Measuring Market Power of Search Algorithms: Application to JD.com's Ecommerce Platform

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1 Introduction

The digital era has heralded a transformation in the way we consume goods. Product, content, and information discovery are now heavily shaped by the intricate mechanics of the ranking algorithms embedded within online platforms. These algorithms wield significant influence, dictating the user search experience across a diverse set of platforms. The increasing control wielded by platforms with incentives that are not aligned with their users has raised competition concerns. For instance, the relevancy rankings of Google search results may not be the same as the profitability ranking for Google. Consequently, it stands to reason that the competitiveness of the online search market plays a role in Google's decision about how much to weigh the relevancy of links versus their profitability.

These competition concerns have been raised by the FTC and DOJ in prominent lawsuits against Amazon and Google. They are accused of leveraging market power to manipulate ranking algorithms in favor of their own interests. Amazon is accused of using monopoly power in ecommerce markets to distort product discovery in favor of sellers utilizing Amazon distribution or advertising services. For instance, the FTC complaint against Amazon claims that sellers using Amazon advertising services were 45 times more likely to have their products shown in search results (Complaint, FTC). Similarly, Google is accused of using its market power to manipulate advertising auctions on the Google ad exchange to favor bids of advertisers using the Google Ad service (Complaint, United States).

Assessment of these market power claims is an empirical question. While you can look at the HHI of a market to evaluate market concentration, traditional methods to assess the consequences of market power rely on price markups. Price markups are endogenous choices made by firms that depend on their market power and directly relate to consumer harm. However, ranking algorithms lack tangible prices, so traditional methods to evaluate market power are inadequate for evaluating the consumer harm caused by the market power of a platform offering search as a service. Therefore, this paper develops a novel framework to evaluate market power with respect to search algorithms. Like a price markup, the framework specifically relies on an endogenous decision made about the platform's algorithm in response to the level of competition it faces.

I develop a model that can estimate the degree to which a platform trades off between the ranking incentives of the platform and the ranking preferences of users. This model reduces to a decision to set the distance between these two ranking alternatives and reveals the extent to which the platform faces competitive pressures within its market. I show that estimating this choice is analogous to estimating a nash bargaining problem between the user and the platform.

Moreover, the model is generalizable across many platform functions like search engines, social media feeds, or ecommerce search results. Estimation and identification of the model does require data from two stages of the user experience: consideration data and action data. While this is more data than demand estimation requires, the two types of data are not uncommon in research (consideration data is often observed with Clickstream data) and would be easily accessible to any government auditing a platform.

Next, I apply this model to a prominent Chinese ecommerce platform: JD.com. Leveraging data on consumer clicks and purchases I estimate the search process as a bargaining problem between optimal consumer search and optimal platform search. This produces an estimate of the relative influence of platform incentives on search outcomes and the profit incentives of the platform. The findings reveal that over 97% of click outcomes are driven by the platform's preferences and only 3% come from the consumer preferences.

Then, I use my estimates to simulate counterfactual search and purchase processes to assess the impact of the misalignment of incentives on both consumers (shoppers) and sellers (product manufacturers). Counterfactual analysis reveals that a platform with incentives perfectly aligned to consumers would cause a 25% increase in consumer utility per shopper and 2% increase in seller sales per shopper. After incorporating the impact on number of platform participants the total increase in consumer surplus is over 130% and an over 85% increase in seller revenue (equivalent to increases of 25 million and 120 million yuan per year). These are accompanied by a 62% drop in platform profits.

Using additional data about distribution services and first party products I assess the impact of potential policies that could limit the platform's ability to preference their own products. Treating all products as third products results in almost 10% improvements per consumer for consumers and sellers and a 16% decrease in platform profit per consumer. However, the separation of ecommerce and distribution business units would have negligible impact on outcomes.

Additionally, the business structure of JD.com allows me to estimate the platform power in two different settings: traditional ecommerce and social commerce. Social commerce occurs when ecommerce platforms and social media platforms partner to allow ecommerce search and purchases to run directly on the social media platform. It is a growing industry with almost 1 trillion dollars in sales worldwide in 2023 and is expected to grow to over 6 trillion dollars globally by 2030 (Statista). However, it was not a main feature of US ecommerce until recently. In the fall of 2023 Amazon announced partnerships with Meta and Snap to operate social commerce platforms within Instagram and Snapchat. "Customers in the U.S. will see real-time pricing, Prime eligibility, delivery estimates, and product details on select Amazon product ads in Snapchat as part of the new experience" (Vanian, 2023).

The connection between these two ecosystems raises further questions about the competition for search and product discovery. However, this analysis suggests regulators should not have additional concerns about the competitive impact of these partnerships on the underlying algorithms. Comparison to the social commerce data reveals that the platform has roughly equal power to exert its preferences in the outcome of social search: 95% of the clicks can be explained by platform incentives when searching with social commerce. In addition, the incentives of the platform within social commerce appear more closely aligned with consumers as simulations of traditional ecommerce outcomes using social commerce platform preferences slightly improve the outcomes per consumer.

The paper proceeds as follows. Section 2 examines the most closely related literature. Sections 3 and 4 provide background information on the fundamental properties of rankings algorithms and the model to estimate the ranking algorithms. Section 5 introduces the relevant institutional details about JD.com and the data used in the subsequent analysis. Section 6 provides information about the estimation process and estimation results. And, Section 7 details counterfactual market simulations to understand the impact of the observed platform search power.

2 Related Literature

This paper is most closely related to a growing literature on the relationship between consumer search and platform algorithms. Reimers and Waldfogel (2023) is the closest paper as they develop a test for whether a platform biases their rankings in the awareness stage. Lee and Mussolf (2021) look at platform dynamics and the implications for seller entry/exit decisions with regards to the self-preferencing in the Amazon Buy Box algorithm. Hagiu and Jullien (2014) and Acemoglu, et al (2023) approach this literature from a theoretical perspective to understand conditions where users may benefit from specific classes of algorithms. Their work provides foundational insights into the theoretical underpinnings of competition and search diversion. This paper develops a framework to empirically analyze these same issues inside and outside of ecommerce markets and extend the empirical analysis to incorporate a platform conduct decision.

A second literature, closely related to the first, is platform self-preferencing. Empirical studies by Chen and Tsai (2019), Aguiar with Waldfogel (2021), and Raval (2023) focus on the phenomenon of platforms giving their own products preferential visibility on their platforms. They investigate different methods ecommerce platforms use to steer user choices toward options owned by the platform. On the theoretical end, Bourreau and Gaudin (2021) and Bar-Isaac and Shelegia (2023) analyze incentives for platforms to steer with fees, ad auctions, and algorithms. This paper empirically examines the entire search process together and empirically looks at the impact of a platform's power to steer based on ads or fees, but does not explicitly investigate the methods deployed by the platform to steer customers.

The next literature this paper touches on is limited consideration in consumer demand. Goeree (2008), Wildenbeest (2011), and De Los Santos et al. (2018) investigate the impact of limited consideration in demand estimation and pricing decisions. Lam (2021) develops a model of consumer search based on the cost of scrolling and proposes alternative product rankings to improve consumer welfare. Dinerstein et al (2018) also investigates the power of the platform algorithms to influence prices and consumer choices with limited consideration. Similarly, I estimate the impact of platform algorithms on consumer formed consideration sets and shopping outcomes.

Finally, while these are not the main contributions, this paper makes empirical contributions to the literatures on price discrimination and the value of consumer data. Works by Shiller (2021 and 2020), Dubé and Misra (2019), Hupperich et al. (2018), Hitsch and Misra (2018), Reimers and Xie (2017), and Iordanou and Sirivianos (2017) examine empirical examples of price discrimination. I document clear price discrimination and use this as variation to estimate platform preferences. Other works by Sun et al. (2022), Shiller et al. (2018), and Morath and Münster (2018) explore the intrinsic value of consumer data and its correlation to price discrimination. This paper presents an introduction to the role data plays on platform search power and makes observations about the role market power plays with respect to potential incentives for consumers and platforms to want shared data.

3 Industry Background

The search and discovery process of digital platforms is designed to match users that arrive at a platform to one of potentially billions of options on the platform. Throughout the tech industry, this process is designed and managed via product funnels (see Figures 1 and 2 for examples) that delineate the journey of users[1]. The journey culminates in a final stage where the consumer takes an action that hinges upon their preferences. Across platforms that provide search as a service the three crucial stages are awareness, consideration, and consumer action. For example, for true search platforms (Google or Bing) the consumer action may be a click of a link while the awareness and consideration stages may be the same (any links they were exposed to, impressions); for ecommerce search the consumer action may be a product purchase decision, the consideration stage is clicking on potential purchases, and the awareness stage and is any product they saw a link for; and, for social media the consumer action may be some sort of post engagement, consideration is pausing on a post for a period of time (active impression), and the awareness stage is an impression. While the final stage is a consumer action, the choices of the platform in previous stages alter the state of the world for the consumer's final choice.

Across all these domains, platforms employ sophisticated ranking algorithms that shape the selection of content in the awareness stage. These dictate the display of advertisements, products in e-commerce, tweets on social media, search engine results, etc. A platform may start with billions of potential content options and it needs to curate these options down to

[1] See the Five Day Startup and Luxafor for more details.

Figure 1: Instagram Product Funnel Example

Figure 2: Amazon Product Funnel Example

a handful of potential choices to present to the user. Although the underlying technology driving these algorithms are guarded as proprietary secrets, we do know the fundamental principles of many advertising ranking algorithms (Wernerfelt et al, 2023 and Tadelis, 2023) and the twitter feed ranking algorithm (Twitter). Understanding the basics of these two ranking systems will help inform the model presented in Section 4.

For advertising, advertisers supply bids for their ads and the platform combines these with estimates of the probability of the desired consumer action (some ads may want a click while others want a product purchase) and a platform generated quality score to create ad specific values. Then, the top values are selected for the user to see (the awareness stage). Thus, ad rankings can be summarized by the ranking of values of the form in Equation 1 where b is the bid, Pr is the probability of the action in the final stage of the product funnel, and q is a platform defined quality score for each advertiser.

$$V_i = b_i \; Pr_i + q_i \tag{1}$$

Notice that the bids times probability represents platform expected revenue and the quality score represents a tool for the platform to potentially favor certain advertisers. This may be for retention reasons or potentially to favor advertisers participating in another line of the platform's business.[2]

Similarly, Twitter calculates a ranking score that is a combination of the probability of ten different actions they care about. Then, these probabilities are combined with heuristic filters to decide what shows up in a twitter feed. Filters include reducing the frequency of tweets from the same author or ensuring there is balance between people you follow and other authors. Within these filters the algorithms favor accounts that post consistently, tweets containing videos, and tweets that are part of replies to other threads, among many other heuristics (Twitter). Like the role of the bids and quality scores in ad ranking these

[2] To the extent that advertising plays a role in consumer discovery the bid distorts the advertising rankings from the best consumer rankings.

heuristics serve as means to aid long term retention and increase monetizability of a user's feed, but may depart from the purely action based ranking.

