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Publication Date

2017

Peer reviewed|Thesis/dissertation

Essays on Online Platforms

by

Zemin Zhong

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Business Administration

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Ganesh Iyer, Co-chair
Professor John Morgan, Co-chair
Associate Professor Zsolt Katona
Associate Professor Ben Handel

Summer 2017

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Abstract

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Professor Ganesh Iyer, Co-chair

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In three essays, I present my findings in three interrelated aspects of online platforms. In the first chapter, I empirically study the economics of consumer limited attention in online markets and how sellers react to this bias. The second chapter focus on studying consumer search in online platforms under targeted search technology. And in the third chapter I study the platform's search and revenue design problem.

How do sellers react to consumer biases in online markets? In the first chapter I examine whether consumers are limited attentive to online ratings, and how sellers respond to it. Using 6.8 million transaction records on Taobao, I first demonstrate that consumers are limited attentive. The Taobao platform assigns each seller a summary symbol based on his/her rating score (net number of positive ratings) , and both the rating score and the symbol are made available to consumers. I show that the demand exhibits a discontinuous jump when a seller's rating score passes the threshold of a new summary symbol. More importantly, I find sellers appear to be responding by using different pricing strategies before and after reaching thresholds. As a seller's rating score gets closer to the next threshold, the seller's prices gets lower until the rating score reaches thresholds. Once the seller obtain a new summary symbol, the prices begin to increase. The kink in price levels is significant, suggesting sellers are responding to consumer limited attention.

Major online platforms such as Amazon and eBay have invested significantly in search technologies to direct consumer searches to relevant products. These technologies lead to targeted search, implying consumers are visiting more relevant sellers first. For example, consumers may directly enter their desirable attributes into search queries, and the platform will retrieve relevant sellers accordingly. The platform may also let consumers refine the search outcomes by various criteria. This study characterizes the role of targeted search, and examines how targeted search affects market equilibrium and platform design.

In the second chapter, I model targeted search in a differentiated market with many firms where consumers search sequentially for the best product match. One of the central results of the analysis is how targeted search affects equilibrium prices. I find its impact on price

is not monotonic. When targeting is not too precise, targeted search lowers the equilibrium price. It makes sellers more similar and intensifies price competition, despite the fact that all consumers face sellers with better fit. However, once the targeting becomes sufficiently precise, the equilibrium price increases, because highly targeted search discourages active consumer search and gives sellers monopoly power. Using a unique dataset from Taobao, I find some suggestive evidence that is consistent with the model predictions.

Within this setup, I endogenize the search design by allowing the platform to choose the precision of targeted search and the revenue model contract in the third chapter. I consider two major platform revenue models, commission and promoted slots, with consumer search. The platform, by providing targeted search with precision up to the aforementioned limit, can extract more consumer surplus through higher commission rates, because targeted search improves consumer surplus by lowering search cost, increasing fit, and lowering price. With targeted search up to the limit, the platform can also extract more surplus from sellers by offering promoted slots, because sellers can use promoted slots to better target consumers. However, once targeted search becomes too precise, the market will face a price hike, hurting the platform revenue in both models. Therefore, I find that in both revenue models, the platform may want to limit the precision of targeted search even if improving it is costless, with or without consumer entry.

To my family and friends.

Acknowledgments

I am indebted to my committee: Ganesh Iyer, John Morgan, Zsolt Katona, and Ben Handel, for inputs at all stages of my graduate school study. I also thank Yuichiro Kamada, Steve Tadelis, Stefano DellaVigna, Teck-Hua Ho, Minjung Park, J. Miguel Villas-Boas, and Przemyslaw Jeziorski, as well as seminar participants at University of Florida, UT-Dallas, University of Minnesota, University of Rochester, University of Toronto, HKUST, Chinese University of Hong Kong, National University of Singapore, and the Northwestern University for helpful suggestions. I gratefully acknowledge financial support from the NET Institute summer research grant. All errors are my own.

Chapter 1

Limited Attention in Online Platforms

1.1 Introduction

Starting from [Simon \(1955\)](#), economists have come to realize that decision making processes often suffer from biases. More recently, there is a large and growing literature on identifying consumer biases using observational data or experiments. For example, consumers are found to be subject to reference dependence, present bias, projection bias, and limited attention.¹ Naturally, more and more behavioral IO models emerge, trying to incorporate behavioral biases into market settings ([Ellison, 2006](#); [Grubb, 2015](#)). The models feature some rational agents, such as sellers, reacting to the bias of others such as consumers. However, there are much less empirical studies on such market responses.

This study focuses on a common bias, namely consumer limited attention, and how sellers respond to it in online markets. I first provide evidence that consumers neglect the exact form of rating information, but pay full attention to its summary symbols, exhibiting limited attention. [Figure 1.1a](#) shows how Taobao (China’s largest e-commerce platform) assigns summary symbols to sellers solely based on their rating scores.² For example, a Taobao seller with a rating score between 5,001 and 10,000 will be assigned “five diamonds”, whereas one with a rating score between 10,001 and 20,000 will get “one crown.” Therefore, consumers have direct access to the same information both in its exact form, e.g. 6,796 and its coarse form, e.g. five diamonds. The summary symbols are plausibly easier for consumers to process and remember than the exact rating scores. The underlying rating scores, although equally visible, are harder to incorporate in consumers’ decision making process. Limited attentive consumers will pay more attention to the summary symbols while partially ignore the rating score. Hence, consumer limited attention predicts a discontinuity in demand: A

¹For a recent review, see [DellaVigna \(2009\)](#)

²Taobao calculates the rating scores as follows. After every verified transaction, a buyer leaves a rating for the seller, either positive (+1), neutral (rating score unchanged), or negative (-1). Hence, the rating score counts the net number of positive ratings in the entire history of a Taobao seller. [Figure 1.1b](#) shows eBay uses a similar mechanism based on similarly defined rating score.

seller with a rating score just above a threshold (for example, 10,001) will face substantially different (presumably higher) demand than one just below (for example, 9,999).

Responding to consumer limited attention, sellers should use different pricing strategies before and after reaching thresholds. Given over 98% of ratings are positive, most sellers' rating scores will increase monotonically. Intuitively, when a seller's rating score is far away from the next threshold, she should price close to static profit maximization. As her rating score gets closer to the threshold, the same seller has more incentive to decrease the price, because doing so will help her to collect more ratings and reach the threshold more quickly.³ Yet once she reaches the threshold, facing a positive demand shock due to consumer limited attention, she should increase the price to take advantage of it. To summarize, we would expect the prices to exhibit a V-shape pattern near a neighborhood of each threshold, with the lowest price at the exact threshold. This is one of the key predictions to be tested in this study.

To test both consumer limited attention and seller response, I collect a rich and highly granular dataset. It consists of nearly 3,000 Taobao sellers and their complete transaction record (6.8 million entries) during a 40-day window. The sampling is customized such that most sellers are near the thresholds. I then use regression discontinuity (RD) design to identify consumer limited attention. Notice continuous rating scores lead to discontinuities in levels. Because a shop with a rating score just below the threshold should be otherwise (statistically) the same as one just above except for the symbols, finding a significant jump in demand at thresholds shows consumers are less than fully attentive to the readily available exact rating scores. I implement the RD design using local linear regression, and I find that an extra level leads to an over 9% jump in sales, conditional on the same seller and the same item with the same price.

Having shown that what appears to be limited attention on the consumer side, I now get to the heart of the analysis, namely sellers' dynamic pricing as a response. I track sellers' pricing strategies using transaction prices in the same dataset. Note that the theory predicts a V-shape price pattern. Consistently, I find sellers keep lowering their prices until they reach the thresholds, and increase them afterwards. A regression kink design (RKD) shows that there is a significant kink in prices at thresholds. The heterogeneity in the price changes allows me to test ancillary predictions of the theory of sellers responding to consumer limited attention. Intuitively, when a seller is selling both cheap and expensive items, they should lower the prices of their *cheaper* items more steeply before thresholds. The intuition is that discounts on cheaper items are less costly, yet a good rating from a cheaper item is just as good as one from a more expensive item. Consistent with such predictions, I find that sellers indeed tend to lower the prices of their cheaper items more steeply before thresholds. I also show suggestive evidence that sellers facing stronger effects of consumer limited attention also use steeper price cuts before thresholds.

An implicit assumption of interpreting the price changes as a response to demand shifts

³Anecdotally, we observe Taobao sellers list their items with "Diamond sale" or "Crown sale" in their titles, in reference to the summary symbols of Taobao's rating system, to justify their price discounts.

is that sellers' costs are fixed, at least in a small neighborhood of threshold. This assumption seems quite reasonable. However, in interpreting the sales jumps as a result of consumer limited attention, we implicitly assume that the jump in sales is driven by demand rather than supply. The sellers' response seems to contradict such an assumption. It may pose two potential threats to the identification of consumer limited attention. First, there may be a selection problem. Sellers before and after the thresholds may have different compositions. To control for the selection, I estimate how demand changes at the thresholds conditional on the same seller and the same item. I also check if observable seller attributes such as average dynamic ratings were smooth near the thresholds, and indeed they were.

The second potential threat is that even the same sellers could use *discontinuously* different price and promotion strategies before and after passing thresholds. Such immediate supply response does not change the causal effect of summary symbols on sales. However, it could change how we interpret the effect. Furthermore, such supply response is quite plausible: after all, the major goal of this paper is to study seller response. I note two observations in the results of seller's dynamic price response and how I am able to separately estimate the demand side effect of summary symbols in light of the two observations.

First, the direction of the price change suggests that supply response would bias against finding a sales jump at threshold. This is because sellers decrease their prices before reaching thresholds, and increase them afterwards. To demonstrate how it could lead to an underestimate of the demand side effect, I separately estimate the jump in sales in two subsamples. In the main specification, I used a subsample of items with constant prices to estimate the demand effect of summary symbols on sales. And as a robustness check, I separately estimate the same effect using items with non-constant prices. The estimated sales jump is weaker compared to the main specification, although still significantly positive, as we would expect from the V-shaped pricing response. Admittedly, this exercise is limited to seller responses in either listing prices or price discounts. Yet it is likely that the same intuition can be extended to non-price responses. If a promotion activity increases sales, a seller would have a larger incentive to use it just before reaching a threshold compare to just afterwards.

Second, the observed smoothness of price response suggests seller responses are unlikely to be discontinuous at thresholds. The observed price pattern exhibits a kink, rather than a jump, at thresholds. This suggests that if we use a sufficiently small bandwidth in the RD estimation of summary symbols' effect on sales, the potential impact of supply response is likely to be modest. Indeed, I find that the estimated effect is stronger with smaller bandwidth when using the sample with non-constant prices.

To augment the analysis, I show that the main results of demand jump at thresholds are robust to different measurement of sales and different estimators. It passes the falsification test, because I find no demand jumps at artifact thresholds. It is also robust after controlling for observable shop attributes and time fixed effects.

This study contributes to the limited attention literature by testing the market response to the bias in a new domain. Consumer limited attention has been found in many domains including shipping fees (Hossain and Morgan, 2006; Brown et al., 2010), taxes (Chetty et al., 2009; Finkelstein, 2009), outside buy-it-now options (Malmendier and Lee, 2011), car mileage

(Lacetera et al., 2012), bank overdraft fees (Stango and Zinman, 2011) and quality scores of hospitals and colleges (Pope et al., 2009). In marketing, there has been a large literature on .99 price ending (see for example Schindler and Kibarian (1996); Schindler and Kirby (1997); Anderson and Simester (2003) and Thomas and Morwitz (2005)). Most of the studies focus on identifying limited attention on the demand side ⁴, while this study contributes to the literature by identifying limited attention in the new domain of online reputation. More importantly, this study relates to the behavioral IO literature by providing evidence for supply-side responses to consumer limited attention (Gabaix and Laibson, 2006; Bordalo et al., 2013, 2015; Manzini and Mariotti, 2016; Zhu and Dukes, 2017). See Grubb (2015) for a more recent review. More generally, it contributes to models in quantitative marketing that incorporate various behavioral aspects of consumers (Bhardwaj et al., 2008; Chen et al., 2010; Guo and Zhang, 2012; Chen and Cui, 2013; Guo, 2015; Li and Jain, 2015).

The setting of this study is online reputation systems which have played a major role in the success of online marketplaces by addressing potential information asymmetry. ⁵ Across the major online platforms, the total number of ratings and/or its summary symbols are essential elements of sellers' reputation profile. Therefore, understanding how buyers make use of seller rating information and how sellers respond has broad implications for the Internet economy. Compared to the existing studies of online reputation ⁶, this study distinguishes itself by focus on the *local* reputation premium driven purely by the summary symbols and consumer limited attention. The seller response identified in this study is similarly focused on only local price response, i.e. different pricing strategies just before and after thresholds, to provide clear evidence for sellers responding to consumer limited attention rather than responding to (rational) reputation premium.

The rest of this chapter proceeds as follows. Section 1.2 describes the setting and data while Section 1.3 explains the identification strategy. Section 1.4 discusses the key findings. Section 1.5 concludes.

⁴With the exception of Lacetera et al. (2012) in which dealers apparently took into account of consumers' left-digit bias.

⁵Online markets have gained a significant share of retail sales. Global online retail was estimated to be worth \$1.3 trillion in 2014, or 5.9% of total retail sales (eMarketer, 2014). It is projected to grow significantly to 8.8% in 2018. In China, online retail has already taken over 10% of the total retail sales in 2014 Q3 (iResearch, 2014).

⁶They usually estimate the reputation premium in online markets by comparing low-reputation shops with highly reputable ones by using cross-sectional variations (Dellarocas, 2003; Bajari and Hortacsu, 2004; Livingston, 2005), panel data (Cabral and Hortacsu, 2010; Fan et al., 2016), or across multiple platforms (Chevalier and Mayzlin, 2006). For recent reviews, see Cabral (2012) and Tadelis (2016). The RD design in this study is also similar to two recent studies on Yelp ratings (Anderson and Magruder, 2012; Luca, 2011), although the research questions are very different.

1.2 Setting and Data

1.2.1 Setting

The setting of this study is Taobao.com, a Chinese C2C platform that belongs to Alibaba Group. Together with its B2C sister site Tmall.com, Taobao is the largest online marketplace in the world. Its GMV (Gross Merchandise Volume) in 2013 was US\$248 billion, larger than eBay and Amazon combined. According to the IPO filing of Alibaba in 2014, Taobao and Tmall had 231 million active buyers, 6 million sellers, and 11.3 billion annual orders. Taobao is almost exclusively a posted-price platform. In this study, all sellers used posted prices for all their listings.

Taobao has been using largely the same rating system since its establishment in 2003. Every user has two separate rating scores, one as buyer and the other as seller. After every verified transactions, buyers and sellers can leave a rating for each other, either good (rating score +1), neutral (rating score unchanged), or bad (rating score -1). And the rating score counts all the ratings received in the entire history of a Taobao user. And Taobao display both the rating score as buyer and the one as seller separately. Crucial to this study, Taobao further assigns summary symbols (using one to five “hearts”, “diamonds”, and “crowns”) to users based on their rating scores (Figure 1.1a). Originally Taobao had only 11 levels of summary symbols. At the time of the sample period, Taobao expanded the scale of symbols to five “golden crowns”, which represents a rating score greater than 10 million.

As with many other reputation systems, continuous attempts have been made to game Taobao’s rating system by leaving fraudulent ratings. Taobao has been actively coping with such attempts. For example, a buyer can only rate the same seller up to six times per month, beyond which ratings will be displayed yet do not count toward the rating score. Also, every transaction must be associated with a valid tracking number of a delivery service.⁷ In so far as we believe fake ratings are costly for sellers to produce, the effect of fake ratings is similar to price discounts. Sellers make costly effort to collect ratings faster by either offering discount for more sales, or incur costs to produce fake ratings. Therefore, even if fake ratings exist, it is likely to bias against finding a sales jump at threshold, because a positive rating is more valuable if it could help seller pass a threshold. And if fake ratings are cheaper to produce for some sellers, they may use less price discounts before passing thresholds, which will attenuate the price response to the summary symbols.

Taobao also introduced a dynamic shop rating (DSR) system that is much like the Yelp rating system to complement the rating score. The DSR has three dimensions including “Item as described,” “Service,” and “Shipping.” A buyer can rate sellers on the three dimensions for one to five stars. Taoba display the average star ratings in the past six months by rounding them to the nearest tenth stars. Notice that DSR ratings are average measures that cannot replace rating scores. For instance, a consumer could prefer a shop

⁷The exception is virtual goods such as phone credits that are delivered electronically. To avoid sellers building a reputation through selling virtual goods and then switching to other industries, Taobao also displays the percentage rating coming from transactions of virtual goods for each shop.

with DSRs of 4.9 stars and a rating score of 2,000 over one with perfect 5.0 stars DSRs yet a rating score of only 20. In theory, consumers might also be limited attentive to DSRs and sellers might respond. Yet such effects will be harder to identify since the changes in the star ratings (for example, 4.8 vs 4.9 stars) are less dramatic than in summary symbols (for example, one crown to two crowns). In this study, I also collected the DSRs as controls, but they are smooth near thresholds, and adding them to the model does not affect the results.

1.2.2 Data and sample

The data consists of datasets at three levels, including a shop-level daily panel, two sets of item-level data, and all the transaction records for all the items during the sample period. These data are all publicly available, scraped directly from Taobao’s web pages.

First, the seller-level dataset is a daily panel of 2,976 sellers for November 15 to December 23⁸, 2013, in total 100,865 entries. Every entry has a shop ID, an exact timing of scraping, and shop attributes at the time of scraping, including its rating score, good rating percentage, three dynamic ratings, return policy, consumer protection, major industry, history, and location, among others. Notice the data is not a random sample of the entire population of Taobao sellers. Instead, the sampling is tailored to maximize the statistical power of estimating the effect of summary symbols. I focus on sellers whose rating scores are close to the thresholds between level 5 and 10.⁹ Other than limited the scope of this study to sellers with medium level of experience, the sampling does not bias the representativeness of the sample. Every shop in the population within the range of level 5 to 10 has the same probability of being near a threshold and being sampled. For example, in terms of industries represented, the sample represents reasonably well all the major industries, including clothing, electronics, and so on. See the summary statistics for more detail.

Second, at item-level, I have two snapshots of all listings on December 04 and December 22, 2013, respectively. Every entry has the item ID, shop ID, and timing of scraping. I used Taobao’s SKU as the item identifier, which assigns different SKUs to the same items if they are sold by different sellers. Therefore, a SKU or item-ID is both product-specific and seller-specific. I will refer to it simply as “item” hereafter. In total, I have 201,792 items. This dataset is mainly used to match transaction records to seller attributes at the time of transaction. Note that an item typically has multiple inventories. Also, a given item may have different styles or models, for example, a shirt with different colors and sizes, a cellphone with different storage spaces. I call all these variants “models.” On average one item has 8.82 models.

Third, I have the complete transaction records for the items from November 11 to December 22, 2013, for a total of 6.8 million transaction records of 25,900 items. For each

⁸The only exceptions are November 25, November 26, and December 20, due to technical problems in scraping.

⁹For level 1-4, the thresholds are too discrete, while beyond level 10 the transaction data will be exceedingly large.

transaction, I have entries of transaction price, quantity, date-time when the order is placed, item id, model, and buyer levels. In total I find 228,433 item-models have non-zero transaction records.

Using the shop-level data, I first construct the rating scores R_{it} , i.e. the running variable that determines the summary symbol. Since the shop attributes, including the rating scores, are scraped on a daily basis, I have precise R_{it} for one time every day throughout the sample period. I then use the data to interpolate the rating scores at every point in time at the hourly level, using a subset of detailed rating records.¹⁰ This approach could lead to a measurement error in the interpolated rating scores. Yet because I have one observation per shop per day with exact scrapped R_{it} , the measurement errors of interpolated R_{it} will be bounded to be small. In the worst-case scenario, the measurement error will be up to the difference of R_{it} between two consecutive days. Notice that with an extra assumption that the error is independent of assignment variable, the RDD is still identified (Pei, 2011). Moreover, in my setting, the measurement error should bias against finding a result, because it makes the assignment of summary symbols based on the running variable more “fuzzy.” A formal treatment of measurement error is beyond the scope of this study. I further convert R_{it} to percentage distance to the nearest thresholds in order to pool the data near multiple thresholds (see Section Table A.1.2 for detail).

I measure the outcome variable, namely the sales at D_{it} by aggregating the quantity sold in the transaction data for item-model i at the hour t . For the main specification of the empirical model, I further normalized the hourly sales D_{it} to one for each item-model by taking the ratio of its hourly sales over the average hourly sales. This is motivated by the fact that item-models have very large heterogeneity in their scales of quantity sold (the mean of total sales for each item-model is 2,406 while the standard deviation is 324,577, as in Table 1.3 in Section 1.2.3). Without such a normalization, the changes in sales will be very noisy and mostly driven by a small percentage of items with large number of transactions. The normalization also helps to improve efficiency by control for the item-model fixed effect. Because an item-model identifies a unique seller, the normalization also controls other fixed effects beyond item levels, such as seller and industry fixed effects. For details of the aggregation and normalization, see section A.1.2 in the Appendix. To show the robustness, I also test the model using raw hourly sales data in section A.1.3 in the Appendix. The findings are consistent with the results based on normalized sales: the effect of symbols on sales is positive and statistically significant across most specifications.

I prepared my final sample by the following criteria. First, I excluded all the hourly sales data when I failed to match the shop-level attributes data with the sales data.¹¹ Second, I excluded all item-models with less than five transactions, because they are too noisy.

¹⁰See section A.1.2 in Appendix for detail. Ideally, one could recover R_{it} at every point in time using the history of rating records as Anderson and Magruder (2012) did with Yelp ratings. However, Taobao has a strict anti-scraping rule for the detailed rating records, effectively preventing such practice in large scale. Moreover, it will make the measurement of R_{it} very sensitive to the completeness of rating records, because any potential errors in scraping will add up.

¹¹The failure to match happens because of a longer window for transactions than rating scores.

Including them does not make the results qualitatively different. In the end, I have 73.6 million item-model-hourly observations for my main specification.

For the supply side, I construct the price changes using transaction prices. Since I only observe prices changes at transactions, I interpolate the prices at hourly level between two consecutive transactions as follows. If there's no price change, I assume the price stay constant throughout. In case of observed price change, I assume it happens in the middle (alternative assumptions do not change the result).¹² To minimize measurement error in the timing of price changes, I also experimented with restricting my sample to price changes between two transactions within 24 hours, 48 hours, or 120 hours for which I have more precise timing of price changes, and the results remain the same. Finally pool the prices of different items together, I normalize them by taking the ratio of each observed transaction price over the first observed price for the same item-model.

1.2.3 Summary Statistics

Table 1.1 shows some summary statistics for shop-level data. The data have rich variations near the thresholds. Out of 2,976 sellers, 1,556 passed at least one threshold, and 1,294 passed exactly one threshold during the sample period. Table 1.2 shows the distribution of industries. All major industries on Taobao (Clothing, Electronics, Furniture, Sports and Outdoor, Kids and Baby, etc.) are well represented in the sample.

Table 1.3 shows some summary statistics at the item level, item-model level, and hourly sales level. Panel A shows that on average, one item has 8.82 models or styles, is priced at 60 CNY (around US\$10), has 261.2 transaction records, and 21,218 total sales.¹³ Panel B shows the statistics for prices and sales for each model. The average price is 71.29 CNY (around US\$12),¹⁴ with a large variance. On average, 29.62 transactions occur per item-model. The percentiles of both total sales and transactions also show that 90% of the models have total sales no greater than 47, and total transactions no greater than 31. Panel C shows some summary statistics at the hourly sales level, both raw and normalized. The hourly sales data is very sparse: 97.8% of the hourly sales are zero. These observations motivates the normalization of hourly sales data in the estimation, as discussed in Section 1.2.2

¹²For instance, for a given item-model with initial price \$10, if I observe one transaction record at 9AM, December 1st, with price \$10, and the next transaction record at 12PM, December 1st, with price \$12, I code the normalized price for 9-10AM as \$1, and the price for 11AM and 12PM as \$1.2.

¹³The sales are much higher than transactions due to some outliers. For example, a seller selling a 200 CNY item could post a price of 0.01 CNY and ask the buyer to purchase 20,000 units.

¹⁴This average price is higher than the average price of items, presumably because higher-priced items such as clothing and electronics are more likely to come with more different models and styles, effectively increasing the weights of higher-priced items when calculating the mean price at the item-model level.

1.3 Identification

The identification of both consumer limited attention and seller response is based on the discontinuity of summary symbols at thresholds of rating scores. And the key challenge is how to use this single variation to separately identify two effects: its effect on demand due to consumer limited attention, and its effect on supply as a seller response. In this section I will begin by discussing the identification in the supply side, and how I use the observations in the supply side to inform the empirical strategy in identifying the demand side. Once I identify a casual effect of summary symbols on demand due to consumer limited attention, I can interpret the casual effect of summary symbols on price levels as a seller response.

To identify the supply response, we want to show sellers use different strategies (e.g. prices) before and after thresholds. Theory suggests that sellers keep lowering their prices until their accumulated ratings reach the thresholds, and increase prices afterwards. This intuition implies there are two testable hypotheses. First, observed price levels may be discontinuous higher after rating scores reach thresholds. And its identifying assumption is that the costs are continuous at a neighborhood of thresholds. Second, observed price levels may exhibit a V-shape pattern with a kind point at threshold. And its identifying assumption is slightly stronger: costs are not only continuous but sufficiently smooth, with no kink point at thresholds. Those two assumptions seems reasonable. To violate them, one need a theory in which sellers have specific cost shocks that somehow coincide with the timing of their rating score passing thresholds. The raw data on price levels shows a clear kink but no clear discontinuous jump at thresholds. I tested for both discontinuity and kink point of price levels at thresholds, and I only find consistent evidence for the latter.

On the demand side, we want to show there is a positive demand shock at thresholds. However, its identifying assumption is that the other variables, including potential supply side responses to thresholds, are sufficiently smooth at thresholds. The identified supply response could violate the assumption in two ways. I discuss the two potential threats and how I address the challenges in the empirical strategy.

First, the fact that the running variable (rating score) is endogenous suggests that seller attributes may not be smooth at thresholds. Indeed, sellers have at least some control over their rating scores through pricing and other strategies such as promotions.¹⁵ For example, if highly reputable sellers bunch just above thresholds, it could lead to a spurious jump in sales. I address the selection problem by utilizing the panel nature of the data, comparing sales just before and just after passing thresholds for the same seller and same item. This approach largely addresses the challenge of the possible selection problem across sellers.

Second, even the same sellers may behave differently before and after the thresholds. If sellers use lower prices or more attractive promotions immediately after they pass thresholds,

¹⁵In this case, even without panel data, RD is still consistent as long as sellers cannot control rating scores perfectly (Hahn et al., 2001). This scenario is exactly the case in the Taobao setting, because sellers cannot control *perfectly* how and when the buyers rate. Even if they can manipulate rating scores through fraudulent transactions and ratings, they will have more incentive to manufacture ratings before reaching thresholds, which biases against finding a positive effect of symbols.

it may lead to a jump in sales at thresholds that cannot be attributed to consumer limited attention. However, two observations in the price response (see Section 1.4.5 for details) suggest we can address this challenge. The first observation is that sellers actually increase prices afterwards, which would bias against finding a sales jump at threshold. Indeed, I demonstrate such a possible bias by separately estimate the sales jump at threshold for two subsamples. For items with constant prices, I find a higher and more significant effect of summary symbols on sales, compared to items with non-constant prices. This suggests the potential bias from sellers' price or discount strategies would likely strengthen the results supporting consumer limited attention. The second observation is that price levels are continuous as sellers' rating scores pass thresholds. This suggests that if we use a sufficiently small bandwidth in implementing the RD design on the demand side, the potential impact of supply response is likely to be modest. And I find some evidence supporting this claim: When I use a smaller bandwidth to estimate the jump of sales at thresholds for items with non-constant prices, I find a stronger and statistically more significant effect. To summarize, I consistently use a small bandwidth and use items with constant prices to estimate how summary symbols affect demand. These empirical strategies help me to separately identify the demand effect of summary symbols.

