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Abstract

The platform—a business model that creates value by connecting groups of users—is increasingly popular in many industries. Extant papers largely assume that platforms dominate the pricing decision, whereas in practice, prices in business-to-business transactions are often determined by a bargaining process. We study how the relative bargaining power of business partners affects pricing and competition in a two-sided market. We compile a unique and comprehensive dataset using sales data from the US daily deal market and specify a structural model based on Nash bargaining solutions. We find that Groupon, the larger deal platform, has more price-bargaining power than LivingSocial and that larger and chain merchants have more bargaining power than smaller and independent merchants. The difference in bargaining power between different types of merchant, interestingly, is more substantial on LivingSocial than on Groupon. Therefore, the size of a platform has two faces: while a larger customer base helps attract merchants, the platform's bargaining power may motivate some merchants to work with its smaller competitors, over which they have more influence on price setting. Our counterfactual results show that the allocation of price-bargaining power plays an important role in the daily deal markets and that merchants are significantly worse off if platforms have higher price-bargaining power during the negotiation. Furthermore, as it increases the bargaining power, LivingSocial would be able to boost its profits but lose its attraction in acquiring merchants.

Keywords: business-to-business marketing, platform competition, two-sided market, price bargaining, daily deals, structural model

1 Introduction

"Winning companies can no longer just be great product companies; they have to be great product and platform companies that enable the contributions of others."

— Brad Smith, CEO of Intuit

We typically think companies compete over products: "build a better mousetrap and the world will beat a path to your door." However, this proverbial business strategy does not apply to the fast-growing stream of platform businesses which grow by connecting groups of customers. Platform companies such as Amazon, eBay, and Groupon had notable growth momentum and attracted much attention among researchers and practitioners. Numerous start-ups operate on the platform concept and even traditional companies are looking for ways to become platforms. Understanding the strategy for platform competition has become more important than ever.

A platform business serves at least two groups of customers, often referred to as "sides". A business is considered a platform if (a) its end-users exhibit network externalities (that is, the benefit to one side from using the platform increases with the size of other sides) and (b) the growth of the platform depends on the relative prices charged to all sides. While the strength of the network effect is largely an empirical question, the pricing strategy is a central topic for theoretical research on platform competition (e.g., Armstrong 2006; Rochet and Tirole 2003, 2006). Most of the literature assumes that platforms have full pricing discretion and make take-it-or-leave-it offers to the sides. In practice, prices are sometimes determined by a bargaining process between the platform and one side of the market, when the side consists of business partners such as goods or service providers. After all, price bargaining is pervasive in business-to-business (B2B) contexts and the interactions between platforms and providers are no exception. An eye-catching example is that Amazon and Hachette, the fourth-largest publisher in the US, settled a much-debated dispute in 2014 and signed a contract concerning pricing and profit margins for e-books.[1]

[1] Streitfeld, David. "Amazon and Hachette Resolve Dispute". *New York Times*, November 13, 2014.

Intuitively, the price-bargaining dynamics between platforms and their business partners are critical for understanding platform competition. Depending on its relative control over pricing, a goods or service provider may obtain different payoffs on different platforms, which naturally influences its choice of platform. Due to the network effect, the provider's choices would in turn affect a platform's appeal to consumers, and hence influence the platform's competitiveness in the demand market. Bargaining thus makes it theoretically challenging to predict market outcomes, as the competition critically depends on the magnitude of platforms' and providers' bargaining power, the nature of consumer preferences, and the heterogeneity in providers. For precisely this reason, it is an interesting and important empirical question to examine how the bargaining power of platforms and providers affects pricing and the competition between platforms.

In this paper, we empirically analyze the effect of price-bargaining power in a two-sided market. In particular, we allow both sides of the market to be heterogeneous and do not restrict them to one platform. We compile a unique and comprehensive dataset on the demand and supply in the US daily deal market, where deal platforms create value by connecting local merchants and consumers and offering daily assortments of discounted goods and services. Merchants use deal sites primarily to bring in potential consumers as well as generate revenue by selling deals.

We choose this empirical setting for several reasons. First, the daily deal market is a representative platform business and price bargaining is an important element in transactions between platforms and merchants. Second, since the market is largely a duopoly competition between two deal sites—Groupon and LivingSocial, understanding merchants' tradeoffs in their platform choices is relatively straightforward. Third, the daily assortment of deals provides much-needed data variation in the number and variety of merchants within a short period of time, allowing model identification. Fourth, the daily deal business in 2014 had $3 billion in revenue in the US market alone and even more in developing economies, making it an important market to study in its own right.[2]

This research setting poses two modeling challenges. First, the size of the consumer base for a deal platform is endogenously determined by the size and composition of the other side—the

[2] *IBISWorld*. "Daily deals sites in the US: Market Research Report." December 2014.

merchants. Furthermore, as pointed out in the platform literature, a consumer's decision should condition on her expectation of the other side. Second, both platforms and merchants act strategically on price setting. Platforms do not have full pricing discretion, as we will show in Section 3.5, so merchants internalize their bargaining power in the decision to work with particular platforms.

Taking those two challenges into account, we specify a two-stage structural model. In the first stage, deal platforms and merchants negotiate—through an independent bargaining process—the price charged to consumers. Despite being prominent in B2B markets, price bargaining has only recently been examined empirically. We model the outcomes of the platform-merchant negotiations following the Nash bargaining solution pioneered by Horn and Wolinsky (1988) and further developed by Crawford and Yurukoglu (2012). The solution of this supply model specifies the prices that solve the Nash bargaining problem between a platform and a merchant, conditional on other observed prices.

In the second stage, we examine consumers' decisions of choosing platforms and deals given the prices determined in the first stage. A consumer first needs to decide which platform(s) to use. Conditional on that choice, she decides whether to buy a particular deal. We formulate that a consumer's choice of a platform is consistent with her expectation of its value, which depends on (a) the number of deals offered, with a larger assortment potentially yielding a higher option value, and (b) the perceived quality of the deals. By this specification, we endogenize the network effect such that the size of the customer base depends on the quantity and quality of merchants. In contrast to many two-sided-market papers that simply specify the number of consumers as a function of the number of merchants, our approach explicitly takes the composition of the merchants into consideration.

Our demand specification incorporates the heterogeneity of consumers' price sensitivity, but the distribution of price elasticity needs to be estimated based on aggregate sales data rather than on individual-level data that are hard to obtain on a large scale.[3] To address this challenge, we cast our estimation using the "BLP" model—the random-coefficient aggregate discrete-choice model developed by Berry, Levinsohn, and Pakes (1995). We modify the BLP method to allow the deal decisions to nest under the platform choices. We also adopt a technique to accelerate the computation speed, because the original BLP estimation performs extremely slowly for such a large sample size as ours. We use the squared polynomial extrapolation method (SQUAREM) to speed up the convergence. To address the concern that deal prices are endogenous to unobservable demand shocks, we use instruments to estimate the price coefficients.

Our estimated distribution of price elasticity indicates that customers in the daily deal market are price-sensitive, with an average estimated elasticity of -2.85. Our estimate is comparable to the benchmark value for typical elastic goods. There is significant heterogeneity among consumers; those who are older, have higher incomes, or are from a larger household tend to be less price-elastic. Furthermore, our results reveal varying consumer preferences for different deal categories. Restaurant and beauty deals are the top two categories that help platforms grow their customer base. Deals on family activities, home and automobile services, life skill classes, sports, and travel activities are effective as well.

Results from our supply model shed light on the relative bargaining power of platforms and merchants. As expected, we find that Groupon, the larger platform, has higher bargaining power than LivingSocial and that larger and chain merchants have higher bargaining power than smaller and independent merchants. The bargaining-power leverage for larger merchants, interestingly, is more substantial on LivingSocial, the smaller platform, which helps explain why those merchants are more likely to choose LivingSocial despite its smaller customer base. In a nutshell, when prices are negotiated, lack of bargaining power actually helps smaller platforms attract merchants while the larger platforms are, to a certain extent, disadvantaged by the bargaining power.

[3] When modeling competition in a two-sided market, it is important to incorporate the full scale of both sides in order to account for the network effect. Using individual-level data from a representative sample is sufficient.

Results from our counterfactual analyses show that bargaining power plays an important role in the daily deal market. If platforms are able to boost their bargaining power, deals would be priced higher and yield lower sales. This would mean fewer customers reached for merchants and undermine their efforts to reach potential customers through deals. With a 5% increase in platforms' bargaining power, merchants would end up with an 11.3% sales drop on Groupon and 10.7% on LivingSocial. Note that this counterfactual is similar to the case of a vertical structure between a monopoly manufacturer and a monopoly retailer. That is, if the manufacturer sets the wholesale price and the retailer sets the retail price charged to consumers, the retail price includes two successive markups (double marginalization) and hence is higher than the one with the manufacturer and retailer being integrated (Spengler 1950). This intuition applies to our setting as well. Our results show that merchants' bargaining power mitigates the price distortion for deals and increases the total sales quantity.

Price-bargaining power also seems to play a role in platforms attracting merchants. Our counterfactual results show that, if LivingSocial is to increase its bargaining power, it would obtain a bigger margin and hence higher profits; however, a higher price leads to lower sales and LivingSocial would lose the pricing advantage that attracts merchants to work with it in the first place.

The rest of the paper proceeds as follows. Section 2 reviews the related literature. Section 3 describes the empirical setting, reports summary statistics, and provides some model-free evidence. Section 4 specifies the model, and Section 5 presents the estimation and identification strategy. Section 6 presents the parameter estimates and the counterfactual results. We conclude and discuss future research directions in Section 7.