Both ranking processes described above are just the final stage of the ranking algorithm. It is computationally costly to estimate the probability of user actions. As a result, platforms employ a series of simpler ranking algorithms that are meant to mimic this process and reduce the number of items that need a full probability calculation. Effectively, these stages reduce the amount of time and computer resources necessary to create a user's feed, but they also introduce noise and randomness into the platform's ultimate ranking.[3]

In summary, a platform that provides search and discovery as part of its service guides the user from platform arrival to a user action by making them aware of a set of options and providing additional information on this set of options. This facilitates the consideration of a smaller subset of products by the consumer before a final consumer action. The platform chooses the awareness set, information, and arrangement to guide the process before the user takes over. These choices are made by algorithms designed to optimize overall long-term platform profit, which may not fully align with the incentives of the consumer that simply wants to optimize for the short term consumer action.

4 Modeling Framework

4.1 General Model

Based on the industry background, I will generalize the complete consumer search process to just two stages. These are the two stages with consumer choices: consideration and action. In stage 1, all potential options are filtered down to a set of choices that will be considered by the user (this combines the awareness stage and consideration stage of the product funnel into one stage). In stage 2, the consumer chooses their action. In other words, first all options are filtered to a set of considered options and then the relevant consumer action is

[3] In some two-sided markets there is even a desired level of randomness (Bai et al., 2021).

taken over these options: purchase a product, click a link, watch a video, engage with a post, leave the platform without taking any action, etc.

I will treat stage 2 like a typical discrete choice problem conditional on the options following the filtering process. That is, for each choice, j, in the consideration stage, user i chooses the choice which maximizes its utility:

$$\max_{j \in c_i} u_{ij}(X_i, D_i) + \epsilon_{ij} \tag{2}$$

where consumers are characterized by a vector of characteristics D, products are characterized by a vector of characteristics X, ϵ is an error term that is distributed extreme value type 1, and c represents the result of the consideration stage (stage 1).

I will characterize the consideration stage by the filter $\Gamma()$ which maps a vector of probabilities, Pr, into a new vector of probabilities, Pr', such that each new probability is at least as small as the original corresponding probability. That is, the output for a filter given an input of a vector of ones corresponds to the probability that each option is considered in stage 1, and the sum of these probabilities is the expected number of options in the consideration stage.

If this process was controlled entirely by the consumer, the process could be characterized by the consumer optimal filter, $\Gamma_I()$. Likewise, if the process was controlled entirely by the platform and the platform solely desired to maximize the profits from the arrived consumer, the process could be characterized by the platform optimal filter, $\Gamma_P()$. In reality, the process is characterized by a platform filter, followed by the consumer's filter (the awareness and consideration stages):

$$\Gamma() = \Gamma_I(\Gamma_{P'}()) \tag{3}$$

Proposition 1: If the platform knows the consumer's optimal filter and both filters are surjective, then the platform can choose $\Gamma_{P'}()$ and Z such that any equation 4 holds for any filter, where 1 represents an input vector of ones for all products.

$$\Gamma(1) = \Gamma_I(\Gamma_{P'}(Z)) \tag{4}$$

An implication is that in a setting where the choice of filter does not impact the number of platform users, the platform would choose the arrangement and details of the awareness set such that the consumer will consider the options with the same distribution of probabilities as the platform optimal filter. If we define search competition as the elasticity of platform demand for search quality (where quality is defined as the distance between the consumer optimal filter and the deployed filter), then the greater the search competition a platform faces the more incentive it has to offer a search algorithm similar to the consumer optimal search algorithm.[4]

Notice that if Pr_I is the vector of probabilities resulting from the consumer optimal filter and Pr_P is the vector of probabilities resulting from the platform optimal filter then any option, j, probability can be written as $\nu_j Pr_{P_j} + (1 - \nu_j) Pr_{I_j}$. This leads directly to proposition 2.

Proposition 2: If platforms preferences are defined such that they prefer any filter where the sum of $(1 - \nu)^2$ *is the smallest (usual distance metric), and users prefer any filter where the sum of* ν^2 *squared is smallest, then the platform will always choose a filter that can be defined as*

$$\nu\Gamma_P() + (1 - \nu)\Gamma_I() \tag{5}$$

Here it becomes obvious that without any threat of competition for users the platform sets ν equal to 1. The greater the competition for users is over the search algorithms the smaller ν will be. Thus, ν can be interpreted as the "platform search power" parameter with respect to consumers. Intuitively, this is analogous to the solution to the filter outcome if we represented the choice of filter as a Nash Bargaining problem over the two optimal filters.

[4]This is the result found in Hagiu (2014) where they find that the greater the elasticity of participation with respect to search diversion the less search diversion occurs.

4.2 Potential Model Applications

This framework requires data from multiple stages of the product funnel. Since the filters represent the entire search process until the final consumer action stage you need data on the considered options and the user actions conditional on consideration. The data could take the form of link clicks given all links on a page, social media engagement given an impression lasting a certain amount of time (active impression), or purchases given product clicks.

Fortunately, in some settings these data are available in the form of clickstream and purchase data. Even in the worst case scenario, all of this data is extensively logged internally by platforms and could be requested by the government in potential lawsuits or for compliance oversight studies like those described in the Digital Services Act (European Commission).[5]

By parameterizing the filter process it is possible to estimate a structural model of the search process and recover the platform power parameter as well as consumer and platform incentives. For instance, the literature on ecommerce search sometimes represents product search process as a choice from a hypergeometric distribution. In this case, the weights of the distribution are defined by the consumer and platform preferences, respectively. First use the conditional action stage to recover consumer preferences over options. Next, assume that any deviations in consideration probability from a distribution formed only by consumer preferences must be the result of platform power and platform incentives. With this assumption and exogenous consumer demand shifters like consumer type or in the case of ecommerce, exogenous price changes, the platform incentives and platform power parameter can be separately identified.[6]

The process can be summarized into the following steps:

1. Estimate demand for the desired action, conditional on the consideration data to the consumer preferences

[5] Under the digital services act large online search engines would be subject to yearly independent audits to assess compliance of legislation. These audits could potentially apply the models described in this paper to assess market power and compliance with any legislation designed to improve market conditions.

[6] Additional details on identification of an application to ecommerce are provided in the estimation section.

2. Parameterize the click process as a linear combination of a function of consumer preferences and function of platform profits

3. Use exogenous variation shifts in consumer preferences to identify both the platform search power parameter and any unobserved portions of platform profits

5 Application: JD.com

5.1 JD.com

I will apply the model to JD.com (henceforth 'JD') and estimate the platform search power of an ecommerce platform. JD operates a traditional ecommerce platform and an integrated social commerce channel on WeChat (a social media platform). Thus, I will also investigate any potential differences in platform search power between traditional ecommerce and social commerce. Critically, these two channels only differ in their access method, so any differences in search power can be interpreted as an impact from the social commerce setting.

JD is China's largest retailer with over 580 million active users as of 2023 (JD.com). It has one large competitor in Alibaba and is known for having the most advanced distribution network in the world.

JD's ecommerce platform is primarily accessed through mobile phones. On the mobile phone, shoppers have 3 options: use the direct JD app (app in Figure 3), access JD through the mobile web browser (mobile in Figure 3), and access JD through a social media store within the social media app WeChat (wechat in Figure 3). Each of these three access points grants users access to the same set of products (see Figure 3 for details on the breakdown of channel access). However, the full shopping experience, like checkout process or information displayed, may be unique to each channel.

WeChat is China's most popular social media app. In 2014, WeChat's parent company,

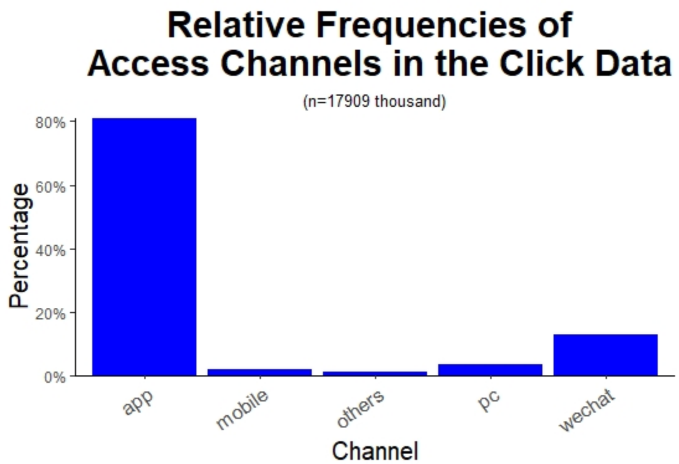

Figure 3: Channel Frequency

Tencent, bought a 15% stake in JD and gave JD exclusive access to Tencent's social media data. In 2015, the two companies together launched the Jingteng Plan to combine their datasets and offer targeted advertising tools for retailers on WeChat. Crucially, this implies any advertising ranking models that impact the consideration set are using the same information regardless of channel.

The social marketplace within WeChat can be accessed in two ways. A user can click a link taking them to a product within the JD social commerce store or a user can search directly for a 'mini program' that takes them to the JD social commerce store. Links can come in the form of advertisements, ad posts, or from friends that send you a link to a specific product.

Finally, JD sells three types of goods to consumers: first party products, third party products shipped through JD's distribution network, and third party products shipped through a third party service. Third party products are products made and sold by outside sellers, but some use JD shipping. JD earns a commission off of all third party sales and an additional commission for any sale using the distribution channel. First party products can be products made by JD or products made by an outside seller and sold by JD. In these cases, JD.com owns the entire sale experience from advertising to pricing, to storage, to shipping.

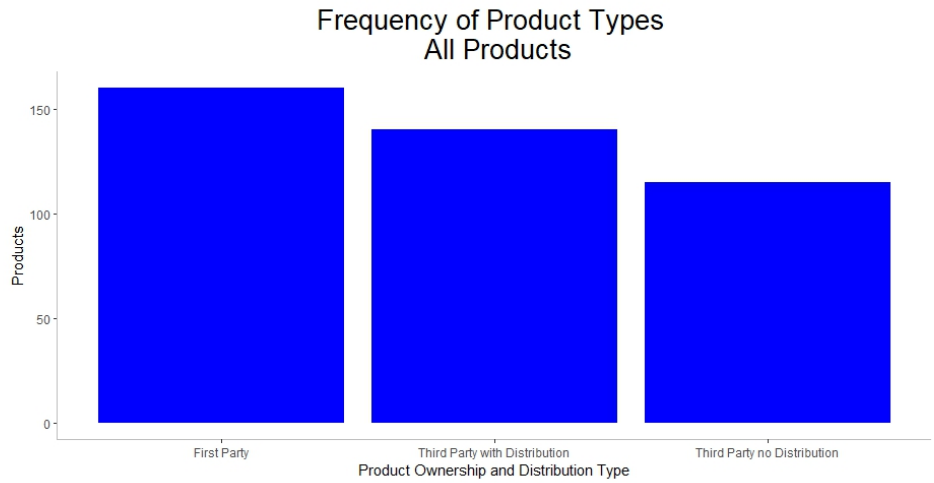

Figure 4: Product Types

5.2 Data Summary

I will rely on data from the Manufacturing and Service Operations Management 2020 Data Challenge (see Shen et al., 2020, for a detailed description of the data). This data tracks over 2.5 million shoppers in March 2018 that use JD. The data produces a 'complete' search experience for each of the 2.5 million shoppers that clicked on any products within a single product market (an example of a 'complete' search experience is shown in Table 1). The product market and all user information is anonymous, but the product market is described as a rather generic product with two differentiating attributes that are observed in the data.

