostly contain a short episode of cross-sectional consumer search behaviors, abstracting from the possibility of product discovery in the search process (Bronnenberg et al. 2016, Honka et al. 2019).

To address these challenges, we take advantage of a detailed click-stream data set with quasi-experimental variation in the quality of search results. This data set comes from a particular change in search algorithms that refine the product categories on Alibaba, one of the world's largest e-commerce platforms.[4] Alibaba creates multi-level categories to classify products so that the search engine can index and associate each product with different search queries. Before the category refinement, cat lovers who submit the query "cat food" will get pages for a mix of cat food and dog food in the search results. By refining the category "pet food" into two

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[3] E-commerce websites are one of two-sided platforms which get sellers and buyers on board and enable interactions between them (Caillaud and Jullien 2003, Rochet and Tirole 2003, Parker and Van Alstyne 2005, Armstrong 2006). The changes in the search algorithms of the platform have impacts on both parties.

[4] Unlike Amazon, Alibaba does not hold inventory to sell directly to consumers. It mainly manages and hosts its e-commerce platforms to enable third-party sellers to sell products online. Thus the innovation of search technology is at heart of its core business as to facilitate transactions between sellers and buyers. This also provides us an ideal environment to observe how buyers and sellers adapt to the advance of search technology.

subcategories “cat food” and “dog food”, the search engine is more likely to retrieve only cat food. As a result, the matching between consumers’ preferences and sellers’ relevant products can be substantially improved after the category refinement. Since consumers are not aware of these behind-the-scenes adjustments of search algorithms, we can causally identify how consumers’ search activities respond to the improvement in search targetability and estimate the economic benefits associated with it. [5]

Our search data is at a very granular level and include around 7 million consumers over two-year period ending in December 2019. Two advantages of our dataset help overcome the limitations in previous studies on consumer search. First, our sample provides a more comprehensive observation of consumers’ engagement with the e-commerce platform. Most previous studies cannot connect searches made by the same user over time when using data from PC search. Consumers are not often signed in when searching on the browser/computer even if they have an account on the platform (Bake et al, 2016). We overcome this limitation by using the mobile search data. Consumers are automatically logged in when starting a search session on their mobile phones. We can track multiple sessions across time conducted by the same consumer rather than multiple people in the same residence.[6] Thus we able to link their search sessions from the initial arousal all the way through to either a purchase or an abandonment of the search. We not only know how many clicks or purchases a consumer makes in a search session but also the total time they engage with the platform. Second, we focus on a basket of goods instead of a single category. Previous studies use search data in a single-category setting such as hotels and books (Ghose et al.2012, Hong and Shum 2006). In contrast, sellers sell several hundreds of thousands of categories of products on Taobao.com. Consumers search across categories and refine search queries across search sessions. Later search queries are related to former search results, which generates cross-category dependencies.

As the platform only selected a small group of product categories for refinements, we are able to employ a difference-in-differences design to causally estimate the effects of the improvement in the quality of search

[5] Two recent theoretical papers define search targetability as the quality of search or the precision of search results that are determined by search algorithms (Yang 2013, Zhong 2019). This concept is related to the concept of advertising. targetability that have been well studied in the literature (Goldfarb and Tucker 2011, Wattal et al 2012).

[6] All consumers are anonymized in our sample. We don’t use any personal information of consumers for the analysis.

results. Our sample is from the refinement of one particular category "trash can". We choose this product category as it is well defined and has quite steady demand throughout the year. Alibaba refined the product category "trash can" into two independent subcategories "general trash can" and "smart trash can". We use consumers whose search queries related to "smart trash can" as the treatment group. Our control groups come from several unaffected product categories that are complements to smart trash cans for house cleaning purposes and share the parallel trends with smart trash cans in click-through rates and purchase rates before the category refinement. We use consumers whose search queries related to "robot vacuum" as the control group in our main analysis and the others as robustness checks. We compare the changes in consumers' matching outcomes and search intensity in the treatment group before and after the category refinement relative to the same changes over time among consumers in the control group.

To rule out the alternative explanation such as potential selection bias in refining categories, we further include consumers whose search queries are related to "general trash can" as another treatment group and use a triple differences analysis as a placebo test. Since smart trash cans are niche products which caters to a small population of consumers, the matching probability of smart trash cans on the platform is significantly lower compared to that of general trash cans. Thus the category refinement should significantly improve the matching outcomes of consumers searching for smart trash cans but have insignificant effects on consumers searching for general trash cans, if other confounders do not affect consumers' search behaviors.

Using this dataset, we find that the matching between consumers and products significant increases with the improvement of search targetability. Specifically, the average click-through rate of consumers who search for smart trash cans increases by 37.3% after the category refinement, relative to consumers who search for unaffected categories. The purchase rate of smart trash cans also increases by roughly 37.1%, resulting in a 64.4% increase of gross merchandise volume. This positive matching effect is disproportionate and more pronounced for consumers who have specific shopping needs and know exactly which products to buy.

Our findings are also robust to alternative samples and alternative selection of control groups. As a placebo test, we find that for consumers who search for general trash cans, neither their click through rates or purchase rates significant change after the category refinement, alleviating the concern of selection bias in category refinements.

To explore the underlying mechanism of improved search targetability on matching outcomes, we go to the supply side and document sellers' adaptive entry behaviors in response to the changes in search targetability. We find that the search engine gives more targeted search traffic to the products listed under the niche product category such as "Smart Trash Can" after the category refinement, thus increasing the matching outcomes between consumers and products. As the more targeted search traffic attracts more sellers to enter, the refined category results in the number of smart trash cans on the platform increasing by 150%. With increasing number of specialized products that cater to more specific consumers, niche products gain more market shares and the distribution of sales becomes flatter.

The improvement in matching outcomes, however, is accompanied with a substantial decrease in search intensity and consumer engagement with the platform in the long run. This reduction in search intensity is more significant for consumers who only have a category of products in mind and are at the early stage of a shopping journey. On average, these consumers view 4.3% fewer listings and spend 6.2% less time on clicking when the search targetability improves. This implies that the improvement in search targetability can increases the surplus of consumers who have specific shopping targets by helping them finding their matches more quickly. But one untended consequence is that consumers reduce engagement with the platform after finding what they want in the search results. We find that consumers log into the platform 3.4% fewer days and conducted 1.2% fewer searches in the following week after the search precision increases.

Overall, these findings illustrate the tradeoff between exploitation and exploration in platform search design. On the one hand, the more precise the search results are, the more likely consumers will find and purchase products that well match their preferences. The improvement in search precision can boost transaction volumes on the platform in the short run. On the other hand, imprecise search results can stimulate exploration and entice consumers to spend more time on the platform. Some randomness in the search results may deliver serendipity to consumers and trigger further exploration, increasing consumer engagement with the platform in the long run. Thus, e-commerce platforms should take into consideration both a matching effect and a serendipity effect when determining the optimal level of search quality.

2. Literature Review

Our study is related to three strands of literature: consumer search, platform search design, and the exploitation-exploration model. In this section, we briefly talk about the key models and results that inform the development of our paper and how our research contributes to the existing literature.

2.1 Consumer Search

This paper is related to the literature on consumer search. Starting from the seminal work of Stigler (1961) on the economics of information, theatrical studies have centered around how information frictions affect consumer welfare, market structure, and equilibrium outcomes (Wolinsky 1986, Stahl 1989, Anderson and Renault 1999). Consumer search models indicates that substantial search costs can discourage consumers from considering all available products in the market, thereby resulting in price dispersion (Varian 1980, Burdett and Judd 1983). A burgeoning empirical studies have developed techniques to quantify the magnitudes and consequences of consumer search costs in various markets.[7] There papers often consider a single category setting where consumers have an exact product in mind and their purpose of searching is to acquire information and resolve uncertainty about the product.[8] The critical identification assumption of search costs is that consumers have rational expectation about the distribution of product attributes before searching (Ursu 2018,

[7] For example, prescription drugs (Sorensen,2000), gasoline markets (Mitsukuni and Marc 2018, Luco 2019), supermarkets (Wildenbeest 2011), mutual fund (Hortaçsu and Syverson, 2004), automobile markets (Moraga-Gonzales et al 2018), personal consumer markets(Li et al 2017), mortgage markets (Alexandrov and Koulayev 2018), illicit drugs (Galenianos and Gavazza 2017)

[8] Early studies focus on searching in offline retail markets and assume that price is the main characteristic of the goods consumers are uncertain of when they are searching (Sorensen 2000, Hortacsu and Syverson 2004, Hong and Shum 2006). The rise of e-commerce draws the research attention to the more complex process of multi-attribute search as the detailed web browsing data become available (Bronnenberg et al 2016). Recent empirical studies examine consumers search behaviors within a platform when the purpose of search is for a good fit (Kim et al 2010, Koulayev 2014, Ursu 2018).