2 Literature Review

This paper builds on two streams of research. First, it extends the rich literature on platform competition. Ever since the pioneer paper by Katz and Shapiro (1994) that highlighted the importance of network externalities, a series of theoretical papers (Rochet and Tirole 2006; Rochet and Tirole 2003; Armstrong 2006; Caillaud and Jullien 2003) have studied the platform business and examined the role of the pricing structure on platform competition. The key insight is that the price charged to a side is inversely related to its price-elasticity adjusted by its strength of network externality on the other side. This makes it rational for some platforms to provide free services to one side and earn revenues from the others, as practiced by digital platforms such as eBay. However, existing theoretical papers largely assume that platforms set prices such that only platforms act strategically on pricing. But in reality, the pricing decision is often complicated and platforms may not have the market power to fully control price setting.

Some recent papers relax this assumption. Hagiu and Lee (2011) study the pricing control between content distributors (platforms) and providers. By examining two extreme conditions—in which either the platforms or the content providers set the price, they find that how pricing control is distributed between platforms and content providers may determine the extent to which content providers are willing to be exclusive on one platform. One obvious restriction of this paper is that it studies the extreme cases and neglects the fact that prices are jointly determined through negotiations in many B2B settings. Shao (2015) studies more flexible price negotiations between platforms and content providers, and finds that an entrant platform's greater bargaining power would make content providers more willing to work exclusively with the incumbent.

Our paper is similar to Hagiu and Lee (2011) and Shao (2015) in the sense that we examine the extent to which control over pricing (that is, the allocation of price-bargaining power) affects prices and market outcomes. We differ by empirically examining the phenomenon using transactional data from a two-side market. In addition, we incorporate heterogeneity among consumers and merchants. Allowing merchant heterogeneity enables us to attribute the relative bargaining power to merchant characteristics, such that we can conduct counterfactual analyses more targeted to different types of merchants. Incorporating consumer heterogeneity allows us to estimate the distribution of price elasticity and to better understand the intensity of competition on the consumer side.

The second related line of research is price bargaining between firms and suppliers. Despite the pervasiveness of bargaining in B2B environments, empirical work on this subject has only recently gained traction. The bilateral Nash bargaining model proposed by Horn and Wolinsky (1988) is advanced by Crawford and Yurukoglu (2012) to study pricing decisions between content distributors and conglomerates in the cable television industry. This Nash solution has since become the workhorse bargaining model for predicting the payoff split during B2B transactions in many applied settings. Grennan (2013) examines the role of bargaining power in price discrimination among hospitals in a medical device market. Gowrisankaran et al. (2015) estimate a bargaining model of competition between hospitals and managed care organizations. Different from those papers emphasizing the effect of bargaining on social welfare, our research aims to better understand the managerial implications for platform managers in growing their business as well as for merchants in choosing platforms.

Empirical marketing studies of price bargaining are sparse. The closest to our paper are Misra and Mohanty (2008) and Draganska et al. (2010), both of which examine bargaining in the retailing setting. The former estimated the relative bargaining power of manufacturers supplying to a single retailer and the latter extended the framework to include competition between retailers. In contrast to their works, the current research focuses on bargaining in a two-sided market, which distinguishes itself from retailing in two critical ways. First, the network effect between merchants and consumers is more prominent in a two-sided market than in retailing. Hence, it is critical to capture the externality value of a merchant to a platform and further allow that to enter the pricing decision. Second, the two settings also differ in terms of where the strategic actions may posit. In the retailing setting, retailers typically are the only strategic players when competing for consumers after they already contract with manufactures. However, platforms often facilitate the transactions between merchants and consumers, and hence both platforms and merchants may be strategic in setting the prices charged to consumers (Hagiu and Lee 2011). In other words, the bargaining outcomes may have a more direct impact on consumers in a two-sided market than in retailing.

To the best of our knowledge, this is one of the first empirical marketing papers that examine price bargaining in a competition with network externalities. While two-sided markets have attracted marketing researchers in recent years (e.g., Dubé et al. 2010; Wilbur 2008), price bargaining is either assumed away or inapplicable; so little is known about this important business practice. We bridge this gap and believe that our approach offers a good modeling framework to study platform competition where platforms do not have full control over pricing.

3 Data and Model-free Evidence

3.1 Empirical setting

Daily deal sites emerged around 2008 as a marketplace that connected merchants to consumers by offering discounts. This business model experienced skyrocketing revenue growth for several years. In 2010, the Chicago-based market leader, Groupon, became the "fastest growing company in history."[4] Several factors may have accounted for such growth: consumers enjoyed a wide variety of deep discounts while merchants could use the deal platforms' large customer bases to build awareness and generate extra revenue. Even though growth has slowed in recent years, the daily deal business remains a multibillion-dollar market.

The name of the business—daily deals—refers to the fact that the sites in their early years typically featured one deal per day. This quickly evolved to multiple deals a day. A platform's customers now have access to a searchable inventory of available deals and typically learn about new deals through email alerts or mobile app notifications or by visiting the platform's website. The vast majority of the deals are from local businesses, although platforms do occasionally promote deals offered by national merchants to build awareness, acquire new customers, and generate additional revenue.

The business model attracted a number of competitors, ranging from small local deal aggregators to large companies that offer deals as a sideline; Google Offers and Amazon Local are prominent examples. By and large, the market is dominated by two sites—in 2013, Groupon and LivingSocial earned roughly 59.1% and 16.6% of the US market's revenue, respectively.[5]

We compiled a comprehensive dataset from these two market leaders. It has four components: (1) deal data including sales, price, and other deal-level characteristics; (2) platform-level market

[4] CNBC, December 2010, http://www.cnbc.com/id/40454493, accessed February 10, 2015.
[5] *Statistica* 2015. Retrieved from http://www.statista.com/statistics/322293/groupon-market-share-us/ on February 15, 2015.

shares; (3) the distribution of consumer characteristics; and (4) merchant characteristics. Figure 1 illustrates the data components and the sources.

<Figure 1>

3.2 Deal sales

We acquired deal sales from YipitData, a premium business database. Our data include all the deals offered by Groupon and LivingSocial in 2012. Each observation is a sales record for which we know the deal title, price, sales quantity, discount depth, face value, starting date, ending date, category, city, and merchant information. For example, Groupon featured a restaurant deal titled "$79 for an Italian Steak-House Prix Fixe Dinner for Two with Wine at Padre Figlio (Up to $189 Value)" from June 27 to July 3 in New York. In this case, the price is $79, the original face value of the voucher $189, and the discount depth 63%. We also know the sales quantity for each deal.

Table 1 presents summary statistics for the deal data. In 2012, Groupon promoted a total of roughly 129,000 deals, with an average price of $59.26 (SD=$61.15) and an average sales quantity of 244.2 (SD=886.0). Deals were evenly distributed over the months with slightly more offered in the third quarter. LivingSocial offered approximately 69,000 deals. The average price was $48.3 (SD=$48.1) and the average sales quantity was 274.45 (SD=1,259.8).

<Table 1>

A deal belongs to one of twelve categories. Table 2 presents the size of each category and the summary statistics for price and sales by category. Across both platforms, the largest category is beauty followed by home and automobile services deals and restaurant deals. The relative sizes of the categories are largely comparable across platforms except that Groupon offered more goods deals than LivingSocial but the latter had more family deals and fitness deals.

Deal prices vary substantially across categories. In general, the average deal price for a category was higher on Groupon than on LivingSocial except for live events deals, which had a higher average deal price on LivingSocial. Sales varied across categories and platforms. Groupon had higher average sales than LivingSocial for family, fitness, live events, and restaurants categories; LivingSocial had higher average sales for the others. We depict the number of deals and the average sales per category in Figure 2.

<Table 2>

< Figure 2>

3.3 Market definition and platform shares

We acquired platform market usage data from two premium data sources that capture Web-browsing behaviors for Internet users across the US. From Compete—the industry's largest consumer behavior database that updates daily clickstream data based on a panel of 2.3 million US consumers—we obtained the number of unique visitors to www.Groupon.com and www.LivingSocial.com for each month of 2012.[6] Compete data also provide the number of unique visitors who visited both sites, which was important for this study. From the comScore Media Metric database, which has a representative US consumer panel of roughly 47,000 members, we retrieve the geographical distribution of active users of Groupon, LivingSocial, and both. Combining these two data components, we computed the number of active users for each platform per market per month. We used these numbers to define the aggregate platform choices in the subsequent analysis.

Groupon and LivingSocial divide the US market into so-called "divisions" which largely correspond to the metropolitan statistical areas (MSAs) defined by the Office of Management and Budget.[7] A typical MSA is centered around a large city that has economic influence over a region. For example, the "Chicago-Naperville-Joliet, IL-IN-WI" MSA surrounds Chicago and includes areas in Indiana and Wisconsin. In the context of our data, Groupon served 156 markets and LivingSocial served 166, with 131 served by both.

For each market, our analysis requires the "market size" for platform choices; that is, the total number of users who could possibly use one or both deal platforms. Potentially, any user with Internet access can use a deal site. Therefore, we use the number of Internet users to define the size of each market. The data are retrieved from the "October 2012 School Enrollment and

[6] In our data-collection period, mobile usage was very limited for daily deal business, though it has since become an important channel. In 2014, more than 50% of the transactions on Groupon were completed on mobile devices (*Groupon 10-K form 2014*).

[7] The Office of Management and Budget divides the US into 388 MSAs.

Internet Use Survey," a supplement of the Current Population Survey (CPS) by the US Census Bureau.