The data includes information about which products are clicked on (a product must be clicked on to be purchased), user information, product details, and the platform shopping channel. I will limit the analysis to the two main shopping channels: WeChat and App. Although the products offered on the channels are the same, the shopper preferences and the platform's ability to advertise may both differ which could impact the level of platform search power or platform preference weights. For instance, the exclusive agreement between JD and WeChat may make shoppers that prefer social commerce more reliant on JD and increase the platform search power through WeChat. As a result, estimation of both the demand and search models (described in Section 6) are separated for each platform shopping channel.

	education	age	married	gender	purch.power	customer.time	spend level
Min.	1.00	1.00	1.00	1.00	1.00	0.00	1.00
1st Qu.	3.00	2.00	1.00	1.00	2.00	8.00	1.00
Median	3.00	3.00	2.00	2.00	2.00	24.00	2.00
Mean	2.88	3.02	1.51	1.74	2.30	30.24	2.34
3rd Qu.	3.00	4.00	2.00	2.00	3.00	46.00	3.00
Max.	4.00	5.00	2.00	2.00	5.00	171.00	4.00

Table 1: Characteristics of Users Making Purchases

The user data includes variables corresponding to user demographics: age, education, marital status, gender, and purchasing power.[7] However, JD does not have access to the actual customer demographics. Instead they use the customer shopping habits along with data from WeChat and machine learning algorithms to predict each customer's demographic information. For roughly 20% of users these predictions are not accurate enough to produce a result and they are categorized as 'unidentified.' The user demographic predictions can be combined with known user information like user level and JD membership status to create user types.[8] I will define a type as a unique vector of user demographic characteristics. This creates over 6,000 types in the dataset. Table 2 displays summary statistics about some of the user characteristics.

Figures 5 and 6 suggest that these types are exactly the relevant variation that defines platform treatment of users. We see that the prices offered to any user at a given time may differ, but within a type the prices offered are relatively consistent. Based on this information the prices of products during the shopping experience are estimated as the daily median purchase price for the given customer type. This accounts for 86% of the intraday price variation and $\geq$ 99% of the interday price variation seen in purchase prices.

To truly model the customer search experience I filter the data to remove any products

[7]Purchase power is interpreted in this literature as a mix of income and price sensitivity.

[8]User level is defined in the dataset as historical spending on the platform and is just quantified in terms of the amount of dollars a user spends.

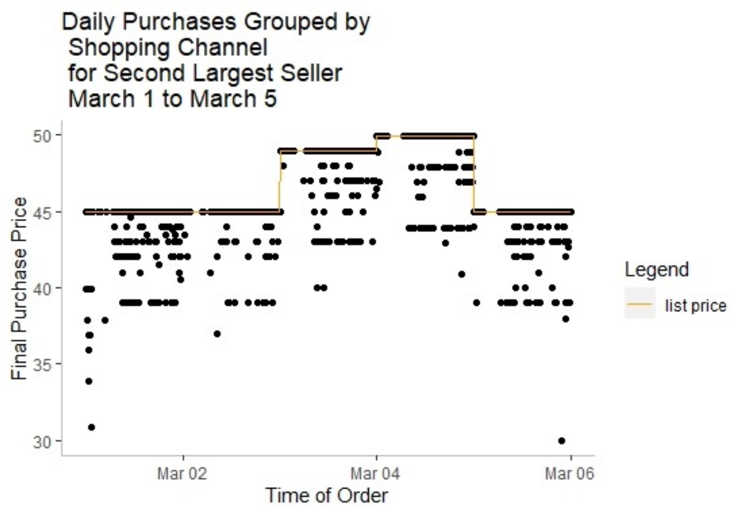

Figure 5: Purchase Prices for ALL Consumer Types

Note: List price represents the price the literature often uses as the selling price of this product. It is estimated as a moving mode.

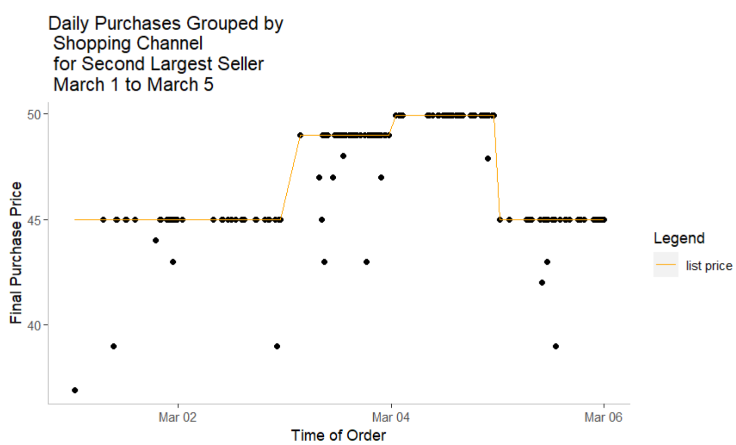

Figure 6: Purchase Prices for Single Consumer Type

Note: This graph is just the purchases that correspond to a single vector of demographic information (user type). I used the most frequent user type to illustrate that the estimated list price is just the price for the most common type of consumer to purchase this product.

purchased as part of a bundle, with a quantity discount, or received as a free gift. Furthermore, I restrict the analysis to only the top 202 products sold as these all have sales ≥ 150 which corresponds to roughly 5 sales per day.[9] Figure 7 breaks down the types of these 202

[9] One additional product meets this threshold, but is dropped because there are observations of purchases without clicks even though the data provider says this is impossible. This only impacts a single product, so it is removed from analysis.

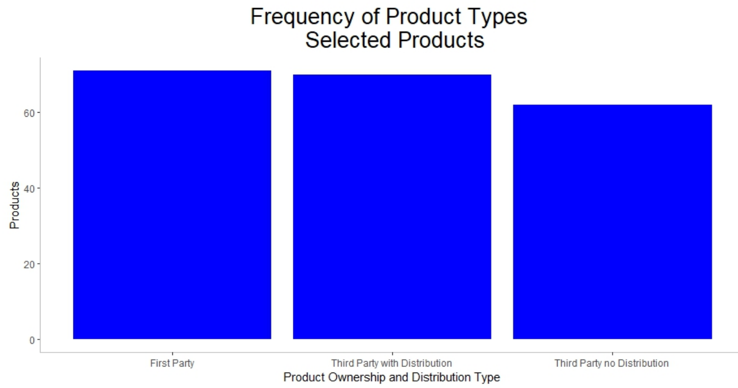

Figure 7: Product Types

products and shows that we have a relatively even split that is consistent with the distribution of product types of the entire sample found in Figure 4. Finally, I remove any shoppers that do not click on more than 1 of these products as I want to understand the behaviors of buyers that engage in search. That leaves me with 105,536 buyers out of 587,542 shoppers on the App channel and 18,533 buyers out of 106,488 shoppers via WeChat.[10]

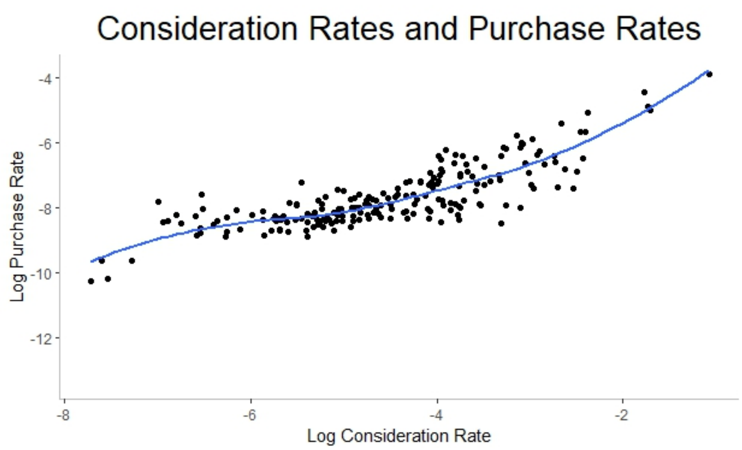

Figure 8: Consideration Rates and Overall Purchase Rates

Figures 8 and 9 summarize the relationship between consideration and purchase rate. Products that are considered more often are also purchased more often. However, the products that are clicked more often are purchased less often conditional on being clicked. This suggests that more than just user preferences drive consideration probabilities because the

[10]These purchase rates are extremely close to the overall dataset purchase rate of 20.6%, with the difference likely coming from dropping gift orders.

Figure 9: Consideration Rates and Purchases Conditional on Consideration

products users are considering more often are not the ones they most often want to buy after they have considered some products. Furthermore, Figure 10 demonstrates a positive correlation between mean price and consideration probability. A simple linear regression (see Table 3) of consideration probability on price and product party shows that first party products are more likely to be considered. In summary, product characteristics that are likely correlated with platform revenue appear predictive of consideration.

Figure 10: Consideration Rates and Prices

	Model 1	Model 2
Intercept	0.05^{***}	0.05^{***}
	(0.01)	(0.01)
3rd Party	-0.02^{***}	-0.02^{***}
	(0.01)	(0.01)
JD Shipping	-0.00	-0.00
	(0.01)	(0.01)
Mean Price	0.00^{**}	0.00^{**}
	(0.00)	(0.00)
Purchase Rate Conditional on Click		-0.05
		(0.04)
R^2	0.19	0.19
Adj. R^2	0.18	0.18
Num. obs.	202	202

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 2: Consideration Rate Regressions

6 Search Model Estimation

The overall goal of this demonstration is to estimate a model that identifies the platform search power and do this in a way that we can estimate counterfactual outcomes for different levels of platform search power or different profit incentives for the platform. This requires estimation of a structural model of both consumer search and purchase decisions so we can simulate outcomes with different search processes and understand the total impact of changes to search/consumer consideration.

Thus, the structural model assumes that consumers make their purchase decisions in the same two stages described in section 4. First, the platform chooses a level of visibility for each product leading the consumer to form a consideration set. In stage 2, the consumer observes information about each product in the consideration set. This additional information leads the consumer to decide in stage 2 which product they feel gives them the best utility. If this product has more utility than the outside option, then the consumer purchases this product. If the outside option has the largest utility, then the customer will not make a purchase.

I will describe the procedures used to estimate both stages below (these follow the three steps listed at the end of section 4) and then estimate each stage separately for shoppers that search through the App and shoppers that search through WeChat.

6.1 Stage 1 Model Parameterization

The recommendation algorithms governing the formation of the consideration set in stage 1 are unknown. As a result, I will follow the description in section 4 and the literature (see Bai et al. 2020, and Dinerstein et al. 2018) to make simplifying assumptions that abstract away from the actual permutations of product rankings, buy boxes, and similarity recommendations. Instead, I will assume the platform exerts a visibility influence (like what page to display results, how often to show an ad, or what product to put in the buy box). To reach the desired platform outcome, the platform will adjust visibility given the choices they expect consumers will make following the recommendation rankings. These visibility parameters will be set to achieve the same outcome as a linear combination of the user optimal visibility weights and the platform optimal visibility weights.