Honka et al 2019). [9]Thus a consumer stops searching either because of a high valuation for the products already found or because of a high search cost (De los Santos and Koulayev 2017, Chen and Yao 2017).

Instead of examining the impacts of search costs, we contribute to the literature by empirically identifying search quality as another essential component of search frictions, especially in online markets. We join two recent theoretical papers in defining search quality as the precision of search results that can be altered by the search technologies of online retail platforms (Yang 2013, Zhong 2019).[10] Consistent with the theoretical prediction in Yang (2013), we confirm that an decrease in search costs and an increase in search quality have different qualitative effects. We find that an increase in search quality can discourage consumers from exploring unrelated products and decrease their engagement with the platform in the long run. Our findings thus challenge the conventional wisdom that minimizing search frictions is always the optimal strategy for e-commerce platforms (Brynjolfsson and Smith 2000). [11]

By considering the role of search technologies in shaping the search results, our paper is also related to recent studies on the effect of ranking algorithms on consumer choices (Ghose et al 2012, 2014; Chen and Yao 2017; De los Santos and Koulayev 2017; Ursu 2018). We contribute to this literature by relaxing two assumptions in previous search models: (1) rational expectation (2) category independence. First, we incorporate bounded rationality into the traditional search model. Consumers are not supposed to know exactly what to buy and expect correctly which products to encounter at the beginning of a search process. Second, we track consumer

[9] A further distinction of search models in the literature is the search method consumers are using when searching. Theoretical papers imply that consumers adopt either a sequential or simultaneous search model (McCall 1970, Weitzman 1979, Burdett and Judd 1983, Stahl 1989). Researchers have developed empirical tests to differentiate these two search methods based on search path data (De Los Santos 2012, Honka and Chintagunta 2017).

[10] Yang (2013) incorporates the quality of search into the traditional search model to explain how the widespread of Internet leads to the long tail effects. He finds that decrease in search costs and increases in search quality have different qualitative effects. Zhong (2019) incorporates search precision into the search process. His model suggests that when the search precision is extremely high, increasing precision could discourage consumer search and lead to higher market prices.

[11] In terms of findings, our paper echoes the literature on the impacts of search frictions on in-store shopping behaviors, much of which measures the effect of in-store travel distances on unplanned spending. Papers find that requiring shoppers to travel more of the store can increase unplanned spending by exposing them to more products (Silley et al 2010, Hui et al 2013). Thus, offline retailers have come up with marketing strategies that deliberately increase consumers' search frictions, such as scattering popular product categories throughout the store (Granbois 1968, Iyer 1989).

search activities across multiple categories. We allow the precision of search results for one category to have an impact on consumer search behaviors in another category. In contrast, most papers only study consumer search behaviors in a single category. Table 1 compares our paper with recent papers on consumer online search behaviors.

[Table 1 about here]

2.2 Platform Search Design

Our study also contributes to the research on platform search design. E-commerce platforms match buyers and sellers using search technologies and recommendation systems (Bakos 2001, Brynjolfsson et al. 2011).[12] There has been a productive effort in optimizing search designs to increase consumer surplus and boost search engine revenues (Chen and Yao, 2017, Ghose et al, 2019, Gu and Wang 2018, Gardete and Hunter 2019, Zhang et al. 2019, Yoganarasimhan 2020). For example,. Chen and Yao (2017) highlight the value of refinement tools in consumer online search. Their model predicts consumers will search less and have lower utilities when sorting or filter options are not available. Gu and Wang (2018) discuss the optimal information layout of platform search design, His results suggest that platforms should consider consumers' cognitive costs when deciding what types of product attributes should be presented in the outer layer of search results. Ghose et al (2019) show that platforms can improve consumer online search experience by incorporating social textual content on the search results summary page. However, most of these papers focus on the short-run effects of platform designs on consumer search and purchase behaviors. In addition, current empirical studies mainly focus on the changes from the demand side and abstract away from the possibility of changes from the supply side that can affect market equilibrium outcomes.

Our long search panel data allow us to make two contributions to this literature. First, we analyze the effects of platform design on consumer behaviors both in the short run and in the long run. Our findings imply that search algorithms that increase search engine revenues in the short rum may not be optimal in the long run.

[12] By alerting the research attention to the matching role of e-commerce platforms, our study is also closely related to a growing number of studies on peer-to-peer service markets, where platforms play an active role in matching heterogeneous buyers and sellers (Hitsch et al 2010, Einav et al 2016, Chen and Shelton 2016, Fradkin 2017, Horton 2018).

Second, we extend the analysis to the supply side and examine how sellers adapt to the changes in platform designs. We document sellers' strategic entry behaviors after the search precision improves. The closest paper to ours is Dinerstein et al (2018), which highlights the trade-off of efficient platform design. They show that the platform design could not only reduce consumers' search costs, but also intensify price competition among sellers. In contrast, we focus on the role of platform in splitting the markets to improve matching between buyer and sellers. Our results indicate that niched products gain more market shares and the distribution of sales will become flatter as search precision improves. In term of findings, our paper is also related to the literature on product design and long tail effect in online markets (Kuksov 2004, Brynjolfsson et al 2011, Bar-Issac et al 2012, Yang 2013, Larson 2013).

2.3 Exploitation and Exploration

We finally build on the exploitation and exploration models that have been well studied in computer science, statistics, organization science, and economics literature (Schumpeter 1934, Holland 1975, Kuran 1988, March 1991, Sutton and Barto 1998, Benner and Tushman 2003). By refining and extending existing knowledge or solutions, exploitation can bring us great certainties of short-term gains. On the other hand, exploring new ideas and experimenting alternatives can help us increase long-term competencies and adapt to future environmental changes. Researchers have applied the theories of exploitation-exploration in the study of doctor drug prescription (Currie and MacLeod 2020), organizational innovation (Sorensen and Stuart 2000, Benner and Tushman 2003), professional hiring (Groysberg and Lee 2009), reinforcement learning (Holland 1975, Sutton and Barto 1998), and recommendation system design (McInerney et al 2018, Dzyabura and Hauser 2019). Although diverse in research topics, these studies can be unified in the multi-armed bandit framework where agents solve complex dynamic programming problems (Lai and Robbins 1985, Bubeck and Cesa-Bianchi 2012). The optimal decision rule hinges on balancing immediate rewards with the long-term benefits from learning about the distribution of rewards to inform future choices (Dzyabura and Hauser 2019).

Our study extends the literature on exploitation and exploration to the study of platform search design. The problem of determining the optimal precision of search results share the property of multi-armed bandit problems. Search engines can exploit short-term gains from immediate transactions by providing most relevant products to consumers. Alternatively, they can reap the long-term benefits from continuing consumer engagement and cross-category spillovers by displaying diverse and serendipitous items in the search results.[13] Therefore, e-commerce platforms have to balance exploitation with exploration in search design.

3. Empirical Setting

3.1 Product Categorization and Search Engine Indexing

E-commerce platforms use multi-level categories to classify products into different categories so that search engines can index and associate each product with different search queries. Figure1 provides an example of category hierarchy on e-commerce platforms. "sports" is the first-tier category. Under the "sports" category, there are four second-tier categories. "Sports shoes", "Sport clothes", "Equipment", and "Accessories". The category "Sports Shoes" is further refined into three subcategories: "Tennis Shoes", "Soccer Shoes", and "Basketball Shoes". Categorization can not only directly navigate consumers to the products they want, but also organize all products for the search engine to retrieve.

[Figure 1 about here]

Consumers can directly go through the category menu and choose these product categories to search. Alternatively, consumers can search for a specific query. Once understanding the search query, the search engine will relate several product categories that are most likely to match the search query and further restrict its attention to products belong to these product categories. Then the search engine ranks all these products and delivers search results to consumers. The categorization is crucial in this matching and ranking process. By classifying each product into the exact and differentiated product category, the search engine can better understand consumers' needs behind the search query.