Groupon's and LivingSocial's market shares are computed by combining data from the monthly platform-level usage data and the distribution of users across regions. Table 3 summarizes these data. To construct the measures, we make the following calculation: (1) From comScore data we obtain the distribution of active users across census regions for each platform. For example, roughly 15.4% of Groupon users are from the mid-Atlantic region. (2) Within each region we assume that the number of users of a particular deal platform is proportional to the number of Internet users. For example, because Internet users in New York City make up 17.3% of the mid-Atlantic region total, the number of Groupon users in New York City is calculated as 17.3% of the number of Groupon users in the mid-Atlantic region. (3) Combining the distributions from steps (1) and (2) with the number of active Groupon users in a given month—e.g., 18 million—we calculate the number of active Groupon users in New York City in that month as 17.3% x 15.4% x 18 million ≈ 480,000. Dividing these numbers by the market size gives us the market share for each platform choice in a market.

<Table 3>

During our data-collection period, approximately 6.5% of the Internet users exclusively used Groupon, 2.5% exclusively used LivingSocial, and 1.7% used both. The remaining 89.3% chose the "outside option": either they purchased daily deals from other platforms or they did not participate in this market.

It is noteworthy that our platform market shares are based on "active users"—visitors to one or both platforms during our data-collection period—who may be a subset of the subscribers who have signed up to receive email alerts. We consider active users to be a better measure of platform size than subscribers because the former better represents the pool of users who actively consider deal offers. A subscriber may use an inactive email account to sign up and not truly be a platform user. Indeed, Groupon's 2012 annual report stated that retaining active users was its strategic emphasis[8].

3.4 Other variables

To estimate consumer heterogeneity in price sensitivity, we collected data on consumer characteristics. These data are also from the October 2012 CPS, which provides the empirical distributions of demographic and socioeconomic variables (such as income and household size) for Internet users in each market.

We obtained the merchant profile data from OneSource, one of the most comprehensive providers of business and company data. For each merchant, we know the number of employees, the annual sales, and whether it belongs to a chain.

3.5 Model-free evidence

To understand pricing bargaining in this empirical setting, the immediate questions are: (1) is there evidence that platforms and merchants split the control over pricing, and (2) if yes, how do the price-bargaining dynamics differ by platforms? Below, we provide some model-free evidence to answer these two questions.

Allocation of price-bargaining power within a platform: One way to measure a platform's relative pricing power is through the Lerner index (Elzinga and Mills 2011), calculated as $(p-mc)\,/\,p$, where p is the deal price charged to consumers and mc, the marginal cost, corresponds to the amount that the platform pays the merchant. A higher Lerner index value indicates that the platform has greater discretion to set a price above the marginal cost.

Computing the Lerner index requires knowing how much the platform pays the merchants, which is typically unavailable in public data sources. Fortunately, we were able to acquire a proprietary dataset from one of the two deal sites being studied in this paper. Due to the confidentiality agreement, we are not allowed to say which one. The uniqueness of this dataset is that, for all the deals (N=11,683) in a major category in 2012 and 2013, we observed the amount

[8] *Groupon 10-K form 2012*

that the platform paid the merchant. We will refer to this dataset as the “payment” data, from which the Lerner index for each deal was computed and used to generate model-free evidence.

First, we examine how the platform’s pricing discretion varies by merchant size. The platform internally coded the merchants as small, medium, or large. Figure 3a depicts the average Lerner index across deals for each of these three merchant sizes. Clearly, the focal platform has the highest average Lerner index for deals from small merchants and the lowest for deals from large merchants.

Another way to gauge the platform’s pricing discretion is to slice the deals by their perceived quality. The argument is that when the platform and merchant know they are negotiating over a high-quality deal, the merchant’s threat to withdraw from the negotiation becomes more credible and hence, everything else equal, this merchant should have relatively higher bargaining power. In the payment dataset, the platform internally coded deals into four tiers; the higher the tier, the higher the perceived quality of a deal.[9] Figure 3b depicts the average Lerner index by deal-quality tiers. Again, we observe that the focal platform has higher pricing discretion for deals in lower tiers and vice versa, showing that the platform was able to price deals with a higher margin over the cost when deals were perceived to have a lower quality.

<Figure 3>

Evidence on differences between platforms: By now we have seen that there is heterogeneity in a platform’s pricing discretion across different merchants. Naturally, the next question is: how does the pricing discretion vary between platforms?

To answer this question, we have to use our full sample of deals, for which we do not observe how much the platforms paid the merchants; hence, we are unable to compute the Lerner’s index as in the previous section. Nevertheless, comparing deal prices can shed some light on platform differences. Table 4 shows that Groupon charged a higher average price than LivingSocial. Given that deals may also vary by their face value, we split the sample into those with a low, medium,

[9] The platform coded the “tier” variable based on its private information about the merchants. Roughly, the information includes the merchant’s type and size, previous sales performance, and number of social media followers.

and high face value. Within each level of face value, the average deal price is higher on Groupon than on LivingSocial by roughly 9%, 2%, and 9%, respectively. This seems to suggest that Groupon was able to set a higher price than LivingSocial given a fixed face value. In addition, we see a similar pattern when we split the deals by categories: the average deal price is always higher on Groupon than on LivingSocial within each category except for live events (see Table 2).

<Table 4>

Next, what kind of merchants tends to use each platform? Here, we examine two merchant-specific characteristics—size as measured in the number of employees and whether the merchant belongs to a chain business. Table 5 summarizes the average merchant size and the proportion of chain businesses for Groupon and LivingSocial. When deals have a low to medium (<\$220) face value, larger merchants and those belonging to a chain are more likely to use Groupon than LivingSocial. Interestingly, the pattern switches for merchants offering a high-face-value deal: in this case, those working with LivingSocial tend to be larger size (two-sample t test, $p < 0.001$) and are more likely to belong to a chain ($p = 0.052$). We hypothesize that it is perhaps because larger and chain merchants offering high-face-value deals may have a disproportionate pricing advantage on LivingSocial. Thus, they can better influence the pricing decision on LivingSocial and achieve more sales despite LivingSocial's smaller customer base to begin with. To test this hypothesis, we then develop a structural model to examine the pricing decisions between platforms and merchants.

<Table 5>

4 Model

In this section, we model consumer choices and the price negotiation between platforms and merchants. We first describe our demand model and then the supply-side specification.

4.1 Demand

We study consumers' decisions using a random-coefficient aggregate discrete-choice model. In our setting, a consumer follows a two-stage decision process: she needs to choose which platform(s) to use and then, given the choice of platform(s), she considers whether to buy a particular deal. This nested structure is similar to how consumers choose intermediaries in vertical markets (e.g., Ho

2006). Again, we present our model specification backwards: we present the model for deal demand followed by that for platform choices.

4.1.1 Deal demand

Consumer i, active on platform k, derives utility from deal j on that platform in market m at time t. Her utility is specified as

$$u_{ijkmt} = \alpha_i + \alpha_i^p p_{jkmt} + \beta x_{jkmt} + \xi_{jkmt} + \varepsilon_{ijkmt} \ , \tag{1}$$

where α_i and α_i^p are individual-specific deal preference and price parameter; x_{jkmt} is observable deal characteristics; ξ_{jkmt} is deal-specific shocks unobservable to the econometrician but observable to the consumer and the platform, and ε_{ijkmt} is the idiosyncratic utility shocks. In the deal-demand specification, index j uniquely identifies a deal that is offered on platform k in market m at time t. Hence, subscripts for platforms, markets, and time are omitted to avoid redundancy in this section.

Our demand model follows the BLP specification pioneered by Berry, Levinsohn, and Pakes (1995). An important deviation in our model, however, is that we assume that a consumer makes the decision to purchase deal j independently of her decision to purchase another deal $j' \neq j$. In other words, the deals are treated as neither substitutes nor complements. We make this independence assumption for two reasons. First, in this empirical setting, deals vary substantially, even when they are in the same category in the same market around the same time. For example, tickets to different theaters in a city are for different shows and dinner at an Italian restaurant is very different from lunch at a Chinese buffet. Therefore, it is challenging to argue that consumers treat deals as substitutes and have to choose one over the others. Rather, we think deals are better treated as independent options. Second, this independence assumption enables us to construct the *total deal utility* that a consumer derives from the option of being able to purchase from a specific platform. By this specification, we allow more deals on a platform to potentially yield a higher option value for the platform. The same assumption was made by Lee (2013) to model the total option utility that a video gamer derives from a game console.

The taste parameters for overall deal preference and prices are allowed to be individual-specific and are specified as a function of observable and unobservable individual characteristics:

$$\begin{aligned} \alpha_i &= \alpha + \pi D_i + \sigma \nu_i \\ \alpha_i^p &= \alpha^p + \pi^p D_i + \sigma^p \nu_i^p \end{aligned}, \tag{2}$$

where α and α^p are the grand means for the overall preference and price sensitivity, respectively; D_i are the observable individual-level socio-demographic variables and are assumed to follow an empirical distribution $D_i \sim F_i(D_i)$; π's are the deviation from the mean preference that is attributable to D_i; ν_i's are individual-specific idiosyncratic shocks and are assumed to follow a multivariate normal distribution $N(\mathbf{0}, \mathbf{I})$; and σ's capture the degree of preference heterogeneity related to ν_i.

Plugging the individual-specific parameters into the deal utility, we get

$$\begin{aligned} u_{ij} &= \alpha + \alpha^p p_j + \beta x_j + \xi_j \\ &\quad + (\pi D_i + \sigma \upsilon_i) + (\pi^p D_i + \sigma^p \upsilon_i^p) p_j + \varepsilon_{ij} \end{aligned}. \tag{3}$$

We rewrite the utility as the sum of three components: the grand mean utility across all individuals, $\delta_j = \alpha + \alpha^p p_j + \beta x_j + \xi_j$; the individual deviation from the grand mean, $\mu_{ij} = (\pi D_i + \sigma \upsilon_i) + (\pi^p D_i + \sigma^p \upsilon_i^p) p_j$; and an idiosyncratic shock ε_{ij} . Following the BLP notation, we refer to $\theta_1 = (\alpha, \alpha^p, \beta)$ as the linear parameters and $\theta_2 = (\pi, \pi^p, \sigma, \sigma^p)$ as the nonlinear parameters.