From the perspective of the users the optimal consideration probability for product j and user i would be the result of a draw from a hypergeometric distribution with weights corresponding to the probability of purchasing product j, multiplied by the number of draws, K_i.[11]

$$R_{ij} = K_i \frac{(Pr_{ij})^{\lambda}}{\sum_{j=1}^{J}(Pr_{ij})^{\lambda}} \tag{6}$$

Similarly, the weights for the platform will be based on expected profit: $Pr_{ij} * p_{ij} * v_j$. Here v_j acts as a product specific term that increases visibility for all consumer types. A possible interpretation of v is the relative profitability of product j as compared to product one because I will set v_1 equal to 1 since V will only be identified up to relative ratios. The profits could vary based on shipping distribution, product party, and ad spending which are

[11] For simplicity, this is modeled as if there are choices with replacement, which Bai et al (2020) found does not influence the estimation. The model also assumes the number of clicks is not a result of the quality of the algorithms.

all features that are constant across consumers.[12]

Combining the two sides of the consideration model results in the probability that product j is considered by user i, where user i considers K_i products:

$$R_{ij} = K_i(\nu \frac{(Pr_{ij} p_{ij} v_j)^{\lambda_1}}{\sum_{j=1}^{J} (Pr_{ij} p_{ij} v_j)^{\lambda_1}} + (1-\nu) \frac{(Pr_{ij})^{\lambda_2}}{\sum_{j=1}^{J} (Pr_{ij})^{\lambda_2}}) \tag{7}$$

Reimers and Waldfogel (2023) define the user optimal weight as a point on the frontier between the preferences of consumers and sellers (this reflects the nature that ecommerce platforms are two sided markets where the users are either consumers or sellers). In this setting the user weight could be represented by Pr_{ij} and the seller weight could be represented by $Pr_{ij} * p_{ij}$, where Pr_{ij} is the probability a user would purchase the product in a consideration set with just the outside option. This mimics weights based on utility for the users (with all positive values) and weights based on expected revenue for the sellers. While the sellers are not explicitly modeled in equation 7, their preferences represent the same preferences as the platform if the product weights are all uniform. Thus, platform profit incentives also capture the long term profit bargaining power between the platform and sellers and the user frontier would be any point where V is a vector of ones. While a search power parameter with respect to sellers is not separately estimated like between the platform and users, the simulations in Section 7 evaluate the impact of the platform's power to deviate from uniform product weights.

6.2 Stage 2 Model Parameterization

In stage 2, the shopper chooses which product, if any, to purchase from their consideration set (the outcome of stage 1). Now, the shopper observes any attributes unobservable in the data and draws a random error term that is distributed type 1 extreme value. They then

[12] This requires a reasonable assumption that the platform is aiding the advertiser bids to adjust for increases in prices. The ad auctions are designed to induce optimal bids of the product markup, so a platform would see a relatively constant revenue percentage from ads as well.

choose the product with the largest utility, u_{ij}, where utility is a function of the product attributes, x_j, (including whether the product is first or third party), the individual price, p_{ij} , consumer segment demographics, d_i , and a product fixed effect for unobserved product quality, ξ_j . Consumers chooses the product to satisfy equation 8.

$$\max_{j \in c_i} u_{ij}(x_j, p_{ij}, d_i, \xi_j) + \epsilon_{ij} = \max_{j \in c_i} \delta_j + \mu_{ij} + \xi_j + \epsilon_{ij} \tag{8}$$

δ_j is a constant average product utility across all consumers, μ_{ij} is a consumer specific portion of utility based on consumer demographic interactions with product characteristics and individual price discounts, ϵ_{ij} is a user and product specific error term that is distributed type 1 extreme value, and c_i is the consideration set outcome for consumer i from stage 1. The outside option is considered not purchasing one of these 202 products from JD and has a mean utility normalized to 0.

6.3 Stage 2 Estimation Procedure

Following the procedure described in section 4, after parameterizing the entire model I need to first estimate the preference parameters from stage 2. The preference parameters estimated in stage 2 will be used to estimate the first stage, so I will begin by describing the estimation of the second stage conditional on the observed results of the first stage. I will largely follow Berry, Levinsohn, and Pakes (1995, BLP) and use GMM estimation with a share inversion to estimate the discrete choice mixed logit model defined in equations 9 to 12. Each individual i chooses the option j that is found in their consideration set c_i to maximize their utility. Utility of each product is made up of a part that is constant across users and a part that varies with users. In the portion that varies with individuals, D_i represents the vector of all user demographics that are found in the data and d_i is the specific demographic information for price sensitivity (purchase power). p_{ij} is the individual price a shopper faces after price discrimination, while $\overline{p_j}$ is the portion constant across users and $\tilde{p}_{ij}$ is the individual deviation from $\overline{p_j}$ ($p_{ij} = \overline{p_j} + \tilde{p}_{ij}$).

$$\max_{j \in c_i} u_{ij} \tag{9}$$

$$u_{ij} = \delta_j + \mu_{ij} + \epsilon_j \tag{10}$$

$$\delta_j = X_j\beta - \alpha\overline{p_j} + \xi_j \tag{11}$$

$$\mu_{ij} = X_j\Omega D_i - \alpha\tilde{p}_{ij} - p_{ij}\psi d_i \tag{12}$$

An outside option to not purchase any product is included in each consideration set, so the market shares in market t can be represented by:

$$s_{jt} = \theta_{jt}(\delta_{jt}, C_t; \mu_{ijt}) = \int\int \frac{exp(\delta_{jt} + \mu_{ijt})\mathbb{1}(j \in c_{it})}{1 + \sum_{j=1}^{J} exp(\delta_{jt} + \mu_{ijt})\mathbb{1}(j \in c_{it})} dF(C)dF(D) \tag{13}$$

There are a few additional modifications for the estimation that are described below to overcome issues in the data. The first issue is zero shares. Since I observe price discrimination in the data it would be logical to separate markets by consumer type. However, there are over 6,000 types in the data and this creates a significant number of observed share portions as zeros which are not permitted within the share inversion described in BLP. Following the literature on overcoming zero shares issues (see Quan and Williams, 2018 or Hortaçsu et al, 2023), I will aggregate the data back up to the entire market level and use the observed market level shares as the share constraint for the BLP inversion. The market shares are calculated by simulating over the entire population of observed users in the data and utilizes their observed consideration sets (because the sets are in the data, the simulation of the sets found in Goeree (2008) is unnecessary). Mathematically this just reduces to dropping the subscript t from equation 13.

The second issue is missing demographic data. The consumer demographic types are only known for consumers that make a purchase and not known for consumers who choose the outside option. Fortunately, the total share choosing the outside option is observed in the data. I will overcome this limitation by imputing the implied share of each observed consumers in the entire dataset given the observed purchasers. In other words, for a given set of parameters there is an implied probability that each observed purchaser in the data would not have purchased, s_{i0}. This implies that the share of consumers in the entire dataset with the same consideration set and those demographics is $\frac{\frac{1}{(1-s_{i0})}}{\sum \frac{1}{(1-s_{i0})}}$. Taking the weighted sum of the estimated purchase share for each choice in the consideration set over all purchasers gives us the estimated purchase share for each product and the estimated share of non-purchasers. Thus, aggregate market shares are approximated by:

$$s_j = \sigma_{jt}(\delta_j, C; \mu_{ij}) = \sum_{i=1}^{N} s_{ij} \frac{\frac{1}{1-s_{i0}}}{\sum_{i=1}^{N} \frac{1}{1-s_{i0}}} \tag{14}$$

$$s_{ij} = \frac{exp(\delta_j + \mu_{ij})\mathbb{1}(j \in c_i)}{1 + \sum_{j=1}^{J} exp(\delta_j + \mu_{ij})\mathbb{1}(j \in c_i)} \tag{15}$$

The estimated market shares are used in the BLP inversion. For any guess of the individual specific parameters, the overall market shares are constrained to equal the estimated overall market shares. Then, an aggregate market moment is used along with a set of micromoments are used to calculate the GMM loss. The micromoments are made up of market shares conditional on purchasing for random set of demographic groups and the implied aggregate probability of consideration for each product.[13]

Altogether the algorithm to estimate the mixed logit demand system conditional on consideration set is:[14]

1. Guess parameters for individual deviations in μ term, Θ_2, and calculate each μ_{ij} term

2. Invert the shares to recover the δ_j such that estimated aggregate product shares are

[13] Consideration sets are known for both shoppers that buy and shoppers that do not buy so the actual consideration rates are known.

[14] See Conlin and Gortmaker, 2020 and 2023 for additional details on best practices for computation of these steps.

equal to observed product shares: $\delta_j = \sigma_j^{-1}(s_j; x_j, p_j, \mu_{ij})$

3. Recover the estimated error terms, ξ_j, from the linear product equation, $\delta_j = X_j\beta - \alpha\overline{p_j} + \xi_j$

4. Construct aggregate moments $\epsilon_j \cdot z_j$, $\hat{g}_A$

5. Calculate the conditional product shares for each observed user demographic in the data

6. Estimate the distance loss for each conditional product share, $\hat{g}_m$

7. Calculate the GMM loss by stacking the aggregate product moments and the micro-moments into vector $\hat{g}$ and estimate $t(\hat{g})W\hat{g}$

8. Iterate steps 1 to 5 until GMM loss is minimized

This leaves two more parts of the estimation to discuss: identification of the endogenous price parameter α (note that the ψ parameter is exogenous because individual price deviations are based on individual preferences and not correlated with the unobserved quality) and aggregate moment calculation. I use an instrumental variables approach with the aggregate moment satisfying $E(\xi_j Z = 0)$. I use a modified versions of the BLP and differential IVs (see Gandhi and Houde, 2020 or Conlon and Gortmaker, 2020) as instruments, Z. They are modified to use the expected characteristics of other products in the consideration set conditional on a given product being in a consideration set. I calculate the instruments separately for each observed consideration set and then take the average over all consideration sets that include a given product, for each product, to compute the expected BLP and differential IVs. This creates a first stage regression with strong power, as shown in Table 4. This identification strategy is implemented within the share inversion. After all the individual relevant parameters are guessed (excluding price), a vector of potential δ_js is guessed. This vector is used to get the IV price parameter and then the aggregate market shares are estimated using this price parameter for the entire price. Guesses of δ vectors are repeated based on the contraction described in BLP until the share inversion is complete and the correct price parameter is known for a given guess of individual parameters. The share inversion can be described below:

1. Guess vector δ
2. Using IV and δ, obtain the estimate for $\hat{\alpha}_{IV,\delta}$
3. Using δ and $\hat{\alpha}_{IV,\delta}$ estimate $\hat{s_j}$ for each product and the outside option: $\hat{s}_j = \sigma(\delta; \Theta_2)$
4. Compute $\delta' = log(s) - log(\hat{s})$
5. Update $\delta = \delta'$ until $\delta - \delta'$ meets a convergence threshold

	BLP.and.Differential	Differential.Only
R Squared	0.67	0.55
Adj R Squared	0.63	0.53
F Statistic	17.04	33.21

Table 3: First Stage Regression Power

6.4 Stage 2 Estimation Results

Table 5 displays the price sensitivity demand estimation results for App shoppers and WeChat shoppers. The main detail is the random coefficients associated with purchasing power match the description of each variable with the least sensitive consumers having the least price sensitivity (outside of the highest purchase power for WeChat users). The coefficients themselves are compared to the group of users with an unknown purchase power.