Furthermore, I add the following robustness checks. First, I compared observable shop attributes just before and after the thresholds. No discontinuity exists for any of the attributes across a wide range of specifications. Second, I added observable shop attributes as controls into the empirical demand model. Adding them or not should not change the estimates, and indeed it does not. Third, I note that no discontinuity exists in advertising ranking (determined by bids and conversion rate) or search rankings (determined by search engine optimization, recent transaction, and rating scores) across the threshold. Therefore, discontinuity in traffic at the rating score thresholds is unlikely.

Finally, as a technical note that is often overlooked, using discrete running variables for RD carries another caveat. Technically, RD is only consistent with a continuous running variable. However, most of the RD applications use some version of discrete running variables, for example, car mileage (Lacetera et al., 2012) or Yelp ratings (Luca, 2011; Anderson and Magruder, 2012). In this setting, given that the rating scores are mostly in the magnitude of thousands, and some can be as high as over 10,000, the rating score should approximate a continuous running variable reasonably well. Moreover, using the more robust CCT (Calónico et al., 2014) estimator of RD shows consistent results.

1.4 Empirical Model and Results

1.4.1 Empirical Model

In this study, consumer limited attention is captured by the demand effect of summary symbols that are uninformative conditional on rating scores. If sales exhibits discontinuous jump at threshold rating scores, consumers must be paying less attention to rating scores

compared than to summary symbols. Specifically, I estimate

$$D_{it} = f(R_{it}, X_{it}) + \beta 1_{R_{it} \geq T_{it}} + \epsilon_{it}$$

where D_{it} denotes the sales¹⁶ for item i and hour t , R_{it} is the rating score, and T_{it} is the nearest threshold, X_{it} includes a set of shop-level attributes and time fixed effects. The main variable of interest is β that captures the jump at thresholds. Any potential endogenous relationship between rating score and demand is fully captured by the flexible function $f()$. In the estimation, the rating scores are replaced by percentage distances to the nearest thresholds to allow for pooling over multiple thresholds.¹⁷

For the supply response, I estimate a RKD model

$$p_{it} = \alpha_0 + \alpha_1 R_{it} + \alpha_2 R_{it} 1_{R_{it} \geq T_{it}} + g(R_{it}, X_{it}) + \epsilon_{it}$$

where p_{it} denotes the normalized price of item-model i at time t . And the key variable of interest is coefficient α_2 of the interaction term of the R_{it} and the summary symbol dummy. It captures whether the slope of prices on rating scores changes discontinuously once rating scores pass thresholds. The $g()$ captures higher order polynomial terms of R_{it} as well as other shop-level controls and time fixed effects. The reason for using RKD instead of RD is based on observed data, as the results on price changes indicate. The estimation is implemented following the [Calonico et al. \(2014\)](#) approach. See [Card et al. \(2015\)](#) for more detail on RKD. And similarly with the demand model, The rating scores are also replaced by percentage distances to the nearest thresholds to allow for pooling over multiple thresholds.

1.4.2 Demand-Side Result

As in Section 1.3, the empirical strategies to separately estimate the demand effect of symbols is to (a) use items with constant prices and (b) use small thresholds. The demand side results in this section are based on the sample with constant prices, unless otherwise noted. To find out how bandwidth choice could affect the estimates, I also test for the optimal bandwidth in implementing the RD design. Regardless of the estimator ([Imbens and Kalyanaraman \(2011\)](#) and [Calonico et al. \(2014\)](#)), I consistently get an optimal bandwidth greater than 5%.¹⁸ Therefore, I choose to estimate the model using 5% as the major choice of bandwidth, and to show the consistency of the results I add results using 2.5% and 10%

¹⁶Depending on specification, it is either normalized sales or raw sales.

¹⁷See Section A.1.2 in the Appendix for the pooling.

¹⁸I used the standard RD package using IK bandwidth ([Imbens and Kalyanaraman, 2011](#)) and local linear estimator implemented by ([Nichols, 2012](#)). [Calonico et al. \(2014\)](#) (hereafter CCT) proposed a theoretically more appealing estimator as well as bandwidth selector. Yet the current implementation of the CCT package runs several magnitudes more slowly and I only test it using a few specifications. The result is consistent with the standard RD package, and the CCT bandwidths turn out to be not very different from the IK bandwidths.

bandwidths. I use local linear regression in the estimation.¹⁹

The key result in the demand side is the jump of sales at thresholds. To illustrate the discontinuity of sales as sellers' rating scores pass thresholds, I plot the bin-means of hourly sales over percentage distance to the nearest thresholds in [Figure 1.2](#). I then add the local polynomial fit (degree 2, bandwidth 5%) and its 95% confidence interval of hourly sales over percentage distances. Clearly, there is a discontinuous jump of hourly sales at the thresholds. The confidence interval further suggests the jump is statistically significant.

[Table 1.4](#) shows the main demand-side result: the RD estimates of the effect of summary symbols on hourly sales. Given that the sales data is normalized to one, we can interpret the point estimate as a percentage increase. We observe a sizable jump of sales at thresholds across different specifications and bandwidths. Even the smallest estimate (at a 2.5% bandwidth and with full controls) shows that getting a higher summary symbol increases sales by 9.48% for the same seller, the same item, and with the same price. The effect is significant in all the specifications for bandwidths ranging from 2.5% to 10% using the conventional standard error. If they are clustered at the shop level as in [Table 1.5](#), the effect is still significant except at the smallest bandwidth of 2.5%. Adding time dummies and controlling for shop attributes hardly make any difference, as expected.

In discussing the identification, I argue that seller response is likely to weaken the effect of summary symbols on demand. Specifically, for items with non-constant prices, the prediction is (a) the estimated effect of symbols on sales will be similar to the estimate using constant-price sample for a small bandwidth, in which the sellers have not yet changed the prices, and (b) the effect will be smaller for a larger bandwidth due to gradual price increases after the threshold. [Table 1.10](#) shows the RD results of symbol effects using items with price changes. As expected, we observe a similar effect at a 2.5% bandwidth (one extra level leads to a 7.5%-8.2% increase in sales, comparable to around 9.5% for items with constant prices), but a much smaller and less significant effect for larger 5% and 10% bandwidths. The finding suggests that the listings whose prices are adjusted by sellers become less appealing after passing thresholds, thereby offsetting some of the symbol effect on sales, especially for larger bandwidths that pick up more price adjustments. It supports the identification strategy of separating the demand effect using constant price items and a small bandwidth. It also supports the idea of sellers using prices as a response to the symbol effect. We will return to seller pricing in [Section 1.4.5](#) using observed transaction-price.

After we show the average effect of passing a threshold, one natural question is when the effect may be larger or smaller. I explore the heterogeneity of the symbol effect by breaking down the full sample into different subsamples for shops at different levels, in different industries, or for items with different ticket values. First, I separately estimate the effect for shops at different levels. I pooled the data of shops near levels 6 to 9 to get enough statistical power and to make the sample sizes approximately equal across the three

¹⁹Many of the earlier RD applications use a series of polynomials of the running variable as RHS variables in their regressions. Local linear regression is more appealing because it avoids imposing any parametric assumption on functional form of the running variable. I also tried using polynomials for up to 5th order. I still get significant effects of summary symbols on sales.

subsamples. The results are shown in Table 1.6 (Table 3 shows the same estimates with clustered standard errors). The main finding is that the effect is only significant for Level 10 (rating-score threshold 5,001, five diamonds) and Level 11 (rating-score threshold 10,001, one crown). The effect size for Level 10 is consistently larger than the effect in Table 1.4. The symbol effect of Level 6 to 9 sellers is statistically insignificant. It seems to suggest that the Taobao market became so competitive that only very high level symbols had signaling value to consumers. And the lower level symbols have very little marginal effect.²⁰

Second, I tested the effect for subsamples of four major industries, and the results are in Table 1.7. I find a large effect for the three major industries: passing thresholds leads to a 21.3% increase in sales for Electronics, a 21.1% increase for Furniture, and a 33.9% increase for Kids and Baby (all at the 5% bandwidth). Compared to the Clothing industry that has no significant effect, they are either high-ticket-value items that involve after-sale services (Electronics and Furniture), or possess particular health risk (Kids and Baby). The magnitude of the effect is possibly driven by consumers caring more about reputation when buying these items. Consumers only buy when they are very comfortable with the quality.

Finally, I compared the effects for different ticket-value items. I divided the sample into four subsamples using quartiles of the item-model prices. See Table 1.8. Interestingly, the results are not monotonic in price. The jump is largest (22.4%) for low ticket value items with price less than 10 CNY,²¹ whereas it is small and insignificant for the second quartiles with prices ranging from 10 to 30 CNY. For the latter two quartiles with prices between 30 and 59 and prices larger than 59, the effects are statistically significant with point estimates of 14.2% and 10.4%, respectively.

1.4.3 Robustness Checks on Demand-Side

This section shows two standard RD robustness checks. First, I checked whether observable attributes are changing discontinuously at the threshold. As in Table 2, using the same local linear estimator in our main empirical model, the estimates show that across all the specifications and bandwidth choices, no shop attributes have discontinuity at the threshold except for “Percentage good rating” at a large (10%) bandwidth. Even so, the effect (-0.03) is negligible, as opposed to the mean (98.2), and is biased against a positive demand shock at threshold. This finding suggest that observable shop attributes are smooth near thresholds, which is consistent with the RD assumption as desired.

The second robustness check I performed was the placebo or falsification test. To show

²⁰There are some models that do predict a increasing return to reputation with endogenous firm size (Rob and Fishman, 2005) or specifications of market learning (Board and Meyer-ter Vehn, 2013). There are also some career reputation models that explains increasing return to reputation for employees, due to competition (Harstad, 2007) and employer heterogeneity (Casas-Arce, 2010), which also shed light on why the same phenomenon might arise in a retail market.

²¹10 CNY was about US\$1.53. The especially large effect for very low-price items might be due to the fact that some sellers could use low prices as “units.” For example, a seller selling a 200 CNY item could post a price of 0.01 CNY and ask the buyer to purchase 20,000 units.

that the discontinuity is not spurious, I created four alternative artifact thresholds: -10%, -5%, 5%, and 10% away from the true threshold. I used the same local linear estimation to test the “placebo” effect of those artifact levels on sales. [Table 1.9](#) shows the results with conventional standard errors, and [Table 4](#) shows the results with clustered standard errors (at the shop level). Notice that once standard errors are clustered, only the effect at the true threshold remains significant in any of the bandwidths. Even if not clustered, the results at a small bandwidth (2.5%) show a significant effect of symbols only at the true threshold. The point estimates for artifact thresholds are also small. Notice this finding is not driven by lack of statistical power in those artifact thresholds. The estimates of effects on false thresholds have similar standard errors compared to that of the true threshold. Therefore, I conclude that the main result of the effect passes the falsification test, implying that it is not driven by some particular mechanic structure of the data or sample construction.

1.4.4 Limited Attention Parameter

One might be interested in estimating the inattention parameter θ in [DellaVigna \(2009\)](#). Adapting the model to the Taobao context, suppose the perceived reputation V is given by $V = L + (1 - \theta)R$, in which L denotes level, a visible component, whereas rating score R is the percentage rating score above the threshold, an opaque component. For instance, a rating score of 601 will have level $L = 7$ (two diamonds) and $R = \frac{601 - 501}{1001 - 501} = 0.2$ (the upper and lower thresholds for Level 7 are 1001 and 501, respectively). When the rating score passes a threshold, the possible jump in V at the threshold can be represented by $V_+ - V_- = (L + 1) + (1 - \theta) \times 0 - (L + (1 - \theta) \times 1) = \theta$. Notice θ represents the proportion of the reputation value at just the thresholds. A fully rational consumers will have $\theta = 0$, and therefore have no discontinuity in V . Limited attentive consumers will have $\theta > 0$, leading to a discontinuous jump in V , which then leads to a jump in sales, as the main result implies. Fully inattentive consumers will have $\theta = 1$, for whom only the summary symbol matters.

To identify θ using the data requires a much stronger assumption on the exclusive restrictions of R_{it} , because RD only identifies the “local” effects instead of how rating scores affects demand when they are away from the thresholds. Still, suppose R_{it} is exogenous near a narrow intervals of the threshold. I model (normalized) sales as a linear function of V : $Y = \alpha V$, similar to [Lacetera et al. \(2012\)](#). Then I have that the jump in sales $\beta = \alpha\theta$. Therefore, $\theta = \frac{\beta}{\alpha} = \frac{0.0948}{0.296} = 0.32^{22}$. This finding, with the caveat in mind, is largely consistent with $\theta = 0.29$ in [Lacetera et al. \(2012\)](#) and much of the literature reviewed in [DellaVigna \(2009\)](#).

²²The estimated α is sensitive to the sample and specification. Here I uses the sample of sales that is within 20% of the thresholds.

1.4.5 Supply-Side Responses

The dynamic pricing model provides two testable predictions. First, sellers should gradually decrease their prices before passing a threshold. Second, they should immediately increase their prices afterwards. I now examine both predictions using transaction prices. To separate price response to summary symbols from other potential demand shifters, such as seasonality and changes in other shop attributes, I control for time fixed effects and shop attributes to get the residual price changes. I will refer “net price change” as the residual of observed price changes that are not explained by time fixed effect and other shop attributes.

First, I look at the log of normalized prices ($\log \frac{p_t}{p_0}$).²³ I plot the means of prices for each 1% bin of percentage distance to thresholds, and its local linear fit with bandwidth 5%. See [Figure 1.3](#) for the residuals of normalized price levels and [Figure 3](#) for the normalized price levels. In both cases, before the threshold, we observe sellers lowering the price more than 2% until they reach the threshold. The prices are lowest at thresholds. Both are predicted by the model of dynamic pricing in response to consumer limited attention. However, I did not find an substantial and immediate price jump at the threshold as predicted by the model. Several factors could explain this lack of price hike. For example, sellers could also be inattentive, may have some menu cost, or fear of “antagonizing” customers.²⁴ Still, a kink clearly exists in the price level at the threshold. Using RKD to formally test for the kink shows that it is indeed significant the confidence interval for the kink of log prices at the threshold is [0.416, 1.937] (p-value=0.002). Adding time fixed effects and shop attributes as controls, the confidence interval is [0.047, 1.559] (p-value=0.037).²⁵

When a seller is selling multiple products simultaneously, we have an ancillary prediction: sellers should adjust the prices of their lower priced items more steeply before thresholds. The intuition is that in terms of collecting good ratings, a good rating from selling a cheap item is just as good as one from selling an expensive item. Therefore, under the assumption that the elasticities are similar²⁶, sellers should cut prices of their cheaper items. To test this prediction, [Figure 1.4](#) plots the same scatters and local linear fits for two subsamples: high priced items (with prices above mean price of each seller) and low priced items (with prices below mean price for each seller). It shows that the decrease in prices for low priced items are much steeper than the high priced items. See [Appendix A.1.4](#) for the formal tests.

²³Taking the log helps take care of outliers. It does not change the qualitative result.

²⁴For related literature, see, for example, [Goldfarb et al. \(2012\)](#), [Zbaracki et al. \(2004\)](#) and [Anderson and Simester \(2010\)](#)

²⁵The running variable is, as always, the percentage distance to thresholds, whereas the dependent variable is log of price levels. It is implemented by the RDROBUST package as in [Calonico et al. \(2014\)](#), with 5% bandwidth and the robust method. The estimator is given by a local linear regression for point-estimate and local quadratic regression for bias-correction, with triangle kernel. Main bandwidth and pilot bandwidth are set as the same. Using raw prices, the confidence interval for the kink is [1.615, 15.955] (p-value=0.016). Using only time fixed effect, the confidence interval for the kink is [0.0126, 1.524] (p-value=0.046).

²⁶Or the high priced items are not having a much higher elasticity than lower priced items, which is not very likely.

I also show the heterogeneity of price responses as we did for the demand effect. [Figure 4](#) to [Figure 6](#) in the Appendix shows the log price levels for sellers with Level 6-9, Level 10, and Level 11. Not surprisingly, for Level 10 sellers who face the strongest symbol effect on demand, the price changes before and after the threshold are the steepest: sellers lower prices for about 5% before threshold, and increase prices for 5% afterwards, with a significant jump at threshold. This is also consistent with the model’s prediction that sellers facing stronger effect of summary symbols should respond by adjusting prices more steeply.

Overall, the findings of price changes strongly support the theoretical model of sellers responding to the effect of summary symbols by lowering prices before the threshold and increasing prices afterward. In the Appendix [A.1.5](#), I discuss two pieces of suggestive evidence in product offering that also support the theory. These findings suggests that sellers are aware of consumer limited attention in ratings and respond largely as the theories predict.

1.5 Concluding Remarks

Using panel RD design based on Taobao’s level categorization, I find a significant effect of summary symbols on demand. Passing thresholds increases sales by over 9% for the same seller, the same item, and with the same price. The effect is robust to different specification and bandwidth choices. It also passed standard robustness checks for RD. I find significant heterogeneity across industries, different level thresholds, and different ticket-value items.

This effect suggests consumers are not fully incorporating the readily available rating scores into consideration. At least two explanations are possible. First some consumers might be rationally inattentive to the rating score. And this explanation could apply more naturally if utilizing the rating scores is more costly. For example, [Figure 1](#) in Appendix [A.1.1](#) shows Taobao’s newer template that applies to some of our sample. Buyers have to click just once to jump from the default display (on the left, with only the one crown) to see the underlying rating score (16,726, as on the right). In this case, a small cost in searching for the rating score is plausible and it may lead to some rational inattention.²⁷ Another explanation is that some consumers are paying limited attention to visible rating scores. This behavioral explanation focuses on the fact that levels are salient symbols, whereas rating scores are less salient (but equally visible) numbers.²⁸ This is consistent with limited attention found in other many domains, as well as the 9-price ending effects. I derive the inattention parameter using the model of [DellaVigna \(2009\)](#). I get a $\theta = 0.319$, largely consistent with the literature. On that front, this study is related to the behavioral IO literature, such as [Goldfarb and Xiao \(2011\)](#).

²⁷Similar effect may drive consumer’s inattention to outside buy-it-now options on eBay ([Malmendier and Lee, 2011](#)).

²⁸[Figure 2](#) shows how eBay and Taobao (older template) display the rating scores and symbols on their web pages: rating scores are always displayed right next to the symbols. Given that both rating scores and levels are readily available, the limited attention explanation makes more sense compared to the rational inattention model.

Regardless of whether consumers are limited attentive rationally or due to behavior biases, the findings in this study show sellers use dynamic pricing as a response to it. For items with observed price changes, sellers gradually decreased the prices by up to 2% before the thresholds. They increase their prices after passing thresholds. The kink in their price changes is significant and robust. And the pattern of price changes across listings and sellers is also consistent with the theory of sellers responding to consumer limited attention.

How do these results speak to the theories of reputation? The main result of a significant summary symbol effect is unsurprisingly consistent with most models that predict reputation volume increases sales. The heterogeneity of the symbol effect across industries is more or less expected as well, as pointed out by [Dellarocas \(2006\)](#).

These results could help in modeling optimal information revelation mechanisms for platforms, given that buyers are limited attentive to informations such as rating scores once platforms offer a categorization. Choosing a categorization scheme is a strategy of platforms. Comparing Taobao ([Figure 1.1a](#)) and eBay ([Figure 1.1b](#)), for example, one can find that eBay has 13 levels for ratings up to 1 million, whereas Taobao has 18 levels for the same range. There are many research opportunities to explore the optimal categorization, or more broadly, information aggregation for platform design in general. Practically, the existence of consumer limited attention might be a concern for the platform and regulators, yet the sellers' response suggests that the welfare implication for consumer limited attention could be more nuanced.

1.6 Figures and Tables

4分-10分	❤️	Yellow star (🌟) = 10 to 49 ratings
11分-40分	❤️❤️	Blue star (🌟) = 50 to 99 ratings
41分-90分	❤️❤️❤️	Turquoise star (🌟) = 100 to 499 ratings
91分-150分	❤️❤️❤️❤️	Purple star (🌟) = 500 to 999 ratings
151分-250分	❤️❤️❤️❤️❤️	Red star (🌟) = 1,000 to 4,999 ratings
251分-500分	💎	Green star (🌟) = 5,000 to 9,999 ratings
501分-1000分	💎💎	Yellow shooting star (🌟) = 10,000 to 24,999 ratings
1001分-2000分	💎💎💎	Turquoise shooting star (🌟) = 25,000 to 49,999 ratings
2001分-5000分	💎💎💎💎	Purple shooting star (🌟) = 50,000 to 99,999 ratings
5001分-10000分	💎💎💎💎💎	Red shooting star (🌟) = 100,000 to 499,999 ratings
10001分-20000分	👑	Green shooting star (🌟) = 500,000 to 999,999 ratings
20001分-50000分	👑👑	Silver shooting star (🌟) = 1,000,000 ratings or more
50001分-100000分	👑👑👑	
100001分-200000分	👑👑👑👑	
200001分-500000分	👑👑👑👑👑	
500001分-1000000分	👑	
1000001分-2000000分	👑👑	
2000001分-5000000分	👑👑👑	
5000001分-10000000分	👑👑👑👑	
10000001分以上	👑👑👑👑👑	

(a) Taobao

(b) eBay

Figure 1.1: Levels and rating scores of Taobao and eBay

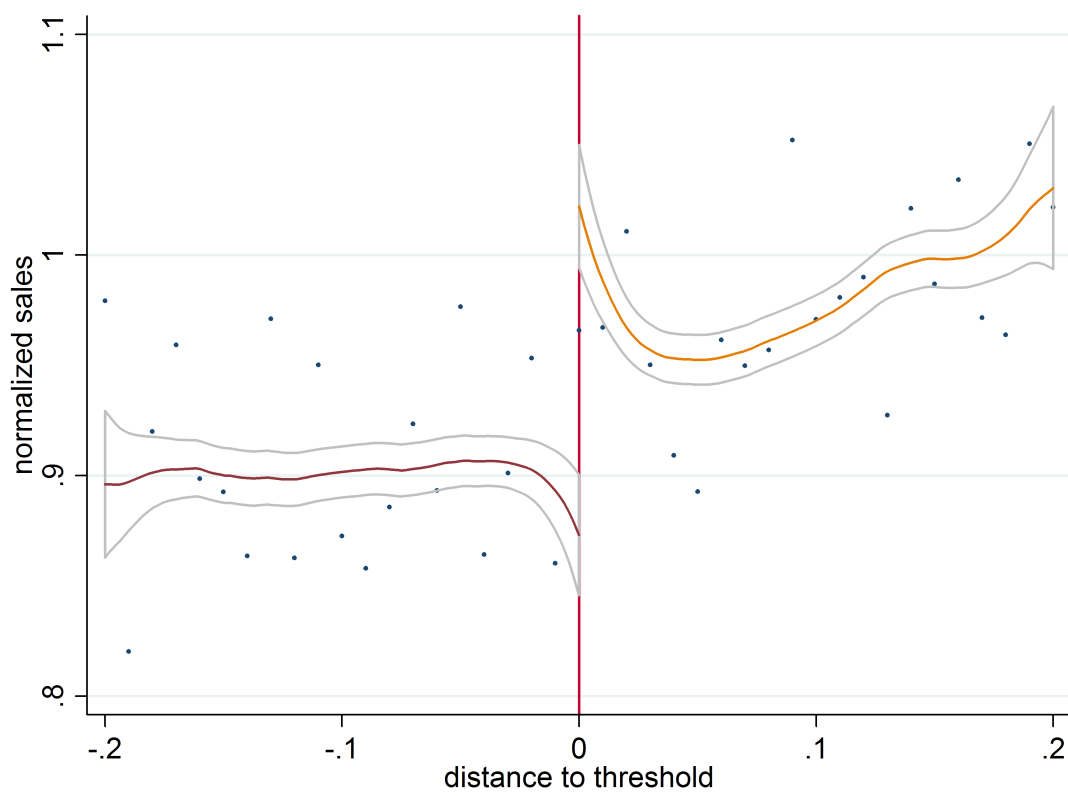


Figure 1.2: Normalized hourly sales and distance to threshold

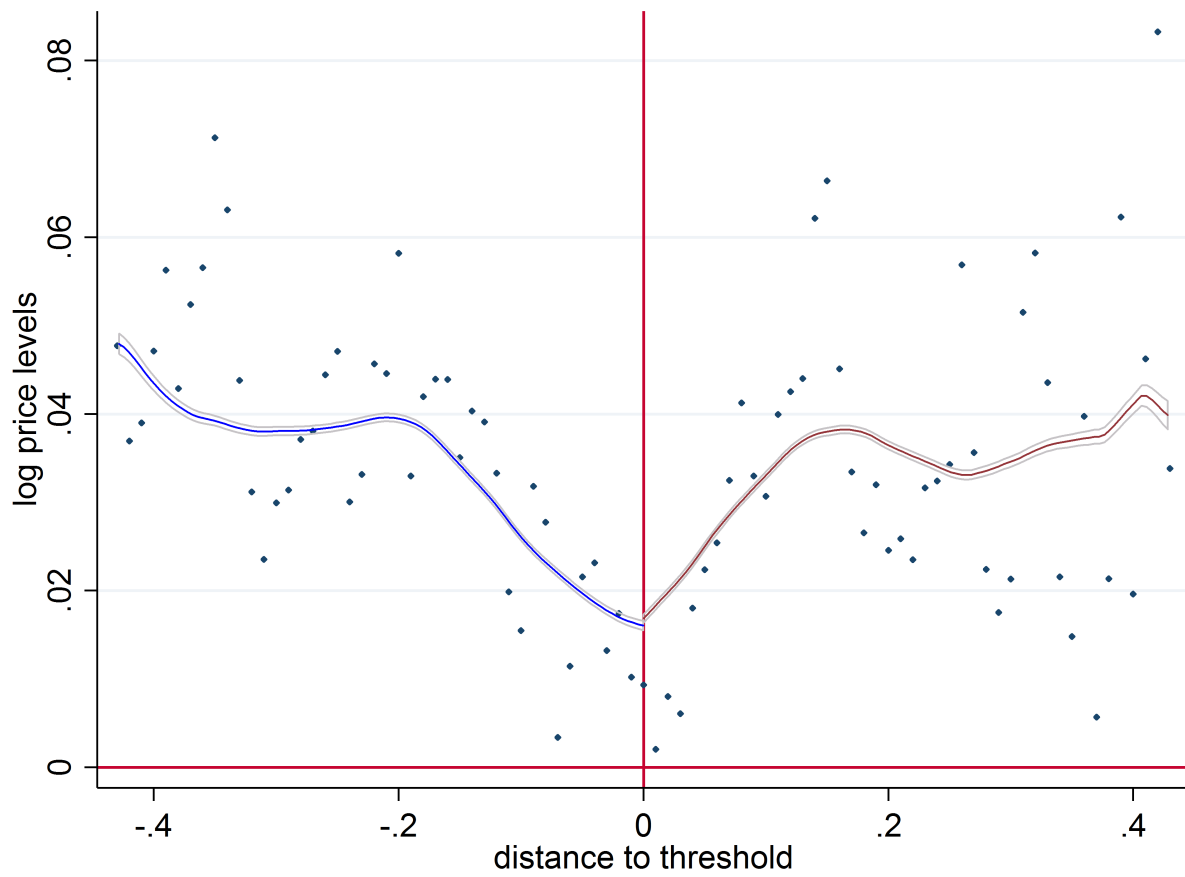
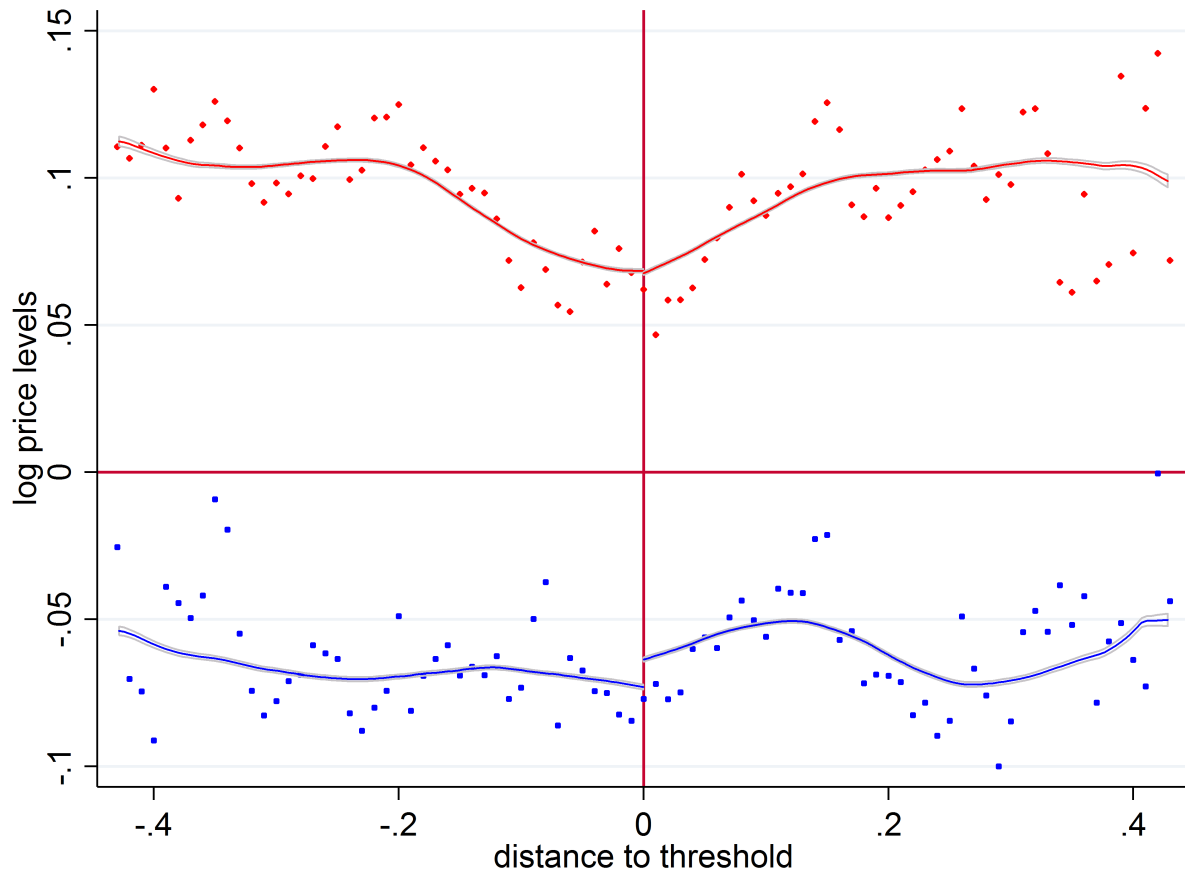


Figure 1.3: Normalized price levels: Local linear fit with time fixed effect and control



The prices levels for low priced items (with prices below the mean price for each shop as the diamond scatters and red line above) and high priced items (with prices above the mean price for each shop as the square scatters and blue line below).