A consumer may choose not to buy deal j, yielding the outside option, which can be understood as the best alternative to purchasing the deal. A consumer buys the deal if its utility exceeds that of the outside option. Because the scale of utility is arbitrary, we set it by defining the utility of the outside option to be a constant plus ε_{i0}.

We assume that ε_{ij} are independently and identically distributed (i.i.d.) from a type I extreme value distribution with mean 0 and variance scaled at $\pi / 6$ (Train 2009). With this distributional assumption, the percentage of consumers purchasing deal j is given as

$$s_j = \int \frac{\exp(\delta_j + \mu_{ij})}{1 + \exp(\delta_j + \mu_{ij})} dF(D_i, \upsilon_i), \tag{4}$$

which corresponds to our observed data and hence forms the basis for estimation.

It is noteworthy that deal prices are likely to be determined endogenously, as deals with positive or negative demand shocks may sell at a higher or lower price. In our specification, this means that p_j and ξ_j are not independent; we therefore need instruments for identification, which we discuss in Section 5.1.1.

4.1.2 Platform choices

Next, we model a consumer's decision to choose platform(s). Three main considerations underline our model formulation.

(1) At the moment of choosing platforms, a consumer may not observe the idiosyncratic demand shocks for deals. Therefore, she forms expectations of the utility that may be derived from each platform. In other words, the appeal of a platform to a consumer reflects the value that she expects to derive from being exposed to the deals offered on the platform. We use EU_{ikmt} to denote the *total expected deal utility* that individual i expects to receive from platform k in market m at time t.

(2) Consumers may have varying preferences for deals in different categories. For example, fitness deals may be more popular than deals for life skill classes. Therefore, we decompose the total platform utility into platform-category-specific utility and, thus, EU_{ickmt} denotes the total deal utility that consumer i expects to derive from deals in category c on platform k in market m at time t.

(3) Consumers can single-home or multi-home: in our empirical setting, some only used Groupon, some only used LivingSocial, and some used both. Our model incorporates this flexibility and does not treat platforms as mutually exclusive options. Instead, we regroup platform choices so that each consumer may fall into one and only one of these four groups: Groupon only, LivingSocial only, multi-homing, and neither (the outside option). This coding

scheme allows us to cast the platform decision under the discrete-choice model framework and take advantage of the closed-form formulation that such models entail.

The ex-ante expected utility of a deal is given by $EU_{ijkmt} = E_{\varepsilon}(\max(u_{ijkmt}))$, where u_{ijkmt} is the utility that consumer i derives from deal j. As i does not observe the idiosyncratic shock ε_{ijkmt} when she makes her platform decision, $E_{\varepsilon}(\max(u_{ijkmt}))$ captures her expectation of the utility for deal j integrated over the distribution of ε_{ijkmt}. Assuming i.i.d. type I extreme-value distribution for ε_{ijkmt}, we reduce this formula to

$$EU_{ijkmt} = \log(\exp(\delta_{jkmt} + \mu_{ijkmt})) = \delta_{jkmt} + \mu_{ijkmt}. \tag{5}$$

The total expected category-level utility, EU_{ickmt}, is defined as

$$EU_{ickmt} = \log \sum_{j \in J_{ckmt}} \exp(EU_{ijkmt}), \tag{6}$$

which is summed over all individual deals in category c on platform k in market m at time t, denoted as J_{ckmt}. Ho (2006) used a similar formulation to model the total expected utility over a set of hospitals in the context of patients choosing medical providers.

Here, EU_{ickmt} can be understood as capturing the expected option value for a deal category; that is, a consumer has the option to purchase every deal in this category offered by the platform. Everything else equal, the more deals offered and the higher their quality, the higher the option value.

As mentioned earlier, we assume that a consumer can choose either, both, or neither of the platforms. Let $r \in R \equiv \{g, l, gl, 0\}$ denote the set of platform choices. A consumer's choice is coded as $r = g$ if she uses only Groupon, $r = l$ if only LivingSocial, $r = gl$ if both, and $r = 0$ if neither. The utility that consumer i derives from platform choice r in market m at time t is

$$u_{irmt}^{pf} = \sum_{k \in r} \left(\sum_{c \in C_k} \gamma_c EU_{ickmt} \right) + \omega_t + \eta_{rm} + \Delta\eta_{rmt} + \varepsilon_{irmt}^{pf}, \tag{7}$$

where γ_c is the taste parameter for deal category c; $\sum_{c \in C_k} \gamma_c EU_{ickmt}$ is the consumer i's total expected utility for category c on platform k that belongs to set r; ω_t is the fixed effect for month t that captures the time-specific shocks at the industry level (for example, mass media may broadcast stories on daily deals that boost (or diminish) consumers' overall interest in this market); η_{rm} represents the time-invariant fixed effects that capture the overall preference towards option r across consumers in market m; $\triangle\eta_{rmt}$ is the time-specific deviation from η_{rm}; and ε_{irmt}^{pf} represents the idiosyncratic demand shocks specific to individual, platform, market, and time. A consumer chooses whichever set r maximizes her utility.

We define the outside option as an individual choosing neither platform ($r = 0$) and scale the utility by restricting the outside option utility as $u_{i0mt}^{pf} = 0 + \varepsilon_{i0mt}^{pf}$.

The fixed effects for platform and market, η_{rm}, represent the market-level mean time-invariant set-specific value (independent of the deals being offered) net of the cost associated with using the platform(s) in set r. This value could be a manifest of things, including but not restricted to each platform's reputation and the quality of its customer services, such as shipping speed and return policy. There could also be search cost or other nonmonetary costs of using deal platforms; for example, the disutility of having to deal with the multiple daily email alerts that deal platforms typically send out. Without the fixed effects, one would expect consumers to always multi-home, as more deal options would always yield higher expected total utility. In reality, however, many consumers single-home, suggesting that there is a cost for consumers to consider multiple platforms.

Again, under the assumption that ε_{irmt}^{pf} is i.i.d. from a type I extreme value distribution, the market share for set r becomes

$$s_{rmt}^{pf} = \int s_{irmt}^{pf} dF(D_i, \nu_i) \ ,$$

where $$s^{pf}_{irmt} = \frac{\exp\left(\sum_{k\in r}\left(\sum_{c\in C_k}\gamma_c EU_{ickmt}\right) + \omega_t + \eta_{rm} + \Delta\eta_{rmt}\right)}{\sum_{q\in R}\exp\left(\sum_{k\in q}\left(\sum_{c\in C_k}\gamma_c EU_{ickmt}\right) + \omega_t + \eta_{qm} + \Delta\eta_{qmt}\right)}. \tag{8}$$

4.2 Supply model

On the supply side, platforms and merchants bargain to set the price charged to consumers. Formally, the outcomes of these negotiations are the equilibrium of bilateral Nash bargaining problems in the sense that neither the platforms nor the merchants want to deviate from the determined prices. The Nash model, developed by Horn and Wolinsky (1988), has become the workhorse for empirical work on bilateral negotiations. In our application, the prices maximize the Nash product of the payoffs to the platform and to the merchant with an agreement relative to the payoffs without an agreement. That is, the prices solve

$$\max_{p_{jkmt}}\left[q_{jkmt}(p_{jkmt})(h_{jkmt} - c_{jmt})\right]^{b_{jmt}(k)}\left[\pi_{kmt}(p_{mt}) - d_{jkmt})\right]^{b_{kmt}(j)} \qquad \forall j \in J_{kmt}, \tag{9}$$

where h_{jkmt} is the payment that merchant j receives from platform k, c_{jmt} is the merchant's marginal cost of fulfilling the deal, π_{kmt} is platform k's profits in market m during time t if an agreement is reached between j and k, and d_{jkmt} is the platform's disagreement payoff if an agreement is not reached. The platform's profits depend on the deal demand and margin[10] across all the deals it offers in the market: $\pi_{kmt} = \sum_{j\in J_{kmt}} q_{jkmt}(p_{jkmt})(p_{jkmt} - h_{jkmt})$.

Parameter $b_{jmt}(k) \geq 0$ is the price-bargaining power of merchant j when facing platform k, and $b_{kmt}(j) \geq 0$ is k's bargaining power when facing j. Bargaining parameters are not separately identifiable, hence we normalize them by $b_{kmt}(j) + b_{jmt}(k) = 1$. If $b_{kmt}(j) = 1$, the platform sets the price and the merchant uses a take-it-or-leave-it strategy. Similarly, if $b_{jmt}(k) = 1$, the

[10] Notice that we assume the platform have zero marginal cost in selling an additional deal; this is reasonable because deal sites operate online.

merchant sets the price and the platform uses the take-it-or-leave-it strategy. Hence, this Nash bargaining model nests the Bertrand pricing model as a special case.

As in the bargaining literature, different threat points lead to different disagreement payoffs. Following Horn and Wolinsky (1988), we assume that other contracts—possibly including those between the platform and other merchants—would not be renegotiated if platform k and merchant j do not reach an agreement. The platform's disagreement payoff thus becomes $d_{jkmt} = \pi_{kmt}(\mathrm{p}_{mt}; J_{kmt} \setminus \{j\})$; that is, the profits for platform k in market m during time t given the prices of all remaining deals.