Table 5 also illustrates a difference between traditional app shoppers and those using social commerce. Social commerce searchers tend to be more price sensitive as the mean price sensitivity is almost 50% greater for WeChat shoppers than for App shoppers.

	IV.App.Estimates	IV.WeChat.Estimates
Mean Price Sensitivity	-0.0095	-0.0151
Purchase_Power1	0.0027	-0.0003
Purchase_Power2	0.0024	0.0048
Purchase_Power3	-0.0005	0.0023
Purchase_Power4	-0.0020	0.0012

Table 4: Price Sensitivity Estimates

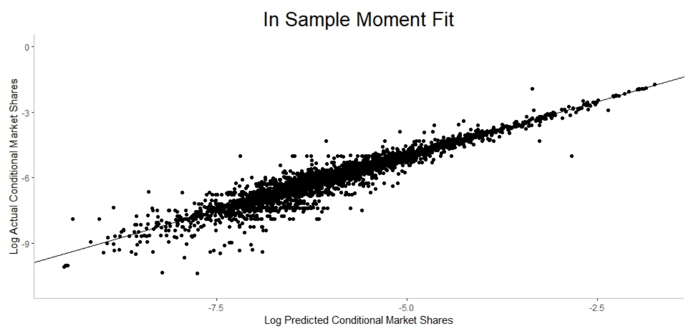

Figure 11: In Sample Moments Fit

Figures 11 to 13 illustrate a comparison of in sample and out of sample moments. The in sample moments are the conditional purchase shares for a random selection of demographics and the 4 purchase power demographics. Additionally, I include the implied proportion of clicks for each product as a set of in sample moments. The out of sample moments include the purchase shares for products conditional on buying for all other demographic dummy variables. We can see the fit is very strong with a pseudo r-squared greater than .95 and the implied proportions of clicks nearly match the observed clicks in the total sample perfectly, as seen in Figure 12.

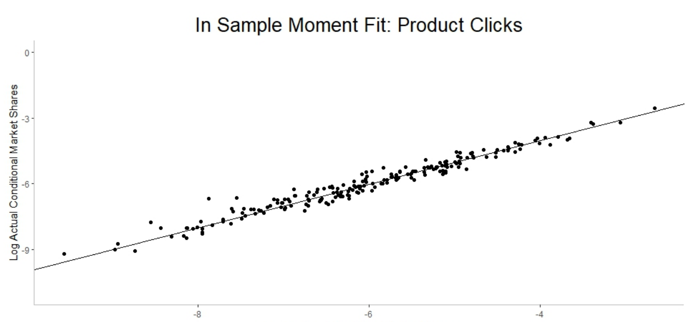

Figure 12: In Sample Moments Fit: Clicks

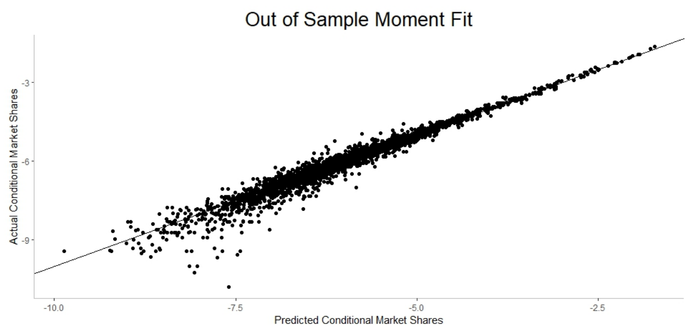

Figure 13: Out of Sample Moments Fit

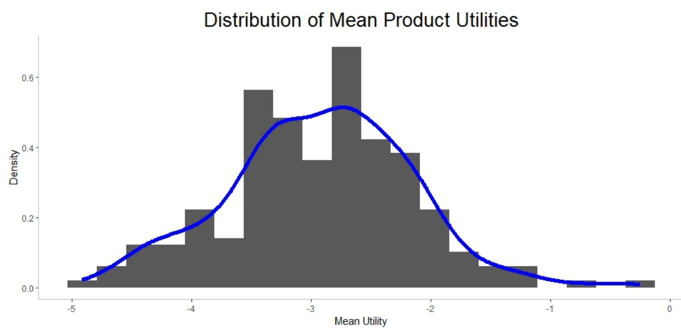

Figure 14: Variation in Utility Across Products

Recall that identification in stage 1 requires variation in utility for a given product across consumers and variation in utility between products. Figures 14 and 15 illustrate these variations in utility relative to the outside option. Figure 14 shows that the mean utility across individuals for each product has substantial variation following a relatively normal distribution that is centered around roughly -3. Figure 15 shows that within products we also see very significant variation due to price changes and heterogeneous consumer tastes. The within product variation is generated by subtracting the mean product utilities from Figure 14 from each observed individual product utility pair (this normalizes everything around 0 for all products).

Finally, I plotted the mean utilities from Figure 16 against the observed proportion of product consideration. The results are consistent with the data summary. Products that are seemingly better in the eyes of the consumers are actually clicked less often than inferior products.

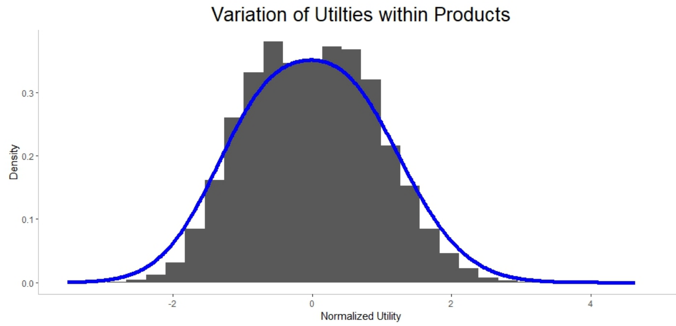

Figure 15: Variation in Utility Within Products

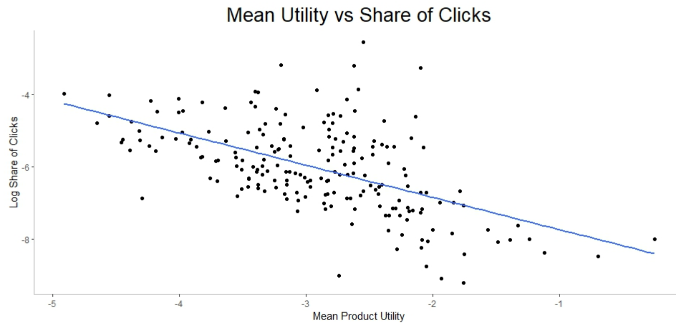

Figure 16: Utility and Consideration Rates

6.5 Stage 1 Estimation Procedure

Using the preference parameters estimated in the Stage 2 estimation we can calculate Pr_{ij}, the probability of consumer i purchasing product j when compared just with the outside option, for each product/individual pair. Plugging these into the Stage 1 estimation model we can estimate the probability of each consumer clicking on any of the products. Summing across different demographics results in estimates for the expected consideration rate conditional on a demographic:

$$E[R_j | i \in D] = \frac{\sum_{i \in D} R_{ij}}{\sum_{i \in D} 1} \tag{16}$$

We can then use these estimates in a GMM to match with the observed conditional consideration rates as moments. There are J+2 parameters to estimate (one visibility parameter will be normalized to 1). With greater than 6,000 consumer types and price changes within each consumer type we have more than enough variation to identify each parameter using a selection of conditional consideration rates.

The visibility parameters, v_j, are identified by mean deviations from the consumer preference implied weights (the consideration rates if we only consider the consumer side of equation 7) that correlate with both variation in Pr_{ij} and p_{ij} for a given product j. In other words, the visibility parameters fit the difference between the overall observed consideration rates and the expected conditional consideration rates if the platform weighed expected revenue from each product equally. Because the visibility parameters are only identifiable up to a scaling factor, the value of the most purchased product is normalized to 1.

The platform search power parameter, ν, is identified by variation in conditional consideration rates. As prices and preferences for different demographic groups change, the consumer and platform sides of equation 7 change at different rates and the search power parameter will be identified by correlations between the changes in consumer/platform implied conditional consideration rates and the observed changes in conditional consideration rates. Finally, the lambda terms (which represent long run optimal randomization in product discovery) are identified by variation in hypergeometric weights (purchase probabilities for consumers and expected weighed revenues for the platform) correlated with variation in observed click probabilities.

I have created a sample of consumers based on the implied number of consumers of each type from stage 2. Then as validation of the consideration model, I split the sample into a training and test set for cross validation. A randomly selected group of 20% of the consumers are placed in the test set. For both sets, I calculate the GMM loss and convert this to a pseudo r-squared value defined as: $1 - \frac{RSS}{TSS}$ where RSS is the GMM loss and TSS is the GMM loss corresponding to using the mean of all the moments for each prediction.

6.6 Stage 1 Estimation Results

Table 6 displays the results of the stage 1 estimation for App users and WeChat users. Most importantly, I find that the search process is almost entirely influenced by the platform's profit incentives with clicks driven 97% by the platform optimal distribution and only 3% by the users. Within the platform incentives, the estimated product profit weights vary considerably from a uniform distribution suggesting the platforms also wield considerable market power over the seller side of the market. We can also see that the lambda terms (which govern the amount of randomness added to their preference rankings) are relatively equal for the consumer and platform sides of the model. Table 6 also summarizes some results found in Table 8 by computing the mean weight placed on first party and third party products (both relative to the top product). Unsurprisingly, the platform favors first party products which is consistent with their decision to take control of this set of products.

	WeChat_Est	WeChat_Est
Platform Search Power	0.973	0.954
Consumer Randomness	0.948	0.969
Platform Randomness	0.976	0.888
First Party Weight	0.586	0.865
Third Party Weight	0.295	0.295

Table 5: Stage 1 Parameter Estimates

While the estimate that 97% of product clicks are driven by platform profit incentives seems large it makes sense given the observations of the demand model. In Figure 16, I showed that there is a negative correlation between the likelihood of purchasing a product and the likelihood of clicking on this product. In the context of the model, this implies there are products that would be some of the likeliest predicted clicks if consumers had market power that were in fact among the least likely products to be clicked on. Since the smallest percentage that the platform optimal click rates can generate on their own is greater than 0%, there is a lower bound on possible platform search power estimates that generate a perfect match to the overall observed click probabilities. This lower bound is around 99% which is in line with the estimate.[15]

Table 7 and Figure 17 report the overall model fit and compare it to relevant restricted

[15] Since the model is overidentified it is not bound to this lower bound, but it does serve as a useful sanity check of the results.