[13] Studies on recommendation systems have argued that predictive accuracy should not be the only focus of recommendation algorithms (McNee and Konstan 2006, Fleder and Hosanagar 2009). Many authors suggest that platforms should avoid recommending products that are most likely to be chosen. Instead, recommendations should include diverse items that are not similar to each other and serendipitous items that are unexpected and relevant (Delgado-Battenfeld, and Jannach 2010, Zhou, et al. 2010, Vargas and Castells 2011, Adamopoulos and Tuzhilin 2014).

Online search is the communication process between consumers and search engines. Consumers express their demands through search queries. Search engines are answer machines. They try to poll out relevant web pages or products in the hopes of solving the searcher's query by indexing products for relevant keywords. If a product is indexed for a keyword, that means it will show as a result when a customer uses that search term in the search bar. The primary method of getting indexed for a keyword on e-commerce platforms is by selecting a relevant category. For example, sellers who list their products under the category of "tennis shoes" are more likely to be indexed with keywords related to tennis shoes. Their products, however, are less likely to show up as a result for consumers who search for soccer shoes. Thus which category they list products can influence how they are found and what sellers they are competing against. Without opening physical stores, this is the most essential way for firms to "locate" themselves in this electronic world is to list their products into a particular category and let the search engine guide consumers toward to them. Figure 2a is the snapshot of a seller's category selection process on Alibaba. The seller has to choose one specific category node to list a product. See Figure 2b for the similar process on Amazon.

[Figure 2 about here]

3.2 A Quasi-Experiment: Product Category Refinements on Alibaba

Alibaba is the leading e-commerce company in the world, with its three primary e-commerce sites – Taobao, Tmall and Alibaba.com – boasting 654 million active users annually and a gross merchandise volume (GMV) of $853 billion in 2018[14] and capturing a 55.9% share of all Chinese e-commerce retail sales[15]. Its sites mainly work as the marketplaces to connect various third-party sellers and willing buyers. Similar to eBay, Taobao is consumer-to-consumer focused, enabling small businesses and individuals to reach consumers. In contrast, Tmall is a business-to-consumer type of marketplace focusing more on large companies and multinational brands such as Nike and Apple. While Taobao and Tmall cater individual consumers, Alibaba is a business-to-business trading platform for manufacturers and suppliers to find vendors and purchase merchandise in bulk.

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[14] https://www.alibabagroup.com/en/news/press_pdf/p190515.pdf

[15] https://www.emarketer.com/content/alibaba-jd-com-lead-in-china-but-a-few-others-are-making-dents-too

To provide better matching outcomes and increase purchase conversion, Alibaba refined part of categories during 2019, which generated quasi-experimental variation for our identification. There are two types of category refinements. The first is to separate a combined category into two independent categories. The products in these two categories are different from with each other. The reason they were once bundled together is to save administrative costs of managing and monitoring since there are very few sellers in both categories. For example, the e-Cigarette and e-Cigarette accessories both belonged to the same leaf category before the refinement. Then Alibaba divided this combined leaf category into two separate leaf categories: an "e-Cigarette" category and an "e-Cigarette accessory" category. The other type of refinements is to single out one or several special types of products from a general product category. For example, the category "Tissue" was refined into three subcategories: "Paper Towel", "Napkin", and "General Tissue". By its nature, Paper towel, napkin, and tissues are all paper products. But they are used at different scenarios. These are all behind-the-scenes changes in categorization that consumers are not aware of.

4. Data

4.1 Sample Selection

To estimate the effect of category refinement, we focus on the refinement of one particular category. After 4/18/2019, Alibaba divided the category "Trash Can" into two categories: "Smart Trash Can" and "General Trash Can". Smart trash cans are one special type of trash cans which use advanced infrared sensor technology to open the lid automatically when consumers approach the bin, and close when consumers walk away. Thus, consumers who want to buy a smart trash can may not be satisfied if they see general trash cans in the search results.

We choose this product category for two reasons. First, it has quite steady demand throughout the year. Other product categories on the platform exhibit a time trend of demand, complicating our estimation of the effect of platform search design. One of the assumption we need for the estimation is that the distribution of consumers who search for smart trash cans are the same before and after the refinement. Second and more crucially, this category refinement brings us two natural treated groups with different treatment effects so that we can tease out potential selection bias of category refinement that threaten our identification. As a niche product that caters to a small population of consumers, the number of smart trash cans on the platform is nearly negligible compared to that of general trash cans. Thus the category refinement should significantly improve the matching outcomes of searching for smart trash can but have insignificant effects on searching for general trash can. With one heavily treated group (smart trash can) and one slightly treated group (general trash can), we can control the platform's other potential marketing efforts that may influence the search and matching outcomes.

We use consumers whose search queries related to "smart trash can" as the treatment group. Our control groups come from several unaffected product categories that are close in the product attributes and consumer characteristics with the refined category. We use consumers whose search queries related to "robot vacuum" as the control group in our main analysis and the others as robustness checks. We compare the changes in consumers' matching outcomes and search intensity in the treatment group before and after the category refinement relative to the same changes over time among consumers in the control group.

4.2 Summary Statistics

The shopping experience in e-commerce platforms can be summarized as search, click, and purchase. It started with a consumer describes what she wants to buy by putting in a query in the search box. Then the search engine interprets the query and returns the relevant products to the consumer. Then the consumer looks through the list of products in the search results and clicks on some of them which matches her preferences to get further information. After comparing pros and cons of every item she has clicked, she may end up with buying one that she likes most. Our data records what consumers see and every decision they make throughout this journey.

Our data for the analysis comes directly from Alibaba. For each refined category, we use search and purchase data four weeks before and after the refinement took effect. To sample all searches that belong to a particular category, we first rank the top 100 popular search queries that consumers use within the category. Then we pull out all search records that are derived from these search queries. We drop consumers who search more than once during my sample period and consumers who use more than one search query during a search. We only keep all search results derived from a user's first search query at the first search. The idea is to rule out consumers who would learn from the first search and adjust search queries.

The unit observation is at search level. Each search is defined by a unique user ID, a search query, and a specific date. At the search level, we observe how many listings a consumer view and how many pages she scrolls down. We also capture the consumer's engagement with the search results by calculating the number of clicks she makes and total amount of time she spent on all clicked listings. Based on whether a consumer makes any clicks or any purchases after a search, we further generate two dummies to summarize the degree of consumer's satisfaction with the matching of the search results. At the consumer level, we can observe each consumer's entire search and purchase histories throughout our sample period. At the seller level, we observe a detailed transaction history of every item a seller ever published. So we can directly calculate the transaction revenues a seller earns from each item.

Table 2 reports summary statistics for matching outcomes and search intensity of consumers searching for the refined category "smart trash can" and for the unaffected category "vacuum robot" before and after the category refinement. The average click through rate and purchase rate of both categories are higher in the after period. These differences, particularly the increase in smart trash can category, could be a consequence of the platform category refinement. In addition, consumers who search for smart trash cans on average view and click fewer listings after the category refinement, while there is no significant change in search intensity for consumers who search for vacuum robots.

[Table 2 about here]

5. Empirical Strategy

5.1 Difference in differences

We provide several quasi-experimental research designs beginning with a difference-in-differences analysis of the platform’s category refinement design. Specifically, we begin by estimating the following model.

$$y_{iqt} = \beta_0 + \beta_1 After_t \times SmartTrashCan_q + \gamma' X_i + \mu_q + \nu_t + \varepsilon_{iqt} \quad (1)$$

Where y_{iqt} is a measure of search decision or purchase decision for consumer i who searches for query q in day t. Each observation in our sample is unique defined by a consumer ID, a search query, and the search date. We include data from 3/18 to 5/18, and *After* equals to one for 4/18 through 5/18. X_i is a vector of covariates capturing consumer i's previous search and purchase behaviors, including whether she searched or purchased any related products. We also include fixed effects for search query μ_q and week by moth ν_t.

The estimates for this and all subsequent models are weighted using the number of consumers at the query-by-week level. Drawing on Bertrand et al. (2004), we cluster the standard error at the query level to allow for correlation of errors over time within each of the sample's 200 search queries. We have also explored alternative levels of clustering, including: category level, query-by-month. Statistical inference results are robust to these alternative clustering choices. In our first specification, we compare consumers whose search query is related to the refined product category "Smart Trash Can" to those whose search query is related to the unrefined product category "Robot Vacuum". β_1 measures the impact of the category refinement on consumers' search and purchase behaviors.