Figure 1.4: Normalized price levels for high and low priced items: Local linear fit with time fixed effect and control

Table 1.1: Shop-level summary statistics

	Mean	SD	Min	Max
year of establishment	2012	1.67	2004	2013
start rating score	3291	3292	62	15972
start level	8.27	1.64	3	11
start percentage good rating	98.5	1.66	82.6	100
start dynamic rating 1	4.75	0.121	4	5
end rating score	5112	5349	109	83584
end level	8.9	1.63	4	13
end percentage good rating	98.2	2.22	67.9	100
end dynamic rating 1	4.74	0.13	3.8	5
N=2976				

Table 1.2: Industry Distribution

Industry	Number	Percentage
Clothing	696	23.4%
Electronics & Computers	449	15.1%
Furniture	417	14.0%
Sports and Outdoor	225	7.6%
Kids and Baby	221	7.4%
Home Improvement	185	6.2%
Beauty	178	6.0%
Automotive	170	5.7%
Food	128	4.3%
Virtual Goods	92	3.1%
Service	75	2.5%
Jewelry and Accessories	70	2.4%
Collectibles	37	1.2%
Others	33	1.1%

Table 1.3: Item, Item-Model/Style, and Hourly sales level summary statistics

<i>Panel A</i>		Item level							
		N	Mean	Stdev	Percentiles				
					10	25	50	75	90
Number of Models		25900	8.82	13.45	1	3	5	10	18
Average Price		25900	60.00	238.1	1.85	6.10	24.84	49.0	109.9
Sales		25900	21218	1280798	14	25	50	136	436
Transactions		25900	261.2	2109	10	14	31	84	271
<i>Panel B</i>		Item-Model level							
		N	Mean	Stdev	Percentiles				
					10	25	50	75	90
Price		228433	71.29	260.3	3.5	9.9	33	68	138
Sales		228433	2406	324577	1	2	5	15	47
Transactions		228433	29.62	347.9	1	2	4	11	31
<i>Panel C</i>		Hourly sales level							
		N	Mean	Stdev	Percentiles				
					10	25	50	75	90
Sales (raw)		73607661	6.561	13675	0	0	0	0	0
Normalized	hourly sales	73607661	0.9511	11.72	0	0	0	0	0
Non-zero sales (raw)		1624627	297.2	92048	1	1	1	2	4
Non-zero	normalized hourly sales	1624627	43.09	66.41	2.12	6.31	19.27	52.50	111.2

Table 1.4: RD estimates for normalized hourly sales over distance to thresholds

	(1)	(2)	(3)
	hourlysales	hourlysales	hourlysales
5%	0.123*** (5.78)	0.124*** (5.84)	0.126*** (5.93)
2.5%	0.0976** (3.28)	0.0968*** (3.30)	0.0945** (3.22)
10%	0.0941*** (6.12)	0.110*** (7.14)	0.111*** (7.22)
N	31076708	31076708	31076708
Time F.E. ¹	No	Yes	Yes
Control ²	No	No	Yes

Standard errors in parentheses. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. See [Table 1.5](#) for results using clustered standard errors. The IK optimal bandwidth is 13.7%. The estimator is given by a local linear regression with triangle kernel. Using uniform kernel does not change the result.

Sample: normalized hourly sales for item-models with the same price throughout the sample period, and for shops that passed at least one threshold during the sample period.

¹ Including dummy variables for each day and each hour-of-the-day.

² Including percentage good rating, all three dynamic ratings, and return policy.

Table 1.5: RD estimates of symbol effect on hourly sales

	(1)	(2)	(3)
Bandwidth			
5%	0.124* (0.0586)	0.124* (0.0505)	0.126* (0.0509)
2.5%	0.0980 (0.0798)	0.0971 (0.0661)	0.0948 (0.0664)
10%	0.0942* (0.0415)	0.110** (0.0376)	0.111** (0.0377)
N	31076708	31076708	31076708
Time F.E. ¹	No	Yes	Yes
Control ²	No	No	Yes

Clustered (by shop) standard errors in parentheses. ⁺ $p < 0.1$, ^{*} $p < 0.05$, ^{**} $p < 0.01$, ^{***} $p < 0.001$. The estimator is given by a local linear regression with triangle kernel. Using uniform kernel does not change the result.

Sample: normalized hourly sales for item-models with the same price throughout the sample period, and for shops that passed at least one threshold during the sample period.

¹ Including dummy variables for each day and each hour-of-the-day.

² Including percentage good rating, all three dynamic ratings, and return policy.

Table 1.6: RD estimates of symbol effect for different thresholds

	Levels 6-9	Level 10	Level 11
Bandwidth			
5%	-0.0400 (0.0515)	0.245*** (0.0411)	0.0946** (0.0312)
2.5%	-0.0948 (0.0709)	0.273*** (0.0596)	0.100* (0.0427)
10%	-0.0159 (0.0369)	0.144*** (0.0300)	0.0924*** (0.0229)
N	6603320	8893753	10659103
Time F.E. ¹	Yes	Yes	Yes
Control ²	Yes	Yes	Yes

Standard errors in parentheses. See [Table 3](#) in Appendix [A.1.1](#) for results of clustered standard errors. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimator is given by a local linear regression with triangle kernel.

Sample: normalized hourly sales for item-models with constant price throughout the sample period, and for shops that passed at least one threshold during the sample period.

¹ Including dummy variables for each day and each hour-of-the-day.

² Including percentage good rating, all three dynamic ratings, and return policy.

Table 1.7: RD estimates of symbol effect for different industries

	Electronics	Clothing	Furniture	Kidsd&Baby
5%	0.213*** (0.0503)	0.0394 (0.0282)	0.253** (0.0826)	0.622*** (0.104)
2.5%	0.408*** (0.0741)	-0.0172 (0.0404)	0.211* (0.101)	0.339* (0.156)
10%	0.104** (0.0368)	0.105*** (0.0209)	0.160** (0.0596)	0.322*** (0.0723)
N	5250066	16309671	3087080	2199618
Time F.E. ¹	Yes	Yes	Yes	Yes
Control ²	Yes	Yes	Yes	Yes

Standard errors in parentheses. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.. The estimator is given by a local linear regression with triangle kernel.

Sample: normalized hourly sales for item-models with constant price throughout the sample period, and for shops that passed at least one threshold during the sample period.

¹ Including dummy variables for each day and each hour-of-the-day.

² Including percentage good rating, all three dynamic ratings, and return policy.

Table 1.8: RD estimates of symbol effect for different ticket value items

	$P < 10$	$P \in [10, 30]$	$P \in (30, 59]$	$P > 59$
Bandwidth				
5%	0.224*** (0.0417)	0.00509 (0.0385)	0.142*** (0.0359)	0.104* (0.0523)
2.5%	0.269*** (0.0577)	-0.0869 (0.0547)	0.0640 (0.0508)	0.0759 (0.0726)
10%	0.105*** (0.0303)	0.0781** (0.0282)	0.174*** (0.0274)	0.0900* (0.0373)
N	8887913	8382881	8440951	5364963
Time F.E. ¹	Yes	Yes	Yes	Yes
Control ²	Yes	Yes	Yes	Yes

Standard errors in parentheses. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimator is given by a local linear regression with triangle kernel.

Sample: normalized hourly sales for item-models with constant price throughout the sample period, and for shops that passed at least one threshold during the sample period.

¹ Including dummy variables for each day and each hour-of-the-day.

² Including percentage good rating, all three dynamic ratings, and return policy.

Table 1.9: Falsification test: RD estimates of artifact thresholds

Thresholds	-10%	-5%	0%	5%	10%
Bandwidth					
5%	-0.00995 (0.0237)	-0.00633 (0.0224)	0.126*** (0.0212)	0.0225 (0.0206)	-0.0653** (0.0235)
2.5%	0.0252 (0.0335)	0.0283 (0.0328)	0.0948** (0.0294)	0.0100 (0.0286)	-0.0366 (0.0329)
10%	-0.00613 (0.0168)	-0.0206 (0.0158)	0.111*** (0.0154)	-0.0200 (0.0151)	-0.0360* (0.0167)
N	31076708	31076708	31076708	31076708	31076708
Time F.E. ¹	Yes	Yes	Yes	Yes	Yes
Control ²	Yes	Yes	Yes	Yes	Yes

Clustered (by shop) standard errors in parentheses. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimator is given by a local linear regression with triangle kernel. Once standard errors are clustered at shop level, only 0% shows significant symbol effect across different bandwidth choices, see [Table 4](#) in Appendix.

Sample: normalized hourly sales for item-models with the same price throughout the sample period, and for shops that passed at least one threshold during the sample period.

¹ Including dummy variables for each day and each hour-of-the-day.

² Including percentage good rating, all three dynamic ratings, and return policy.

Table 1.10: RD estimates of symbol effect for items with non-constant prices

	1	2	3
Bandwidth			
5%	0.0715** (0.0253)	0.0438+ (0.0257)	0.0376 (0.0257)
2.5%	0.0765* (0.0353)	0.0822* (0.0363)	0.0751* (0.0363)
10%	0.0363* (0.0182)	0.0405* (0.0182)	0.0362* (0.0182)
N	18263549	18263549	18263549
Time F.E. ¹	No	Yes	Yes
Control ²	No	No	Yes

Standard errors in parentheses. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimator is given by a local linear regression with triangle kernel.

Sample: normalized hourly sales for item-models with at least one price change during the sample period, and for shops that passed at least one threshold during the sample period.

¹ Including dummy variables for each day and each hour-of-the-day.

² Including percentage good rating, all three dynamic ratings, and return policy.

Chapter 2

Targeted Search

2.1 Introduction

Search technology enables consumers to more easily find their desired goods or services. Imagine a consumer searching for a black leather case for her iPad mini. She can directly type in “iPad mini leather black case” on Amazon, where she will find 87,182 related listings, ranked by “Relevance.” She can also use the refinement tools to select the desirable attributes, such as product category, material, and color. Amazon is certainly not alone – all major platforms adopt similar search technologies. For example, eBay also offers a variety of refinement tools. And the same search query on eBay generates 12,976 listings ranked by “Best Match.” In the world’s largest online market place Taobao-TMall, the default ranking is by “Comprehensive” which is based largely on relevance, and various refinement tools are also readily available. [Table 2.1](#) summarizes the default ranking and refinement tools used by major online platforms. Most platforms use either relevance ranking or comprehensive ranking by default, and search refinement tools are widely available.

Conceptually, refinements are filters that can be applied to search results to keep more relevant ones. In the Amazon example, users can choose the category (e.g., between Tablet Cases, Tablet Stands, and Tablet Keyboard Cases). They can also refine by attributes, such as material (leather, plastic, etc.), and colour, as well as delivery day, Prime or not, and brands, among others. On eBay, buyers can further refine by the location of sellers, listing format (auction vs. buy-it-now), and so on. These refinements help matching sellers with search queries more precisely.

And relevant ranking has a similar effect on search. Consumers can directly enter the desirable attributes in their search queries, and the search engine will try to use relevance ranking to match the search query with sellers by algorithms. A ranking mechanism is a retrieval function that takes the user input to rank possible outcomes. ¹ Following the

¹There is an extensive literature in Computer Science on training the algorithm using various data. For instance, see [Agichtein et al. \(2006\)](#) and [Liu \(2009\)](#) for advances and reviews on information retrieval. For on-going work on how consumers form search queries, see [Liu and Toubia \(2016\)](#).

previous example, when a consumer types “iPad mini leather black case” in the search box of Amazon, the website’s search engine will select a subset among its hundreds of millions of items according to the relevance of listing attributes to the keywords in the search query. Tablet cases with features that match “iPad mini,” “leather,” and “black” will get more prominent slots. Furthermore, recent developments in natural language processing and AI allow the platform to understand conversational language in addition to the traditional keywords, and e-commerce platforms are investing in such search technologies.²

In addition to refinements and relevance ranking, platforms can use personalized data to further improve the match between buyers and sellers. Potential data includes, but is not limited to, a consumer’s device, location, IP address, cookies, and historical activities such as clicks and purchases. Empowered by developments in machine learning techniques and the availability of data, personalized search is becoming increasingly common, especially in mobile devices. For instance, Google has been using personalized ranking for all searches since 2009. In Table 2.1, the default ranking of Tripadvisor, “Just for You,” uses the customers’ past browsing and review data to rank hotels. In a recent Kaggle competition,³ Airbnb asked participants to design an algorithm to predict users’ preferences using demographics, web session records, and attributes such as device and browser for user activities. Continuing our example of shopping for iPad cases, eBay adjusts the ranking of listings by a user’s past purchase and browsing history as well as her location and device. The personalization of search will lead to different search outcomes and rankings for different customers even if they are using the same search query. And it has the potential to achieve remarkable precision of matching between consumers and sellers.

These advances in search technology have profound implications for consumer search and platform design. I use the concept of targeted search to summarize the aforementioned search technologies that help consumers to find better matches to their preferences. Targeted search changes consumer’s optimal search strategy, and hence the demand sellers face. As search becomes more targeted, consumers are facing better-matched sellers, which increases the demand. However, targeted search also makes sellers more similar, leading to fiercer price competition. These two effects have opposite pricing implications. Therefore, the impact of targeted search on equilibrium prices is not obvious. Furthermore, the price and consumer surplus will not only affect the profitability of sellers, but also the platforms. Because the adoption of search technology is a platform decision, the interaction between search design and revenue models is also important. How will targeted search affect the platform’s optimal fee structure? Will it help or hurt the platform’s monetization such as advertising revenue?

This paper is among the first to study search technology and its implications for e-commerce platform design. I model consumer targeted search in a horizontally differentiated

²The list includes Amazon Echo, Google Assistant, and Apple Siri. Alibaba, the parent company of Taobao and TMall, invested in Twiggle, a company that develops e-commerce search engine, that delivers more accurate results than current options, while allowing shoppers to write queries in conversational language.

³See <https://www.kaggle.com/c/airbnb-recruiting-new-user-bookings/data>.

BEAUTIFUL THINGS ON AMAZON UPDATED DAILY **EXPLORE**

amazon Prime All iPad mini leather black case **amazon** **FREE SAME-DAY PICKUP ON MILLIONS OF ITEMS**

Shop by Department Shopping History Zachary's Amazon.com Today's Deals Hello, Zachary Your Account Your Prime Your Lists Cart

1-16 of 87,182 results for "iPad mini leather black case" Sort by Relevance

Show results for

- Computers & Accessories >
 - Tablet Cases
 - Tablet Keyboard Cases
 - Tablet Accessories
 - Laptop Accessories
 - Tablet Stands
- Sports Fan Shop >
 - Sports Fan Tablet Accessories
- Office Products >
 - PDA & Handheld Accessories
- Toys & Games >
 - Baby & Toddler Toys
- * See All 24 Departments

Define by

SUPCASE
SUPCASE Rugged Case for iPad Air & iPad Mini
Shop now

Dealgadgets 360 Degrees Slim Rotating Stand Leather Case Cover for Apple Ipad Mini 1/2 /3 Black
by Dealgadgets
\$9.98 \$46.98 Prime
Get it by Tomorrow, Mar 28

★★★★☆ 220
1 free items on purchase of 1 items and 2 more promotions
Product Features
... in the case for ... leather ... Specific designed for Ipad Mini 1/2 /3 ...
Electronics: See all 72,698 items

Hit Sign in or register | Daily Deals | Gift Cards | Sell | Help & Contact WELCOME THE SEASON My eBay

Shop by category iPad mini leather black case All Categories Search Advanced

Refine your search for iPad mini leather black case

Categories
Computers, Tablets & Networking
Tablet & eBook Cases, Covers & Keyboard Folios
More
See all categories

Condition see all
☐ New (12,924)
☐ Used (52)

Price
\$ to \$

Format see all
☒ All Listings (12,976)
☐ Auction (86)
☐ Buy It Now (12,014)

Item Location see all
☒ Default
☐ Within
100 miles of 94404
☐ US Only
☐ North America
☐ Worldwide

All Listings Auction Buy It Now Sort: Best Match View: [icon]

iPad mini leather black case 12,976 listings Follow this search

Did you mean: ipad mini leather back case? (7329 items)

Black PU Leather Folio Stand Business Portfolio Case Cover for iPad mini Retina
\$17.78
or Best Offer
Free shipping
266 sold

Poetic Slimline Magnetic Leather Case For Apple iPad Mini 2 with Retina Display
\$8.99
Buy It Now
Free shipping
270 sold

Figure 2.1: Relevance ranking examples: Amazon (Relevance) and eBay (Best Match)

Table 2.1: Default rankings by major online platforms and OTAs

Platform	Category	Default Ranking	Refinement Tools
Amazon	general merchandise	Relevance	Yes
eBay	general merchandise	Relevance	Yes
craigslist	general merchandise	Relevance or time of posting	No
etsy	handmade or vintage items	Relevance	Yes
Rakuten	general merchandise	Relevance	Only category
Bestbuy	electronics	Relevance	Yes
Sears	general merchandise	Relevance	Yes
Newegg	electronics	Featured	Yes
Walmart	general merchandise	Relevance	Yes
Taobao	general merchandise	Comprehensive	Yes
Tmall	general merchandise	Comprehensive	Yes
JD	general merchandise	Comprehensive	Yes
Suning	general merchandise	Comprehensive	Yes
Tripadvisor	hotels	personalized "Just for you"	Yes
Booking	hotels	"recommended"	Yes
Expedia	hotels	"recommended"	Yes
Orbitz	hotels	"recommended"	Yes
Hotels	hotels	"recommended"	Yes
Hotwire	hotels	"popular"	Yes
Priceline	hotels	"popular"	Yes
Kayak	hotels	"recommended"	Yes

market. In this setting, the platform uses buyers' search query, refinement, and personalized data to select and rank sellers by their match values with buyers. And as the platform improves its search technology, the search becomes more targeted, leading to even better matches. I show the effect of targeted search is not monotonic on the equilibrium price. When the targeting is not too precise, targeted search makes consumers visit only sellers that have better matches and hence more similar. This intensifies competition, leading to more marginal consumers for relevant sellers. And the more elastic demand reduces the equilibrium price. I further show this effect is equivalent to reducing the search cost by saving on the cost of visiting irrelevant sellers. However, when the targeting becomes so precise that consumers do not search actively, the equilibrium price will be discontinuously higher and increasing in targeting precision, because "no-search" gives sellers monopoly power and the power is increasing when buyers have better matches. This effect is not captured by reducing search cost because negligible search cost implies extremely intense competition and razor-thin margins. To supplement the theoretical predictions, I show some suggestive evidence using Taobao data: under a measure of search precision, the market price and search precision exhibits the predicted non-monotonic pattern.

Targeted search can increase consumer surplus in three ways: saving search costs, reducing prices (up to a limit), and offering better matches. Therefore, it encourages consumer entry until it becomes sufficiently precise to discourage active search, and hence leads to monopoly prices. Combining with its implication on equilibrium prices, the platform faces a design problem in choosing the optimal search precision, since there are interactions between targeted search and platform revenues. I consider two commonly observed platform revenue models: commission and promoted slots. And I find that in both models, the platform has strategic reason to limit its targeted search precision. The reason is that the platform can use some degree of search imprecision to enforce a lower market price by encouraging seller competition, which leads to more consumer entry.

The commission model is motivated by the observation that platforms often charge a percentage commission for each transaction. For example, Amazon charges 5% for most categories. I model the platform as a monopoly and chooses a commission rate to maximize its profit. I show that as search outcomes becomes more targeted, the optimal commission rate becomes higher, leading to a higher profit for the platform. When I allow for consumer entry, targeted search increases both the platform profit and consumer surplus up to a threshold. Once targeting becomes very precise, there is a price hike. And it could decrease the platform revenue with or without consumer entry. Therefore, the platform may want to limit its precision of search targeting even if improving it is costless.

Many platforms also sell promoted slots. For instance, Amazon sells "Sponsored Products" slots on page one of search results page. In the promoted slot model, targeted search, up to the aforementioned precision limit, could increase the value of top promote slots by increasing the relative market share of promoted sellers. The platform can get higher profit from selling the same top promoted slots with targeted search. Notably, this effect is exactly the opposite of reducing search cost, because reducing search cost makes promoted slots less valuable as more consumers continue search. Again, once the precision is above the limit,

the platform’s revenue from selling promoted slots may be lower due to low consumer entry. I also show some suggestive evidence using the same Taobao data that is consistent with the prediction.

2.2 Literature Review

Broadly, this study relates to two sets of literature: consumer search and the economics of platforms. This paper contributes to the search literature by modelling targeted search in e-commerce platforms. To the platform literature, this study contributes by pioneering in investigating how optimal platform revenue models interact with targeted search.

Studies on consumer search in differentiated market lead to a large literature. [Wolinsky \(1986\)](#) and [Anderson and Renault \(1999\)](#) propose models of sequential search in a market with horizontal differentiation. [Kuksov \(2004\)](#) further endogenizes product design in the search context. He finds that lower search cost increases product differentiation, which may increase prices. [Bar-Isaac et al. \(2012\)](#) explores the possibility of broad versus niche designs in a search context by allowing firms to have both vertical and horizontal differentiation. These studies do not model targeted search. Instead, they interpret the effect of online search technology as reducing search cost, leading to different – sometimes opposite – implications compared to this study.

A growing literature on ordered or directed search deviates from the standard assumption of random search. [Arbatskaya \(2007\)](#) explores the market equilibrium of homogeneous goods when consumers are forced to visit sellers in a particular order. [Armstrong et al. \(2009\)](#) model one firm as “prominent” as being the first to be sampled, whereas the rest are sampled randomly. [Armstrong and Zhou \(2011\)](#) and [Chen and He \(2011\)](#) further endogenizes the prominence by assuming firms either pay or have lower prices to gain prominence. The main finding is that because the prominent firm faces more elastic “fresh” demand compared to demand from recall, its price will be lower. By contrast, this study endogenizes prominence by modelling targeted search, that is, making consumers visit more relevant firms first. Furthermore, I model the design of search targeting as a strategic choice of the platform.

The study is closely related to recent progress in targeted search. [Yang \(2013\)](#) modelled targeted search by endowing consumers with exogenous discrete types, and as the quality of search increases, the probability of finding matched type increases. [Yang \(2013\)](#) does not capture the idea that as online search technology advances, platforms will be able to better segment consumers *within* each category as is the case in this study. The difference leads to quite different, and sometimes opposite, effects of targeted search technology. [De Corniere \(2016\)](#) models consumers as uniformly distributed in a circle, and improvement of targetability is modelled as a better match between the locations of advertisers and consumers. Apart from the set up, one major difference is that this model focuses on the organic search results instead of sponsored advertisement. Unlike advertisers choosing their targets, e-commerce platforms decide how sellers match buyers, which leads to different pricing implications. The search engines also have instruments and incentives that are different from e-commerce

platforms. Therefore, the optimal contract and design of the two kinds of platforms differ substantially from each other.

Recent empirical studies have investigated some aspects of online targeted search. [Ghose et al. \(2014\)](#) explore how rankings affect consumer search and platform revenues. One of their key findings, that relevance ranking increases platform revenue, is consistent with our model prediction. [Chen and Yao \(2016\)](#) find that refinement tools increase consumer utility of purchased products, also consistent with our model prediction. [Ursu \(2016\)](#) shows that relevance ranking affects consumer search and increases consumer welfare by reducing search cost. This study proposes some predictions on how targeted search affects market price and structure, as well as platform revenue and contracts. This study also contributes to the economics of platforms literature by combining platform contracts with underlying consumer search. [Sriram et al. \(2015\)](#) point out that “advertising and consumer search are critical for web-based commerce....The optimal quantity of search functionality and/or regulated advertising is therefore a crucial platform management question.” [Eliaz and Spiegler \(2011\)](#) consider how the search engine might want to include more firms with less relevance to generate more clicks, and the key difference is that relevance is defined by the probability of matching between consumer and seller, yet conditional on matching, the realized utility follows the same distribution. In other words, their model does not capture the idea that as search becomes more targeted, the sellers becomes more homogeneous, which leads to a new insight in this study. [Hagiu and Jullien \(2011, 2014\)](#) considered the platforms’ incentive to diver searches, and the key difference of their set-up is that the platform has complete control over the sequence of consumer search. More broadly, this study is also related to the two-sided market literature ([Rochet and Tirole, 2003, 2006](#); [Armstrong, 2006](#); [Rysman, 2009](#)) by micro-modelling the network externalities in the search process. The ad-slot model is related to the sponsored-search literature ([Athey and Ellison, 2011](#); [De Corniere, 2016](#); [De Corniere and De Nijs, 2016](#)). [Dukes and Liu \(2015\)](#) also model search design by letting the platform choose a search cost in a setting where consumers have to search in two dimensions, both between and within products. However, unlike our study, they do not explicit model targeted search, nor do they model the revenue models of the platform.