To better understand the equilibrium properties of our model, we solve the first-order condition (FOC) of this Nash bargaining problem and obtain the following pricing equation:

$$\begin{aligned} p_{jkmt} = h_{jkmt} &+ \frac{b_{kmt}(j)}{b_{kmt}(j) + b_{jmt}(k)} \cdot \frac{q_{jkmt}}{-\partial q_{jkmt} / \partial p_{jkmt}} \\ &+ \frac{b_{jmt}(k)}{b_{kmt}(j) + b_{jmt}(k)} \cdot \left[\left(p_{jkmt} - h_{jkmt} \right) - \frac{\pi_{kmt} - d_{jkmt}}{q_{jkmt}} \right] \end{aligned} . \tag{10}$$

The first term in Equation (10) is the payment made by the platform to the merchant. The second component is the platform's markup resulting from the Bertrand-Nash best-response price, weighted by the platform's relative bargaining power. It is obvious that, when $b_{kmt}(j) = 1$, the equilibrium price becomes the platform's Bertrand-Nash best-response price. The third component captures the merchant's "externality value" to the platform through $\frac{\pi_{kmt} - d_{jkmt}}{q_{jkmt}}$. A merchant contributes to a platform's profits not only through generating revenues from the focal deal but also through growing the platform's customer base. The greater the externality value for a deal, the lower price the platform is willing to accept.

To gain further understanding of the pricing equation, we make algebraic manipulation of Equation (10) and obtain the following relation:

$$p_{jkmt} - h_{jkmt} = \frac{q_{jkmt}}{-\partial q_{jkmt} / \partial p_{jkmt}} - \frac{b_{jmt}(k)}{b_{kmt}(j)} \cdot \frac{\pi_{kmt} - d_{jkmt}}{q_{jkmt}}, \tag{11}$$

which indicates that the platform's markup is upper bounded by the Bertrand-Nash best-response markup when the platform sets the price. The markup is lower when (1) the merchant's relative bargaining power is higher, or (2) the merchant's externality value to the platform is higher.

Note that h_{jkmt} is unobservable to researchers. We therefore set a structure and specify it to be proportional to the face value of a voucher:

$$h_{jkmt} = (\kappa_k + \kappa_c)\,\mathrm{Face}\,Value_{jkmt} \ , \tag{12}$$

where κ_k and κ_c are parameters to be estimated. By this specification, we assume that the payment made to merchant j is linearly related to the voucher's face value, which may be a fairly strong assumption. In Section 5.2, we provide robustness checks on this linear functional form. We do allow the ratio of h_{jkmt} to $FaceValue_{jkmt}$ to vary by category and platform, though it is assumed to be homogeneous within the same category-platform combination.

After regrouping the terms, we rewrite Equation (11) and further parameterize the price-bargaining ratio as a function of observable platform and merchant characteristics, χ_{jkmt}, and unobservables, ς_{jkmt}:

$$g_{jkmt}(p_{jkmt};\kappa) = \frac{b_{jmt}(k)}{b_{kmt}(j)} = \chi_{jkmt} + \varsigma_{jkmt} \ , \tag{13}$$

where the left-hand side of the equation, $g(p_{jkmt};\kappa) = \left[\dfrac{q_{jkmt}}{-q'_{jkmt}} - (p_{jkmt} - h_{jkmt})\right] / \dfrac{\pi_{kmt} - d_{jkmt}}{q_{jkmt}}$, can be constructed based on the estimated structural parameters. We describe the choice of observable characteristics, χ_{jkmt}, and other estimation details in Section 5.2.

5 Estimation, Identification, and Computation

In this section, we present our estimation strategy, discuss parameter identification, and provide details on the computation.

5.1 Estimation of the demand-side parameters

We adopt the BLP method to address price endogeneity and incorporate consumer heterogeneity in deal preference and price sensitivity. The parameters are estimated by minimizing an objective function based on a set of moment conditions as defined in the generalized method of moments (GMM) (Hansen 1982).

5.1.1 Deal-demand estimation

We begin by describing the variables used in the deal-demand specification. The vector of observable deal characteristics, x_j, includes price, the voucher's face value, the month in which the deal was offered (to capture any seasonal effect), deal category, and the size of the market (dummy variables indicating top-20 markets, markets ranked 21 to 40 markets, and otherwise). We use the logarithm of prices in the estimation to address the skewness in this variable. Deals may be substantially different even within the same category. For example, a ticket package to a premium children's play, such as "How to Train Your Dragon" at the IZOD Center, is priced around $80-90, while a fine play like "Sesame Street Live: Can't Stop Singing" typically have a face value around $30. We include the voucher's face value to at least partially control for deal heterogeneity.

For individual characteristics, D_i, we include annual income, household size, and age. As in Equation (2), we allow the overall deal preference and price sensitivity to depend on those individual characteristics. We simulate the values for each variable based on its empirical distribution.

When estimating the price parameter, α^p, we need to account for a nonzero correlation between p_j and ξ_j. Because a deal with higher demand shocks, ξ_j, may cost more but still end up with higher sales, failing to account for endogeneity would bias the price estimate towards zero. A valid price instrument should be correlated with p_j but exogenous to ξ_j. We choose as price instruments (a) the average price of all the deals from the same category in other markets during the same month on the focal platform and (b) the same average for the other platform. These instruments are similar to those used in (Hausman 1996; Nevo 2001). Because the instruments are averaged across deals of the same category around the same time, they should be correlated with p_j, due to common cost shifters at the category level. Because the averages are based on deals from other markets, it is reasonable to assume that the price instruments are uncorrelated with the demand shocks in the focal market. We set the restriction criteria as $E\left(Z \cdot \xi_j\right) = 0$. Note that these instruments would be invalid if they were only weakly correlated with the focal deal's price (causing weak-instrument problems) or if the unobservable demand shocks were correlated across markets (violating the exogeneity requirement). We provide diagnostic statistics for the instruments in the results section.

5.1.2 Platform demand estimation

Equation (7) specifies the total utility that a consumer expects to derive from each platform set. We further use $\Gamma_{ikmt}(\delta(\theta_1);\gamma,\theta_2) = \sum_{c \in C_k} \gamma_c EU_{ickmt}$ to denote the part of the utility directly related to deals being offered. Here, γ is the vector of category-specific taste preferences, δ is the vector of deal mean utilities, and θ_2 is the vector of nonlinear utility parameters in the deal demand.

After plugging in $\Gamma_{ikmt}(\delta(\theta_1);\gamma,\theta_2)$ and regrouping terms, we write the aggregated market shares for platform sets as

$$
\begin{aligned}
s^{pf}_{r,mt} &= \int \frac{\exp(\Gamma_{irmt}(\delta(\theta_1);\gamma,\theta_2) + \omega_t + \eta_{rm} + \Delta\eta_{rmt})}{1 + \sum_{r=\{g,l,gl\}}} dF(D_i, \upsilon_i) \\
&= \int \frac{\exp(\Gamma_{irmt}(\delta(\theta_1);\gamma,\theta_2) + \delta^{pf}_{rmt})}{1 + \sum_{r=\{g,l,gl\}}} dF(D_i, \upsilon_i)
\end{aligned}
\quad \text{, for } r = \{g,l\} \text{ and}
$$

$$
\begin{aligned}
s^{pf}_{gl,mt} &= \int \frac{\exp(\Gamma_{i,g,mt}(\delta(\theta_1);\gamma,\theta_2) + \Gamma_{i,l,mt}(\delta(\theta_1);\gamma,\theta_2) + \omega_t + \eta_{gl,m} + \Delta\eta_{gl,mt})}{1 + \sum_{r=\{g,l,gl\}}} dF(D_i, \upsilon_i) \\
&= \int \frac{\exp(\Gamma_{i,g,mt}(\delta(\theta_1);\gamma,\theta_2) + \Gamma_{i,l,mt}(\delta(\theta_1);\gamma,\theta_2) + \delta^{pf}_{gl,mt})}{1 + \sum_{r=\{g,l,gl\}}} dF(D_i, \upsilon_i)
\end{aligned}
$$

where $\sum_{r=\{g,l,gl\}} = \exp(\Gamma_{i,g,mt} + \delta^{pf}_{g,mt}) + \exp(\Gamma_{i,l,mt} + \delta^{pf}_{l,mt}) + \exp(\Gamma_{i,g,mt} + \Gamma_{i,l,mt} + \delta^{pf}_{gl,mt})$.

The linear component of the aggregated platform shares becomes

$$\begin{aligned} \delta^{pf}_{g,mt} &= \omega_t + \eta_{g,m} + \Delta\eta_{g,mt} \\ \delta^{pf}_{l,mt} &= \omega_t + \eta_{l,m} + \Delta\eta_{l,mt} \\ \delta^{pf}_{gl,mt} &= \omega_t + \eta_{gl,m} + \Delta\eta_{gl,mt} \end{aligned} \quad . \tag{14}$$

Here, we are also concerned with potential endogeneity problems. A popular platform may offer more and better deals, introducing a nonzero correlation between η_{rm} and $\Delta\eta_{rmt}$. To address this concern, we use the within-group fixed-effect estimator and use the first-differences transformation to eliminate the fixed effects. After the transformation, Equation (14) becomes

$$\begin{aligned} \delta^{pf}_{rm,t} - \delta^{pf}_{rm,t-1} &= (\omega_t - \omega_{t-1}) + (\Delta\eta_{rm,t} - \Delta\eta_{rm,t-1}) \\ D\delta^{pf}_{rm,t} &= D\omega_t + D\Delta\eta_{rm,t} \end{aligned} \quad , \tag{15}$$

where $D\delta^{pf}_{rm,t} = \delta^{pf}_{rm,t} - \delta^{pf}_{rm,t-1}$, $D\omega_t = \omega_t - \omega_{t-1}$ and $D\Delta\eta_{rm,t} = \Delta\eta_{rm,t} - \Delta\eta_{rm,t-1}$. We then form the identification restriction as $E(D\omega_t \cdot D\Delta\eta_{rmt}) = 0$.