Identification of the difference-in-differences model requires that in the absence of the category refinement the control group (consumers searching for robot vacuums) should have similar trends to the treated group (consumers searching for smart trash can). To explore the validity of the design, we do an "event time" analysis. This allows an examination of the pre-trends. We replace *After* $\times$ *Smart Trash Can* with a full set of week dummies interacted with *Smart Trash Can* in equation (2).

$$y_{iqt} = \beta_0 + \sum_{\delta \neq -1} \beta_\delta Time\_to\_Treat_\delta \times SmartTrashCan_q + \gamma' X_i + \mu_q + \nu_t + \varepsilon_{iqt} \quad (2)$$

5.2 Triple Differences

To rule out the alternative explanations such as potential selection bias in refining categories, we further include consumers whose search queries are related to "general trash can" as another treatment group and use a triple differences analysis (Goldfarb and Tucker, 2011; Rishika et al.,2013) as a placebo test. The first part of the triple differences analysis is the difference in matching outcomes and search intensity between the two treatment groups (Smart Trash Can and General Trash Can) and the control group (Vacuum Robot) after the category

"Trash Can" was refined into two subcategories "Smart Trash Can" and "General Trash Can", minus the difference in matching outcomes and search intensity between the treatment groups and the control group before the category refinement. This is captured by β_1 in equation (3), and is a difference-in-differences analysis of the effects of the category refinement. The second part of the triple differences analysis, shown by $After_t \times TrashCan_q \times SmartTrashCan_q$, is the difference in matching outcomes and search intensity between two treatment groups, consumers searching for the niche category "Smart Trash Can" and ones searching for the broad category "Trash Can", after the category refinement, minus the difference between in matching outcomes and search intensity in these two treatment groups before the category refinement.

$$y_{iqt} = \beta_0 + \beta_1 After_t \times TrashCan_q + \beta_2 After_t \times TrashCan_q \times SmartTrashCan_q + \gamma' X_i + \mu_q + \nu_t + \varepsilon_{iqt} \qquad (3)$$

A difference-in-differences analysis controls for any omitted factors that influence consumers' search and purchase decisions differently for the affected and the unaffected categories and that are constant across time. The benefit of the triple differences analysis is that, in addition to control for those factors, it will also remove confounders that are accompanied with the category "trash can" being the targeted category after the refinement. For example, if Alibaba gives special attention to the target category and allocates more marketing expenses into that category, we should see significant changes in both the category "Trash Can" and the category "Smart Trash Can" after the refinement. However, if becoming the targeted category per se does not affect consumer behaviors, the category refinement should significantly improve the matching outcomes of consumers searching for smart trash cans but have insignificant effects on consumers searching for general trash cans.

6. Results

6.1 Matching Outcomes

We begin by presenting results for the difference-in-differences model using the category refinement of the category "trash can". After the refinement, the product category "trash can" was divided into two separate categories: "general trash can" and "smart trash can". Our treatment group for the main estimates is the consumers who search for a smart trash can during our sample period, while the control group is those who search for a robot vacuum during the same period. We use two dummy variables to capture consumers' responses to what they see after they put in a search query. The first one indicates whether a consumer makes at least one click after being presented with the search listings. The other one indicates whether a consumer make at least one purchase after the first search. These two variables generally summarize whether a consumer is interested and satisfied with the search results that the search engine delivers according to her search keyword. We expect that consumers are more likely to make a click and make a purchase when the search results well match their preferences.

Results from the Difference-in-differences model are shown in the first two columns of Table 3. Each column represents estimates from a separate regression with a different dependent variable. The first column indicates that consumers who search for smart trash cans, relative to those who search for robot vacuums, are 0.69 percentage points more likely to make a click after the category refinement, translating into 37.3% increase in the average click-through rate. The purchase rate of products in the affected category also increases by roughly 37.1% after the category refinement.

As a placebo test, we estimate the triple differences model from equation (3). We expand our sample by adding consumers who search for general trash cans as another treatment group into our existing sample. The results are reassuring. As shown in the last two columns of Table 2, the coefficients of $After_t \times TrashCan_q$ are not statistically significant but the coefficients of $After_t \times TrashCan_q \times SmartTrashCan_q$ are positive and significant. The results suggest that for consumers who search for a general trash can, neither the click through rate or purchase rate significantly changes after the category refinement. Thus the category refinement has negligible effect on these consumers, alleviating the concern of the selection bias in category refinements.

To explore the validity of the design, we use an "event time" analysis. This allows an examination of the pre-trends. In Figure 3, we plot the week by *Smart Trash Can* interactions using estimation form equation (2). where we leave out week 16 as the reference point. Prior to the category refinement, we find little evidence of differential group trends. For week dummy smaller than 16, most treatment coefficients are less than 0.005

points in magnitude and seldom reach statistical significance. After the category refinement, click-through rates and purchase rates increase significantly among consumers who search for smart trash can.

[Table 3 about here]

[Figure 3 about here]

6.2 Search Intensity

Besides matching outcomes, we further explore how the improvement in search quality affects consumer search intensity. We use the same difference-in-differences model with another set of dependent variables to examine how consumers' search intensity changes due to the category refinement. We develop three measures to describe consumers' search intensity during a search session. The first is how many listings a consumer views after putting in a search query. The key decision a consumer make in this viewing process is whether to scroll down or not. If she is particularly interested in one of the listing in the search result, she needs to obtain additional information by clicking on it. In light of this, the other two measures focus on how many listings a consumer clicks during the viewing process and total time spent on these clicked listings. These two measures represent the search on the extensive margin and the search on the intensive margin respectively (Ursu et al., 2018). Clicking induces higher search costs and demands longer engagement than viewing.

Similar to Table 3, Table 4 presents results from for the difference-in-differences model and the triple differences model. We restrict our sample to consumers who make at least one click during a search session. The first columns of table 4 show results with the dependent variable being number of listings viewed by a consumer. The other two columns estimate the same model using number of clicked listings and total time spent on these clicked listings as the dependent variable respectively. We take logs for all these three dependent variables when running regressions.

Results from Table 4 indicate that consumers reduce search intensity after the category refinement. For consumers who clicks on listings, the total number of viewed listings decreases by 4.4% after the category refinement. The category refinement also makes consumers click 3.7% fewer listings and spend 6.6% less time on clicking. Our findings are consistent with the theoretical prediction in Yang (2013). His model predicts that the overall search of consumers could possibly decrease if there is an increase in search quality. On the one hand, an increase in search quality makes consumers search more within the right category. On the other hand, consumers now are more likely to meet the right product and end up purchasing during the search process. These results combine with results in Table 2 suggests that rather than simply reducing search costs, the category refinement mainly increases quality of search and increase consumer welfare by offering better matches.

[Table 4 about here]

6.3 Consumer Heterogeneity

To understand how matching outcomes and search intensity vary across different consumers, we have estimated the heterogeneous treatment effects of category refinements. In Table 3 and Table 4, we group all consumers who search for a product category together and get a general estimate of average treatment effect for all consumers. Since each category consists of several related search queries, in this section, we further zoom into the specific search query a consumer use during the search to understand how consumers' shopping intents behind these search queries moderates the impact of the category refinement.

We classify all search queries related to the "Smart Trash Can" into two subgroups: general interest and specific need. The "general interest" subgroup only include search queries with a category name of the products or an imprecise description of desirable features of the product. For example, "smart trash can" and "sensor motion trash can" are the two most searched queries in the category of smart trash cans. 30.49% consumers in our sample search these two generic queries for smart trash can. These consumers only have a category of products in mind and are often at the early stage of shopping. They learn and adjust their preferences as exploring more products in the search results. We identify the "specific need" subgroup as those search queries which either contain specific brand names or express particular application scenarios. One example is the query "Smart Trash Can+Automatic Packaging+Perfect for Home". Consumers should know exactly which products at the time when they put this query into the search box. They have gathered enough information about smart trash cans and are ready to land a deal. After grouping all search queries into two subgroups, we replace *After* × *Smart Trash Can* with two dummies interacted with *After* × *Smart Trash Can*. These two dummies indicate which subgroup a search query belongs to. We estimated how treatment effects various across different subgroup of queries.