2.3 Modelling Targeted Search

I start from the classic model of sequential search for horizontal differentiated products. Consider a product sold by n distinct sellers denoted by $i = 1, 2, \dots, n$. I focus on thick markets with large n , a feature shared by many categories in major platforms. Each seller produces a single product with constant marginal cost c . There is a set of consumers (per seller mass normalized to 1), each with unit demand. The utility of buyer j consuming x_0 numeraire good and a unit of brand i is given by $u_j(x_0, i) = x_0 + v_{ij}$, where v_{ij} captures how good seller i ’s product matches the need of consumer j . I assume that v_{ij} are realizations of an i.i.d. distribution with CDF G that has finite support $[\underline{v}, \bar{v}]$. I further assume its density $g(v)$ is strictly positive, smooth, and log-concave with no further restrictions, unless otherwise

specified. The value of the outside option is normalized to zero, an assumption to be relaxed when considering consumer entry.

By assuming v_{ij} is an i.i.d. draw across both i and j , I am focusing on horizontal differentiation. For example, think of sellers as different brands of iPad cases with different colors, styles, and materials. Different types of consumers prefer different combinations of these attributes. The i.i.d. assumption requires that no correlation exists between preferences of different types of consumers. Meanwhile, all sellers are symmetric in the sense that matched values are identically distributed across sellers. These properties are essential to getting a unique pure pricing equilibrium, and this feature of the model is consistent with [Wolinsky \(1986\)](#).

The timing of the game is as follows. All sellers choose prices simultaneously. Consumers know only the number of sellers yet not prices or values v_{ij} . Based on their belief about the equilibrium price, they decide whether to participate, and if they do, they search sequentially. They pay search cost s per visit to learn both the price and value of the particular seller, and decided whether to purchase (stop), continue, or exit. They search without replacement and with perfect recall.

In the baseline, consumers visit sellers randomly. I then introduce targeted search as follows. I assume the platform only has imperfect knowledge about the matched value because of limited consumer inputs by keywords in queries and/or refinements. Following the previous example, a consumer might enter the keywords “iPad mini leather black case.” Among all cases for iPad mini, Amazon will firstly show all listings with two desirable features, namely those cases with black color and leather material. Then it will show those cases that are black but not leather, or vice versa, followed by cases that are neither black nor leather. Within cases that are both black and leather, however, Amazon does not have consumer-specific information to further differentiate the sellers. This buyer may be looking for a case with stripe patterns. But without providing such a refinement option or recognizing such a keyword, Amazon will not be able to show such cases to her first.

This observation motivates the following modelling of targeted-search technology. Consider a finite set of thresholds $x_i \in X$ such that $\underline{v} < x_i < x_j < \bar{v}$, $\forall x_i, x_j \in X, i < j$. Specifically, I assume the platform only observed $\{1_{\{v > x_i\}}, x_i \in X\}$, that is, whether the matched value exceed thresholds x_i . I interpret the set X as the targeted search technology of the platform: if the platform recognizes more attributes in the search query, offers more refinement tools, or uses more consumer personalized data, there will be more thresholds x_i in the set X , and the highest threshold will get closer to $\bar{v}$. It will become clear that the key parameter of X is the highest threshold, denoted by $x = \max\{X\}$. x is a measure of the precision of targeted search, because as x increases, targeted search helps consumers find better matches, i.e., sellers with value greater than x . I call the set of sellers with values greater than x relevant sellers (those sellers whose features perfectly fit consumers’ input and refinement, as all the sellers with black leather cases in our iPad case example), and call the rest irrelevant sellers.

Upon observing $1_{\{v > x\}}$, the platform ranks every seller with $v > x$ randomly to buyers

first, followed by a random sequence of the next best set of sellers, and so forth.⁴ It is easy to see that within relevant sellers, where $v > x$, the matched values are i.i.d. with cumulative distribution given by $G_x(v) = G(v|v > x)$. I also assume consumers know the set X and, before deciding whether to incur search cost to visit one seller, know whether the seller is relevant or not. Therefore, consumers behave as if they know the number of firms in each “bucket”. This assumption makes the transition between relevant and irrelevant sellers not contingent on the depth of search. It is innocuous when the number of sellers is large, because such a transition probability will be negligible throughout the search. I focus on such cases in this study, and this assumption does not affect the result in any substantive way.

2.4 Equilibrium Analysis

2.4.1 Baseline: Random Search

I first consider the case in which the platform does not adopt targeted search, as might be the case in the early days of e-commerce.⁵ Consumers search randomly, and the value distribution of any sample visit is $G(v)$. Wolinsky (1986) focuses on symmetric price equilibrium, showing consumers search with reservation value defined by

$$\int_{w^*}^{\bar{v}} (v - w^*) dG(v) = s \quad (2.1)$$

And if no such w^* exists, let $w^* = \underline{v}$. The search strategy is characterized by (1) consumers participating if $w^* \geq p^*$, and (2) consumers stopping if and only if they find a value no less than w^* . In the case they have exhausted all n sellers, they either recall the option with highest value if it is higher than the price, or exit. Consider the case when s is not too large, such that $s < \int_{\underline{v}}^{\bar{v}} (v - \underline{v}) dG(v)$, which guarantees consumers do actively search. Let $w(p) = w + p - p^*$. The demand of any seller with price p (whereas all other sellers charge p^*) is given by

$$D(p, p^*, n) = [1 - G(w(p))] \frac{1 - G(w^*)^n}{n[1 - G(w^*)]} + \int_p^{w(p)} G(p^* - p + v)^{n-1} g(v) dv \quad (2.2)$$

in which the first component captures the probability that a consumer stops at and purchases from the focal seller with price p immediately, whereas the second component captures

⁴The platform is assumed to be “faithful” in the sense that it always ranks all relevant sellers above irrelevant ones. Later this strategy can be shown to be readily rationalizable in both commission and ad-slot models: it is profit maximizing for the platform to be faithful in ranking.

⁵Depending on the search query, Craigslist sometimes uses the time of posting as the default ranking, which is quasi-random.

demand from consumers who have exhausted all available options and recall this particular seller who yields the highest surplus.

As with most search models, there exist a set of uninteresting equilibria in which prices are so high that no consumer participates. [Wolinsky \(1986\)](#) shows the existence of symmetric pure price equilibrium with $p^* < w$ such that consumers do participate. The equilibrium price is simply given by

$$\begin{aligned} p^* &= c - \frac{D(p^*, p^*, n)}{D_p(p^*, p^*, n)} \\ &= c + \frac{1 - G(p^*)^n}{g(w^*) \frac{1 - G(w^*)^n}{[1 - G(w^*)]} - n \int_p^{w(p)} G(v)^{n-1} g'(v) dv} \end{aligned} \quad (2.3)$$

Having derived the equilibrium price, I show how it changes with search cost s to compare its effect with targeted search. I focus on the case when the number of sellers n is large, as in many online markets. We know that by [Equation 2.3](#), as $n \rightarrow \infty$, $p^* \rightarrow c + \frac{1 - G(w^*)}{g(w^*)}$, leading to the following corollary:

Corollary 1. *When $n \rightarrow \infty$, the equilibrium price p^* is increasing in search cost s .*

Proof. See [Appendix A.2.1](#) □

The intuition is that as search cost s decreases, consumers become more particular about finding the best match (their reservation utility w^* increases). Therefore, the probability of stopping at any seller $1 - G(w^*)$ decreases, implying that, on average, they visit more sellers. Sellers in turn faces more “traffic,” and hence more marginal consumers. And more marginal consumers make the demand more elastic. In response, the equilibrium price decreases. In the extreme case, when $s \rightarrow 0$, price approaches marginal cost when n is arbitrarily large. The following example uses uniform distribution to illustrate the mechanism.

Example 2.4.1. When $G(v)$ is uniform, and $G(v) = \frac{v - \underline{v}}{\bar{v} - \underline{v}}$, $g(v) = \frac{1}{\bar{v} - \underline{v}}$, and $g'(v) = 0$, we have

$$p^* = c + \frac{(\bar{v} - w^*)[1 - (\frac{p^* - \underline{v}}{\bar{v} - \underline{v}})^n]}{1 - (\frac{w^* - \underline{v}}{\bar{v} - \underline{v}})^n} \quad (2.4)$$

in which w^* is given by $w^* = \bar{v} - \sqrt{2s(\bar{v} - \underline{v})}$, clearly decreasing in s . When $n \rightarrow \infty$, the explicit form is given by $p^* = c + (\bar{v} - w^*) = c + \sqrt{2s(\bar{v} - \underline{v})}$, increasing in s , and goes to c when $s \rightarrow 0$.

2.4.2 Equilibrium in Targeted Search

To derive equilibrium under targeted search, I use the same method as in the previous analysis. I also focus on symmetric pure price equilibria. Notice that introducing the cutoff x of relevant sellers changes both the underlying value distribution $g(v)$ to a truncated one $g_x(v) = g(v|v > x)$ and the number of relevant sellers to k , which follows a binomial distribution with n sellers and probability $1 - G(x)$. Define $g_x(v) = g(v|v > x) = \frac{g(v) \cdot 1_{v>x}}{1 - G(x)}$

as the truncated PDF. Similarly, the CDF is given by $G_x(v) = \frac{\int_x^v g(y)dy}{1 - G(x)}$. Because all sellers with $v > x$ have i.i.d. values for each consumer, we still have that consumers search with a stationary reservation value given by

$$\int_{w^*}^{\bar{v}} (v - w^*)g(v)dv = (1 - G(x))s \quad (2.5)$$

Let us discuss whether such w^* exists. Intuitively, when x gets closer to $\bar{v}$, the incentive to continue search decreases. For instance, when $\bar{v} - x \leq s$, consumers have no incentive to search beyond the first visit, because even the highest possible marginal benefit $\bar{v} - x$ does not offset the search cost s . In fact, we can find that there exists a unique x^* , such that for any $x > x^*$, consumers have no incentive to search, and for any $x < x^*$, they do, with w^* defined by Equation 2.5. The cutoff x^* is given by $\int_x^{\bar{v}} (v - x)g_x(v)dv = s$. As it will become clear, x^* is a key parameter that decides the effects of targeted search. The following lemma states the assumptions to guarantee its existence and uniqueness.

Lemma 1. *There exists a unique threshold precision of targeted search that consumers facing more precise targeted search do not have incentive to search further, as long as the search cost is not too large, i.e. $\exists x^*$ defined by $\int_x^{\bar{v}} (v - x)g_x(v)dv = s$ if $\int_{\underline{v}}^{\bar{v}} (v - \underline{v})g(v)dv > s$. Moreover, $\int_x^{\bar{v}} (v - x)g_x(v)dv < s$ if and only if $x > x^*$.*

Proof. See Appendix A.2.2. □

For comparative statics, we have that $\frac{\partial w^*}{\partial x} > 0$ and $\frac{\partial w^*}{\partial s} < 0$. Both are readily verifiable using the implicit function theorem: let $f = \int_{w^*}^{\bar{v}} (v - w^*)g(v)dv - (1 - G(x))s$. We have that $\frac{\partial w^*}{\partial x} = -\frac{\partial f / \partial x}{\partial f / \partial w} = \frac{g(x)s}{1 - G(w)} > 0$. This shows that as targeted search becomes more precise (or search cost decreases), consumers are demanding better fits, which is quite intuitive. These derivatives will become useful in deriving how x affect equilibrium prices.

Adding some mild conditions (the density being not only log-concave, but also weakly concave), we can also show relevance ranking decreases the search depth of consumer search. See Corollary 2.

Corollary 2. *The probability that consumers stop ($1 - G_x(w)$) increases in targeted search precision x when $g(v)$ is (weakly) concave.*

Proof. See Appendix A.2.3. □

Example 2.4.2. Consider the case in which $g(v)$ is uniform at the interval $\underline{v}, \bar{v}$. We then have that $G(x) = \frac{x - \underline{v}}{\bar{v} - \underline{v}}$ and $g_x(v) = \frac{1}{\bar{v} - x}$. Solving w^* , when $w^* > x$, we have $w^* = \bar{v} - \sqrt{2s(\bar{v} - x)}$. We also have the cut-off x^* given by $x^* = \bar{v} - 2s$, decreasing in s as expected. We can show that when $x > x^*$, the w^* given by Equation 2.5 will be smaller than x ; hence, we need to define $w^* = x \forall x > x^*$. When $x < x^*$, the w^* given by Equation 2.5 will be larger than x as desired.

We also have $1 - G_x(w) = \sqrt{\frac{2s}{v - x}}$ that is increasing in x . Therefore, it implies that targeted search (or higher search cost) increases the possibility of a consumer stopping at any seller, reducing the length of search.

Having shown the search process is characterized by a reservation utility given in Equation 2.5, the following proposition characterizes the symmetric price equilibrium when $x < x^*$.

Proposition 1. *When the targeted search is not too precise ($x < x^*$), there exist at least one symmetric pure price equilibrium with price given by:*

$$p^* = c - \frac{\sum_{k=1}^n \frac{n!(1 - G(x))^k G^{n-k}(x)}{k!(n - k)!} [1 - G_x(p^*)^k] + \epsilon}{\sum_{k=1}^n \frac{n!(1 - G(x))^k G^{n-k}(x)}{k!(n - k)!} \left\{ -g_x(w^*) \frac{1 - G_x(w^*)^k}{1 - G_x(w^*)} + \int_{p^*}^{w(p^*)} G_x(v)^{k-1} g'_x(v) dv + \epsilon_p \right\}} \quad (2.6)$$

To prove this proposition, I start by introducing the demand function. One main difference between the demand function in targeted search and the one in random search is that the number of sellers in the first block is uncertain. If there were k firms in the first block, the demand one seller faces when $k > 0$ is simply

$$D(p, p^*, x, k) = [1 - G_x(w(p))] \frac{1 - G_x(w^*)^k}{k[1 - G_x(w^*)]} + \int_p^{w(p)} G_x(p^* - p + v)^{k-1} g_x(v) dv$$

When $k = 0$, I denote the residual demand as $D(p, p^*, x, 0)$ that can be easily shown to be bounded away from ∞ . Notice k follows a binomial distribution of n sellers with probability $1 - G(x)$. Therefore, the expected demand is given by

$$D(p, p^*, x) = \sum_{k=1}^n \frac{n!(1 - G(x))^k G^{n-k}(x)}{k!(n - k)!} D(p, p^*, x, k) + \epsilon$$

where $\epsilon = G^n(x) D(p, p^*, x, 0)$ is the expected residual demand when there is no seller in the first block. Clearly it converges to zero very fast when n increases. Therefore, in our

following analysis that focuses on large n , its contribution will be negligible. Evaluating it at equilibrium price, we have

$$D(p^*, p^*, x) = \sum_{k=1}^n \frac{n!(1-G(x))^k G^{n-k}(x)}{k!(n-k)!} \frac{1}{k} [1 - G_x(p^*)^k] + \epsilon \quad (2.7)$$

Similarly, we have that its derivative with respect to price at equilibrium is given by

$$D_p(p^*, p^*, x) = \sum_{k=1}^n \frac{n!(1-G(x))^k G^{n-k}(x)}{k!(n-k)!} \left\{ -g_x(w^*) \frac{1 - G_x(w^*)^k}{k[1 - G_x(w^*)]} + \int_{p^*}^{w(p^*)} G_x(v)^{k-1} g'_x(v) dv \right\} + \epsilon_p \quad (2.8)$$

The price is given by $p^*(x) = c - \frac{D(p^*, p^*, x)}{D_p(p^*, p^*, x)}$, which is a function of search precision x , number of sellers n and search cost s . Expand it, we have the price given by [Equation 2.6](#). To show the existence of $p^*(x)$, notice that when p^* is large, the right-hand side goes to c (which will be smaller than the LHS), but when p^* is small, the RHS is larger than the LHS. Therefore, by continuity of both sides on p^* , there exist at least one p^* that satisfies $p^*(x) = c - \frac{D(p^*, p^*, x)}{D_p(p^*, p^*, x)}$. Uniqueness, on the other hand, is not generally guaranteed as in the original [Wolinsky \(1986\)](#) model unless we assume some specific functional form of $g(v)$ such as uniformity. However, when $n \rightarrow \infty$, the limit price is unique as the next proposition shows.

When n is relatively large, we can use the normal approximation to binomial distribution. Let $\mu = n(1 - G(x))$, and $\sigma = \sqrt{n(1 - G(x))G(x)}$. We have that the number of sellers in the first block will be approximately normally distributed with $\mathcal{N}(\mu, \sigma)$. The price can be written as

$$p^* \approx c - \frac{\int_k e^{-\frac{(k-\mu)^2}{2\sigma^2}} \frac{1}{k} [1 - G_x(p^*)^k] dk + \epsilon}{\int_k e^{-\frac{(k-\mu)^2}{2\sigma^2}} \left\{ -g_x(w^*) \frac{1 - G_x(w^*)^k}{k[1 - G_x(w^*)]} + \int_{p^*}^{w(p^*)} G_x(v)^{k-1} g'_x(v) dv \right\} dk + \epsilon_p} \quad (2.9)$$

Notice that when $x = \underline{v}$, $G(x) = 0$, the distribution of k degenerate to $k = n$ with probability 1. The price given by [Equation 2.6](#) or [Equation 2.9](#) is exactly the same as the equilibrium price of random ranking ([Equation 2.3](#)).

The following proposition shows the first main result: the equilibrium price decreases in the precision of targeted search when n is sufficiently large and precision x not too large.

Proposition 2. *When there are infinite number of sellers, the equilibrium price is unique, which is given by $\lim_{n \rightarrow \infty} p^*(x) = c + \frac{1 - G_x(w^*)}{g_x(w^*)} = c + \frac{1 - G(w^*)}{g(w^*)}$ when $x \leq x^*$. Furthermore,*

1. *The equilibrium price is decreasing in targeted search precision x : $\frac{\partial p^*}{\partial x} < 0$.*
2. *The same comparative statics holds for finite number of sellers: there exist a finite N such that $\forall n > N$, $p^*(n)$ is strictly decreasing in x when $x \in [\underline{v}, x^*]$.*

Proof. See Appendix [Section A.2.4](#). □

[Proposition 2](#) shows that when the targeted search is not too precise ($x \leq x^*$), the effect of targeted search on equilibrium price is to decrease price. At first glance, this might seem counter-intuitive. After all, as search becomes targeted, consumers face sellers with better fit. The demand, therefore, should be higher. However, targeted search produces another effect: it makes sellers more similar and hence more competitive. Higher targeted search precision x saves the visits to unfit sellers. It increases the marginal benefit of visiting more sellers. Therefore, consumers visit more relevant sellers with higher reservation utility. This increases the number of marginal consumers a relevant seller faces. Responding to more elastic demand, sellers lower equilibrium prices. In fact, [Proposition 2](#) shows the price effect of targeted search (when it is not too precise, i.e., $x \leq x^*$) is equivalent to reducing search cost when there are infinitely many sellers: introducing x effectively reduces search cost to $(1 - G(x))s$. And the percentage of reduced search cost $(1 - G(x))$ is exactly the share of sellers that are filtered out by the search technology. The last claim in [Proposition 2](#) shows this intuition holds when n is large but finite. The proof uses the uniform convergence property of equilibrium price with respect to n . Therefore its comparative statics must also converge for a sufficiently large n .

To complete the characterization of equilibrium price, I now turn to the case with sufficiently high targeted search precision: $x > x^*$. When $x > x^*$, which is given by $\int_x^{\bar{v}} (v - x)g_x(v)dv = s$, we have a very different situation. The participation constraint will be binding because the w^* given by $\int_w^{\bar{v}} (v - w)\frac{g(v)}{1 - G(x)}dv = s$ will be smaller than x . Hence, unless the platform compensates for the first search, consumers will not enter the market. [Proposition 3](#) characterizes the equilibrium price when $x > x^*$.

Proposition 3. *When $n \rightarrow \infty$ and $x > x^*$, equilibrium price $p^* = x$. And there exist a finite N where the same result hold $\forall n > N$.*

To prove [Proposition 3](#), notice the consumer's optimal search strategy is to stop at the very first shop she visited, unless she gets a matched value that is strictly less than the price. The demand has a kink point at $p = x$, being perfectly inelastic when $p \leq x$. The demand is given by

$$D(p, x, n) = \sum_{k=0}^n \frac{n!}{k!(n-k)!} (1 - G(x))^k G^{n-k}(x) \frac{n}{k} (1 - G_x(p))$$

Obviously, we have $p(x) \geq x$ because lowering price below x will not increase demand (notice that $G_x(v) = 0 \forall v \leq x$). Therefore, for the optimal price, we could either have the interior solution of $p^*(x) > x$ or the corner solution $p^*(x) = x$. To eliminate the interior solution, we only need $x - c > \frac{D(p, x, n)}{-D_p(p, x, n)}$, or intuitively, the demand is not too inelastic

at x . When $n \rightarrow \infty$, we have the condition can be written as $p^*(x) = x$ if $x - c \geq \frac{1 - G(x)}{g(x)}$. Because $\frac{1 - G(x)}{g(x)}$ is decreasing in x , we need it to hold at x^* only, or $x^* - c \geq \frac{1 - G(x^*)}{g(x^*)}$, which will hold by assumption that there exists some $x < x^*$ without market breakdown. The result above can be shown to hold even if n is finite but large enough, using similar arguments on the uniform convergence of $\frac{D(p, x, n)}{-D_p(p, x, n)}$ that I used to prove the last claim in [Proposition 2](#).

Notice [Proposition 3](#) is not a Diamond result. When $s \rightarrow 0$, we have $x^* \rightarrow \bar{v}$. It implies that for any precision $x < \bar{v}$, we still have $\lim_{s \rightarrow 0} p^* = c$, that is, the equilibrium price approaches marginal cost when the search cost approaches zero. And $\lim_{s \rightarrow 0} \lim_{x \rightarrow \bar{v}} p^*$ depends on the convergent rate of the two limits. It can be thought of as a version of hold-up problem, in which consumers do not want to participate in the fear of giving all sellers monopoly power under highly targeted search.

At first glance, the finding may look quite striking or even futuristic. Yet as the platforms collect more data and develop highly sophisticated search functionality and algorithms, this result is becoming more relevant. For instance, Google Now pushes relevant information to users with minimal user input. Amazon has developed its Amazon Echo, which allows consumers to talk to its chatbot (named Alexa) to place orders.⁶ AI chatbots such as Siri also directly offer users a single, most relevant search result. In fact, the industry has discussed the future of search being “no-search”.⁷ [Proposition 3](#) shows the “no-search” result may have an implication for e-commerce: such a “no-search” future, although greatly simplifying the consumers’ search process, could give sellers (and potentially platforms) immense monopoly power to extract consumer surplus. As the technology gets more sophisticated, they can extract still more surplus. In a way, precise targeted search makes consumers “royal” to relevant sellers by making additional searches unnecessary.

Combining both [Proposition 2](#) and [Proposition 3](#), we have a full picture on how targeted search affects equilibrium price. When the targeting precision is low ($x \leq x^*$), increase in

⁶See <https://techcrunch.com/2016/07/01/alexa-orders>.

⁷For example, see <http://tiny.cc/hqrlcy>

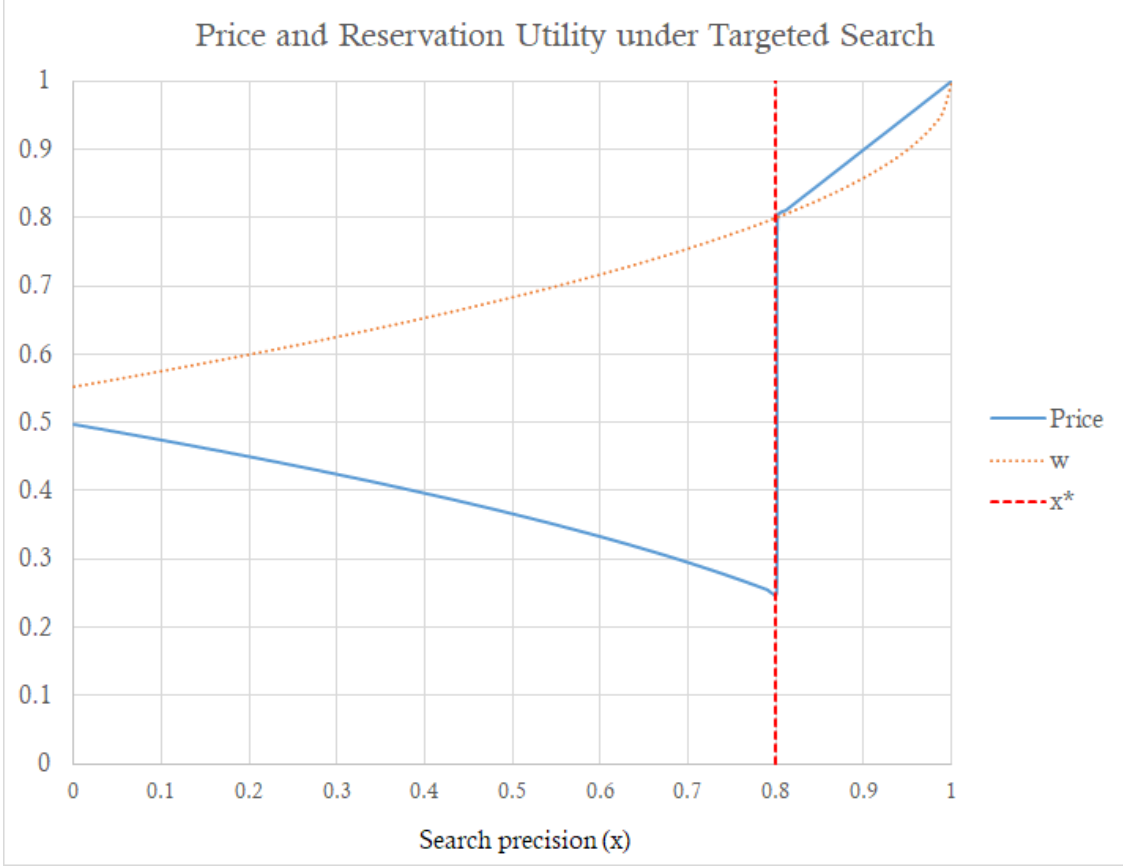


Figure 2.2: Equilibrium price, w versus x with standard uniform v , $s = 0.1$, $c = 0.05$

precision decreases prices. However, when precision is above a cutoff ($x > x^*$), the price becomes high and increasing in precision. Figure 2.2 shows one example with standard uniformly distributed valuation, search cost $s = 0.1$ and marginal cost $c = 0.05$. As we can see, the equilibrium price decreases with precision parameter x when $x \leq x^*$. But if $x > x^*$, we have the price equals x . In some cases the market may not exist unless x is large enough. Figure 2.3 shows such an example with search cost s increased to 0.15. Now we have $w < p^*$ when x is small, which means that only when the platform provides sufficiently relevant search results will consumers be willing to actively search.