5.1.3 BLP computation

Generally perceived as a nested fixed-point (NFXP) algorithm, the BLP method incorporates a contraction mapping step in which one inverts the demand system to recover a vector of mean utility, δ, that equates the predicted market shares with the observed market shares. In the BLP scheme, this contraction mapping step is an inner loop nested within an outer loop to search for the nonlinear utility using GMM.

Berry et al. (1995) prove that the fixed-point iteration used in the BLP scheme is guaranteed to converge. While this global convergence property is appealing, the BLP contraction mapping can be time-consuming, especially when the sample size exceeds 5,000. In order to speed up convergence, a common technique is to (a) relax the inner-loop tolerance value (ε_{in}) in regions where the minimization of the GMM objective function is far from the true solution and (b) tighten the tolerance criterion as the minimization gets closer to the truth. However, this procedure may lead to incorrect estimates, as Dube, Fox, and Su (2012) show that the inner-loop tolerance must be set at 10^{-14} with the outer-loop tolerance at 10^{-6}.

To accelerate the convergence without being penalized for estimation bias, we adopt the squared polynomial extrapolation method (SQUAREM), a state-of-the-art algorithm that can operate directly on the fixed-point formulation of the BLP contraction mapping. Originally developed to accelerate the expectation-maximization (EM) algorithm, SQUAREM has been shown to be not only faster but also more robust (in terms of the success rate of convergence) than the original contraction mapping procedure used in BLP (Reynaerts et al. 2012; Varadhan and Roland 2008). The advantage of SQUAREM is even more substantial when the sample size is large (as in our case) and when the initial values of the parameters are far from the truth.[11]

It is noteworthy that estimating the deal-demand parameters separately from the platform-demand parameters may also yield inaccurate estimates due to selection bias. Consumers may self-select onto different platforms depending on their preferences and the platforms may tailor their offerings accordingly, introducing another source of endogeneity. We therefore jointly estimate Equations (1) and (7) by iteratively solving for the deal-demand and the platform-demand parameters during the optimization search.

The details of the estimation routine are as follows:

1. For each market, simulate NS=1,000 individuals
   a. with observable characteristics from empirical marginal distributions, $F(D_i)$
   b. with unobservable idiosyncratic shocks, ν_i, simulated from a multivariate standard normal distribution
2. Assign initial values for α, α^p, and β and calculate the initial value for δ_j:

   $$\delta_j^{(0)} = \alpha + \alpha^p p_j + \beta x_j$$

3. Given θ_2 and δ_j, predict the share for each deal
   a. given $\theta_2 = (\pi, \pi^p, \sigma, \sigma^p)$: $\mu_{ij} = (\pi D_i + \sigma \upsilon_i) + (\pi^p D_i + \sigma^p \upsilon_i^p) p_j$

[11] For example, in our application, one search for the vector δ_j took 26 iterations and 3.5 minutes using the SQUAREM accelerator and over 5,000 iterations and 3 hours using the BLP contraction mapping with the inner-loop tolerance set at 10^{-14}.

b. given δ_j : $\widehat{\sigma}_j(\delta_j, \mathbf{x}_j; \theta_2) = \frac{1}{NS} \sum_i^{NS} \frac{\exp(\delta_j + \mu_{ij})}{1 + \exp(\delta_j + \mu_{ij})}$

4. Conduct BLP contraction mapping with SQUAREM accelerator to search for δ_j such that $\widehat{\sigma}_j(\widehat{\delta}_j, \mathbf{x}_j; \theta_2) = s_j$ as long as $\left\| \delta_j^{(h+1)} - \delta_j^{(h)} \right\| < \varepsilon_{in}$, where ε_{in} is the inner-loop tolerance set as 10^{-14}

5. Given $\delta_j = \alpha + \alpha^p p_j + \beta x_j + \xi_j$, analytically solve for the deal-demand linear parameters, $\theta_1 = (\alpha, \alpha^p, \beta)$

6. Given δ_j, θ_1, θ_2, and γ, compute $\Gamma_{irmt}(\delta(\theta_1); \gamma, \theta_2) = \sum_{k \in r} \left(\sum_{c \in C_k} \gamma_c EU_{ickmt} \right)$,

7. Given Γ_{irmt}, compute the predicted platform shares

$$\widehat{\sigma}^{pf}_{rmt} = \frac{1}{NS} \sum_i^{NS} \frac{\exp(\Gamma_{irmt}(\delta(\theta_1); \gamma_c, \theta_2) + \delta^{pf}_{rmt})}{1 + \sum_q \exp(\Gamma_{iqmt}(\delta(\theta_1); \gamma_c, \theta_2) + \delta^{pf}_{qmt})}$$

8. As in step 4, perform BLP contraction mapping with the SQUAREM accelerator to search for δ^{pf}_{rmt} δ^{pf}_{qmt} so that $\widehat{\sigma}^{pf}_{rmt} = s^{pf}_{rmt}$ as long as $\left\| \left(\delta^{pf}_{rmt}\right)^{(h+1)} - \left(\delta^{pf}_{rmt}\right)^{(h)} \right\| < \varepsilon_{in}$

9. Form the GMM moment conditions based on $E(Z \cdot \xi_j) = 0$ and $E(D\omega_t \cdot D\Delta\eta_{rmt}) = 0$, and repeat from step 3 for each iteration of the optimization.

5.2 Supply model estimation

In Equation (12), we restrict the payment made to a merchant being proportional to the voucher's face value. To assess the validity of this assumption, we turn to our payment data where h_{jkmt} are observed and find a correlation of 0.849 (N=11,674, p<0.01) between h_{jkmt} and $FaceValue_{jkmt}$, suggesting that the linear functional form is reasonable. Adding a quadratic term only minimally improves the predictive power of $FaceValue_{jkmt}$ for h_{jkmt}; the R^2 of a simple linear regression increases from 0.72 to 0.75. We therefore retain the linear functional form in subsequent estimations.

The function $g(p_{jkmt};\kappa)$ requires the implied deal demand, q_{jkmt}, the platform's profits with the agreement, π_{kmt}, its disagreement payoffs, d_{jkmt}, and the price elasticity term, q'_{jkmt}, all of which are constructed based on our demand parameter estimates. Parameter χ_{jkmt} captures how the relative bargaining power depends on the platform and merchant observables. For platforms, we use the Groupon dummy to measure the difference in bargaining power between Groupon and LivingSocial. The fixed-effect approach, however, does not apply to merchants, because there are too many of them. Therefore, we parametrize the merchant difference based on two important merchant characteristics: the number of employees and whether the merchant belongs to a chain (1=chain; 0=independent). For both variables, we include both the main effect and an interaction with the Groupon dummy, thus allowing the bargaining-power difference between merchants to vary by platform. We also control for the merchant's annual sales and the voucher face value in the analysis. We take the logarithm transformations for the continuous variables, such that our estimates are less influenced by extreme values.

The rest of the estimation is straightforward. Again, we use GMM to solve for the parameters and we set the moment condition as $\mathrm{E}\left[Z^{s'}\varsigma_{jk}\right]=0$. The supply-side instruments, Z^{s}, are set to be χ_{jkmt}, under the assumption that the observables are exogenous to ς_{jk} after controlling for all the included variables.

5.3 Identification

The linear parameters, θ_1, are straightforwardly identified via the cross-sectional variation across deals. The nonlinear parameters, θ_2, are identified through the variation in deals that have similar observables but end up with different sales quantities in markets with varying consumer characteristics. Imagine that two deals, identical except for price, are offered in markets A and B. If market A has higher average incomes, a larger average household size, and an older population and the deal has a higher price in that market but the sales are no less than the sales in market B, this would identify positive price coefficients for income, household size, and age.

The taste parameters for deal categories, γ , are identified through the within-market variation in deal offers and platform market shares. In a given market, if the change in a platform's market share is positively and substantially associated with a change in its offerings in a particular category (e.g., restaurant deals) the taste parameter for that category would be estimated to be large.

The supply parameters associated with the platform fixed effect and the merchant observables are identified through the cross-sectional variation across platforms and merchants. Imagine that two merchants with the same characteristics offer deals with the same face value, one on Groupon and one on LivingSocial. If the one on Groupon has a higher price, this would suggest that Groupon has more bargaining power and its fixed effect would be estimated to be positive. In another scenario, two merchants of the same size offer deals with the same face value on the same platform, but one merchant belongs to a chain and the other is an independent business. If the deal from the chain merchant has a lower price, this would suggest that the chain merchant has more bargaining power and the parameter estimate for the chain indicator would be estimated to be negative. The arguments for identifying the other parameters are similar.

6 Results

6.1 Demand parameter estimates

We examine several specifications of the deal demand and present the linear parameter estimates in Table 6. The first specification is a homogeneous logit model without accounting for price endogeneity or heterogeneity across individuals. This is simply the ordinary least squares (OLS) estimate with the dependent variable being the logarithm of the deal share minus the logarithm of the outside share. Results from specification (1) are used as benchmark values.

In the second specification, we use the Hausman-type price instruments discussed in Section 5.1.1, though we still do not account for consumer heterogeneity. With IV, the price coefficient was estimated to be much stronger: -2.875 with IV versus -0.834 without it. The direction of the change is as expected when prices and the unobservable demand shocks are positively correlated: when popular deals are priced high and unpopular ones are priced low, the OLS estimate of the price coefficient would be attenuated towards zero, as in our case. To assess the validity of the instruments, we run the first-stage regression and find the F statistic to be 1460.9 ($p<0.01$). We also run the Stock and Yogo (Stata 2013) test for weak instruments: our F statistic is higher than the test-critical value of 19.9, rejecting the null hypothesis of weak instruments.