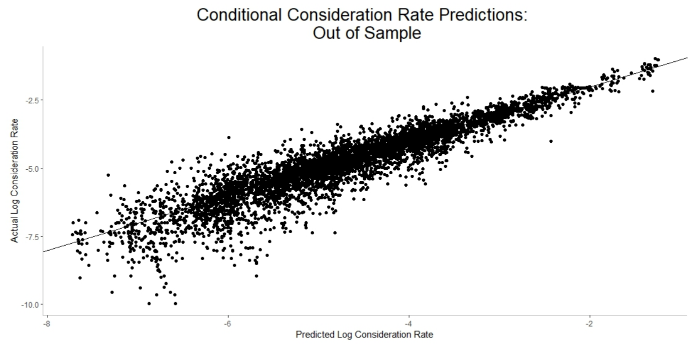

Figure 17: Out of Sample Conditional Click Rate Prediction Fits

models. The first row of Table 7 corresponds to the estimates reported in Table 6 for App users. The second observation represents the results with the parameter for platform search power restricted to 1. The subsequent four rows correspond to a point on the consumer 'frontier' that is referenced by Reimers and Waldfogel. The Nu 0 model represents a model where consumer preferences drive all of the clicks; Uniform W represents the closest point on the frontier to the estimated model and is where the sellers have the same power as the platform in the estimated model, but there are no extra weights placed on any products; Nu 0.5 and Uniform W represents a scenario where the users and sellers are valued equally by the platform and the platform has no market power with respect to either group; and Nu 1 with Uniform W represents a model where expected seller revenue drives all of the clicks. The models corresponding to points on the frontier all have pseudo r-squared values below 0% in comparison to the estimated model off the frontier with a pseudo r-squared over 92%.

	In.Sample.R.Sq	Out.of.Sample.R.Sq
Model Estimate	0.928	0.924
Nu of 1	0.927	0.922
Nu of 0	-0.388	-0.388
Uniform W	-0.155	-0.155
Nu 0.5 and Uniform W	-0.245	-0.246
Nu 1 and Uniform W	-0.151	-0.151

Table 6: Stage 1 Model Fit

Table 8 displays the results of a regression analysis of the product visibility weights. Since the platform only has the incentive to increase visibility of a product if it is a more profitable

	App Model	WeChat Model
Intercept (First Party)	0.67***	0.96***
	(0.11)	(0.15)
Third Party	-0.38***	-0.66***
	(0.09)	(0.12)
First Party Shipping	-0.09	-0.09
	(0.09)	(0.12)
R^2	0.10	0.16
Adj. R^2	0.09	0.15
Num. obs.	201	201

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 7: Linear Model of Platform Profit Weights

product we can interpret the visibility parameters as relative platform profit weights. Consistent with expectations, there is a relationship between the weight and first party or third party product status. However, there was no observed statistically significant relationship between products utilizing JD shipping services and profit incentive weights. For both the App platform and the WeChat platform the third party products have a mean weight of roughly 30% the weight of the most purchased product. For the App, the mean weight of first party products was about 60% of the weight given to the most purchased product, while it was almost 90% of the weight for WeChat.

Differences in platform profit incentives across the two platforms could be driven by changes in the platform search power with respect to sellers or differences in advertising profits. Given the changes were not uniform across the two groups of products, it is unlikely that these differences are driven by changes in search power with respect to sellers. One potential story for the observed differences is that third party sellers do very little advertising on either platform and first party products generally advertise more on WeChat (increasing the incentive to get a sale compared to a non-advertised third party product).

A final validation of both models is shown in Figure 18. Since the purpose of the 2 stage search model is to explain the journey from consumer arrival to purchase decisions, a critical

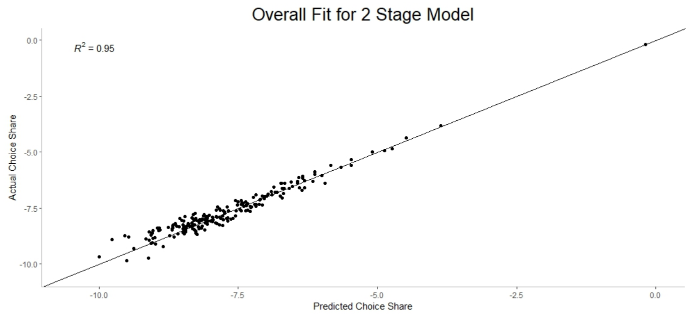

Figure 18: 2 Stage Model Fit

question is how well the two models jointly explain the purchases of consumers. Figure 18 shows that the simulation of the two models together results in predicted overall choice shares very close the actual observed choice shares. The predictions are plotted against the actual shares with the line y equals x. We can see that 95% of the variation in purchase shares are predicted by the models. This joint simulation of these two stages will be used as the baseline model for the counterfactual analysis in Section 7.

7 Counterfactuals

To understand the economic impact of the platform search power of JD I run counterfactual scenarios that compare the purchase outcomes when the search process is governed by different platform power levels. In addition, I explore potential remedies to improve the misaligned incentives between JD and shoppers and JD and sellers.

First, I estimate the baseline model as a comparison point. The baseline model is the same as the one used in Section 6 to illustrate the overall goodness-of-fit of the combined 2 stage model and represents a simulation of the clicks and purchases for every consumer using the estimated consumer type weights from the stage 2 estimation. The first two counterfactual scenarios correspond to two points on the consumer frontier where a platform with no power may choose to favor either consumers or sellers and a third counterfactual that represents a scenario where the platform has half of its current power with respect to both consumers and sellers. The third counterfactual is simulated by reducing the platform consumer search

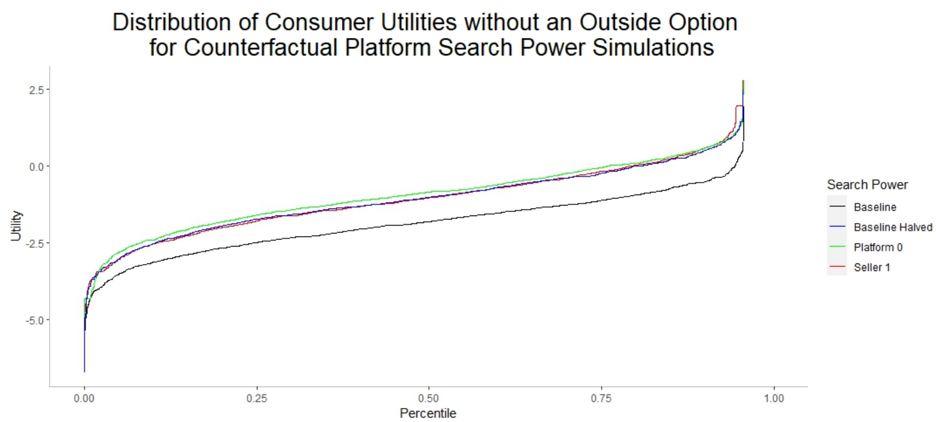

Figure 19: Counterfactual Utility Outcomes

power parameter, ν, by half and also halving the distance between each visibility parameter and 1.

Figures 19 to 22 illustrate the impact of the existing platform power in comparison to these more consumer friendly levels of market power. Figure 19 shows the change in distribution of consumer utilities.[16] Figure 20 shows the change in the distribution of seller revenues. Figure 21 shows the distribution of prices paid by shoppers that purchased an item. And, Figure 22 shows the percentage change in per consumer utility, the percentage change in seller revenues per consumer, the percentage change in relative platform profits per consumer, and the percentage change in seller HHI.[17] Figures 19 to 22 report results on a per user basis as they simulate scenarios keeping the number of users constant.

Unsurprisingly, we can see that the prices paid by consumers are almost completely orderable by FOSD. Consumers pay the most in the baseline, less when sellers have complete control, and the least when consumers have complete control of consideration. For utility, the story is similar. All three counterfactuals with less market power for the platform result in better consumer outcomes throughout the distribution and the scenario where consumers

[16] The utility is measured as if consumers chose the max option not considering the outside option. The outside option was dropped from this counterfactual because results are hard to interpret when consumers are choosing to purchase a product with utility below 0. Graphically this it can appear as though less sales result in greater utility when that is not truly the case.

[17] The platform profit is a normalized figure to represent the estimated profitability weights multiplied by the selling price.