One notable feature of the equilibrium prices is the discontinuity at x^* , as Figure 2.2 shows.⁸ This feature highlights the transition between two mechanisms of targeted search: below x^* , the competition effect reduces market prices; above x^* , highly matched sellers dominate every consumer. And every consumer switch from “shopper” to “royal” at x^* , leading to this discontinuity in price. If we allow for consumer heterogeneity in either search cost or search precision, the price can become smooth in search precision x . For example, if search cost follows a smooth distribution, as x increases, more and more consumers only

⁸I let $p(x)$ to be left continuous at x^* , and clearly it makes no difference if it is right continuous.

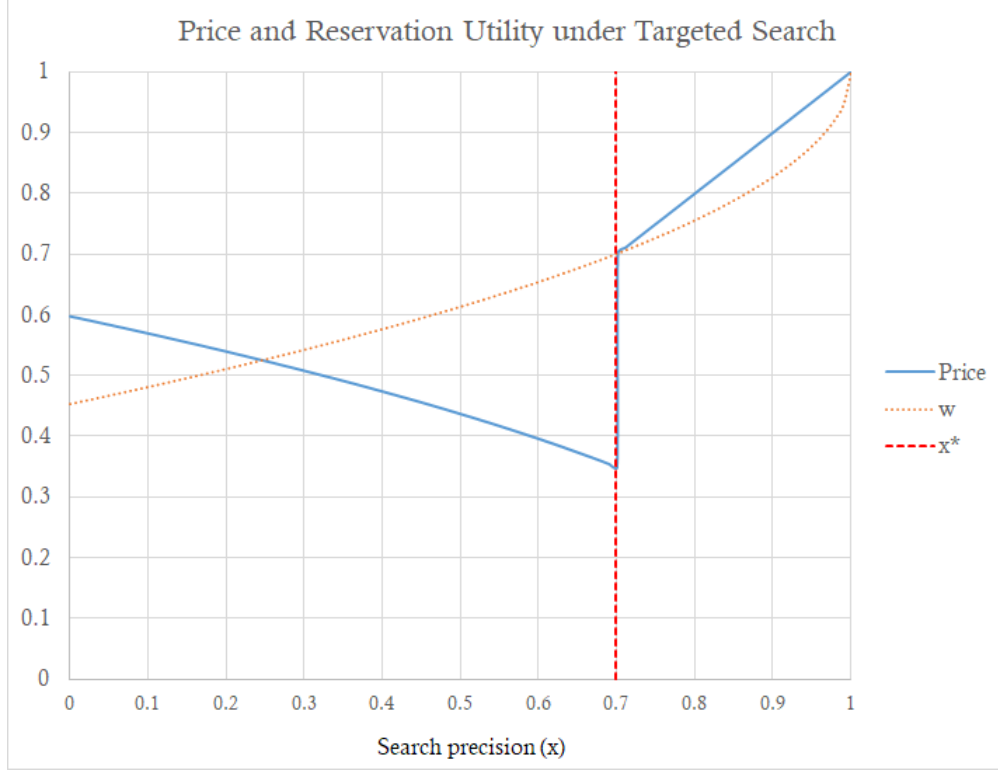


Figure 2.3: Equilibrium price, w versus x with standard uniform v , $s = 0.15$, $c = 0.05$

visit the first seller, and the share of “royal” consumers increase for every seller, and its effect can dominate the competition effect, driving the equilibrium price up.

Although the focus of this study is theoretical, I include a small empirical exercise in Appendix A.3.4. I construct a measure of targeted search precision based on the number of search outcomes, and I test its correlation with observed market price within each category. The results are summarized in Figure 11 and it exhibits a predicted non-monotonic pattern.

Because of lower prices, better fits, and fewer visits, higher x (up to x^*) will surely increase consumer surplus. In the uniform example, the consumer surplus is given by $w - p^* = 1 - c - 2\sqrt{s(1-x)}$. We can separate it into three components: the expected valuation $1 - \frac{1}{2}\sqrt{s(1-x)}$, disutility of expected search cost $-\frac{1}{2}\sqrt{s(1-x)}$, and disutility from price $-c - \sqrt{s(1-x)}$. I plot the consumer surplus and separate contributions of the three effects in Figure 2.4. In this particular case, the effect of saving from search cost equals that of increased valuation, and both are exactly half of the price effect. This observation proves useful in modelling platform design.

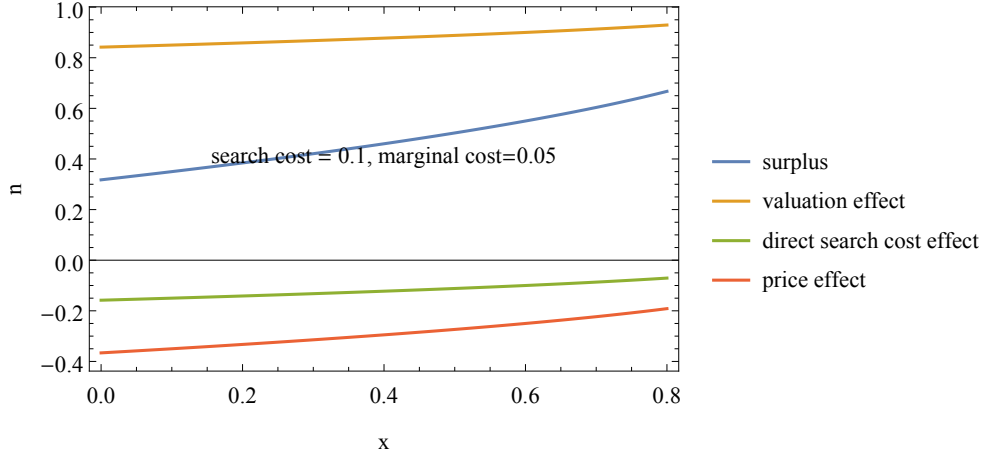


Figure 2.4: Changes of consumer surplus versus x with uniform v

2.4.3 Perfectly Targeted Search

This section explores a special case in which the platform has perfect information (or at least the ranking) of the valuations. For each consumer i , the search sequence is ordered by descending values $v_1 > v_2 > \dots > v_n$. Since the v are i.i.d. across consumers, so the ranking will be i.i.d. as well, retaining the symmetry between sellers. The results of perfectly targeted search are similar to our main model with some slightly different technical properties. Notice with perfectly targeted search, the optimal stopping rule of consumers is no longer stationary. In fact, under (symmetric) pure pricing equilibrium, consumers only visit the highest ranked seller and immediately stop if the realization is satisfactory, and exit otherwise.

To solve the model, it is useful to introduce the order statistics of v . Let $v_{(i)}$ be the i -th order statistic. Therefore, $v_{(n)}$ will be the n -th order statistic, or the maximum value out of n brands. I also denote the distribution of $v_{(i)}$ as $G_{(i)}(v)$. Notice the order statistics are neither independent nor identically distributed. I consider the optimal searching strategy (under symmetric pure pricing) as follows. First, consider the participation condition, given by

$$\int_{p^*}^{\bar{v}} (v - p^*) dG_{(n)}(v) \geq s \quad (2.10)$$

The inequality comes from the fact that in equilibrium, any consumer will visit at most one firm: the one with the highest value. If the realized value of $v_{(n)}$ is smaller than equilibrium price, the consumer will exit; otherwise, she stops immediately with payoff $v - p^*$. The following proposition characterizes the key result of equilibrium prices in this setting:

Proposition 4. *In perfectly targeted search, there exist a unique equilibrium where the price is given as follows: $p^* = c + \frac{1 - G(p^*)^n}{n[G(p^*)]^{n-1}g(p^*)}$, with $\lim_{n \rightarrow \infty} p^* = \bar{v}$. Furthermore, when the*

number of sellers is large enough, the equilibrium price under perfectly targeted search is higher than that of random search or targeted search: $\exists N$ s.t. $\forall n > N$, $p^*(n) > p_x^*(n)$ for any $x < \bar{v}$.

Proof. See Appendix A.2.5. $\square$

Notice that Proposition 4 shows when $n \rightarrow \infty$, we have $p^* \rightarrow \bar{v}$, a Diamond result in which no consumer ever enters the market.⁹ When n is finite, it is possible to have p^* sufficiently small such that the market exists even if the first search is not free.

A particular feature of this finding is that the equilibrium price has nothing to do with search cost s . As long as (2.10) holds, the equilibrium price will be above the marginal cost, below $\bar{v} - s$, and is not a function of s . It is only a function of n . This is because all consumers search exactly once and once consumers arrive the search cost is sunk. The next corollary characterizes some comparative statics with respect to the number of sellers and the marginal cost.

Corollary 3. *When G is log-concave and $n > 1$, the equilibrium price under perfectly targeted search is increasing in the number of sellers and marginal cost: $\frac{\partial p^*}{\partial n} > 0$. And $\frac{\partial p^*}{\partial c} > 0$.*

Proof. See Appendix A.2.6 $\square$

The last piece of Proposition 4 states that the equilibrium price of perfectly targeted search will be higher than (imperfectly) targeted search or random search. The intuition is that perfectly targeted ranking gives monopoly power to sellers with even better fit, allowing them to charge higher prices. The proof is also quite intuitive: When $n \rightarrow \infty$, we have $\lim_{n \rightarrow \infty} p^*(n) = \bar{v}$ for any distribution of v , and it is strictly higher than the equilibrium price of random search or targeted search. By continuity, the equilibrium price under perfectly targeted search will be higher than random search or targeted search for a sufficiently large n .

As a example, consider the case in which v is uniform such that $G(v) = \frac{v - \underline{v}}{\bar{v} - \underline{v}}$, $g(v) = \frac{1}{\bar{v} - \underline{v}}$, and $g'(v) = 0$. The price is given by

$$p^* = c + \frac{(\bar{v} - \underline{v})^n - (p^* - \underline{v})^n}{n(p^* - \underline{v})^{n-1}}$$

Let $\underline{v} = 0$, $\bar{v} = 1$; then $p^* = c + \frac{1 - (p^*)^n}{n(p^*)^{n-1}}$. Compared to the case with random search under the same parameters, in which we have $p_r^* = c + \frac{\sqrt{2s}(1 - (p_r^*)^n)}{1 - (1 - \sqrt{2s})^n}$, I plot it along with the price under perfectly targeted in the Appendix (see Figure 9 and Figure 10 showing the relationship between p^* , n , and c).

⁹Proof: if $p^* < \bar{v}$, according to (10), we have $p^* \rightarrow c + \frac{1}{\lim_{n \rightarrow \infty} n[G(p^*)]^{n-1}g(p^*)} = c + \infty$.

Chapter 3

Platform Design

In the previous analysis, I show that targeted search has a non-monotonic effect on equilibrium price. In particular, there exists a limit of search precision x^* that with a precision below x^* , targeted search lowers equilibrium price, and above x^* , it increases price. In this section, I consider how the platform designs its targeted search (x) under different revenue models. Broadly, the platform cares about the total trades that take place on the marketplace (measured by gross merchandise volume, GMV) and the percentage of GMV it can monetize, or monetization rate. Common ways to monetize include commission and advertising. In a commission model, the platform takes a percentage fee out of each transaction. In the advertising model, the platform often sells promoted slots in the search outcomes to sellers. As summarized in [Table 3.1](#), most major platforms use both commission and promoted slots. In the following analysis, the commission model is presented in [Section 3.1](#). [Section 3.2](#) further allows consumer entry. And [Section 3.3](#) introduces the promoted slot model.

3.1 Optimal Commission

Building on our targeted search model, and suppose the platform charges a percentage commission z ($z \in [0, 1]$), that is, for an item with price p , the seller is receiving $(1 - z)p$ and the platform is getting zp . For equilibrium price, charging a percentage commission z is equivalent to a no-commission world where the marginal cost increases from c to $\frac{1}{1 - z}c$.

This makes the optimal price a function of z , and clearly $p^*(x, z)$ is increasing in z . The profit for the platform is given by $zp^*(x, z)D(x, p^*)$, where $D(x, p^*)$ is the expected demand.

I focus on the case in which the number of sellers are large, or $n \rightarrow \infty$. Because the number of sellers goes to infinity, every consumer who chooses to participate will eventually stop at some seller. There will be neither recall nor exit after consumers exhausting all options. Therefore, $D(x, p^*) = 1\{w(x) \geq p^*\}$ will be either 1 or 0, where $w(x)$ is given by [Equation 2.5](#), or $\int_{w^*}^{\bar{v}} (v - w^*)g(v)dv = (1 - G(x))s$. Because all consumers have the same outside option of zero, the platform should leave exactly zero surplus to consumers.

Table 3.1: Fee structure and promoted slot of major online platforms

Platform	Fee Structure	Promoted slot
Amazon	8-15% commission + listing fee	Yes
eBay	10% commission + \$0.30 listing fee	Yes
Sears	\$39.99 Monthly fee + 8-17% commission	Yes
Newegg	8-14% commission	Yes
Booking	12-15% basic commission	Yes
Expedia	up to 25% commission	Yes
Orbitz	20-30% commission	Yes
Hotels	20-30% commission	Yes
Hotwire	unknown markup	Yes
Kayak	unknown commission rate	Yes
Tripadvisor	pay-per-click fee	Yes
Taobao	free	Yes
Tmall	2-5% commission + annual fee	Yes
JD	1-10% commission + monthly fee	Yes
Suning	2-5% commission + annual fee	Yes

Therefore, we have the optimal z^* for any $x \leq x^*$ as follows. Intuitively, more precise search targeting will improve consumer surplus by lowering price, saving search cost, and improving expected fit. This allows the platform to increase the commission rate to extract the surplus by inducing a higher equilibrium price.

Lemma 2. *When $n \rightarrow \infty$, the optimal commission rate $z^*(x)$ is increasing in x when $x < x^*$. The equilibrium price at the optimal commission rate will be $p^*(x, z^*) = w(x)$, which is increasing in x .*

Proof. See Appendix [A.3.1](#) □

If the platform can choose the precision of targeted search x without transfer to consumers, the following proposition characterizes the optimal search design.

Proposition 5. *If the platform cannot transfer to consumers, the optimal strategy for the platform when $n \rightarrow \infty$ is to set $x = x^*$ and charge z such that $p^* = x^*$, or z^* is given by*

$$x^* = \frac{1}{1-z}c + \frac{1-G(x^*)}{g(x^*)}.$$

The intuition is clear: higher x (when $x < x^*$) lowers prices, gives consumer better match value and saves on search cost. All three effects increase consumer surplus. The platform should increase the commission rate to capture the surplus. It therefore predicts that targeted search under commission model increases both the monetization rate (by higher z) and the GMV (by higher price). Both effects contribute to the revenue of the platform. However, the situation becomes very different once targeted search is sufficiently precise, that is, $x > x^*$. As our previous result shows, at x^* there is a jump in the equilibrium price. Suddenly, a lot of consumer surplus shifts from consumers to sellers. If the platform cannot compensate for the first search, a market failure with zero demand will occur. [Proposition 5](#) shows that the platform want to limit the precision of targeted search to avoid sellers having monopoly power, even if improving it is costless.

Furthermore, this result does not hinge on market failure. To see this, consider the case in which the platform can compensate consumers to make their first search free. I find that it may still choose $x = x^*$ and charge the same commission rate in [Proposition 5](#), because the incremental payoff of having x beyond x^* may not be enough to offset the cost of compensating consumer search. See the following proposition that shows the platform will want to restrict its precision of targeted search even if we allow the platform to compensate consumers.

Proposition 6. *If the platform can transfer to consumers, there exist a upper bound of $x' > x^*$ such that if the platform can choose $x \in [\underline{v}, x']$, the optimal strategy for the platform when $n \rightarrow \infty$ is to set $x = x^*$ and charge z such that $p^* = x^*$, or z^* is given by $x^* = \frac{1}{1-z}c + \frac{1-G(x^*)}{g(x^*)}$. There also exist a finite N such that $\forall n > N$ the result holds.*

To see the proof, suppose that at x' , the optimal commission rate is z' and price is p' . Clearly $z' > z^*$ and $p' > p^*$. The intuition of [Proposition 6](#) is that the cost of compensating for first search is s per consumer, yet the potential benefit of increase in commission rate and price is given by $z'p' - z^*p^*$. Since both z and p are increasing continuously in x , there must exist a x' such that $z'p' - z^*p^* = s$ (if not, let $x' = \bar{v}$), and for which any $\hat{x} \in (x^*, x')$ we have $\hat{z}\hat{p} - z^*p^* < s$, or equivalently the platform profit is strictly smaller compare to that at $x = x^*$.

3.2 Optimal Commission with Consumer Entry

One limitation of the previous analysis is that either all or no consumers enter the market, depending on w^* and p^* . Therefore, it cannot capture the idea that once consumer surplus increases, more consumers are willing to adopt the platform, either due to competition between platforms or market expansion. This section extends the model by generalizing the outside option from zero to a non-degenerated distribution to allow consumer entry.

Suppose the outside option follows some distribution with density $f(v)$ that is smooth and bounded. The corresponding CDF is given by $F(v)$. I assume $f(v)$ is log-concave to ensure that the optimal commission is unique, as is standard in the pricing literature. Notice that introducing heterogeneity in outside option does not change consumers' optimal search strategy if they enter. Consumers still search sequentially with stationary reservation value w as long as they choose to participate. It only changes the number of consumers who will enter the market, which is given by $F(w^* - p^*)$. Therefore, the platform is choosing x and z to maximize its profit when the number of sellers is large so that no consumer exit after choosing to participate:

$$\max_{x,z} \pi(x, z) = F(w^*(x) - p^*)zp^*$$

First, note that allowing consumer entry does not affect the equilibrium price, because once a consumer enters (with infinitely many sellers) her outside option doesn't matter any more. Therefore, I can use the results in [Proposition 2](#) and [Proposition 3](#) to show that when $x > x^*$ the equilibrium price could be discontinuously high. Too high a price will deter consumer entry, making it not desirable for platforms, even if improving the precision of targeted search has not cost.

Firstly, I characterize the optimal commission rate z^* with consumer entry. [Lemma 3](#) shows that z^* increases in x . Intuitively, as precision of targeted search x increases, consumer surplus $w^*(x)$ increases and the equilibrium price p^* decreases. Therefore $F(w^*(x) - p^*)$ will be increasing, implying more consumers will enter the market. This effect should increase the incentive for the platform to raise commission rates, as the marginal benefit of raising commission rate increases.

Lemma 3. *The optimal commission rate z^* defined by $z = \arg \max_z F(w^*(x) - p^*)zp^*$ is unique and increasing in x when $x \leq x^*$ and $n \rightarrow \infty$.*

Proof. See Appendix [Section A.3.2](#). □

Therefore, when targeted search is not too precise ($x \leq x^*$), the platform's commission rate will be increasing in the precision x . Similarly with the case without consumer entry, this result implies a increasing monetization rate as the platform develops advanced search technologies. The next proposition shows our key finding on platform search design with consumer entry. The intuition is similar to [Proposition 5](#): When the precision is below x^* , the platform will always be better off by choosing a higher precision, since it leads to both market expansion and higher monetization rate. However, once the precision reached x^* , the price could become too high, leading to dead-weight loss due to the monopoly power of sellers that discourages consumer entry.

Proposition 7. *If the platform cannot transfer to consumers, the optimal strategy for the platform when $n \rightarrow \infty$ is to set $x = x^*$ and charge z defined by [Lemma 3](#), as long as the profit at $x = x^*$ (which is given by $\max_z F(w^*(x^*) - p^*)zp^*$) is higher than that the highest profit for any $x > x^*$ (which is given by $\max_{x > x^*, z} \pi(x, z) = F(w^*(x) - p^*)zp^*$).*

Proof. See Appendix [A.3.3](#) □

The intuition is as follows. Notice that the platform's profit $\pi^*(x)$ is increasing in x when $x < x^*$ because of more consumer surplus to be extracted. Yet when $x > x^*$, it is possible for the profit to be discontinuously lower.

3.3 Promoted Slots Model

Selling promoted slots (also known as sponsored links, ad slots, etc.) to sellers has become an increasingly common way for platforms to monetize their transactions. This section models how the promoted slots model interacts with targeted search technology.

To set up the model, consider a platform choosing a set of slots within the search outcomes to be promoted slots for all search queries. I denote the set to be $S = \{i : i\text{-th slot being a promoted slot}\}$. For instance, if the platform chooses to make the top two slots as promoted slots, we have $S = \{1, 2\}$.

The timing is as follows. First the platform chooses the set of promoted slots S . The platform then sells the slots through some mechanism such as auctions, such that sellers are indifferent between getting the slot or not. The sellers bid for the slots after observing S . Afterwards, consumers enter and the market clears.

I assume consumers still search sequentially according to the selection of sellers and the ranking that the platform provides. They are fully aware of whether the next seller is an organic search result or a promoted one. And they can choose to skip the promoted seller at no cost. ¹

¹This assumption makes no difference in this case, because consumers will rationally choose not to skip the promoted sellers, who have the same value distribution and the same or lower prices.

One important assumption is how much sellers know when they choose to compete for a slot. In this section, I will assume all sellers, when they choose how much to bid for each keyword, have exactly the same information as the platform, whether their valuation is higher than each $x_i \in X$ or not. In particular, they know whether for the keyword and targeted consumers, they are relevant sellers (with value above x) or not. Consistently with the previous analysis, I focus on the case with a large number of sellers.

Lemma 4. *When $n \rightarrow \infty$, the equilibrium price for promoted slots are given by $p_i^* = p^* = c + \frac{1 - G(w^*)}{g(w^*)}$, $\forall i \in S$. The market share is given by $[1 - G_x(w^*(x))]G_x^{i-1}(w^*(x))$, $\forall i \in S$.*

Proof. As [Armstrong et al. \(2009\)](#) pointed out, when $n \rightarrow \infty$ and $S = 1$, we have that $p_i^* = p^* = c + \frac{1 - G(w^*)}{g(w^*)}$, $\forall i \in S$. That is, the promoted sellers have exactly the same price as the sellers in the organic search results. The intuition is as follows. The first (or i th) “prominent” seller faces exactly the same elasticity as the rest, because consumers follow the same search rules with i.i.d. distribution of matched values. The only difference is that the number of consumers is higher for prominent sellers who rank before organic sellers. It leads to a larger market share for the top promoted sellers that given by $1 - G_x(w^*(x))$. As shown in [Corollary 2](#), it is increasing in x when $g(v)$ is weakly concave. $\square$

The following proposition characterizes the main result for promoted slots model where we focus on a special case in which the platform sells the top k slots as promoted slots of $\text{slotsTS} = 1, 2, \dots, k$. It shows that in the promoted slots model, targeted search (up to a limit) will improve the monetization rate of the platform, but highly targeted search might decrease revenue from selling promoted slots. It is worth noting that although I focus on a simple case without consumer entry or search subsidy, the same intuition can carry over to those cases as I have shown in the commission model.

Proposition 8. *The platform will choose $x \leq x^*$ as the optimal targeted search precision to maximize its revenue when $n \rightarrow \infty$ and $G(v)$ is weakly concave.*

Proof. Notice that the revenue for the top k slots are given by

$$\pi(x, k) = (p^*(x) - c) \sum_{i=1}^k [1 - G_x(w^*(x))] G_x^{i-1}(w^*(x)) = (p^*(x) - c) [1 - G_x^k(w^*(x))]$$

when $x \leq x^*$ and zero when $x > x^*$ due to market failure. Therefore, the platform will never choose $x > x^*$. In general, the profit margin $p^*(x) - c$ is decreasing in x while the quantity $1 - G_x^k(w^*(x))$ is increasing in x . The optimal design of targeted search precision is given by $\arg \max_{x \in [\underline{v}, x^*]} (p^*(x) - c) [1 - G_x^k(w^*(x))]$. $\square$

This proposition also shows promoted sellers receive higher (total) market shares with targeted search. The intuition is that increasing targeting precision x has two effects on promoted sellers: (1) it filters out less relevant sellers, making consumers more willing to

continue search, which could decrease the share of consumers who stop given the same level of fit; (2), it improves the *targetability* of sellers. Sellers can use more options to select which consumer segment to target, therefore increase the fit between consumers and sellers. The propositions shows that when $G(v)$ is weakly concave the latter effect dominates. Notice this result is the opposite of reducing search cost, because reducing search costs will increase w^* , hence making consumers less likely to stop at any seller, including promoted ones. Notice that with the use of quality score and generalized auction, the sellers do not need to explicitly know which keywords or consumer segments to target. The platform, by assigning different quality scores, essentially informs sellers whether they are good fit or not. In the Appendix [A.3.4](#), I show some suggestive evidence on how the share of promoted sellers are negatively correlated with a measure of search precision, which is consistent with the model prediction.

3.4 Discussion and Concluding Remarks

This study focuses on the role of targeted search in online marketplaces. I build a micro model of search engines and apply the model in platform design. There are several new findings. First, targeted search has a non-monotonic effect on the equilibrium price. It decreases the price by intensifying competition when targeting precision is not too high. But when precision is high enough relative to the search cost, targeted search could lead to monopoly (high) prices. The discontinuity in prices is driven by the assumption that all buyers have the same search cost. If we allow some heterogeneity in search cost or precision, we could get a smooth relationship between equilibrium price and search precision. The intuition is when targeting precision is not too high, the competition effect dominates, and targeted search will decrease the equilibrium price. However, as the precision increases, more and more consumers do not want to actively search, because the benefits of search do not compensate their search costs. This effect dominates as search precision becomes sufficiently high, makes the demand more and more inelastic, and leading to higher price. The theory also predicts that the monopoly effect of targeted search may be easier to find in platforms with highly targeted search, and for product markets with low differentiation relative to search cost. With the development of search technology, in particular, the artificial intelligence and personalize data, this finding can be more and more relevant.

The second finding is the optimal platform search and contract design may feature strategic limit in search precision. In both commission and promoted slots models, I find that the platform may want to limit its precision even if improving it is costless. This finding is closely related to the non-monotonicity of how targeted search affects the equilibrium price. The monopoly effect of targeted search could lead to either market failure or dead-weight loss, therefore limiting how much surplus the platform can extract using either commission or promoted slots. This finding provides a strategic reason for the platform to protect consumer privacy, as it shows utilizing more consumer data does not necessarily benefit the platform. Also, in both models, I find targeted search having a positive effect on platform revenue when the precision is below a threshold, particularly through increase in monetization rate.

We are indeed observing the phenomenon in the real world. For example, the monetization rate of Alibaba has been steadily increasing for its mobile consumers, one reason being that richer data from mobile allows Alibaba to better target its consumers.

It is worth noting that the problem of highly targeted search leading to too high a price cannot be solved easily by the platform's contract design. One example is two-part tariff, as many platforms do use commission plus listing fee. Add a listing fee will redistribute platform revenue and seller profit, but not affect the market price when $x > x^*$ since the listing fee is sunk and the monopoly price as a corner solution does not depend on commission rate. Therefore, using two-part tariff does not solve the problem in either the commission model or promoted slots model. Similarly, using both commission and promoted slots cannot solve the problem either. To summarize, the potential hold-up problem poses a new challenge for the platform to regulate the market.

One limitation of this study is that I assume the platform is a monopoly throughout the analysis. Although platforms are often close to natural monopolies, most of them still face some degree of competition. And they can compete on multiple dimensions including search. However, in the model with consumer entry, the distribution of outside option can be interpreted as a (passive) competing platform. And the results show that too precise targeting can lead to high prices, which could drive consumers to competing platforms. The full model featuring platforms competing on both search design and revenue model contracts remains a research opportunity.

This study provides a framework of targeted search that can be applied to a wide range of research topics. First, one can investigate how targeted search interacts with not only platform, but also product design problems. In particular, does targeted search encourage niche design or main-stream design? Second, this study focuses on horizontal differentiation. How targeted search could affect a vertically differentiated market, or a market with both vertical and horizontal differentiation, remains a open question. Third, if sellers can manipulate the search outcomes by search engine optimization, it could also change the implications of targeted search. Finally, although this study is motivated by the development of search technology in online platforms, its intuition could be applied to other intermediaries such as retailers and recruitment platforms.