<Table 6>

Specification (3) is the random-coefficient aggregate logit model that uses the price instruments and also incorporates individual preferences as a function of income, household size, and age. As expected, the mean price coefficient is estimated to be negative and significant ($\widehat{\alpha}^{p} =$ -3.952, $p<0.01$). The corresponding random coefficient estimates are reported in Table 7. We find significant variation in price elasticity across individuals: people who are older, have a higher income, or come from a larger household are significantly less price-sensitive for daily deals. After controlling for those consumer characteristics, there is still significant heterogeneity in price elasticity ($\widehat{\sigma}^{p}$=0.354, $p<0.01$). The overall deal preference varies by individual income, household size, and age as well. Our estimates indicate that consumers who have a higher income or come from a larger household tend to like deals less and that older consumers like deals more.

<Table 7>

Using the estimated demand parameters, we compute the mean price elasticity. Across all the deals, the average price elasticity is -2.85 with the interquartile range of (-3.10, -2.64). Such a high elasticity indicates that customers are highly sensitive to deal price fluctuations. To put these numbers in perspective, the average price elasticity for consumer packaged goods is around -2.50 (Tellis 1988). Soft drinks are typically considered elastic goods: Coca-Cola has an elasticity of -3.8 while Mountain Dew's is -4.4 (Ayers and Collinge 2003). Alcoholic beverages typically have elasticity between -1.0 and -1.5.

Next, we discuss consumers' preferences for different deal categories as they choose platforms. The higher the estimate for γ_c, the more a category is able to attract consumers to a platform. Our results reveal substantial heterogeneity across categories in their capacity to grow a platform's customer base. We find that restaurant deals have the highest appeal (0.011, $p<0.01$).

beauty deals (such as haircuts, hair removals, and facials) come in second (0.005, $p<0.01$). Five other categories—family activities, home and automobile services, life skill classes, sports, and travel activities—are also effective in growing a platform's customer base. The remaining categories—fitness, goods, live events, outdoor activities, and personal care services—exert minimal influence on a consumer's choice of a platform. In general, these categories tend to have fewer deals, lower sales, or both, which partially explains why they are ineffective in attracting users to a platform.

<Table 8>

6.2 Supply parameter estimates

In Table 9, we present the estimates for the supply parameters[12] specified in Equation (13). We are interested in how the relative bargaining power depends on the platform's and the merchants' characteristics. Note that the ratio of bargaining power, $b_{jmt}(k) / b_{kmt}(j)$, is specified as the merchant's bargaining power relative to the platform's; hence, higher parameter estimates correspond to higher relative bargaining power for merchants.

First, we find that merchants have lower bargaining power on Groupon than on LivingSocial (-1.444, $p<0.01$), as we would expect due to Groupon's leading position in the market. We also find that price-bargaining power varies by merchant size and type. Larger merchants—in terms of the number of employees—tend to have higher price-bargaining power than smaller ones (0.016, $p<0.05$). Furthermore, the interaction between the Groupon dummy and merchant size is estimated to be negative (-0.020, $p<0.01$), suggesting that the gap in merchant's relative bargaining power between Groupon and LivingSocial is wider for larger merchants than for smaller ones. A similar pattern is observed for merchants offering vouchers with a higher face value: they have higher bargaining power (0.638, $p<0.01$) than those with a low face value. Even though both types have higher bargaining power on LivingSocial than on Groupon, the gap in their bargaining power between platforms is bigger for merchants with a higher face value.

[12] The current estimates are based on a subset of data (N=17,470 deals). The smaller sample size is due to the time-consuming process of cleaning merchant names to match those in the OneSource database. As we have continued to increase the sample size, the reported patterns have so far been duplicated.

The main effect for the merchant's chain business status and annual sales are also estimated to be positive: chain merchants and those with higher annual revenues tend to have higher price-bargaining power than otherwise.

Furthermore, our results show that LivingSocial pays the merchant between 29.3% and 34.9% of the face value; the percentages vary by categories, with the lowest percentage for the beauty deals and the highest for travel activities. The payment made by Groupon is lower than the payment by LivingSocial by 13.9%.

<Table 9>

Using the supply parameter estimates, we compute the platform's relative bargaining power, $\frac{b_{kmt}(j)}{b_{kmt}(j)+b_{jmt}(k)}$, by normalizing the sum of the bargaining power for a platform-merchant pair to 1. The histogram of the bargaining power is depicted in Figure 4. The average relative bargaining power for Groupon was 0.61 (SD=0.18); the value higher than 0.5 indicates that Groupon on average had higher bargaining power than merchants. The average bargaining power for LivingSocial was 0.36 (SD=0.10), showing that merchants had higher bargaining power than LivingSocial. The high standard deviations tell that substantial heterogeneity exists in bargaining power within a platform across merchants of different characteristics.

<Figure 4>

6.3 Counterfactuals

In this section, we conduct counterfactual analysis to better understand the role of price-bargaining power in the daily deal market. The first question we ask is: what would happen to a deal's price and demand if the platform is able to increase its price-bargaining power? If a platform had a higher ability to influence price to its advantage, we would expect the counterfactual price to rise towards the platform's Bertrand best-response price, and hence the platform would yield higher profits. However, due to the higher price, merchants would receive lower sales and reach fewer customers. Results of this counterfactual analysis can help us understand the magnitude of this effect and shed light on the extent to which price bargaining matters in this market.

To conduct this analysis, we inflate a platform's price bargaining power by 5%, 10%, 20%, and 50%, respectively, and then compute the counterfactual price and demand given the new bargaining power. Results are presented in Table 10. When Groupon's price-bargaining power increases by 5%, our calculation indicates that its average deal price would increase by 4.4%, leading to an average of an 11.3% drop in sales. But the increase in deal margin offsets the drop in demand, resulting in an increase of Groupon's profits by 2.3%. The gain in Groupon's profits is 3.1%, 3.4%, and 13.0% with 10%, 20%, and 50% increases in its price-bargaining power, respectively.

The profit changes are more substantial on LivingSocial because it has lower bargaining power to begin with. We find that LivingSocial's profits would increase by roughly 15.5% corresponding to a 5% increase in its bargaining power. If it increases the bargaining power by 10%, 20%, and 50%, LivingSocial would be able to increase its profits by 26.0%, 38.2%, and 48.0%, respectively.

From the merchant's perspective, however, an increase in a platform's price-bargaining power would mean a drop in sales, as a result of the higher deal price. Given that merchants receive a fixed payment from the platform, the drop in demand would translate into lower payoffs for the merchant. For example, if the platform increases their price-bargaining power by 5%, merchants would end up with an 11.3% drop in payoffs on Groupon and 10.7% on LivingSocial. In other words, this analysis indicates that merchants benefit substantially from having bargaining power when working with platforms.

Note that in this counterfactual analysis we take the merchant-platform pairs as given and do not explicitly account for the possibility that an existing pair may disagree on the new price. Nevertheless, the results still inform us on the relative importance of price-bargaining power in this empirical setting.

<Table 10>

In the second counterfactual analysis, we examine to what extent price-bargaining power influences the merchants' choice of platforms. To answer this question, we first construct a set of hypothetical merchants with certain characteristics that offer a typical deal[13]. Next, for each merchant, we compute its bargaining power on Groupon and on LivingSocial, and then compute the implied deal price and likelihood of purchase on each platform. We then increase the LivingSocial's price-bargaining power over the merchant and compute the new equilibrium price and purchase likelihood.

The results are reported in Table 11. The numbers are the percentage differences between LivingSocial and Groupon. For example, for a small merchant offering a low-face-value voucher, our calculation shows that the deal price on LivingSocial would be lower than that on Groupon by 9.6%; as a result, the likelihood of the deal being purchased would be higher on LivingSocial by 32.6%. The gain in purchase likelihood on LivingSocial is higher for a large merchant (34.4%), as our supply parameter estimates indicate that the bargaining power difference between platforms is higher for larger merchants. With the current low bargaining power, LivingSocial actually offers an incentive for merchants to choose them despite their smaller customer base.

We observe the same pattern for merchants with a higher face value. The purchase likelihood on LivingSocial is higher than that on Groupon by 27.6% for a large merchant and 25.5% for a smaller one. The gain on LivingSocial due to the pricing advantage is 8.2% (=(27.6%-25.5%)/25.5%) between a larger and small merchant with a higher face value and 5.5% (=(34.4%-32.6%)/32.6%); this suggests that we would larger merchants with a high face value would have higher incentives to choose LivingSocial than their smaller counterparts, consistent with the model-free evidence we described in Section 3.5.

As we increase LivingSocial's bargaining power, the pricing advantage that a merchant enjoys on LivingSocial diminishes. For example, with a 20% increase and for a small merchant with low face value, the price on LivingSocial is only lower than that on Groupon by 7.3% and the purchase likelihood is higher by 23.5%. Interestingly, as the LivingSocial's bargaining power increases, merchants' pricing advantage on the platform also converges for small and large merchants.

Combining results from the two counterfactual analyses, we find that the lower price-bargaining power for LivingSocial may have actually helped it grow business. If it is to boost the

[13] By "typical", we assign the sample mean to each deal feature except price and face value.

bargaining power, LivingSocial is able to increase its margin and drive up profits; however, the higher bargaining power would also make LivingSocial lose its pricing advantage and hence become less attractive to merchants, hindering its acquisition of merchants. Those effects make bargaining power an interesting and important factor in platform competition.