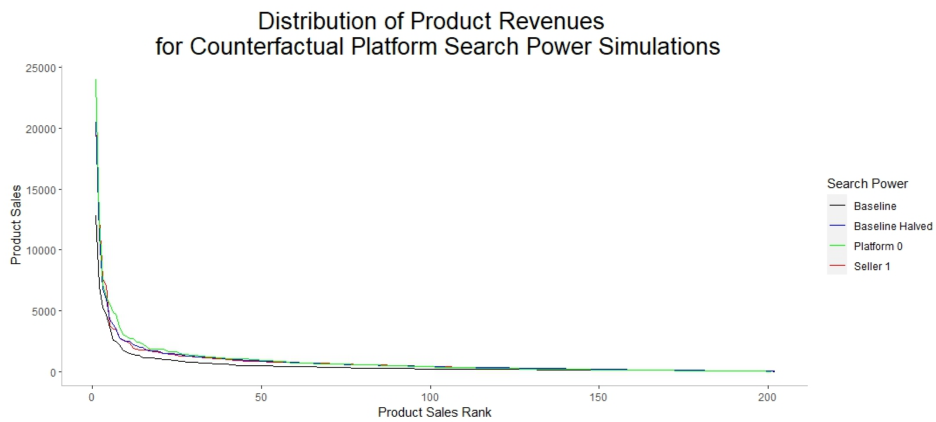

Figure 20: Counterfactual Seller Revenue Outcomes

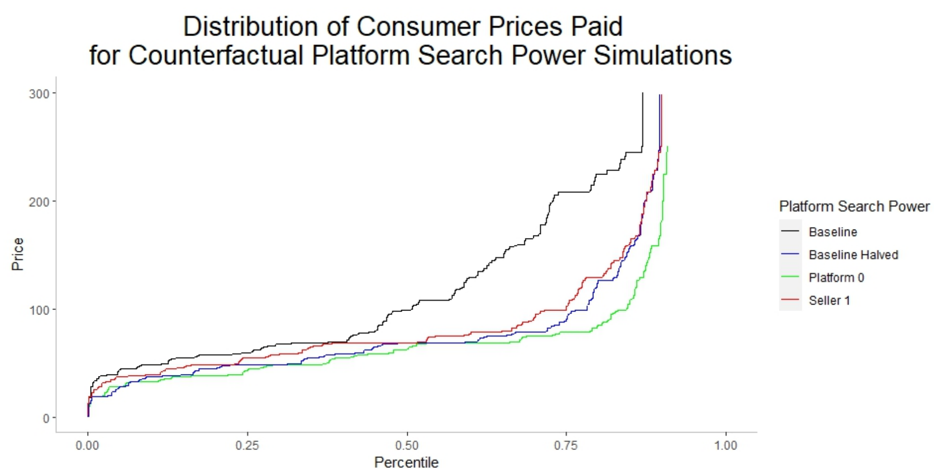

Figure 21: Counterfactual Purchase Price Outcomes

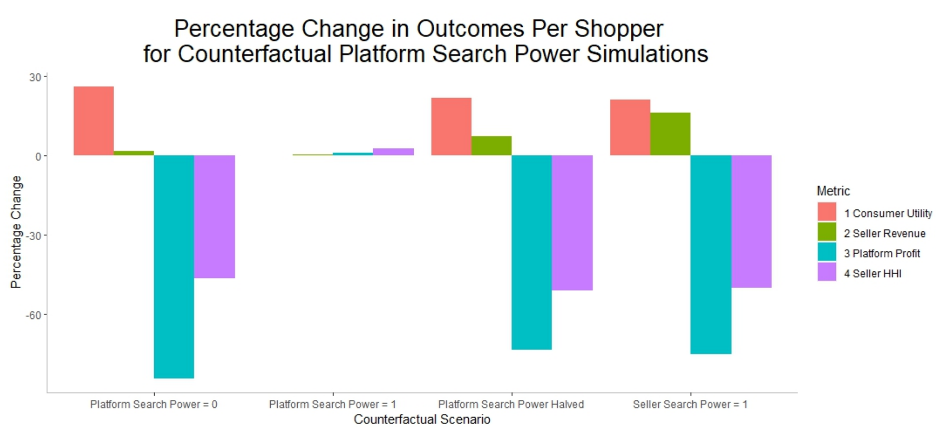

Figure 22: Percentage Changes in Outcomes Per Shopper

have complete market power is the best outcome for almost the every user. For reference, the roughly 25% increase in utility per consumer when consumers have all market power (Figure 22) is equivalent to a 22 yuan increase in consumer surplus per consumer. Interestingly, the scenarios where the platform has half as much consumer and seller market power and the scenario where the sellers have all the market power result in very similar outcomes. In general, the trend seems to be that the greater the platform search power, the worse the quality of the consumer/product match and the more they end up paying.

This trend is also true for the share of shoppers that make a purchase which decreases from 31.6% to 29.5% to 29.2% to 18.5% within the four scenarios (corresponding to the user friendly scenario, halved platform power, seller friendly, and baseline scenarios). As a result, all three counterfactual scenarios result in greater revenues for the entire distribution of sellers than the baseline scenario. One notable finding is that on a per user basis the expected percentage change in utility or seller revenue is far smaller than the impact on the platform profits per user. I also find that the seller HHI decreases with the market power of the platform (the overall levels of the HHI in this market are extremely low no matter the scenario, so it is unclear if this is a result we would also expect in a concentrated market).

As previously mentioned, these simulations are limited to the changes when holding the number of users of JD constant. However, it is reasonable to expect the demand for the JD app to respond to the search power parameter. If I assume the observed platform search power parameter is the optimal decision for the platform, we can recover the demand for the platform ($\frac{\partial N}{\partial \nu}$) with regards to changes in the platform search parameter at the observed equilibrium. If I also assume this is constant then I can adjust the simulations to account for changes in number of consumers using JD. Simulations in Figures 23 and 24 suggest that the change in per consumer utility and platform profit per consumer are well approximated by a linear relationship, suggesting this is reasonable assumption.

Using equation 17 (the platform optimality assumption) I can recover $\frac{\partial Q}{\partial \nu}$ by using the observed number of consumers, N, estimated platform profit, π, and the slope of the regression

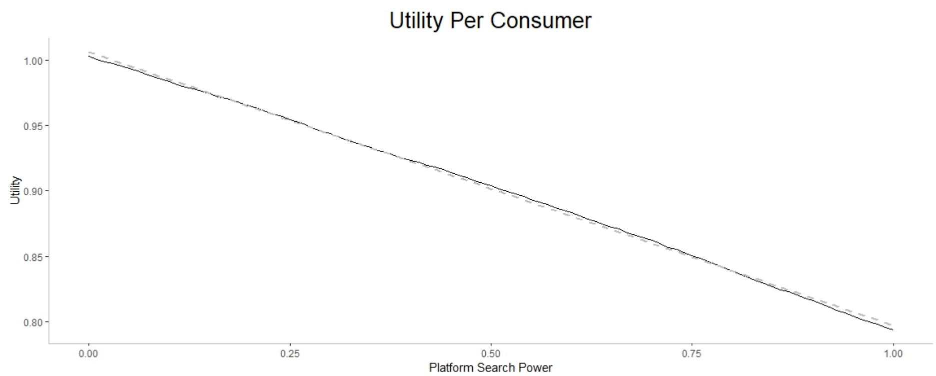

Figure 23: Utility per Consumer as Power Changes

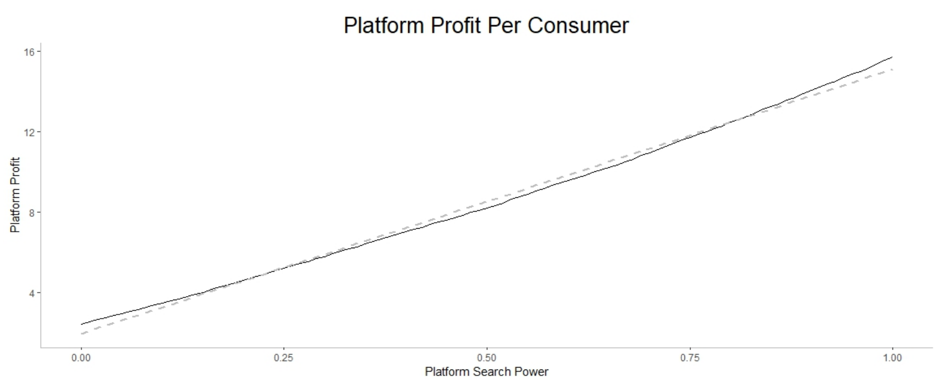

Figure 24: Platform Relative Profit per Consumer as Power Changes

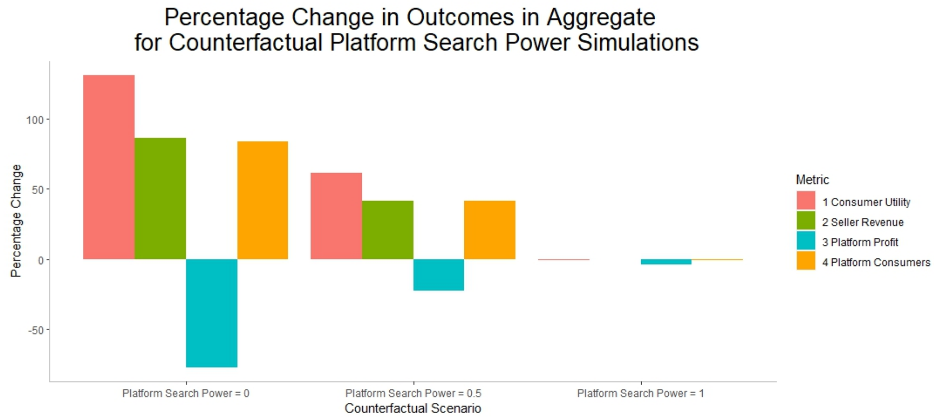

Figure 25: Percentage Changes in Aggregate Outcomes

line in Figure 24 as $(\frac{\partial \pi}{\partial \nu})$.

$$\frac{\partial \pi}{\partial \nu} N + \frac{\partial N}{\partial \nu} \pi = 0 \tag{17}$$

Adjusting the simulation to account for changes in number of consumers produces the counterfactual outcomes in Figure 25. Now the percentage benefit for consumers and sellers would both be larger than the loss in profits to the platform owing to the increase in number of users which magnifies the benefits of consumers surplus and producer surplus while simultaneously offsetting losses for the platform. Reducing just the consumer search market power to 0.5 now increases consumer utility by more than 60%, increases seller revenues by more than 40%, and a reduces platform profit by more than 20%. Giving consumers all the market power would more than double their overall utility (equivalent to a 2.5 million yuan increase in consumer surplus for the month) and increase seller revenues by over 85% (monthly increase of greater than 10 million yuan).

Figure 26 displays 4 counterfactual scenarios that change the visibility parameters of the click model in order to assess potential policies intended to reduce the degree to which sellers and platforms have misaligned incentives. The first scenario simulates a world in which all products are treated as if they are third party products that use third party shipping. Visibility parameters are set to the mean third party visibility value plus the residual of

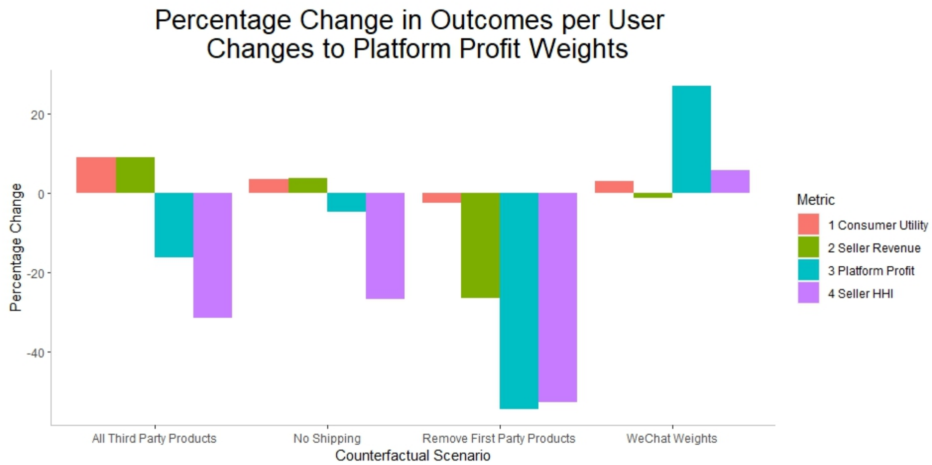

Figure 26: Percentage Changes in Outcomes for Alternative Product Profit Weights

the regression from Table 8. The second scenario removes the ability of the platform to incorporate shipping method into search visibility by simply removing the estimated mean visibility value from Table 8 from each product that used JD shipping. A third scenario bans the sale of the first products entirely by removing these 71 from the market. And the fourth scenario looks at the impact of social commerce by using the WeChat visibility parameters in place of the estimated App visibility parameters.

The impact of treating all products as third party products improves both consumer and seller outcomes by about 8%. This is roughly a third as large as the benefit consumers see from gaining all of the market power. The impact of removing first party shipping from search algorithms results in minimal impact to anyone although it does seem to have a major impact on reducing HHI. Removing the first party products altogether is a negative for all parties as it removes the higher priced products which reduces revenue and the more profitable products for the platform. Finally, we can see that while social commerce is much more profitable for the platform it does not seem to have much of an impact on consumer or seller outcomes so there does not appear to be a reason, from a market power perspective, to fear the growth of social commerce.