Table 5 presents results from this exercise. As for the matching outcomes, the first two columns indicate that the category refinement significantly increases click through rates for two subgroups of consumers, especially for consumers with specific shopping needs. Notably, the increase of purchase rate is mainly driven by these consumers. Interestingly, as suggested by the next three columns, consumers with general shopping interests show significantly lower search intensity as a result the category refinement. These consumers view 4.3% fewer listings, make 3.7% fewer clicks, and spend 6.2% less time on clicking. As for consumers with specific shopping needs, however, we don't find significant changes in their search activities after the category refinement.

Overall, our results illustrate a tradeoff between exploitation and exploration in e-commerce search engine design. As search quality improves, at the extensive margin, more consumers will easily find products that match their preferences and then make a purchase on the products in the search results. On the other hand, at the intensive margin, the more fined search results will discourage consumers' self-exploration efforts and thus make them view and click fewer products before landing a deal. The positive matching effect is more pronounced for consumers with specific shopping intents, while the negative search deterrence effect is disproportionately on consumers with general shopping interests.

[Table 5 about here]

6.4 Robustness Checks

We conduct extensive robustness check for the above results in Table A1 and A2 and our results are robust to alternative control groups and alternative samples.

More specifically, to alleviate the concern of comparability of the control group, we re-estimate our difference-in-differences model using the category "air purifier", "vacuum" and "mob" as the alternative control group respectively while maintaining the category "smart trash can" as the treatment group. These unrefined product categories are candidates for our control groups for three reasons. First, the characteristics of consumers searching for these product categories are close to those of consumers in our treatment group. We identify these product categories by looking into the search records of consumers who search for smart trash cans. "Air purifier", "vacuum" and "mob" are frequently searched categories by these consumers. Second, they all share the similar application scenarios with smart trash cans. They are all used in the home for cleaning purposes and are complements with each other. Third, search and purchase outcomes in these product categories have similar trends to the treated group throughout our sample period, thus meeting the identifying consumption of difference-in-differences model. We get similar estimates of the effects of the category refinement on matching outcomes and search intensity as we see in table 2 and table 3.

We also re-estimate our model using alternative samples to address following concerns. First, our findings may be merely a manifest of seasonal promotions if other marketing efforts are accompanied with the category refinements during our sample period, i.e., 3/18/2019-5/18/2019. Thus we estimate the model using the sample from last year, i.e., 3/18/2018-5/18/2018. We find that there is no significant change in either click-through rates or purchase rates for consumers searching for smart trash cans. Hence our findings are mainly driven by the changes in the search algorithms. In addition, someone may worry that the searchers of smart trash cans are not comparable to the searchers of vacuum robots or searchers in any of the three alternative control groups we mention above. As a response to this concern, we restrict our attention to the consumers who search both "smart trash cans" and "robot vacuums". This leaves us a subsample of around 0.18 million consumers. The idea is to control unobserved consumer characteristics that may result in differences in search and purchase behaviors in these two categories. We find that controlling for this factor in our analysis has no impact in our results. Lastly, we estimate a sample of 6-month time window. We find that our results don't change when we lengthen the pre-treatment window in our difference-in-differences model.

7. Discussion

In this section, we first discuss the underlying mechanism that explains the changes in matching outcomes and search intensity after the category refinement. Then we examine the effects of category refinement on consumer engagement with the platform in the long run. Finally, we document third party sellers' strategic behaviors in response to the category refinement.

7.1 Mechanism: Targeted Allocation of Search Traffic

Search engines help consumers find products by indexing products for relevant keywords. If a product is indexed for a keyword, it will show as a result when a customer uses that keyword in the search bar. The primary method of getting indexed for a keyword on e-commerce platforms is by selecting a relevant category. If a category is indexed with a search query, all products listed under that category as a whole will receive relatively more search traffic from that search query.

To test this hypothesis, we calculate the search traffic of the query "Smart Trash Can" distributed to the category "Smart Trash Can" and the category "Trash Can". We define the search traffic of a category as the total count of how many times consumers view the products belonging to that category. Figure 2 shows the distribution ratios of weekly search traffic to the two categories for the query "smart trash can" throughout 2019. Before the category refinement (4/18/2019), less than 2% of search traffic of the query "Smart Trash Can" was allocated to the category "Smart Trash Can". After the changes in search algorithms, this number rose to over 15% and was increasing to nearly 25% at the end of 2019.

These results suggest that the search engine gives more targeted search traffic to the refined product category. Before the category refinement, consumers who search for a niche product like smart trash can, are more likely to see only general trash can in the search results. After the change, with the "smart trash can" being singled out as an independent category, the search engine would preferentially deliver products from the category "smart trash can" to consumers who search for smart trash can. With more refined and targeted search results by a boosting search engine, consumers have higher chances of meeting the right products.

[Figure 4 about here]

7.2 Long-run Effects on Consumers: Reduced Consumer Engagement with the Platform

In the main analysis, we have documented that increasing search precision helps consumers find matched products more quickly but substantially reduces their exposure of other products on the platform. One follow-up question is what would be the consequences of reduced search intensity of consumers in the long run. Previous literature on in-store shopping behaviors have suggested that increasing travel distances within a store can increase consumer unplanned spending by exposing them to more products (Silley et al 2010, Hui et al 2013). These insights can be applied to in online settings, where imprecise search engines may make consumers stay longer and search more frequently on the platform and lead to more unplanned purchases.

In this section, we examine the impacts of category refinement on consumer engagement with the platform and unplanned purchases over a longer period of time. We track consumers' activities on the platform one week after their initial search session. Our long search panel data enable us to develop three metrics that reflect consumers' engagement with the platform both before and after the improvements in search precision. For the first two measures, we calculate the number of searches and the number different search queries each consumer conduct in the following week after the initial search. The third one counts the number of days each consumer logs into the Taobao app during the same time period. As for the unplanned purchases, we calculate the total purchase amount across categories other than the category "Smart Trash Can" and the number of these categories both in the follow week (7 days) and the following month (30 days) after the initial search.

Table 6 presents the difference-in-differences model estimation similar to our main analysis with the measures of consumer engagement with the platform. Results suggest that consumers conducted fewer searches, change fewer search queries, and log into the platform fewer times in the following week when the search precision increases. The decrease in consumer engagement is sizeable. The number of days a consumer visits the platform during a week decreases by 3.4%, the number of searches in a week decreases by 1.2%, and the number of search queries a consumer uses decreases by 1.0%. These findings indicate that imprecise search results can stimulate exploration and entice consumers to spend more time on the platform.

[Table 6 about here]

However, as indicated in Table 7, we don't find significant changes in consumers' unplanned purchases after the improvement in search precision. One possible explanation is that it may take several weeks for some consumers to finalize a purchase. Imprecise precision brings serendipity, but when this serendipity leads to purchases can vary from consumers. This is especially true in the environment of online shopping as consumers don't face the same time constraint as they do in a physical mall or a shopping center.

[Table 7 about here]

7.3 Long-run Effects on Sellers: Stronger Long Tail Effect

The previous analysis mainly focuses on the reactions from the demand side, trying to understand how the improvement in search quality affects consumers' matching outcomes and search intensity. But sellers could also re-optimize their competition strategies as a result of the change in search quality. Thus in this part, we look at the supply side of the market and examine whether sellers have strategic behaviors after the category refinement.

We find that the number of smart trash cans on the platform increase by 150% as search quality improves. The more targeted search traffic attracts many more sellers to put their products into this niche category. We further pull out all sellers who show up in the search results related to "Smart Trash Can" and divide them into two groups: sellers who enter the niche category "Smart Trash Can" and sellers whose products belong to the category "Trash Can". Our results suggest that sellers who enter the category "Smart Trash Can" are more likely to be: new, fewer ratings and small scale. Small and new sellers can earn a reasonable profit if entering a narrow category with lower operating costs. In contrast, large sellers often hire a team of specialists to help operate their e-commerce stores. Thus entering a narrow category with limited search traffic may not generate enough profits to cover their monthly salary expenses.

Niche sellers as a whole will more profits as the quality of search improves. We document that both total transaction volume and revenues of smart trash cans significantly increase after the category refinement. By reducing the search friction on the platform, the search engine makes it easier for relevant sellers to reach consumers who may have higher willingness to pay to their products. As a result, the total revenues of the refined product category nearly doubled. Sellers who sell niche products are significantly better off with the advance of the search technology. With increasing number of specialized products that cater to more specific consumers, niched products gain more market shares and the distribution of sales will become flatter.