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Appendices

A.1 Appendix to Chapter 1

A.1.1 Figures and Tables



Figure 1: Display of levels and rating scores, Taobao(new)

Seller information
psionic256 (532 ★)
 100% Positive feedback

[+ Follow this seller](#)
[See other items](#)

掌柜档案

蔷薇蔷薇88 和我联系

会员积累信用

卖家信用：309 Rating Score

买家信用：381

卖家好评率：100.0% Percentage Good Rating

买家好评率：100.0%

店铺动态评分

宝贝与描述相符：★★★★★4.8 Dynamic Ratings

卖家的服务态度：★★★★★4.9

卖家发货的速度：★★★★★4.8

宝贝数量：64

创店时间：2007-06-14 Date of Establishment

Figure 2: Display of levels and rating scores, eBay and Taobao(old)

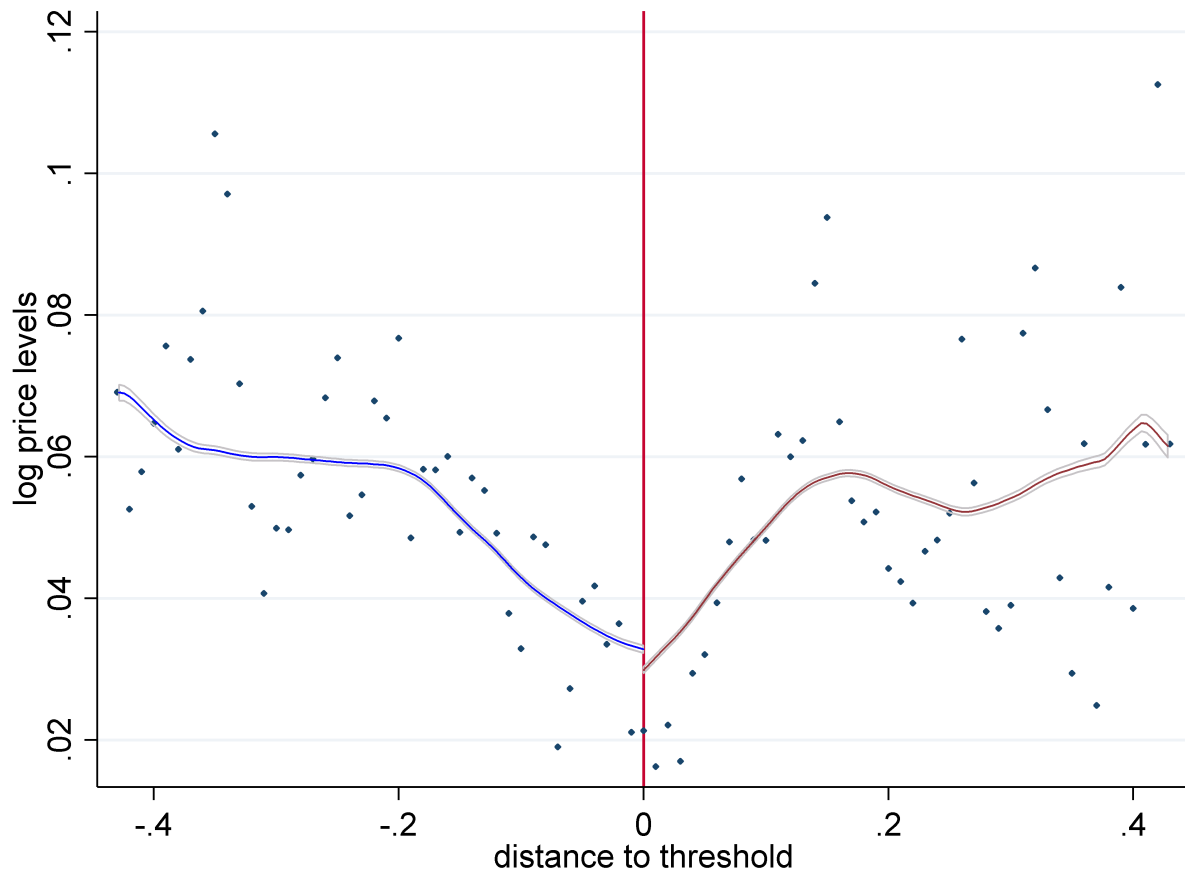


Figure 3: Price change: Local linear fit with confidence interval of log price changes with time fixed effect and control

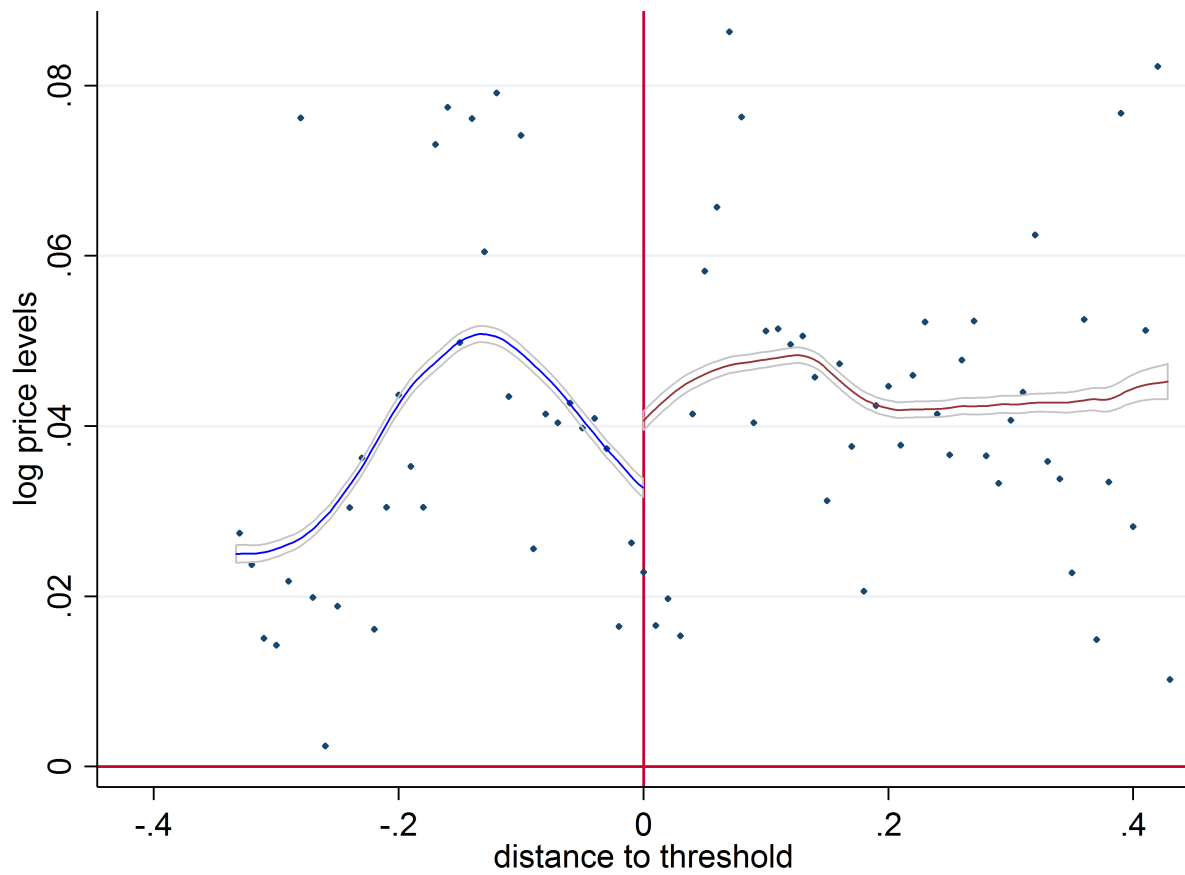


Figure 4: Normalized price levels for sellers with Level 6-9: Local linear fit with time fixed effect and control

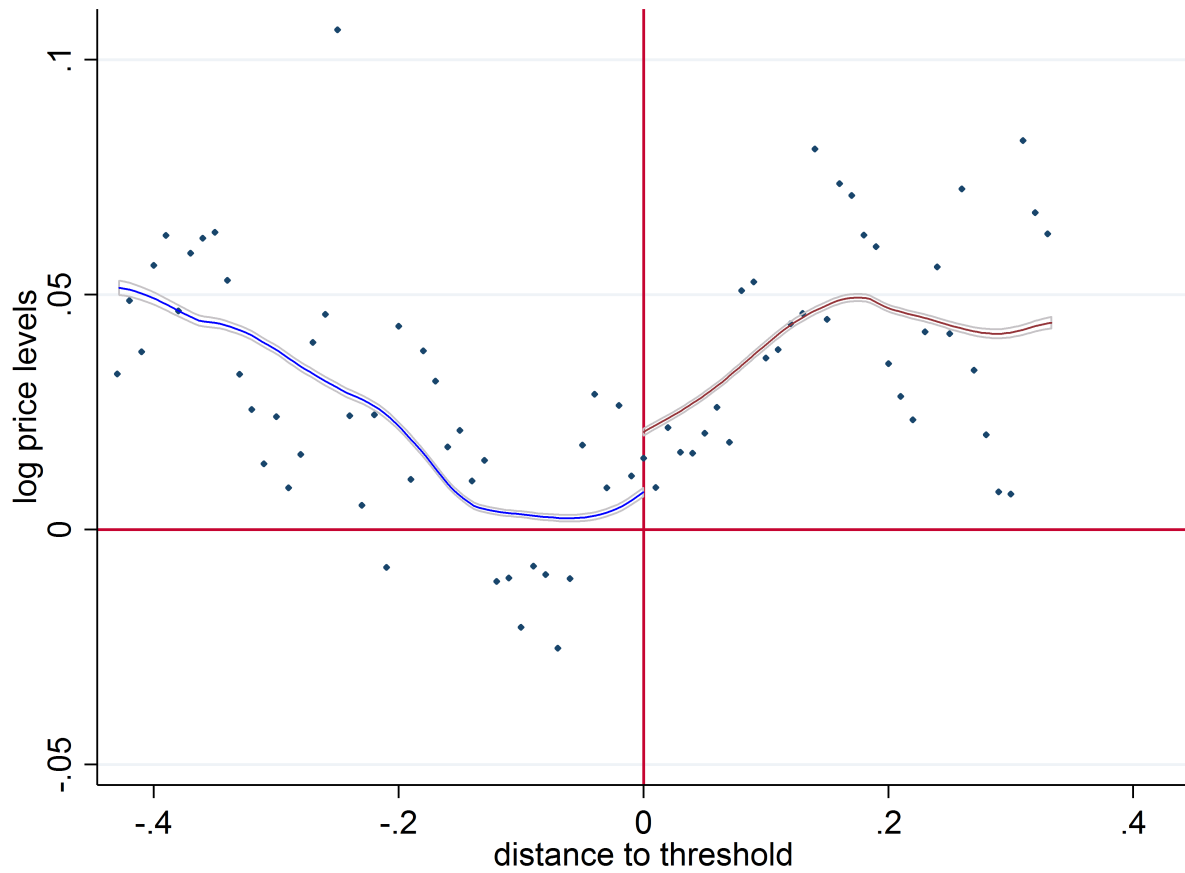


Figure 5: Normalized price levels for sellers with Level 10: Local linear fit with time fixed effect and control

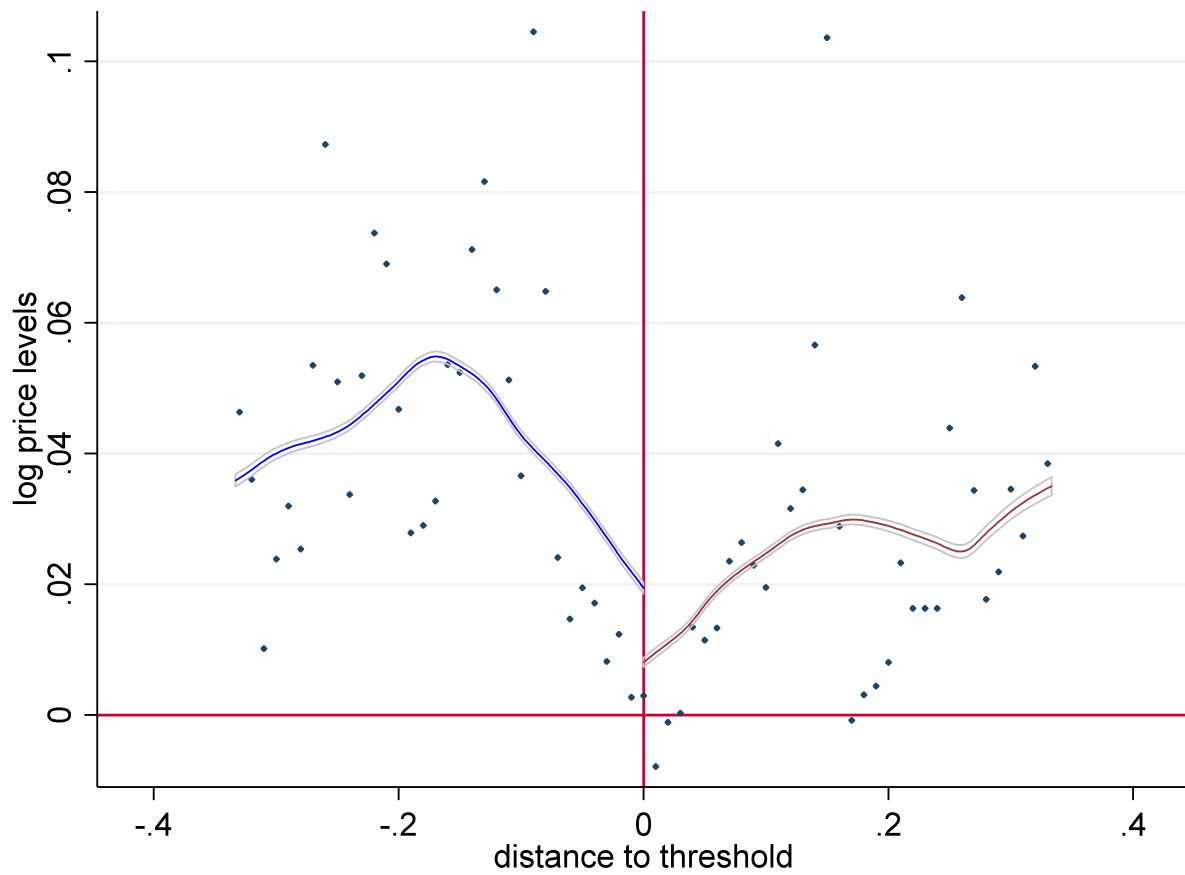


Figure 6: Normalized price levels for sellers with Level 11: Local linear fit with time fixed effect and control

A.1.2 Sample Preparation

Rating Score Interpolation

This section explains how I interpolate the rating scores that will be used to calculate the running variable. The basis is a dataset of rating records with 357,474 observations for a subset of my shops. Every observation has the following entries: seller id, sku id, item title and model/style, time of purchase, rating score(-1 if bad, 0 if neutral and +1 if positive, and -4 if invalid²), time of rating, level of buyer, and the scraping time. 319,418 (89.4%) observations count as valid ratings.

I count the number of ratings received at every hour of the day and calculated the percentages(See [Table 6](#)). The percentages are then used to interpolate the rating scores at every hour of my sample period based on the rating scores I scraped once each day.

Hourly Sales Aggregation and Normalization

I firstly aggregated the raw sales data at hourly level for each item-model. Notice that I have the complete transaction record, yet I do not have data on availability. There are two cases: Firstly, some items may not be available in the beginning. If so, I would have zero normalized sales when they are in fact not available. To deal with it, I count the availability time starting from the hour after first transaction time. I also delete sales before that hour from the total sales. Secondly, some items or models might be out-of-stock during the sample period. As long as that is not systematically associated with when the sellers pass the threshold, it will not bias the results. The items would be available in the end of my sample period because items that are not available cannot be scraped. I also threw away the “tail” of the data: the last hour, because my transaction record could be incomplete for the last hour. In between, I could safely assume that the item-models were available for sale and my transaction record data is complete and accurate. In the end, I have 83,052,728 observations of hourly sales data, out of which 2,127,819 are non-zero. It is implemented in Python and took around 20 GB of RAM.

I also counted the total sales for each item-model during the whole sample period except the first and last hour. For each item-model, I used its total sales and total available time (last hour minus first hour) to calculate its average hourly sales. Then I divided the hourly sales by its average for each item-model. The normalized hourly sales takes into account any item-model level fixed effect. Therefore using the normalized hourly sales as the outcome variable, I only rely on within item-model variations. It also takes care of all possible selection problems at item-model level or higher such as item-level, shop-level or industry-level.

I then match the hourly sales data with item-model characteristics (price, total transactions, and an “same price” whether the item-model has the same price through out the

²A seller can only be rated by the same buyer at most six times per month. Any additional rating will show up on the webpage along with the valid ones, but with a “invalid” sign and do not count towards rating score.

sample period) as well as shop characteristics at each hour (rating scores, percentage distances of rating scores to the nearest thresholds, and good rating percentage, among others). See Table [Table 1.3](#) Panel C for summary statistics after matching. I successfully matched 73,607,661 hourly sales data. The rest is due to that I have a longer window of transaction record (Nov 11 to Dec 22, 2013) compared to the shop level panel (Nov 15 to Dec 22, 2013). Also notice that after the matching, my sample of normalized hourly sales has a mean of 0.9511, smaller than the expected sales of one. This is because the matching excluded sales around Nov. 11, the Chinese counterpart of Cyber Monday when the sales often spikes.

Pooling across Thresholds

I have shops' rating scores near six thresholds. To utilize all the variation, I pooled the data together by defining a percentage distance to nearest threshold as the running variable, and zero as the threshold. There are many possible ways to define such percentage. I chose the most natural way: percentage $p = \frac{R - T}{T}$, in which R is the rating score, and T is the nearest threshold rating score, i.e. the threshold with smallest absolute value of percentage. Given Taobao's thresholds for level 6 through 11 as in [Figure 1.1a](#), the range of percentage is $[-0.428, 0.428]$. The benefit of this definition is that the same change in rating scores will lead to the same change in percentages just before and just after the threshold. An

alternative definition of $p = \begin{cases} \frac{R - T_i}{T_{i+1} - T_i} & \text{if } R - T_i < T_{i+1} - R \\ \frac{R - T_{i+1}}{T_{i+1} - T_i} & \text{if } R - T_i > T_{i+1} - R \end{cases}$ will lead to a more intuitive

range of percentage $[-0.5, 0.5]$. However, this definition implicitly weighted the score changes differently just before and just after the threshold. For example, near threshold 500, every rating score increase just before the threshold leads to a 0.004 change in percentage, while the same score increase just after the threshold leads to only 0.002 change in percentages. This will then give more weighting to sales after passing the threshold for any given bandwidth. The main result does not change qualitatively in this alternative definition.

A.1.3 Additional Robustness Checks

Using raw sales data as dependent variable

In the main text, I normalize the hourly sales to one for each item as the dependent variable across all the models. In this section I summarize some RD results using the raw sales data for the same sample used in the main specification as in [Table 1.4](#). Notice that the raw hourly sales data is naturally a count data. It is also very sparse with mean=6.56 and standard deviation=13,675, and only 2.2% non-zero sales. The count nature as well as overdispersion demands Negative Binomial regression as the appropriate model to use. I used conditional fixed-effects Negative Binomial regression, with a flexible parametric specification by including polynomial of the running variable percentage for up to fifth order. The results are listed in [Table 7](#). Clearly the threshold (Percentage ≥ 0) has a significant effect on sales.

To get a sense of its effect size, notice that $e^{0.101} = 1.106$. Therefore, one extra level (turning on the dummy on percentage) will lead to 10.6% increase in sales, fairly close to the effect in my main model (12.6%) where I use local linear regression with normalized hourly sales as dependent variable.

For reader's reference, I also use Poisson regression and OLS using similar specifications. [Table 8](#) shows the conditional fixed-effects Poisson regression results. It shows that as long as we include time dummies, the effect of threshold is statistically significant at 5% level. The degree of the effect, however, is much larger, presumably due to overdispersion. [Table 9](#) shows the OLS regression, with the symbol effect being large and positive yet statistically not significant due to large standard errors. [Table 10](#) compares goodness-of-fit of Negative Binomial, Poisson and OLS regressions for model (3). Clearly all three measures, namely Log likelihood, AIC, and BIC, greatly favor the Negative Binomial regression.

Table 2: RD for shop attributes over distance to thresholds

<i>Panel A</i>					
Bandwidth	Percentage good rating	Rating1	Rating2	Rating3	Return
10.0%	-0.0196 (0.0110)	0.00111 (0.000684)	0.000498 (0.000669)	-0.000765 (0.000691)	-0.00139 (0.00201)
5.00%	-0.0121 (0.0151)	0.000957 (0.000943)	0.000713 (0.000894)	-0.000242 (0.000943)	-0.00163 (0.00271)
2.50%	-0.0139 (0.0210)	0.000198 (0.00131)	-0.000510 (0.00123)	0.000403 (0.00128)	0.00172 (0.00382)
1.25%	-0.0180 (0.0282)	0.00237 (0.00187)	0.00109 (0.00169)	0.00170 (0.00173)	0.000883 (0.00608)
Shop f.e.	Y	Y	Y	Y	Y
N	100856				
<i>Panel B</i>					
Bandwidth	Percentage good rating	Rating1	Rating2	Rating3	Return
10.0%	-0.0315** (0.0107)	0.000639 (0.000676)	0.0000189 (0.000658)	-0.00126 (0.000678)	-0.00127 (0.00201)
5.00%	-0.0202 (0.0147)	0.000611 (0.000936)	0.000362 (0.000882)	-0.000579 (0.000924)	-0.00157 (0.00271)
2.50%	-0.0148 (0.0205)	0.000173 (0.00130)	-0.000544 (0.00121)	0.000431 (0.00126)	0.00167 (0.00382)
1.25%	-0.0225 (0.0276)	0.00221 (0.00184)	0.000906 (0.00168)	0.00160 (0.00171)	0.000873 (0.00609)
Shop f.e.	Y	Y	Y	Y	Y
Time f.e.	Y	Y	Y	Y	Y
N	100856				

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: RD estimates of symbol effect for different thresholds

	Levels 6-9	Level 10	Level 11
5%	-0.0400 (0.106)	0.245* (0.123)	0.0946 (0.0593)
2.5%	-0.0948 (0.107)	0.273+ (0.154)	0.100 (0.0887)
10%	-0.0159 (0.0873)	0.144+ (0.0818)	0.0924* (0.0422)
N	6603320	8893753	10659103
Time F.E. ¹	Yes	Yes	Yes
Control ²	Yes	Yes	Yes

Clustered (by shop) standard errors in parentheses. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimator is given by a local linear regression with triangle kernel.

Sample: normalized hourly sales for item-models with constant price throughout the sample period, and for shops that passed at least one threshold during the sample period.

¹ Including dummy variables for each day and each hour-of-the-day.

² Including percentage good rating, all three dynamic ratings, and return policy.

Table 4: Falsification test: RD estimates of artifact thresholds

	-10%	-5%	True Thresold	5%	10%
5%	-0.00995 (0.0486)	-0.00633 (0.0405)	0.126* (0.0509)	0.0225 (0.0383)	-0.0653 (0.0498)
2.5%	0.0252 (0.0554)	0.0283 (0.0691)	0.0948 (0.0664)	0.0100 (0.0487)	-0.0366 (0.0627)
10%	-0.00613 (0.0365)	-0.0206 (0.0316)	0.111** (0.0377)	-0.0200 (0.0289)	-0.0360 (0.0387)
N	31076708	31076708	31076708	31076708	31076708
Time F.E. ¹	Yes	Yes	Yes	Yes	Yes
Control ²	Yes	Yes	Yes	Yes	Yes

Clustered (by shop) standard errors in parentheses. ⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimator is given by a local linear regression with triangle kernel.

Sample: normalized hourly sales for item-models with the same price throughout the sample period, and for shops that passed at least one threshold during the sample period.

¹ Including dummy variables for each day and each hour-of-the-day.

² Including percentage good rating, all three dynamic ratings, and return policy.

Table 5: Price changes for high and low priced items

	High price	Low price
Percentage(Percentage < 0)	-0.0139** (0.00434)	-0.197*** (0.00337)
Percentage(Percentage > 0)	0.0572*** (0.00431)	0.157*** (0.00344)
Observations	3133022	5089870
Time F.E. ¹	Yes	Yes
Control ²	Yes	Yes

Sample: High priced and low priced items, and prices with percentage within 20% of thresholds.

¹ Including dummy variables for each hour.

² Including percentage good rating, all three dynamic ratings, and return policy.

Table 6: Percentages of ratings received each hour

hour	percentage	hour	percentage
0	1.78	12	6.41
1	0.72	13	6.43
2	0.30	14	6.04
3	0.18	15	6.12
4	0.11	16	6.08
5	0.15	17	5.79
6	0.47	18	5.66
7	1.26	19	6.24
8	3.69	20	7.03
9	5.65	21	7.13
10	6.46	22	6.03
11	6.38	23	3.89

Table 7: Conditional fixed-effects Negative Binomial regression with raw sales as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
Percentage ≥ 0	0.0728*** (0.00689)	0.114*** (0.00690)	0.110*** (0.00697)	0.0545*** (0.00690)	0.0968*** (0.00691)	0.101*** (0.00699)
Percentage	-0.649*** (0.0433)	-0.657*** (0.0434)	-0.133** (0.0435)	-0.638*** (0.0433)	-0.662*** (0.0435)	-0.108* (0.0436)
Percentage ²	4.174*** (0.0926)	4.758*** (0.0944)	2.702*** (0.0940)	4.424*** (0.0932)	5.010*** (0.0950)	2.777*** (0.0945)
Percentage ³	6.190*** (0.709)	5.912*** (0.712)	-2.435*** (0.713)	6.499*** (0.711)	6.410*** (0.714)	-2.755*** (0.715)
Percentage ⁴	-18.05*** (0.668)	-20.09*** (0.673)	-12.45*** (0.668)	-19.57*** (0.671)	-21.68*** (0.676)	-13.30*** (0.670)
Percentage ⁵	-13.41*** (3.366)	-15.54*** (3.373)	15.34*** (3.370)	-14.86*** (3.372)	-17.69*** (3.379)	16.86*** (3.375)
Observations	30967733	30967733	30967733	30283672	30283672	30283672
Item F.E.	Yes	Yes	Yes			
Item-Model F.E.				Yes	Yes	Yes
Time Dummies ¹		Yes	Yes		Yes	Yes
Control ²			Yes			Yes

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Sample: hourly sales for item-models with constant price throughout the sample period, and for shops that passed at least one threshold during the sample period.

¹ Including dummy variables for each day and each hour-of-the-day.

² Including percentage good rating, all three dynamic ratings, and return policy.

Table 8: Conditional fixed-effects Poisson regression with raw sales as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
Percentage ≥ 0	0.772 (0.879)	1.303* (0.545)	1.253* (0.504)	0.772 (0.792)	1.303* (0.663)	1.253 (0.679)
Percentage	-7.765 (5.333)	-22.13* (9.280)	-22.41* (9.643)	-7.765 (5.584)	-22.13* (9.143)	-22.41* (9.577)
Percentage ²	-23.87 (66.48)	34.74* (16.59)	35.43* (15.34)	-23.87 (52.98)	34.74* (13.53)	35.43** (12.45)
Percentage ³	144.0* (69.13)	339.2* (154.8)	345.6* (157.2)	144.0 (100.1)	339.2* (166.7)	345.6* (170.3)
Percentage ⁴	550.0 (594.0)	-34.54 (164.8)	-50.50 (156.4)	550.0 (487.3)	-34.54 (134.6)	-50.50 (126.8)
Percentage ⁵	-508.9 (293.3)	-1199.8 (722.9)	-1230.5 (710.7)	-508.9 (422.4)	-1199.8 (764.4)	-1230.5 (764.6)
Observations	30967733	30967733	30967733	30283672	30283672	30283672
Item F.E.	Yes	Yes	Yes			
Item-Model F.E.				Yes	Yes	Yes
Time Dummies ¹		Yes	Yes		Yes	Yes
Shop-attribute Control ²			Yes			Yes

Standard errors (clustered by item) in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Sample: hourly sales for item-models with constant price throughout the sample period, and for shops that passed at least one threshold during the sample period.