A final counterfactual begins an investigation into the role data may play in the platform power. To estimate the potential willingness of consumers to provide data to a platform I

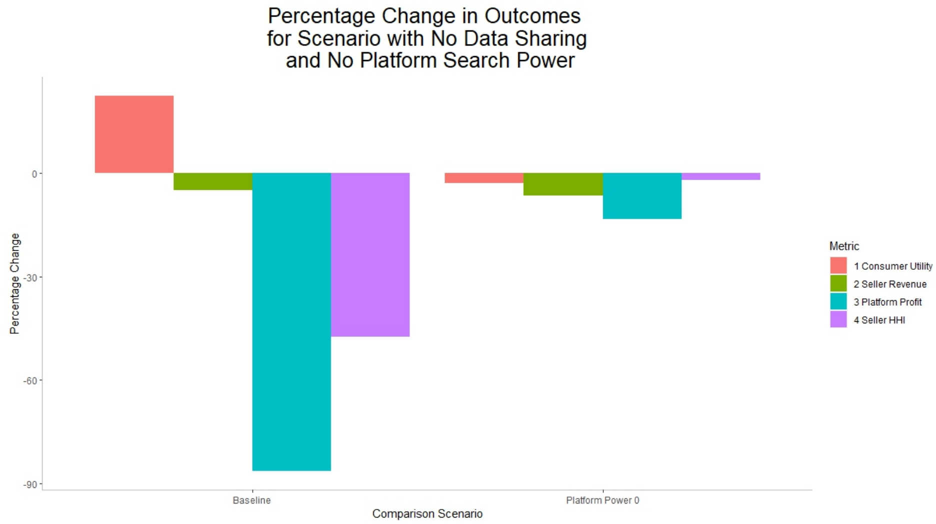

Figure 27: Percentage Changes in Outcomes Per Shopper without Data Sharing

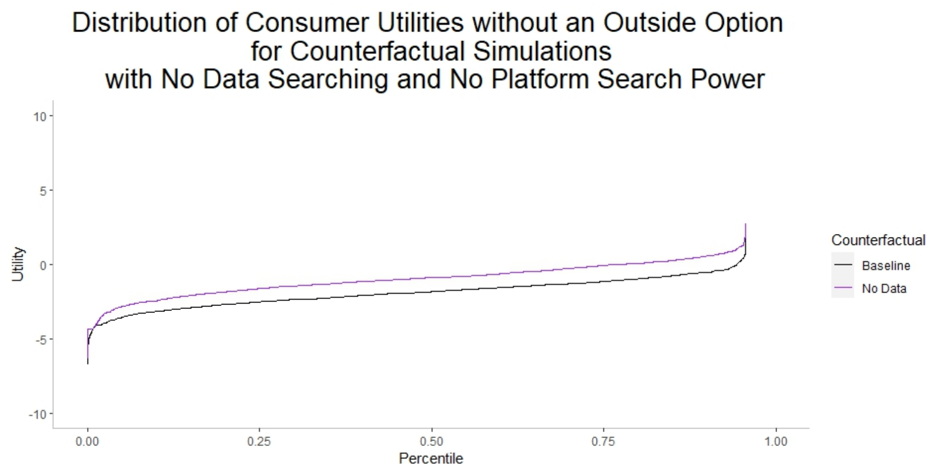

Figure 28: Counterfactual Utility without Data Sharing and Complete User Search Power

simulate the distribution of consumer utility if the search stage used only the mean probability of purchase and the mean price for all consumers, but platform search power is set to 0.[18]

Figures 27 and 28 show that there is room for the entire distribution of individuals to gain from withholding data if they also gain market power in the process. However, the incentive for the platform to acquire the data is much stronger than the incentives of the users to withhold the data. For a given level of platform search power, consumers also benefit from

[18]This scenario violates the assumption that the platform knows the filtering function of the consumer, which motivates future work relaxing this assumption.

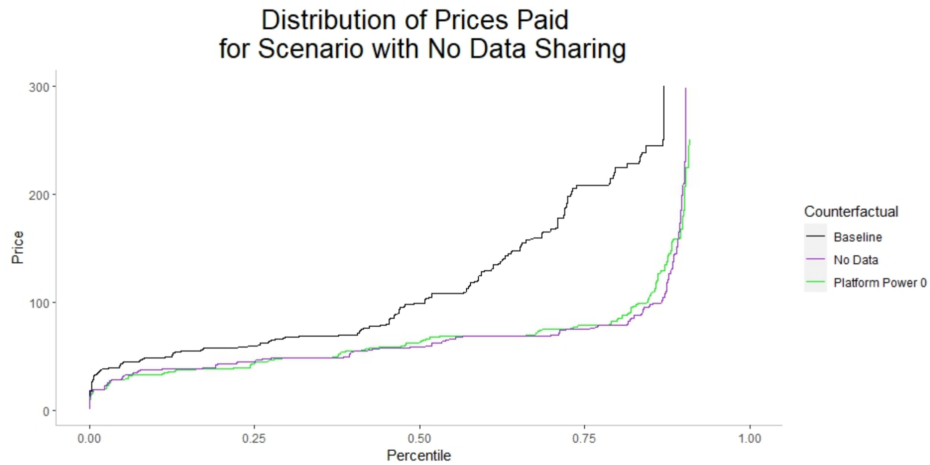

Figure 29: Counterfactual Utility without Data Sharing and Complete User Search Power

sharing their data. However, the acquisition of the data raises the incentives of the platform to increase its search market power which would end up hurting the consumers. These two facts suggest the link between data sharing and consumer outcomes/platform search power may be an area worthy of further exploration. Furthermore, Figure 29 shows that a portion of the benefits of the no data sharing scenario for consumers results from paying lower prices. However, these prices are similar to the expected prices paid of consumers that share data and have all of the market power so it is unclear if the driver of lower prices is the lack of price discrimination or the changes in search market power. Thus, the incentives to share data may also tied to the ability of platforms to engage in price discrimination.

8 Conclusion

This paper presents a framework to investigate market power of platforms that offer search as part of their service. Like methods that look at price setting behavior for tradeable goods markets, this methodology looks at the endogenous choice of the platform on how heavily to weigh user preferences in the design of its ranking algorithms. The greater the sensitivity of users to this weight (whether because of market structure or preferences), the greater user preferences will drive the algorithms. Because the methodology models ranking algorithm outcomes it is generalizable to multiple digital settings like search, social media, ads, and ecommerce. I show that reasonable assumptions on the platform's knowledge of users reduces the platform ranking algorithm decision to setting a Nash bargaining parameter between consumer preferences and the platform preferences.

I apply the model to JD.com, a large ecommerce platform in China that runs a traditional ecommerce channel and a social commerce channel with China's largest social media platform. I find that both the traditional and social ecommerce platforms have significant search market power with over 95% of the distribution of user consideration sets being driven by platform profit incentives. Perfectly realigning the platform incentives with user incentives could result in more than doubling aggregate consumer surplus and almost doubling the total seller revenues (equivalent to increases of 25 million and 120 million yuan per year).

I also explore potential policies to partially realign these incentives. Banning the first party products altogether results in minimal change in consumer utility but a greater than 25% and 50% reduction in outcomes for sellers and the platform, respectively. Alternatively, banning just the platform participation in the market, effectively making all products third party products, results in almost 10% improvements for consumers and sellers and 16% decrease in platform profit per consumer.

As far as differences between social commerce and traditional ecommerce, the results suggest there are no differences in search market power for the platforms. However, the individual product profit incentives differ between the two types of search platforms. The social commerce profit incentives are actually better for both shoppers and the platform.

I believe the findings motivate further research. First the outcome of the search process depends on the platform beliefs about the users, so there is potential for further research into understanding the relationship between platform power and information. The initial scenarios presented in this analysis indicate that users have only a small incentive to try and withhold information, while platforms have a strong incentive to acquire information about shoppers. Additional research into the mechanisms impacting the elasticity of platform participation could also help apply this model to other situations like proposed mergers. It is not clear from this analysis why JD has the level of power it does or why consumers are as insensitive to the platform search power as they are. Potential reasons are the presence of only one other competitor or that prices and shipping time are more important aspects of competition for platform participation in ecommerce. Studies of search power outside of ecommerce markets could also help explain whether large network effects on search platforms just inherently lead to greater platform search power.

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10 Appendix A

Appendix: Proof of Proposition 1 and 2

10.1 Proof of Proposition 1:

Proposition 1: If the platform knows the consumer's optimal filter and both filters are surjective, then the platform can choose $\Gamma_{P'}()$ *and input* Z *to satisfy any filter:* $\Gamma(1) = \Gamma_I(\Gamma_{P'}(Z))$.

1. WLOG, let $\Gamma_a(1)$ be the filter outcome the platform wishes to achieve.

1. If $\Gamma_I()$ is surjective then there exists an input to $\Gamma_I()$such that the output is the same as the output to $\Gamma_a(1)$, call this input Z_I
2. Since $\Gamma_{P'}()$ is surjective there an exists an input such the output of $\Gamma_{P'}()$ is Z_1, call this Z
3. Since there is no restriction on what the initial input to the filter is, the platform can choose input Z_2 if it knows that $\Gamma_I()$ will be the filter used after the awareness stage

We can think of the unbounded input choice as the platform choosing do something extreme like only show a specific product 100 times in a row in search results.

10.2 Proof of Proposition 2:

Proposition 2: If platform preferences are defined such that they prefer any filter where the sum of $(1-\nu)^2$ *is the smallest (usual distance metric), and users prefer any filter where the sum of* ν^2 *squared is smallest, then the platform will always choose a filter that can be defined as* $\nu\Gamma_P() + (1-\nu)\Gamma_I()$

1. Let ν_j be the value such that the output of $\Gamma_I(\Gamma_{P'}) = \nu_j\Gamma_P() + (1-\nu_j)\Gamma_I()$

2. If all ν_j are equal then we can rewrite $\Gamma_I(\Gamma_{P'})$ as $\nu\Gamma_P() + (1-\nu)\Gamma_I()$.

3. Suppose all ν_j are not equal

4. Then there exists a j' and j'' such that $\nu_{j'} \neq \nu_{j''}$

5. The distance to the consumer is $(\sum \nu_j^2) + \nu_{j'}^2 + \nu_{j'\prime}^2$

6. The distance to the platform is $(\sum(1-\nu_j)^2) + (1-\nu_{j'})^2 + (1-\nu_{j''})^2$

7. Consider the filter with the output $\nu_j\Gamma_P() + (1-\nu_j)\Gamma_I()$ for all j except j' and j''. And, the output is $\frac{m}{\sqrt{2}}\Gamma_P() + (1-\frac{m}{\sqrt{2}})\Gamma_I()$ for j' and j'' where $m^2 = \nu_{j'}^2 + \nu_{j''}^2$

8. Then this new distance to the consumer is still equal to $(\sum \nu_j^2) + \nu_{j'}^2 + \nu_{j''}^2$

9. The new distance to the platform is shorter than $(\sum(1-\nu_j)^2) + (1-\nu_{j'})^2 + (1-\nu_{j''})^2$ because $(1-\nu_{j'})^2 + (1-\nu_{j''})^2$ subject to the constraint that $m^2 = \nu_{j'}^2 + \nu_{j''}^2$ is minimized when $\nu_{j'} = \nu_{j''}$.

10. Therefore, if $\nu_{j'} \neq \nu_{j''}$ there exists a filter that leaves the consumer just as happy and the platform better off, so the platform must be choosing a filter such that all ν_j are equal.