8. Conclusion and Implications

This paper explores the role of the e-commerce platform in improving search precision and measure the value of doing so to consumers with different shopping needs. In collaboration with Alibaba, we exploit a particular change in search design for our identification: category refinement. With a difference-in-differences analysis combined with an event study estimation and a triple differences analysis, we find that the matching between consumers and relevant products significantly increases as search precision improves. This positive matching effect is more significant for consumers who know exactly which products to buy. However, the refined search results decrease consumers' search activities and their engagement with the platform in the long run. This negative search deterrence effect is more pronounced for consumers who only have a category of products in mind and at the early stage of shopping. Overall, our results imply a trade-off between exploration and exploitation in the e-commerce search design.

Our findings provide important implications for e-commerce platforms in general. With cutting-edge machine learning techniques and the availability of big data, researchers and engineers in computer science have been working on the designs of product rankings and category refinements for improvements of information retrieval system results (Chen and Dumais 2000, Xing et al 2008, Bilal, D. 2012, Farhoodi et al 2013). Most of these state-of-art algorithms can immediately boost search engine revenues but may be unsustainable in a longer time horizon. From the perspective of economics in search design, our study suggests that platforms should augment accuracy with diversity, novelty, and serendipity when considering the metrics of search algorithms. By encouraging consumers to explore diverse, novel, and serendipitous product categories, e-commerce platforms can increase consumer engagement and generate long-term impacts of user value. In addition, our results indict that e-commerce companies should fully leverage the textual data from online search queries to understand consumers' shopping intents. Product search engines are quite different from information search engines such as Google or Bing (Ghose et al 2014). On e-commerce platforms, people don't ask questions. Instead, they search for products. The semantic match of search queries is not enough. Platforms should extrapolate what products consumers really want when they type in these search queries.

Our study of platform search design has limitations that imply several directions of future research. First, while we have illustrated the exploitation-exploration tradeoff, the optimal design of search precision and the optimal depth of categorization scheme on e-commerce platforms are both beyond the scope of this paper. Our results indicate that search algorithms impact firms' strategic decisions such as category entry. Future work in this direction is required to take firms' incentives into account when designing search algorithms. Second, our analysis provides reduced-form evidences of the impacts of improving search precision on consumer exploratory search behaviors, abstract away from modeling the sequential path of the search refinement process. It is interesting to understand how consumers refine searching objects from initial broad categories all the way to final targeted products and how platforms use search or recommendation algorithms to guide this discovery process. Finally, though as complete and granular as possible, our search data are confined to one particular domain, failing to capturing search activities across other e-commerce websites as well as offline retailers. Data sets that track individual consumers' entire search path both online and offline will further enrich our insights and will enable additional discussions such as how competition from other platforms and consumer multi-homing moderates the impacts of platform search design.

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Tables and Figures

Table 1: Comparison with Search Data in Recent Literature

	Chen and Yao(2017)	Dinerstein et al (2018)	Ghose et al (2019)	Dong et al (2019)	Gu and Wang (2019)	Ursu et al (2019)	Gardete and Antill (2019)	Our Paper (2020)
Search Category	Hotels (unknown)	Video Game (eBay)	Hotels (Travelocity)	Moisturizer (Cosmetic online store)	Hotels (unknown)	Restaurants (Chinese version of Yelp)	Used cars (Shfit)	Multiple categories (Alibaba)
Size	1961 listings 495 users 15days	270 listings 12059 sessions 2 months	2117 listings ~1M sessions 3 months	3577 users 12 months	29065 users 4 months	5465 users 4 months	24116 users 8 months	7 million users 2 years
PC/Mobile Data	PC	PC	PC	PC	PC	PC	PC	Mobile
Transactions	Yes	Yes	Yes	Yes	Yes	Partial	Partial	Yes
Search path	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Search refinements	Yes	No	Yes	No	Yes	No	Yes	Yes
Search queries	No	Partial	No	No	No	No	No	Yes
Search engagement (time on searching /clicking)	No	No	No	No	No	Yes	Yes	Yes
Consumer panel	No	No	No	Yes	Yes	Yes	Yes	Yes
Search purpose	Product fit	Price	Product fit	Product fit	Product fit	Product fit	Product fit	Flexible (goal-directed or exploratory search)

Table 2 Summary Statistics of the Treatment Group and the Control Group

Category	Smart Trash Can (Treatment)			Vacuum Robot(Control)		
	Before	After	Difference	Before	After	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Matching Outcomes						
1(#Click>0)	0.0242	0.0392	0.1500***	0.0124	0.0151	0.027***
	(0.1535)	(0.1940)	[35.95]	(0.1106)	(0.1219)	[28.40]
1(#Buy>0)	0.0009	0.0014	0.0005***	0.0004	0.0005	0.0001***
	(0.0302)	(0.0383)	[6.81]	(0.0188)	(0.0221)	[8.21]
Panel B: Search Intensity						
#Listing	47.66	42.25	-5.41***	46.72	46.08	0.64
Viewed|#Click>0	(54.66)	(47.24)	[-6.63]	(63.22)	(57.38)	[-1.39]
#Listing	3.58	3.22	-0.36***	2.74	2.81	0.07
Clicked|#Click>0	(0.86)	(1.02)	[-6.29]	(0.49)	(0.53)	[1.27]
Clicking	122.09	108.94	-13.15***	103.68	101.11	2.57**
Time(s)|#Click>0	(34.82)	(37.95)	[-5.44]	(24.60)	(23.57)	[2.05]
#Observations	376670	336334		3204014	2881557	

Note: Column (1)-(2) and (4)-(5) show means with standard deviations in parentheses. Column (3) and (6) show the p-value of t-test for the differences with t-statistic in the brackets. * indicates $p < 0.10$,** indicates $p < 0.05$, and *** indicates $p < 0.01$

Table 3: The Effect of Category Refinement on Matching Outcomes

Model	DID		Triple Differences	
Dependent Variable	1(#click>0)	1(#purchase>0)	1(#click>0)	1(#purchase>0)
After × Smart Trash Can	0.0069***	0.00026***		
	(0.0013)	(0.00005)		
After × Trash Can			-0.0015	-0.00003
			(0.0008)	(0.00003)
After × Trash Can × Smart Trash Can			0.0083***	0.00028***
			(0.0009)	(0.00005)
Mean of Dependent Variable	0.0185	0.00072	0.0185	0.00072
Query Fixed Effect	Yes	Yes	Yes	Yes
Week of Month Fixed Effect	Yes	Yes	Yes	Yes
Adjusted R^2	0.0281	0.0011	0.0241	0.0008
Observations	7093315	7093315	14011400	14011400

Note: Table 3 reports the estimates of the difference-in-differences (DID) model and the triple differences model, where the first dependent variable is 1 if a consumer makes at least one click during a search session and 0 other wise, and the second dependent variable is 1 if a consumer makes at least one purchase during a search session and 0 otherwise. We control for search query fixed effects and week of month fixed effects. Standard errors (in parentheses) are robust to heteroscedasticity and clustered by query. * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$

Table 4: The Effect of Category Refinement on Search Intensity

Model	DID			Triple Differences		
Dependent Variable	#Listings Viewed |#click>0	#Listings Clicked |#click>0	Clicking Time |#click>0	#Listings Viewed |#click>0	#Listings Clicked |#click>0	Clicking Time |#click>0
After × Smart Trash Can	-0.0442** (0.0170)	-0.0377*** (0.0083)	-0.0661*** (0.0179)			
After ×Trash Can				-0.0340*** (0.0099)	-0.0094 (0.0074)	-0.0253 (0.0160)
After × Trash Can × Smart Trash Can				-0.0081 (0.0125)	-0.0281** (0.0094)	-0.0405* (0.0173)
Mean of Dependent Variable	47.66	3.58	122.09	47.66	3.58	122.09
Query Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Week of Month Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.1046	0.0445	0.0338	0.1751	0.07288	0.0328
Observations	105464	105464	105464	159697	159697	159697

Note: Table 4 reports the estimates of the DID model and the triple differences model with another set of dependent variables depicting consumer search intensity. We restrict our sample to consumers who makes at least one click during a search session. The first dependent variable is number of listings a consumer view during a search session. The other two are number of listings a consumer clicks and total time she spends on these clicked listings. We take logs for all these three dependent variables and use the same specifications as we did in Table 2. Standard errors (in parentheses) are robust to heteroscedasticity and clustered by query. * indicates $p < 0.10$,** indicates $p < 0.05$, and *** indicates $p < 0.01$