¹ Including dummy variables for each day and each hour-of-the-day.

² Including percentage good rating, all three dynamic ratings, and return policy.

Table 9: OLS regression with raw sales as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
Percentage ≥ 0	14.63 (11.01)	16.15 (12.34)	16.25 (12.34)	14.63 (11.01)	16.15 (12.34)	16.25 (12.34)
Percentage	-122.0 (108.6)	-130.2 (117.8)	-130.7 (117.6)	-122.0 (108.6)	-130.2 (117.8)	-130.7 (117.6)
Percentage ²	304.2 (226.8)	307.4 (236.2)	307.4 (238.4)	304.2 (226.8)	307.4 (236.2)	307.4 (238.4)
Percentage ³	2565.3 (2282.6)	2636.9 (2373.7)	2647.1 (2374.5)	2565.3 (2282.6)	2636.9 (2373.7)	2647.1 (2374.5)
Percentage ⁴	-7.112 (785.9)	-150.9 (624.7)	-161.5 (607.7)	-7.112 (785.9)	-150.9 (624.7)	-161.5 (607.7)
Percentage ⁵	-9884.5 (8438.8)	-10214.2 (8835.7)	-10253.2 (8849.6)	-9884.5 (8438.8)	-10214.2 (8835.7)	-10253.2 (8849.6)
Observations	31076708	31076708	31076708	31076708	31076708	31076708
Item F.E.	Yes	Yes	Yes			
Item-Model F.E.				Yes	Yes	Yes
Time Dummies ¹			Yes			Yes
Control ²		Yes	Yes		Yes	Yes

Standard errors (clustered by item) in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Sample: hourly sales for item-models with constant price throughout the sample period, and for shops that passed at least one threshold during the sample period.

¹ Including dummy variables for each day and each hour-of-the-day.

² Including percentage good rating, all three dynamic ratings, and return policy.

Table 10: Goodness-of-fit for Negative Binomial, Poisson and OLS Regression, Model (6)

Model	Log Likelihood	AIC	BIC
Negative Binomial	-3.25e+06	6.50e+06	6.50e+06
Poisson	-1.01e+09	2.02e+09	2.02e+09
OLS	-3.52e+08	7.03e+08	7.03e+08

A.1.4 Price change

In this section, I summarize some tests for price changes. Table 11 shows that the price decrease for both high and low priced items before thresholds. However, the coefficient of percentage when percentage is negative, i.e. before thresholds, is much larger in absolute terms for low price items.

Table 11: Price levels and percentage distance to thresholds

	High price	High price	Low price	Low price
Percentage	-0.0621***	-0.0139**	-0.260***	-0.197***
(Percentage < 0)	(0.00441)	(0.00434)	(0.00343)	(0.00337)
Percentage	0.198***	0.0572***	0.339***	0.157***
(Percentage ≥ 0)	(0.00434)	(0.00431)	(0.00347)	(0.00344)
Observations	3133022	3133022	5089870	5089870
Time F.E. ¹	No	Yes	No	Yes
Control ²	No	Yes	No	Yes

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Sample: hourly price for item-models with non-constant price throughout the sample period, and for shops that passed at least one threshold during the sample period.

¹ Including dummy variables for each day and each hour-of-the-day.

² Including percentage good rating, all three dynamic ratings, and return policy.

A.1.5 Product offerings

Because two snapshots of all listings on December 04 and December 22, 2013 are available, I can compare how the listings changes before and after a shop passed the threshold. I do find some differences in two attributes. First, sellers list more items with zero transaction record near and after passing the threshold (Figure 7). Second, for items that did have transactions, the total number of transactions for each item decreases after passing the threshold (Figure 8). Both findings show sellers list more new items near and after passing thresholds, which is consistent with dynamic entry models: suppose sellers have some fixed cost of listing a new item. The first-order effect of passing thresholds is that positive demand shock encourages entry, and more new items are listed right after passing thresholds. The second-order effect is that sellers list more items right before reaching thresholds to promote sales and accumulate ratings (similar to price cuts). Combining both effects could explain

the pattern we see in [Figure 7](#) and [Figure 8](#): sellers listing more new items near and after passing thresholds.

A.1.6 Theoretical Framework

This section adapts the canonical model of reputation ³ to illustrate how the level system affects demand and how sellers use dynamic pricing as a response. Consider one seller (female) selling to a sequence of buyers (male), each with unit demand. Suppose there are two types of sellers: an H seller’s product works with probability α_H ; an L seller’s product works with probability α_L , where $0 < \alpha_L < \alpha_H < 1$. Nature assigns the type of the seller in the beginning, which is private knowledge to the seller. Every buyer can decide to purchase or not. If not, he gets the utility of the outside option, normalized to zero. Should he decide to purchase, he would also leave a rating of whether the product delivered works as promised or not truthfully. The ratings constitute the seller’s reputation profile that subsequent buyers will observe. Let us focus on the case for $\alpha_H \rightarrow 1$ and the seller is indeed of Type-H, motivated by the observation that the average good rating percentage was close to 100% on both eBay and Taobao .

Demand Model

Let μ_0 be a buyer’s prior belief about the seller being “good” Type-H. Upon seeing R ratings (they are assumed to be good when $\alpha_H \rightarrow 1$), the Bayesian posterior belief of her being Type-H is given by

$$\mu = \frac{\mu_0}{\mu_0 + (1 - \mu_0)\alpha_L^R}$$

Notice that for small R , μ is close to μ_0 . As R increases, μ gets closer to the truth, and $\lim_{R \rightarrow \infty} \mu = 1$. Intuitively, the rating score R determines *how much* the posterior belief converges to the truth.

Assuming risk neutrality and random utility shock ϵ_i that follows a log-concave C.D.F. $F(\cdot)$, ⁴ the individual demand $D_i(p, \mu)$ is given by $D(p, \mu) = F(\mu\Delta\alpha + \alpha_L - p)$, in which $\Delta\alpha = \alpha_H - \alpha_L$. The simple model illustrates conceptually how rating score R affects demand. Furthermore, we can decompose $\frac{\partial D(p, R)}{\partial R} = \frac{\partial D(p, R)}{\partial \mu} \frac{\partial \mu}{\partial R}$. The first term shows how the belief affects demand, whereas the second shows how the rating score shifts the belief. Therefore, a particularly large effect of rating score on demand might be driven by a very low prior μ_0 and/or informative ratings, both of which affect $\frac{\partial \mu}{\partial R}$, or by consumers

³Researchers have used many theoretical models of reputation in transactions since the 1980s (Klein and Leffler, 1981; Shapiro, 1983; Kreps and Wilson, 1982; Kreps et al., 1982). See Hörner (2002) and Bar-Isaac and Tadelis (2008) for more recent reviews. The theoretical framework of this study builds on the stream of literature that models reputation as Bayesian belief and adds discontinuity to capture the symbol effect, motivated by Taobao’s categorization system (Cabral, 2009).

⁴The log-concavity will be useful in showing price response. Most common distributions have such property.

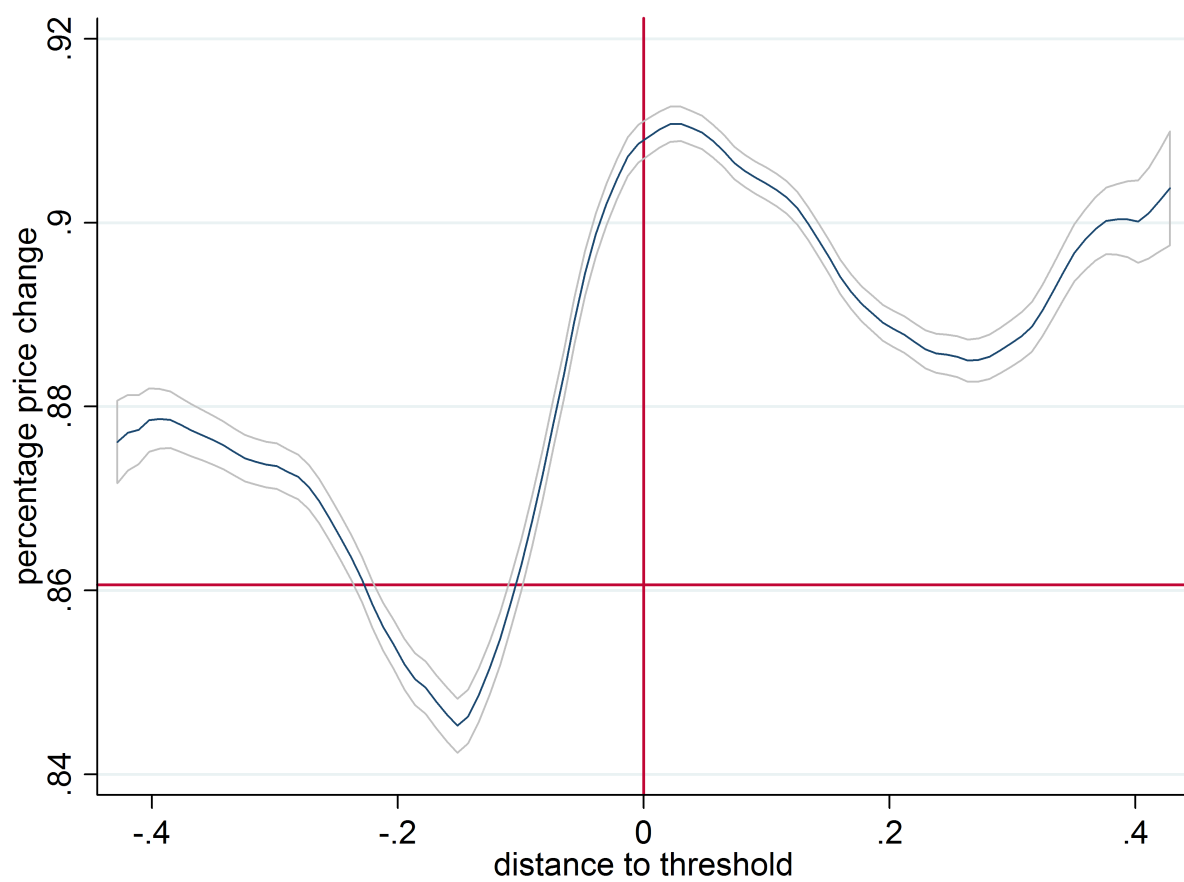


Figure 7: Percentage of no trade items

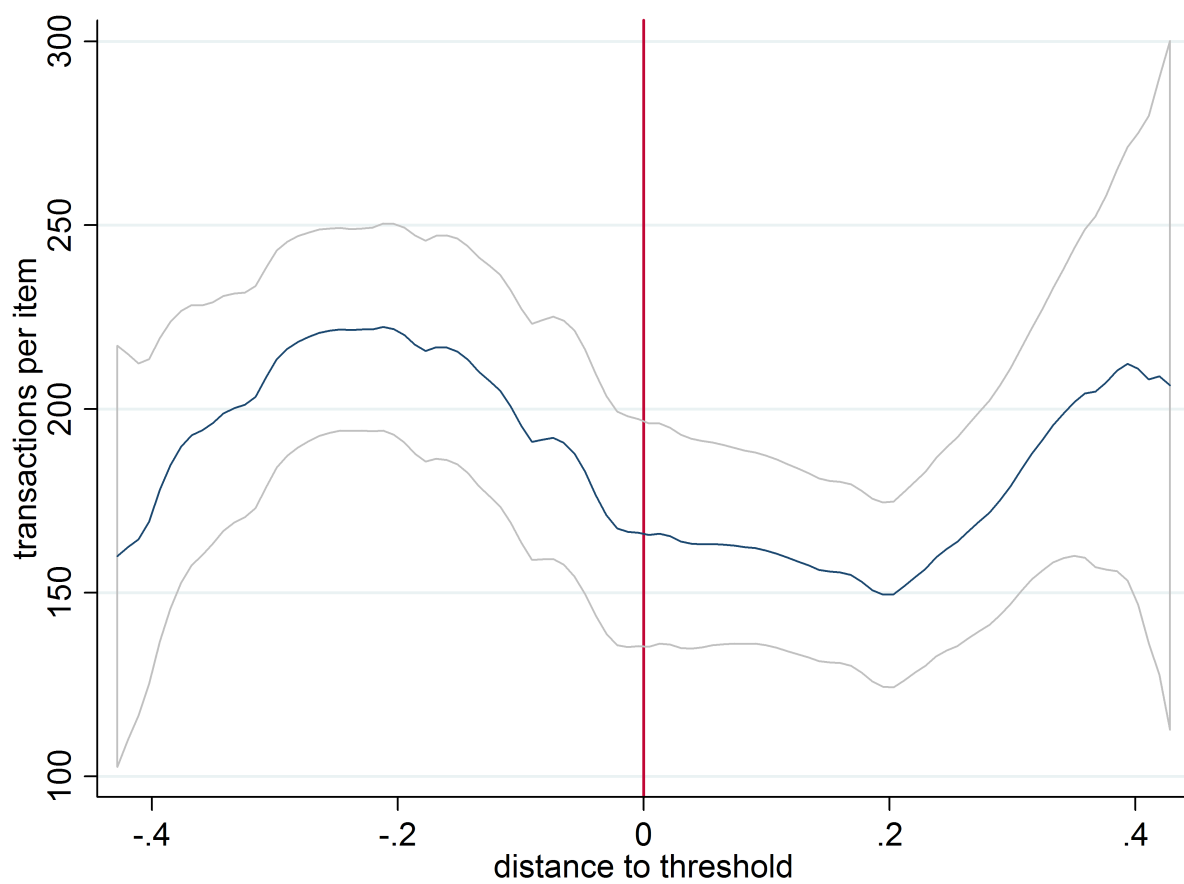


Figure 8: Number of transactions per item

caring a lot about trust, such that $\frac{\partial D(p, R)}{\partial \mu}$ is large. These insights will prove useful in interpreting some results in this study.

Now let us add the levels structure to the demand model. Consider the simplest case possible: there are only two levels such that level l is defined as $l(R) = 1\{R \geq T\}$, in which T is the threshold rating score. All buyers observe levels $l(R)$ at no cost, but they are completely “inattentive” to the underlying rating score R . For these buyers, we have the posterior belief as follows ⁵:

$$\mu = \frac{\mu_0}{\mu_0 + (1 - \mu_0)\alpha_L^{Tl(R)}}$$

which is a step function of R with a discontinuous jump at $R = T$. Denote the jump in μ at $R = T$ to be $\Delta\mu$, that is, $\Delta\mu = \frac{\mu_0}{\mu_0 + (1 - \mu_0)\alpha_L^T} - \mu_0$. A buyer’s utility of buying is given by $U(p, R) = \mu_0\Delta\alpha + \alpha_L + \Delta\mu\Delta\alpha 1\{R \geq T\} - p + \epsilon$. The demand is given by $D(p, R) = F(\mu_0\Delta\alpha + \alpha_L + \Delta\mu\Delta\alpha 1\{R \geq T\} - p)$, which is also a step function at $R = T$.

Supply Response

Suppose the discount rate of the seller is $\beta < 1$, and the seller is perfectly forward-looking. Assume the marginal cost is zero. The rating score R becomes a state variable that affects demand through levels $l(R)$. First, let us consider the static pricing. At $R \geq T$, the seller is facing demand $D(p, R) = F(\mu_0\Delta\alpha + \alpha_L + \Delta\mu\Delta\alpha - p)$. Suppose the optimal price is p_T . At $R < T$, the static (per-period) optimal price is given by $p_0 = \arg \max p F(\mu_0\Delta\alpha + \alpha_L - p)$. It is straightforward to show that $p_T > p_0$ given that $F(\cdot)$ is log-concave. This is the first implication of the supply-side model: the static response to the symbol effect is to increase price immediately after reaching the threshold.

Then let us consider the dynamic pricing. Notice that $R \geq T$ is a more profitable state for the seller. To get to that state, she needs more ratings, and hence more sales. Therefore, she has an incentive to lower prices at $R < T$ to accelerate the state transition. We would expect p_R (the dynamic optimal price) to be even lower than p_0 (the static optimal price) when $R < T$. It does not change the first implication. Formally, denote $\pi_T = p_T D(p_T, R)$, or the per-period profit for the seller at state $R \geq T$. Notice the value function of being in such state is given by $V_T = \frac{\pi_T}{1-\beta}$. Now consider the period in which the rating is just below the threshold, namely $R = T - 1$. The probability of transit to the R state is exactly the demand. The current state value function is

$$V_{R-1} = D(p, T - 1)(p + \beta V_T) + (1 - D(p, T - 1))\beta V_{R-1},$$

⁵This specification assumes buyers have a prior about R such that it has mass points at $R = 0$ and $R = T$, whereas it has a measure of zero elsewhere. It can be easily extended to any other priors without affecting the result as long as it puts positive probability at $R < T$ or $R > T$.

which can be reduced to

$$V_{R-1} = \frac{D(p, T-1)(p + \beta V_T)}{1 - \beta + \beta D(p, T-1)}.$$

The seller is trying to maximize the current state value function:

$$p_{T-1} = \arg \max_p \frac{D(p, T-1)(p + \beta V_T)}{1 - \beta + \beta D(p, T-1)} \quad (1)$$

It is can be verified that p_{T-1} is decreasing in V_T , which is quite intuitive: the more valuable state T is, the larger her incentive she has to reduce prices to transit to state T more quickly. Hence, it predicts that the degree of price change will be correlated with the magnitude of the symbol effect. To get p_{T-2} , we simply substitute V_T by V_{R-1} . Then we get $p_{T-2}^* > p_{T-1}^*$ since $V_T > V_{R-1}$. Similarly, we can show that $p_i^* > p_j^*$, $\forall i < j < T$. Therefore, the model also predicts the seller will keep lowering the price until reaching the threshold.

To summarize, this simple model shows that when a symbol effect exist, (a) before the threshold, the sellers are gradually decreasing prices as their rating scores gets close to the thresholds, (b) after passing thresholds, they increase prices, and (c) the degree of price change will be correlated with the magnitude of the symbol effect. The intuition is that a higher level is a state with higher demand and hence higher profit. The sellers would want to lower prices to get to that state more quickly by accumulating more ratings, and even more so when they are closer to the thresholds and when the symbol effect is stronger. Once they pass the threshold, however, they will respond to the positive demand shock by increasing their prices immediately.

A.2 Appendix to Chapter 2

A.2.1 Proof to [Corollary 1](#)

Proof. Applying the implicit function theorem to [Equation 2.1](#), let $f = \int_{w^*}^{\bar{v}} (v - w^*) dG(v) - s$. We have that $\frac{dw^*}{ds} = -\frac{\partial f / \partial s}{\partial f / \partial w^*} = -\frac{1}{1 - G(w^*)} < 0$. Also notice $\lim_{n \rightarrow \infty} p^* = c + \frac{1 - G(w^*)}{g(w^*)}$. Therefore, $\frac{\partial p^*}{\partial w^*} < 0$ due to the log-concavity of $G(v)$, thus $\frac{\partial p^*}{\partial s} > 0$. $\square$

A.2.2 Proof to [Lemma 1](#)

Proof. $\int_x^{\bar{v}} (v - x) g_x(v) dv = s$ can be written as $\int_x^{\bar{v}} (v - x) g(v) dv = [1 - G(x)]s$. Denote the LHS as $f_1(x) = \int_x^{\bar{v}} (v - x) g(v) dv$ and the RHS as $f_2(x) = [1 - G(x)]s$. Both will be smooth and decreasing in x since $f_1'(x) = G(x) - 1 \leq 0$ and $f_2'(x) = -g(x)s < 0$. Notice $f_1(\underline{v}) > f_2(\underline{v})$ by assumption (ii) of s being not too large, $f_1(\bar{v}) = f_2(\bar{v})$ (both equal zero),

and $f_1'(\bar{v}) = 0 < f_2'(\bar{v})$, by continuity of both functions, there exists at least one x^* such that $f_1(x^*) = f_2(x^*)$. To prove uniqueness, take the smallest of all such x^* that satisfy $f_1(x^*) = f_2(x^*)$. Notice that $\frac{f_1'(x)}{f_2'(x)} = \frac{1 - G(x)}{g(x)s}$. Since $g(v)$ is log concave, the hazard rate $\frac{g(x)}{1 - G(x)}$ will be monotone increasing, therefore we have at most one $\hat{x}$ such that $\frac{f_1'(\hat{x})}{f_2'(\hat{x})} = 1$. Therefore, there does not exist any $x^* < x'^* < \bar{v}$ such that $f_1(x'^*) = f_2(x'^*)$, otherwise there will be at least one $\hat{x}_1 \in (x^*, x'^*)$ and one $\hat{x}_2 \in (x'^*, \bar{v})$ both satisfying $\frac{f_1'(x)}{f_2'(x)} = 1$ by mean value theorem, violating the monotone hazard rate property of log concave $g(v)$. Also, from the analysis above, it is clear that the second condition can be relaxed to that $\exists x_0 \in [\underline{v}, \bar{v}]$ such that $\int_{x_0}^{\bar{v}} (v - x_0)g(v)dv > [1 - G(x_0)]s$.

To show that when $x > x^*$, we have $\int_x^{\bar{v}} (v - x)g_x(v)dv < s$, notice that $f_1'(\bar{v}) = 0 < f_2'(\bar{v})$, therefore when $x \in (x^*, \bar{v})$ we have $f_1(x) < f_2(x) \rightarrow \int_x^{\bar{v}} (v - x)g_x(v)dv < s$. Since x^* is unique, given $f_1(\underline{v}) > f_2(\underline{v})$, whenever $x < x^*$ we have $f_1(x) > f_2(x)$. $\square$

A.2.3 Proof to Corollary 2

Proof. $G_x(w) = \int_x^w g_x(v)dv = \frac{1}{1 - G(x)} \int_x^w g(v)dv$. Furthermore we have $\frac{\partial w}{\partial x} = \frac{g(x)s}{1 - G(w)}$. Therefore, we have

$$\frac{\partial G_x(w)}{\partial x} = \frac{g(x)}{1 - G(x)} \left[\frac{G(w) - 1}{1 - G(x)} + \frac{g(w)s}{1 - G(w)} \right] \quad (2)$$

$$= \frac{g(x)s}{1 - G(x)} \left[\frac{G(w) - 1}{\int_w^{\bar{v}} (v - w)g(v)dv} + \frac{g(w)}{1 - G(w)} \right] \quad (3)$$

$$= \frac{g(x)s}{(1 - G(x))(1 - G(w)) \int_w^{\bar{v}} (v - w)g(v)dv} \left[g(w) \int_w^{\bar{v}} (v - w)g(v)dv - (1 - G(w))^2 \right] \quad (4)$$

The second equality is given by substituting $\frac{1}{1 - G(x)} = \frac{s}{\int_w^{\bar{v}} (v - w)g(v)dv}$. Let us denote

$F(w) = g(w) \int_w^{\bar{v}} (v - w)g(v)dv - (1 - G(w))^2$. To show that $F(w) \leq 0$, notice that $F(\bar{v}) = 0$, therefore $F'(w) \geq 0 \forall w \in [w(0), \bar{v}]$ is a sufficient condition. $F'(w) = g'(w) \int_w^{\bar{v}} (v - w)g(v)dv + 2g(w)(1 - G(w))$. This is clearly positive if $g(w)$ is concave ($g'(w) \geq 0$). $\square$

A.2.4 Proof to Proposition 2

The following proof shows the explicit form of $\lim_{n \rightarrow \infty} p^*(x)$ and its comparative static with respect to x .

Proof. Notice that $p^* - c$ is the ratio of two integrals. We let $f_1(n) = \int_k nD(p^*, p^*, k)\Phi_n(k)dk + \epsilon$, and $f_2(n) = \int_k nD_p(p^*, p^*, k)\Phi_n(k)dk + \epsilon_p$, in which $\Phi_n(k) = \frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(k-\mu)^2}{2\sigma^2}}$ where $\mu = n(1 - G(x))$ and $\sigma = \sqrt{n(1 - G(x))G(x)}$. We can denote the price as $p^* - c = \frac{f_1(n)}{f_2(n)}$. To get $\lim_{n \rightarrow \infty} p^* - c$, if we can show that both $\lim_{n \rightarrow \infty} f_1(n)$ and $\lim_{n \rightarrow \infty} f_2(n)$ exist, as well as $\lim_{n \rightarrow \infty} f_2(n) > 0$, we have $\lim_{n \rightarrow \infty} p^* - c = \frac{\lim_{n \rightarrow \infty} f_1(n)}{\lim_{n \rightarrow \infty} f_2(n)}$.

Consider the interval $k \in [\mu - n^{1/4}\sigma, \mu + n^{1/4}\sigma]$. Clearly, as $n \rightarrow \infty$, the probability that $k \in [\mu - n^{1/4}\sigma, \mu + n^{1/4}\sigma]$ goes to one. Now we consider the value of $nD(p^*, p^*, k)$. It is bounded for all k and therefore,

$$\lim_{n \rightarrow \infty} \int_{-\infty}^{\mu - n^{1/4}\sigma} nD(p^*, p^*, k)\Phi_n(k)dk + \lim_{n \rightarrow \infty} \int_{\mu + n^{1/4}\sigma}^{\infty} nD(p^*, p^*, k)\Phi_n(k)dk = 0 \quad (5)$$

Also notice that when $k \in [\mu - n^{1/4}\sigma, \mu + n^{1/4}\sigma]$, we have $\frac{k}{n} \in [(1 - G(x)) - n^{-1/4}G(x)(1 - G(x)), (1 - G(x)) + n^{-1/4}G(x)(1 - G(x))]$, and the interval approaches $1 - G(x)$ as n increases. We then have

$$\begin{aligned} \lim_{n \rightarrow \infty} \int_{\mu - n^{1/4}\sigma}^{\mu + n^{1/4}\sigma} nD(p^*, p^*, k)\Phi_n(k)dk + \epsilon &= \frac{1}{1 - G(x)} \lim_{k \rightarrow \infty} kD(p^*, p^*, k) \\ &= \frac{1}{1 - G(x)} \end{aligned} \quad (6)$$

Combining Equation 5 and Equation 6, we have that $\lim_{n \rightarrow \infty} f_1(n) = \frac{1}{1 - G(x)}$. Similarly, we apply the same methods to $f_2(n)$, we will get $\lim_{n \rightarrow \infty} f_2(n) = \frac{1}{1 - G(x)} \frac{g_x(w^*)}{1 - G_x(w^*)}$. which is clearly bounded away from zero. Therefore, we have $\lim_{n \rightarrow \infty} p^*(x) = c + \frac{\lim_{n \rightarrow \infty} f_1(n)}{\lim_{n \rightarrow \infty} f_2(n)} = c + \frac{1 - G_x(w^*)}{g_x(w^*)}$ as desired.

The last piece can be derived from the simple fact that $\frac{\partial p^*}{\partial x} = \frac{\partial p^*}{\partial w^*} \frac{\partial w^*}{\partial x}$, and $\frac{\partial w^*}{\partial x} > 0$ whereas $\frac{\partial p^*}{\partial w^*} < 0$ due to log concavity of $g(v)$. $\square$

And the following proof shows the second claims in Proposition 2: there exists a finite number n such that $\frac{\partial p^*(n)}{\partial x} < 0$ when $x < x^*$.