Table 5: The Effect of Category Refinement on Consumers with Heterogeneous Shopping Needs

	Matching Outcomes		Search Intensity		
Dependent Variable	1(#click>0)	1(#purchase>0)	#Listings Viewed | #click>0	#Listings Clicked | #click>0	Clicking Time | #click>0
After × Smart Trash Can × General Interest	0.0010*** (0.0003)	0.00035*** (0.00006)	-0.0433* (0.0182)	-0.0371*** (0.0083)	-0.0619*** (0.0179)
After × Smart Trash Can × Specific Needs	0.0316*** (0.0015)	0.00041 (0.00028)	-0.0528 (0.0354)	-0.0437 (0.0321)	-0.1063 (0.0570)
Query Fixed Effect	Yes	Yes	Yes	Yes	Yes
Week of Month Fixed Effect	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.02845	0.0011	0.1046	0.0411	0.0338
Observations	6798575	6798575	105464	105464	105464

Note: Table 5 reports the estimates of the DID model with two sets of dependent variables we previous used in Table 2 and Table 3. We interact *After* × *Smart Trash Can* with two dummies to allow for consumer heterogeneity in shopping needs. The dummy "Specific Needs" is 1 if the search query contains specific brand names or application scenarios and 0 otherwise. The dummy "General Interest" is 1 if the search query only includes category names and 0 otherwise * indicates $p < 0.10$,** indicates $p < 0.05$, and *** indicates $p < 0.01$

Table 6: The Effect of Category Refinement on Consumer Engagement with the Platform

Dependent variables (take logs)	#Searches consumers conduct in the following week	#Search queries consumer use in the following week	# Days consumers log into the platform in the following week	# Days consumers log into the platform in the following week
After x Small Trash Can	-0.0116***	-0.0101***	-0.0344***	
	(0.0027)	(0.0023)	(0.0094)	
After × Smart Trash Can × General Interest				-0.0435***
				(0.0105)
After × Smart Trash Can × Specific Needs				-0.0256*
				(0.0128)
Query fixed effects	Yes	Yes	Yes	Yes
Week of month fixed effects	Yes	Yes	Yes	Yes
Mean of Dependent Variable	29.85	28.77	5.494	5.494
R^2	0.0220	0.0226	0.0084	0.0084
Observation	64235	64235	64235	64235

Note: Table 6 reports the estimates of the DID model with the level of analysis at the week level. Three dependent variables measure consumer search and log in activities in the following week after seeing the more precise search results. Standard errors (in parentheses) are robust to heteroscedasticity and clustered by query. * indicates p<0.10,**indicates p<0.05, and *** indicates p<0.01

Table 7: The Effect of Category Refinement on Unplanned Purchases

Dependent variables (take logs)	Total amount of purchase in the following week (7 days)	Number of categories consumers purchase from in the following week (7 days)	Total amount of purchase in the following month (30 days)	Number of categories consumers purchase from in the following month (30days)
After x Small Trash Can	0.0134	0.0320	-0.0325	0.0060
	(0.0593)	(0.0227)	(0.0368)	(0.0195)
Query fixed effects	Yes	Yes	Yes	Yes
Week of month fixed effects	Yes	Yes	Yes	Yes
Mean of Dependent Variable	347.97	2.518	631.56	4.242
R^2	0.0194	0.0100	0.0047	0.0093
Observation	16833	16833	30342	30342

Note: Table 7 reports the estimates of the DID model with the level of analysis at the week level. Four dependent variables measure unplanned purchases in categories other than the category "Smart Trash Can" in the following week or month after seeing the more precise search results. Standard errors (in parentheses) are robust to heteroscedasticity and clustered by query. * indicates p<0.10, **indicates p<0.05, and *** indicates p<0.01

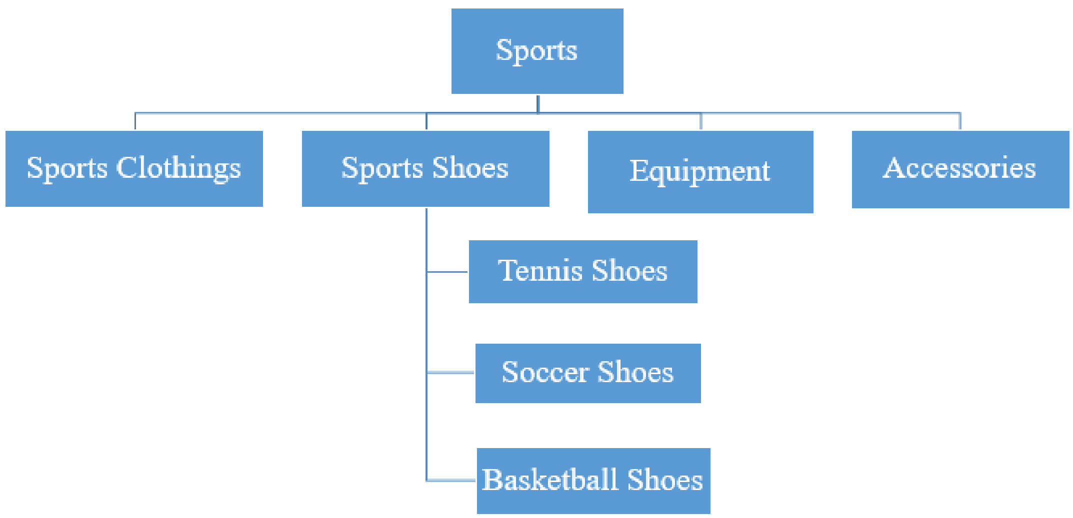

Figure 1: An Example of Category Hierarchy on E-commerce Platforms

Figure 2(a): Category Selection on Taobao

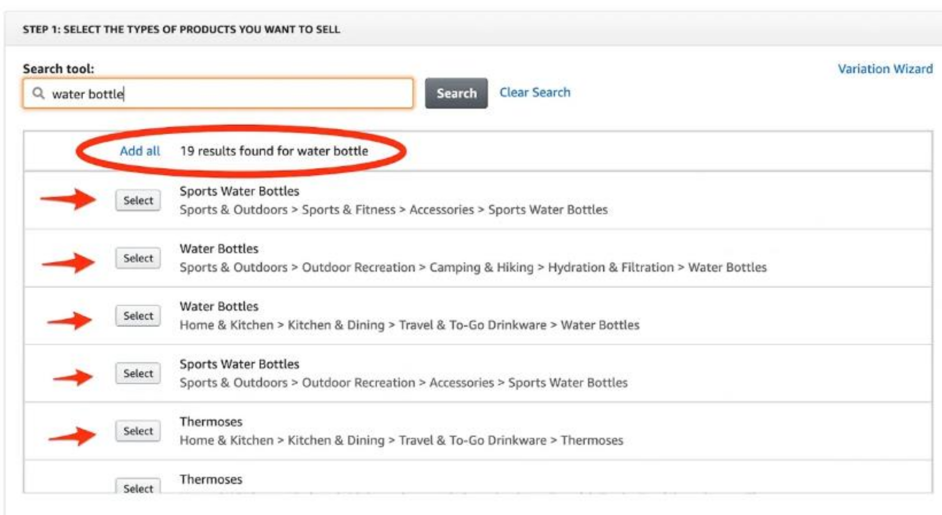

Figure 2(b): Category Selection on Amazon

Note: Figure 2 shows that sellers have to choose a specific category to list their products on e-commerce platforms.

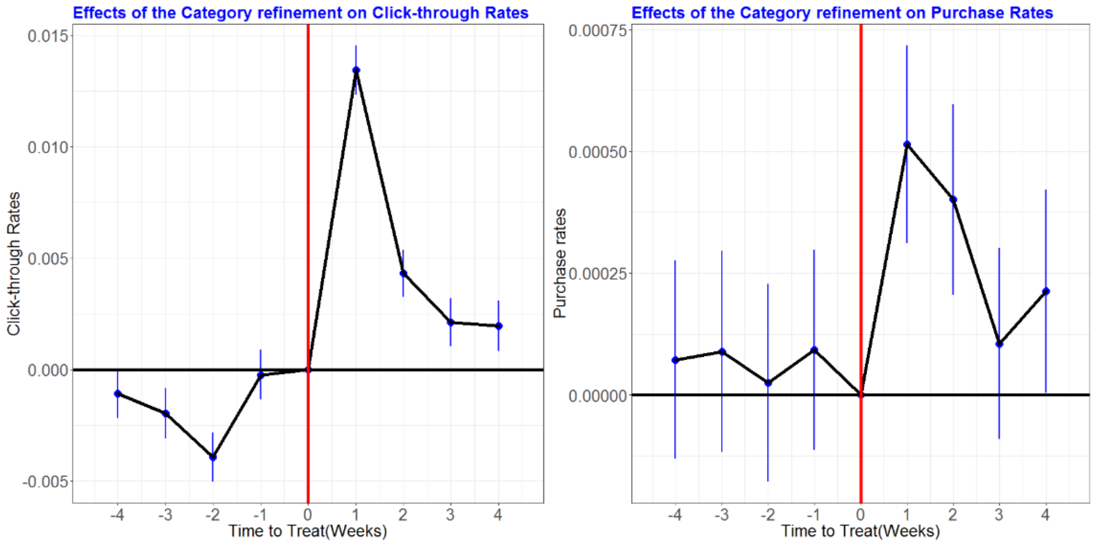

Figure 3 An Event Study of the Effects of Category Refinements on Matching Outcomes
Note: Figure 3 shows DID coefficients and 95 percent confidence intervals from estimation of equation (2) on indicators for category refinement. Standard errors clustered by search query. Includes search query fixed effects and week of month fixed effects. Treatment group defined as search sessions related to the smart trash can category and control group defined as search sessions related to the vacuum robot category. Red vertical line represents time of treatment. Selection on e-Commerce Platforms

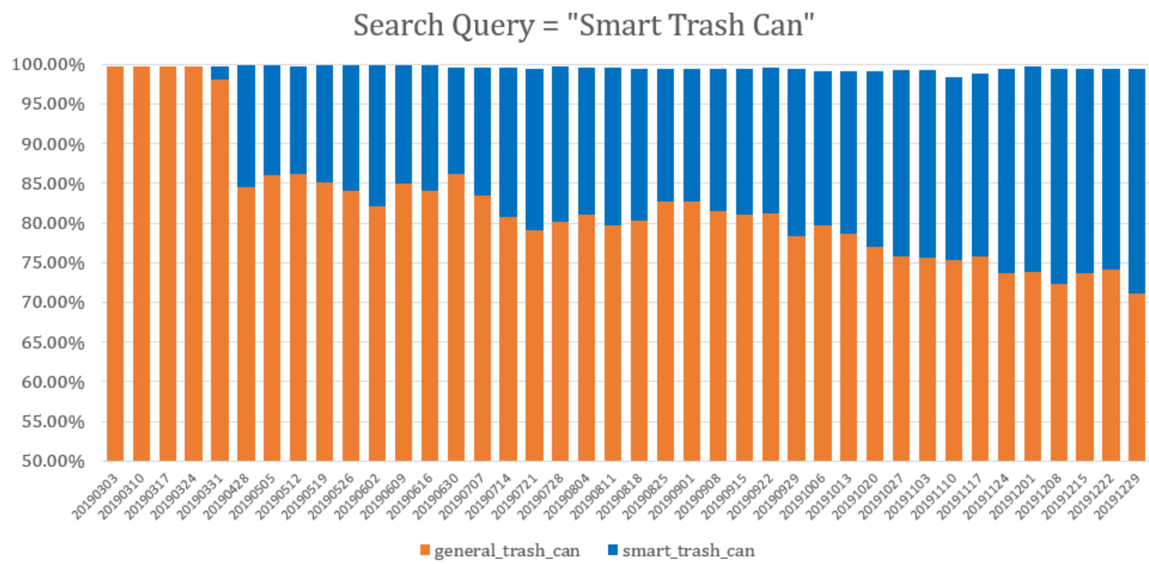

Figure 4: An Example of Targeted Search Traffic Allocation

Note: Figure 4 depicts the distribution ratios of weekly search traffic between two categories for the search query "Trash Can" and the search query "Smart Trash Can". The Sample period is from 03/13/2019 to 12/29/2019. The category refinement took effect at 04/18/2019. The yellow bar represents the ratio of search traffic allocated to the products listed under the category "general trash can" as a whole. The blue bar represents the ratio of search traffic allocated to the products belong to the "smart trash can" as a whole.

Appendix

Table A1: A Partial List of Category Refinement

Effective Date	Original Category	New Category
20190221	E-cigarette/E-liquid	E-cigarette accessories E-liquid E-cigarette
	Candy	Wedding Candy Other Candies
20190318	Other Vegetables	Red pepper Broccoli Other fruits
20190417	Tissue	Paper towel Napkin Tissue
	Trash Can	Smart Trash Can Other Trash Cans
20190517	Smartglasses /VR Device	MR Device AR Device Smartglasses/VR Device

Table A2: Examples of Two Groups of Search Queries

Query Group	Search Query	Number of Consumers	Number of Products
General Interests	Smart Trash Can	2136	12735
	Sensor Motion Trash Can	1476	10069
	Automatic Trash Can	817	8051
	…		
Specific Needs	Trash Can + EKO	151	609
	Smart Trash Can+Automatic Pakaging+Perfect for Home	139	2771
	Trash Can+ Automatic Packaging	95	2797
	…		

Table A3 Robustness Checks I: Different control groups

Dependent Variable	Matching Outcomes		Search Intensity		
	1(#click>0)	1(#purchase>0)	#Listings Viewed | #click>0	#Listings Clicked | #click>0	Clicking Time | #click>0
Panel A: Smart Trash Can vs Vacuum					
Smart Trash Can x After	0.0069***	0.00021***	-0.0462***	-0.0245**	-0.0287
	0.0003	0.00006	0.0119	0.0090	0.0190
Query Fixed Effect	Yes	Yes	Yes	Yes	Yes
Week of Month Fixed Effect	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.0373	0.0022	0.0765	0.0284	0.0220
Observation	5412094	5412094	82959	82959	82959
Panel B: Smart Trash Can vs Mob					
Smart Trash Can x After	0.0086***	0.00028***	-0.0453***	-0.0207*	-0.0516*
	0.0002	0.00005	0.0129	0.0099	0.0204
Query Fixed Effect	Yes	Yes	Yes	Yes	Yes
Week of Month Fixed Effect	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.0326	0.0012	0.0724	0.0281	0.0212
Observation	10952676	10952676	64156	64156	64156
Panel C: Smart Trash Can vs Air Purifier					
Smart Trash Can x After	0.0088***	0.00037***	-0.0250	-0.0132	-0.0142
	0.0003	0.00006	0.0120	0.0094	0.0204
Query Fixed Effect	Yes	Yes	Yes	Yes	Yes
Week of Month Fixed Effect	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.0330	0.0016	0.1305	0.0474	0.0457
Observation	3444954	3444954	61656	61656	61656

Table A4 Robustness Checks II: Different Samples

Dependent Variable	Matching Outcomes		Search Intensity		
	1(#click>0)	1(#purchase>0)	#Listings Viewed | #click>0	#Listings Clicked | #click>0	Clicking Time | #click>0
Panel A: Long Time Window					
Smart Trash Can x After	0.0125***	0.00038***	-0.0370***	-0.0308***	-0.0486***
	0.0019	0.00004	0.0084	0.0062	0.0141
Query Fixed Effect	Yes	Yes	Yes	Yes	Yes
Week of Month Fixed Effect	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0274	0.0013	0.1067	0.04078	0.0342
Observation	14472733	14472733	214866	214866	214866
Panel B: Last Year Sample					
Smart Trash Can x After	-0.0011	-0.00007	0.0655**	0.0381*	0.0028
	0.0012	0.00008	0.0214	0.0152	0.0355
Query Fixed Effect	Yes	Yes	Yes	Yes	Yes
Week of Month Fixed Effect	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0254	0.0011	0.1239	0.0453	0.0323
Observation	5170520	5170520	68494	68494	68494
Panel C: Only Common Users					
Smart Trash Can x After	0.0044***	0.00026***	-0.0329***	-0.0318***	-0.0480***
	0.0015	0.00005	0.0070	0.0072	0.0054
Query Fixed Effect	Yes	Yes	Yes	Yes	Yes
Week of Month Fixed Effect	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0297	0.0042	0.0897	0.0454	0.0368
Observation	186034	186034	4633	4633	4633