Proof. By the convergence argument (we need uniform convergence of $\partial p^*(n, x)$ to $p^*(\infty, x)$ which is strictly negative), it is easy to see that the result of [Proposition 2](#) can be extended to large but finite n . Since $p^*(\infty, x)$ is decreasing in x , if $p^*(n, x_1) < p^*(n, x_2)$ for some $x_1 < x_2$ for all n , we can let $\epsilon = \frac{1}{2}[p^*(n, x_1) - p^*(n, x_2)]$, and since $p^*(\infty, x_1) > p^*(\infty, x_2)$, as well as that there exist some N such that for all $n > N$ we have $|p^*(n, x) - p^*(\infty, x)| < \epsilon$, there is a contradiction.

To show the uniform convergence of $p^*(n, x)$ to $p^*(\infty, x)$, notice that we only need $p^*(n, x)$ being equicontinuous in x when $x \in [\underline{v}, x^*]$ (it is differentiable with uniformly bounded derivatives with $g(v)$ being smooth).

We only need to show that $\frac{\partial p^*(n)}{\partial x}$ is uniformly bounded. Notice that $g(v)$ is sufficiently smooth (with bounded first and second derivatives). The details are as follows:

To get $\frac{\partial p^*}{\partial x}$, I use implicit function theorem. We let

$$\begin{aligned}\Delta_1 &= \sum_{k=0}^n \frac{n!}{k!(n-k)!} (1-G(x))^k G^{n-k}(x) [1-G_x(p^*)^k] \\ \Delta_2 &= \sum_{k=0}^n \frac{n!}{k!(n-k)!} (1-G(x))^k G^{n-k}(x) \left\{ -g_x(w^*) \frac{1-G_x(w^*)^k}{1-G_x(w^*)} + \int_{p^*}^{w(p^*)} G_x(v)^{k-1} g'_x(v) dv \right\}\end{aligned}$$

And $f(p^*, x) = p^* - c + \frac{\Delta_1}{\Delta_2}$. We have $\frac{\partial p^*}{\partial x} = -\frac{\partial f / \partial x}{\partial f / \partial p^*}$. To show that it is uniformly bounded, we only need to show that $\partial f / \partial x$ is uniformly bounded and $\partial f / \partial p^*$ is uniformly bounded away from zero.

Firstly, notice that both Δ_1 and Δ_2 are uniformly bounded. The numerator Δ_1 is simply the mean of $[1-G_x(p^*)^k]$ (with k binomial distributed) that bounded in $(0, 1)$. The denominator Δ_2 is similarly the mean of $-g_x(w^*) \frac{1-G_x(w^*)^k}{1-G_x(w^*)} + \int_{p^*}^{w(p^*)} G_x(v)^{k-1} g'_x(v) dv$ which lives in $(\frac{-g_x(w^*)}{1-G_x(w^*)} + \int_{p^*}^{w(p^*)} g'_x(v) dv, -g_x(w^*))$ if $g(w^*) < g(p^*)$ or $(\frac{-g_x(w^*)}{1-G_x(w^*)}, -g_x(w^*)) + \int_{p^*}^{w(p^*)} g'_x(v) dv$ if $g(w^*) > g(p^*)$. Either way it is bounded and bounded away from zero.

Secondly, $\partial f / \partial x = \frac{\partial(\Delta_1 / \Delta_2)}{\partial x}$ is uniformly bounded. To prove it we only need to show that both $\frac{\partial \Delta_1}{\partial x}$ and $\frac{\partial \Delta_2}{\partial x}$ are uniformly bounded. For the former, notice that it is given by:

$$\begin{aligned}\frac{\partial \Delta_1}{\partial x} &= \sum_{k=0}^n \frac{n!}{k!(n-k)!} \frac{\partial[(1-G(x))^k G^{n-k}(x)]}{\partial x} [1-G_x(p^*)^k] + \\ &\quad \sum_{k=0}^n (1-G(x))^k G^{n-k}(x) \frac{\partial[1-G_x(p^*)^k]}{\partial x}\end{aligned}$$

The first component is given by

$$\sum_{k=0}^n \frac{n!}{k!(n-k)!} (g(x)(n-k)(1-G(x))^k G^{n-k-1}(x) + g(x)k(1-G(x))^{k-1} G^{n-k}(x)) [1 - G_x(p^*)^k]$$

which is uniformly bounded given both series converges. The second component is given by

$$\sum_{k=0}^n (1-G(x))^k G^{n-k}(x) [-g(x) \frac{1-G(p^*)}{(1-G(x))^2}]$$

which is also uniformly bounded for all $x < \bar{v}$. Similarly, we can also expand $\frac{\partial \Delta_2}{\partial x}$ and show it is uniformly bounded.

Finally we consider $\partial f / \partial p^*$. Clearly, it is given by $1 + \frac{\partial(\Delta_1/\Delta_2)}{\partial p^*}$. Yet both $\frac{\partial \Delta_1}{\partial p^*}$ and $\frac{\partial \Delta_2}{\partial p^*}$ are uniformly bounded. $\frac{\partial \Delta_1}{\partial p^*}$ is bounded by the mean of $-g(p^*)kG_x(p^*)^{k-1}$, which is also bounded given that its series is convergent (for all $p^* < \bar{v}$ which always holds). $\frac{\partial \Delta_2}{\partial p^*}$ is bounded by the mean of $G_x(w^*)^{k-1}g'_x(w^*) - G_x(p^*)^{k-1}g'_x(p^*)$ which also has a convergent series. Moreover, we have $\Delta_2 < 0$ and $\frac{\partial \Delta_1}{\partial p^*} < 0$, as well as $\Delta_1 > 0$ and $\frac{\partial \Delta_2}{\partial p^*} > 0$. Therefore, $\partial f / \partial p^*$ is uniformly bounded and bounded away from zero.

Putting the parts together, we've shown that $\frac{\partial p^*}{\partial x}$ is uniformly bounded. Therefore $\partial p^*(n, x)$ converges to $p^*(\infty, x)$ uniformly. Therefore there exists N such that $\forall n > N$, $\partial p^*(n, x)$ is decreasing in x . □

A.2.5 Proof to Proposition 4

Proof. To begin the analysis, let us consider one firm with price p and all others stay with p^* . This seller will only have demand if it has the highest value, the probability of which is $\frac{1}{n}$. Suppose $p > p^*$. Compared to charging equilibrium price, this seller will lose some consumers with $p^* < v_{(n)} < p$. Notice that for a small deviation, we can ignore the consumers who choose to continue their visit to the second highest rated shop, with a sufficient condition $p - p^* < s$. For $p < p^*$, this seller get some extra consumers with $p^* > v_{(n)} > p$. Therefore, the demand is not inelastic as in Diamond. We derive the optimal prices by showing the

demand as follows:

$$D(p, p^*, n) = \frac{L}{n} \int_p^{\bar{v}} g_{(n)}(v) dv \quad (7)$$

At equilibrium, we have $D(p^*, p^*, n) = \frac{L}{n} \int_{p^*}^{\bar{v}} dG_{(n)}(v)$. We also have its derivative with respect to price as follows:

$$D_p(p, p^*, n) = \frac{L}{n} (-g_{(n)}(p)) \quad (8)$$

Therefore, the equilibrium price is given by

$$\begin{aligned} p^* &= c - \frac{D(p^*, p^*, n)}{D_p(p^*, p^*, n)} \\ &= c + \frac{\int_{p^*}^{\bar{v}} g_{(n)}(v) dv}{g_{(n)}(p^*)} \end{aligned} \quad (9)$$

Notice that $g_{(i)}(v)$ is given by

$$g_{(i)}(v) = \frac{n!}{(i-1)!(n-i)!} [G(v)]^{i-1} [1-G(v)]^{n-i} g(v)$$

Therefore,

$$\begin{aligned} g_{(n)}(v) &= \frac{n!}{(n-1)!(1)!} [G(v)]^{n-1} g(v) \\ &= n[G(v)]^{n-1} g(v) \end{aligned}$$

Substituting into [Equation 9](#), we have

$$\begin{aligned} p^* &= c + \frac{\int_{p^*}^{\bar{v}} n[G(v)]^{n-1} g(v) dv}{n[G(p^*)]^{n-1} g(p^*)} \\ &= c + \frac{1 - G(p^*)^n}{n[G(p^*)]^{n-1} g(p^*)} \end{aligned} \quad (10)$$

□

A.2.6 Proof to Corollary 3

Proof. Use implicit function theorem. Let $f(p^*, n, c) = -p^* + c + \frac{1 - G(p^*)^n}{n[G(p^*)]^{n-1}g(p^*)}$. We have that p^* is an implicit function of n and c defined by $f(p^*, n, c) = 0$. Therefore $\frac{\partial p^*}{\partial n} = -\frac{\partial f / \partial n}{\partial f / \partial p^*}$. We have

$$\begin{aligned} \frac{\partial f}{\partial p^*} &= -1 - \frac{n[G(p^*)]^{n-1}g(p^*)}{n[G(p^*)]^{n-1}g(p^*)} - \frac{(1 - G(p^*)^n)(n[G(p^*)]^{n-1}g'(p^*) + n(n-1)[G(p^*)]^{n-2}g^2(p^*))}{(n[G(p^*)]^{n-1}g(p^*))^2} \\ &= -\frac{n[G(p^*)]^{n-2}(1 - G(p^*)^n)}{(n[G(p^*)]^{n-1}g(p^*))^2} [G(p^*)g'(p^*) + (n-1)g^2(p^*)] \\ &< -\frac{n[G(p^*)]^{n-2}(1 - G(p^*)^n)}{(n[G(p^*)]^{n-1}g(p^*))^2} [G(p^*)g'(p^*) + g^2(p^*)] < 0 \end{aligned}$$

The last inequality is from the log-concavity of G . Now we show that

$$\begin{aligned} \frac{\partial f}{\partial n} &= \frac{1}{(n[G(p^*)]^{n-1}g(p^*))^2} [-n[G(p^*)]^{n-1}g(p^*)G(p^*)^n \log G(p^*) - \\ &\quad (1 - G(p^*)^n)([G(p^*)]^{n-1}g(p^*) + n[G(p^*)]^{n-1}g(p^*) \log G(p^*))] \\ &= \frac{-nG(p^*)^n \log G(p^*) - (1 - G(p^*)^n)(1 + n \log G(p^*))}{n^2[G(p^*)]^{n-1}g(p^*)} \\ &= \frac{-1 + G(p^*)^n - n \log G(p^*)}{n^2[G(p^*)]^{n-1}g(p^*)} > 0 \end{aligned}$$

To see how the last inequality works, let $z = \frac{1}{G(p^*)}$, clearly $z \in (1, +\infty)$. The numerator can

be written as $y = -1 + z^{-n} + n \log z$. It equals 0 when $z = 1$, $\forall n$, and $\frac{dy}{dz} = \frac{n}{z}(1 - z^{-n}) > 0$. Therefore the numerator is positive, so is the denominator and hence the ratio.

Having proved that $\frac{\partial f}{\partial p^*} < 0$ and $\frac{\partial f}{\partial n} > 0$, we have $\frac{\partial p^*}{\partial n} = -\frac{\partial f / \partial n}{\partial f / \partial p^*} > 0$. Also note that $\frac{\partial f}{\partial c} = 1$, hence we have $\frac{\partial p^*}{\partial c} > 0$ which is quite expected. $\square$

A.2.7 Figures

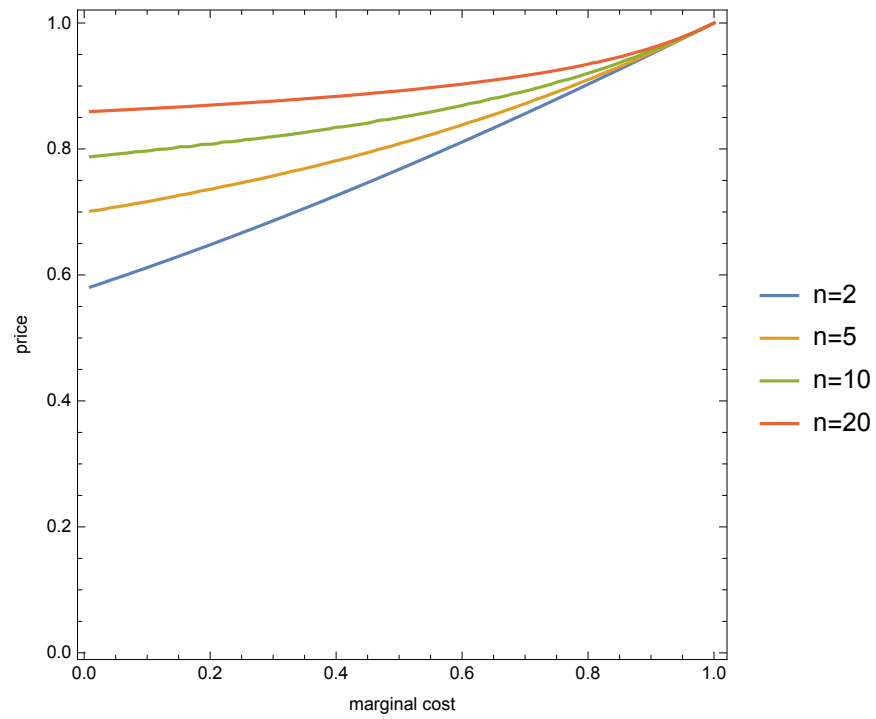


Figure 9: Relevance ranking prices versus n and c with uniform v

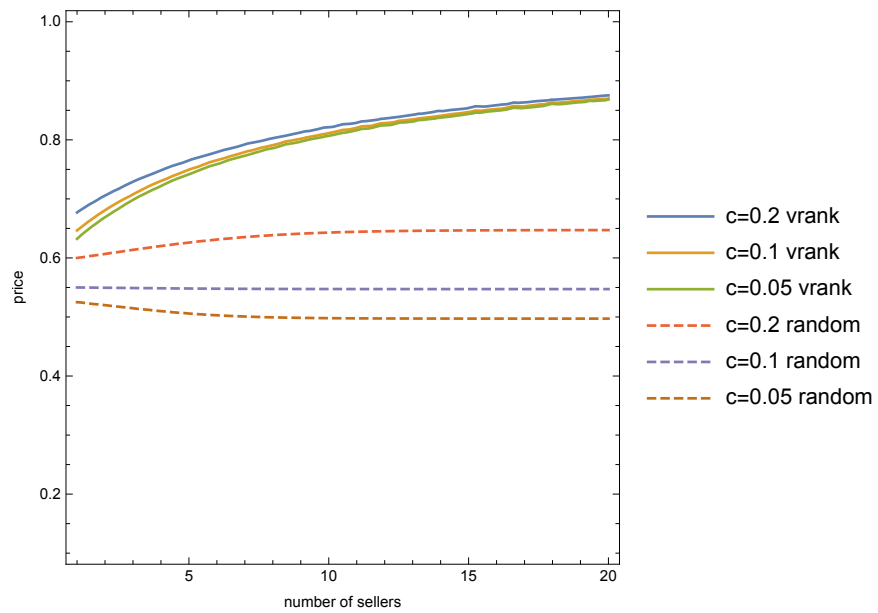


Figure 10: Prices versus c and n with uniform v , for both relevance ranking and random ranking ($s = 0.1$)

A.3 Appendix to Chapter 3

A.3.1 Proof to Lemma 2

Proof. Given x , changing z^* only changes the equilibrium price and consumers' participation constraint, but not their optimal search strategy. As long as $w(x) > p^*$, the demand is constant. Therefore, the platform will set z^* such that $w(x) = p^*(z^*, x)$. As we've shown, in this case, the price is given by $p^*(x) = \frac{1}{1-z}c + \frac{1-G(w^*)}{g(w^*)}$. Therefore we have that the optimal z^* is given by $w^* = \frac{1}{1-z}c + \frac{1-G(w^*)}{g(w^*)}$. Because w^* is increasing in x , we can easily show that z^* is also increasing in x : the LHS is increasing in w^* whereas the RHS is decreasing in w^* . $\square$

A.3.2 Proof to Lemma 3

Proof. Firstly we prove the uniqueness of z^* . Take the F.O.C., we have that

$$-f(w-p)pz + F(w-p)z + F(w-p)p = 0$$

Rearrange the terms, we have $\frac{pz}{p+z} = \frac{F(w-p)}{f(w-p)}$. We want to show that its LHS (denoted by $\Phi_1 = \frac{pz}{p+z}$) is increasing in z whereas the RHS (denoted by $\Phi_2 = \frac{F(w-p)}{f(w-p)}$) is decreasing in z . Notice we have $\frac{\partial \Phi_1}{\partial z} = \frac{1}{(p+z)^2} \left(p^2 + \frac{\partial p}{\partial z}(p+z)z \right) > 0$ given $\frac{\partial p}{\partial z} > 0$. And we have Φ_2 decreasing in p by the log concavity of $f()$, therefore it is also decreasing in z given $\frac{\partial p}{\partial z} > 0$. Therefore the F.O.C. has a unique solution. We can also rule out corner solution by observing $\pi(x, 0) = \pi(x, +\infty) = 0$, whereas any z s.t. $0 < z$ and $p^*(z) < w$ will lead to strictly positive profit.

Next we show that z^* is increasing in x when $x \leq x^*$. Notice that $w - p^*$ is increasing in x when $x \leq x^*$: w is increasing in x whereas p^* is decreasing in x , as we've shown in Proposition 2. Therefore, Φ_2 is increasing in x and decreasing in z . Also notice that Φ_1 is decreasing in x ($\frac{\partial \Phi_1}{\partial x} = \frac{\partial \Phi_1}{\partial p} \frac{\partial p}{\partial x} < 0$) and increasing in z as we've just shown. Combining two pieces together, we have z^* to be increasing in x by implicit function theorem. $\square$

A.3.3 Proof to Proposition 7

Proof. The proof is quite intuitive. I first show that the platform's profit $\pi^*(x)$ is increasing in x when $x < x^*$. Suppose that we have $x' > x$. We have that $\pi^*(x') = \max_z F(w^*(x') - p^*(x', z))zp^*(x', z)$, and $\pi^*(x) = \max_z F(w^*(x) - p^*(x, z))zp^*(x, z)$. Let $z_1 \in$

$\arg \max F(w^*(x) - p^*(x, z))zp^*(x, z)$. We can find a $z_2 > z_1$ such that $p^*(x', z_2) = p^*(x, z_1)$. And therefore $\pi(x', z_2) = F(w^*(x') - p^*(x', z_2))z_2p^*(x', z_2) > F(w^*(x) - p^*(x, z_1))z_1p^*(x, z_1)$ since $z_2 > z_1$ and $x' > x$. Yet by definition $\pi^*(x') = \max_z F(w^*(x') - p^*(x', z))zp^*(x', z) \geq \pi(x', z_2)$, therefore $\pi^*(x') > \pi^*(x)$ as desired.

For the case when $x > x^*$, I show that there are cases in which the profit will be discontinuously lower. This is possible when the price becomes discontinuously higher at x^* . Suppose that the optimal commission rate at x^* is given by z^* , and $p^*(x^*, z^*) < x$. At any $x > x^*$, the price is either an interior solution (which is strictly larger than x) or the corner solution x , both will be strictly and discontinuously higher than $p^*(x^*, z^*)$. Therefore, we have $\lim_{x \rightarrow x^{*+}} p^*(x, z^*(x)) > p^*(x^*, z^*)$, and more importantly, its revenue will be discontinuously lower, that is, $\lim_{x \rightarrow x^{*+}} \max_{x, z} \pi(x, z) < \pi(x^*, z^*)$. If the difference in revenue is high enough, that is, $\max_{x > x^*, z} \pi(x, z) = F(w^*(x) - p^*)zp^* < \pi(x^*, z^*)$, the platform will be better off by choosing a targeted search precision x^* . $\square$

A.3.4 Empirical Study

In this section I use a large and unique Taobao data set to show some suggestive evidence of the theory. I test the correlations between a construct of targeted search precision and market prices, as well as correlations between precision and market share of promoted sellers in the top slot. Readers should interpret the findings as correlations instead of causality, as in this setting the search precision is clearly not exogenous.

The data consist of search outcomes of over 140,000 keywords, scraped from Taobao during February to April, 2016. The keywords are from Taobao's most searched keywords for each categories that Taobao provides to sellers for their SEO. For each keyword, I have the search outcomes (ranked by the default ranking) of the first five pages or the top 224 sellers. In total I have over 31 million observations. And every entry consists of the price and quantity sold, as well as shipping fee, sellers' attributes including its reputation level, good rating percentage, three dynamic ratings, its major industry, and whether it is a Taobao or TMall seller. For each keyword I also have the number of search outcomes as well as its three level categories. For instance, an iPad case keyword belongs to "3C Digital"- "Tablet Accessory"- "Tablet Case". See [Table 12](#) for the summary statistics at keyword level.

I construct a measure of targeted search precision using the number of search outcomes for each keyword. The intuition is that a specific keyword ("iPad Air 2 Thin Case" compared to "iPad Case") should lead to a small number of search outcomes, and the search should be more targeted. I include the 3rd-Level category fixed effect to control for differences in market sizes across different categories. I also take the log to account for its skewness which greatly increases the model fit.

The first finding is the correlation between the share of promoted seller and search precision. The theory predicts that as search precision increases (in my empirical setting, as the number of search outcomes decreases), the market share of promoted seller increases. I construct the market share by taking the ratio of the quantity sold of promoted seller over

Table 12: Summary Statistics of Keyword Search Outcomes

Variable	Obs	Mean	Std. Dev.	P25	P50	P75
Total # Search-Outcome	141974	434141.1	3236884	11129	42179	155304
Average Quantity Sold	142108	346.116	643.044	66.253	181.9	417.417
Average Price	142133	520.361	13045.03	44.539	91.278	179.345
Average Reputation Level	142118	10.692	1.779	9.717	10.839	11.78
Average Favorable Rate %	142117	99.015	.985	98.853	99.2	99.458
Average Dynamic Rating 1	142117	4.844	.078	4.823	4.852	4.881
Average Dynamic Rating 2	142117	4.848	.075	4.828	4.853	4.881
Average Dynamic Rating 3	142117	4.824	.075	4.803	4.829	4.857
Keyword Length	142133	5.891	2.476	4	6	7

the average quantity sold of all sellers for the same search query. As in [Table 13](#), both the share of the first seller (who pays to get promoted) and the share of the first page (first 48 sellers, including one promoted and 47 organic) are negatively correlated with the number of search outcomes. This is suggestive evidence that is consistent with the model prediction.

The theory also predicts that increasing targeted search precision (less number of search outcomes) leads to lower prices when the market is not too precise, and the opposite when targeted search is sufficiently precise. [Figure 11](#) shows the relationship between the measure of targeted search precision ⁶ and the price ⁷ using local linear fit with 95% confidence intervals. The pattern is consistent with the model predictions. When the precision is not too high, increasing targeted search precision is associated with decreasing prices, while the reverse is true when targeted search precision is sufficiently high. [Table 14](#) shows that both correlations are significant in the regression of price over the log number of search outcomes in two subsamples, with high and low search precision as defined by whether a search generates a number of search outcomes that is smaller or larger than the category median.

⁶Defined by the negative of the residual of log number of search outcomes regressing on average shop attributes and 3-rd category fixed effects.

⁷Defined by the residual of log prices regressing on average shop attributes and 3-rd category fixed effects.

Table 13: Correlation between shares of promoted or higher ranked sellers and the number of search outcomes

	First Shop Share		First-Page Share	
Log(# Search Outcome)	-0.738*** (0.0345)	-0.814*** (0.0347)	-0.0535*** (0.00115)	-0.0536*** (0.00109)
N	141930	141930	141930	141926
3rd Category F.E.	Yes	Yes	Yes	Yes
Average Shop Attributes ¹	Yes	Yes	Yes	Yes
First Shop Attributes ²	No	Yes	No	No
First-page Shop Attributes ³	No	No	No	Yes

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

¹ Including average reputation level, good rating percentage, and three dynamic ratings.

² Including the first seller's reputation level, good rating percentage, and three dynamic ratings.

³ Including the first page sellers' average reputation level, good rating percentage, and three dynamic ratings.

Table 14: Correlation between prices and the number of search outcomes

	Average Price		
	Full Sample	Low Precision ¹	High Precision ¹
Log(# Search Outcome)	0.0426*** (0.00127)	0.121*** (0.00238)	-0.118*** (0.00354)
N	141959	70973	70986
3rd Category F.E.	Yes	Yes	Yes
Average Shop Attributes ²	Yes	Yes	Yes

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

¹ Defined by whether the residual of log number of search outcomes regressing on average shop attributes and 3-rd category fixed effects being smaller than its median (-0.164) or not.

² Including average reputation level, good rating percentage, and three dynamic ratings.

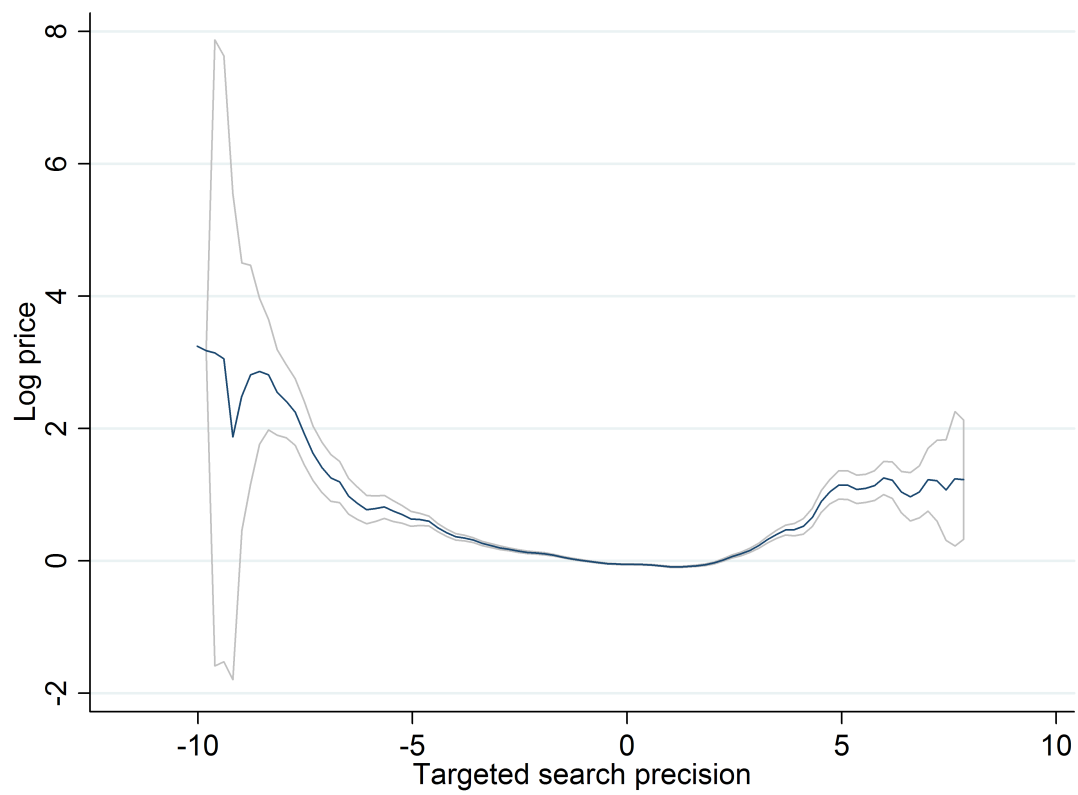


Figure 11: Log prices and targeted search precision