<Table 11>

7 Conclusion

We study how bargaining affects pricing and competition in a two-sided market. Using a unique and comprehensive dataset from US daily deals, we specify a structural model that jointly examines consumer behaviors and the strategic interactions between deal platforms and merchants. We find that a platform's size can have two faces: first, a larger customer base attracts merchants, which in turn helps grow the customer base even further. Second, a larger platform has higher bargaining power in price negotiations, leading to less favorable prices for merchants, which motivates certain merchants to choose smaller platforms over which they have more influence on price setting. In a nutshell, this paper empirically demonstrates that price bargaining power is an important factor to consider in platform competition. When the platform is too big and powerful, its strong bargaining power may push away some business partners and hence slow down its growth. Hence, the network effect and the bargaining power are two counter-balancing factors to shape the growth of a platform. While the network effect has been the study focus of extant empirical literatures on platform competition, the price bargaining power has largely been ignored or assumed away even when it is present in practice. This research bridges this important gap.

To the best of our knowledge, this is one of the first empirical papers in marketing that examine the role of bargaining power in a two-sided market. Due to data limitations, we leave a few interesting and important topics for future research. First, we assume in our paper that platforms are myopic and bargain with merchants to maximize the joint payoffs from the current transaction, regardless of how the outcome may influence future payoffs. In fact, a platform may face a tradeoff between current and future payoffs. If it accepts a price more favorable for merchants, more merchants may be willing to join that platform rather than its competitors. Due to the network effect, this could increase the platform's customer base and boost profits in the long run. Therefore, if a platform behaves dynamically, it should negotiate a price that maximizes the product of the merchant's current profits and its own future discounted total profits, rather than merely its own current profits. Modeling such dynamic decision-making, however, requires a longer time horizon of observations on the platform's pricing decisions and its growth than we could manage in this study. Furthermore, by focusing on the current period's payoffs, we generate insights on how platforms and merchants internalize price-bargaining power in their strategic interactions; this lays a foundation for our follow-up research on platforms' forward-looking decisions.

Second, a platform could undergo a learning process concerning its own bargaining power as it repeatedly transacts with the same merchant. It is reasonable to imagine that, during the first transaction, neither party is fully informed about their relative bargaining power; they each take a guess. Over time, they use the results of their deal sales to update the estimates of their relative bargaining power. A more successful sales history would lead the pair to believe that the merchant can make a more credible threat to withdraw and thus have more bargaining power. Furthermore, the variation in sales for the same merchant affects the speed of learning. If deals are consistently popular or unpopular, the platform and the merchant can update their expectations quickly; with a noisy sales history, it would take longer for them to figure out their relative bargaining power.

Although such learning is plausible, it may not be critical in our setting. During our data-collection period, less than 10 percent of the merchants offered deals more than twice on the same platform. Even when they did, they did not necessarily offer the same deals.[14] While there may not be much learning in our setting, learning of the bargaining power may play a much more important role in other B2B contexts.

Third, we do not try to pin down the exact factors that determine price-bargaining power. To an extent, bargaining ability may depend on the negotiation skills and the incentives behind individual negotiators. Unfortunately, the data in our study are not available to address the

[14] For example, a salon can offer a deal of "40% off $50 for hair treatment" on one deal platform and "50% off $80 for hair treatment" on another platform. It is hard to say whether such deals should be considered the same deal.

mechanisms of bargaining power. Yet, better understanding the determinants could lead to interesting insights concerning how managers can shape market outcomes by influencing their bargaining power.

Lastly, as is true for almost all empirical work, our results may be contingent on the specific characteristics of the study setting. In particular, we treat them as neither substitutes nor complements. As a result, the direct network effect among merchants is not formally modeled. If certain goods and services are indeed substitutes, the platform and merchant need to be mindful that consumers may switch their choices if an agreement is not reached. This could be a critical modeling aspect in markets with only a few differentiated goods. We look forward to seeing our framework extended to such settings.

References

Armstrong, M. 2006. Competition in two-sided markets. *The RAND Journal of Economics* **37**(3) 668–691.

Ayers, R. M., R. A. Collinge. 2003. *Microeconomics: Explore and Apply.* Prentice Hall, London.

Berry, S., J. Levinsohn, A. Pakes. 1995. Automabile prices in market equilibrium. *Econometrica* **63**(4) 841–890.

Berry, S. T. 1994. Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics* **25**(2) 242–262.

Caillaud, B., B. Jullien. 2003. Chicken & egg: competition among intermediation service providers. *The RAND Journal of Economics* **34**(2) 309–328.

Crawford, G. S., A. Yurukoglu. 2012. The welfare effects of bundling in multichannel television markets. *American Economic Review* **102**(2) 643–685.

Draganska, M., D. Klapper, S. B. Villas-Boas. 2010. A larger slice or a larger pie? An empirical investigation of bargaining power in the distribution channel. *Marketing Science* **29**(1) 57–74.

Dube, J. -P., J. T. Fox, C. -L. Su. 2012. Improving the numerical performance of static and dynamic aggregate discrete choice random coefficients demand estimation. *Econometrica* **80**(5) 2231–2267.

Dubé, J. -P., G. J. Hitsch, P. K. Chintagunta. 2010. Tipping and concentration in markets with indirect network effects. *Marketing Science* **29**(2) 216–249.

Elzinga, K. G., D. E. Mills. 2011. The Lerner index of monopoly power: Origins and uses. *The American Economic Review* **101**(3) 558–564.

Gowrisankaran, G., A. Nevo, R. Town. 2015. Mergers when prices are negotiated: Evidence from the hospital industry. *American Economic Review* **105**(1) 172–203.

Grennan, M. 2013. Price discrimination and bargaining: Empirical evidence from medical devices. *American Economic Review* **103**(1) 145–177.

Hagiu, A., R. S. Lee. 2011. Exclusivity and control. *Journal of Economics and Management Strategy* **20**(3) 679–708.

Hansen, L. P. 1982. Large sample properties of generalized method of moments estimators. *Econometrica* **50**(4) 1029–1054.

Hausman, J. A. 1996. Valuation of new goods under perfect and imperfect competition. In *The Economics of New Goods*. Chicago: University of Chicago Press, 207–248.

Ho, K. 2006. The welfare effects of restricted hospital choice in the US medical care market. *Journal of Applied Econometrics* **21**(7) 1039–1079.

Horn, H., A. Wolinsky. 1988. Bilateral monopolies and encentives for merger. *The Rand Journal of Economics* **19**(3) 408–419.

Katz, M. L., C. Shapiro. 1994. Systems competition and network effects. *Journal of Economic Perspectives* **8**(2) 93–115.

Lee, R. S. 2013. Vertical integration and exclusivity in platform and two-sided markets. *American Economic Review* **103**(7) 2960–3000.

Misra, S., S. K. Mohanty. 2008. Estimating bargaining games in distribution channels. *Working paper.*

Nevo, A. 2001. Measuring market power in the ready-to-eat cereal industry. *Econometrica* **69**(2) 307–342.

Reynaerts, J., R. Varadhan, J. C. Nash. 2012. *Enhancing the convergence properties of the BLP (1995) contraction mapping*. No. 35 working paper Katholieke Universiteit Leuven, Faculteit Economie en Bedrijfswetenschappen, Vives.

Rochet, J. C., J. Tirole. 2003. Platform competition in two-sided markets. *Journal of the European Economic* **1**(4) 990–1029.

Rochet, J.-C., J. Tirole. 2006. Two-sided markets : A progress report. *The RAND Journal of Economics* **37**(3) 645–667.

Shao, L. 2015. *Determinants of exclusivity , platforms' contracting decisions, and social welfare*, working paper.

Spengler, J. J. 1950. Vertical integration and antitrust policy. *Journal of Political Economy* **58**(4) 347–352.

Stata, 2013. Stata base reference manual release 13. , 950.

Tellis, G. J. 1988. The price elasticity of selective demand: A meta-analysis of econometric models of sales. *Journal of Marketing Research* **25**(4) 331–341.

Train, K.E. 2009. *Discrete Choice Methods with Simulations* 2nd ed., Cambridge University Press.

Varadhan, R., C. Roland. 2008. Simple and globally convergent methods for accelerating the convergence of any EM algorithm. *Scandinavian Journal of Statistics* **35**(2) 335–353.

Wilbur, K.C. 2008. A two-sided, empirical model of television advertising and viewing markets. *Marketing Science* **27**(3) 356–378.

Table 1: Summary Statistics for Deal Characteristics and Sales

	Platform	Mean	SD	Min	Median	Max
Groupon	Sales	244.19	885.97	1	90	100,000
(N=128,749)	Price	59.26	61.15	1	39	400
	Discount	58.70	12.21	0	53	99
	Face value	196.36	317.16	2	100	9,600
	Small market	0.18	0.39	0	0	1
	Medium market	0.32	0.47	0	0	1
	Large market	0.50	0.50	0	0	1
	January	0.07	0.25	0	0	1
	February	0.07	0.25	0	0	1
	March	0.07	0.26	0	0	1
	April	0.07	0.26	0	0	1
	May	0.08	0.27	0	0	1
	June	0.08	0.27	0	0	1
	July	0.08	0.27	0	0	1
	August	0.09	0.29	0	0	1
	September	0.09	0.29	0	0	1
	October	0.10	0.30	0	0	1
	November	0.10	0.30	0	0	1
	December	0.11	0.31	0	0	1
LivingSocial	Sales	274.41	1,259.82	1	92	94,226
(N=69,340)	Price	48.29	48.11	1	35	400
	Discount	57.39	11.67	0	51	100
	Face value	136.23	173.55	4	85	5,950
	Small market	0.18	0.39	0	0	1
	Medium market	0.35	0.48	0	0	1
	Large market	0.46	0.50	0	0	1
	January	0.07	0.25	0	0	1
	February	0.07	0.25	0	0	1
	March	0.07	0.26	0	0	1
	April	0.07	0.26	0	0	1
	May	0.08	0.27	0	0	1
	June	0.08	0.27	0	0	1
	July	0.08	0.27	0	0	1
	August	0.10	0.30	0	0	1
	September	0.09	0.29	0	0	1
	October	0.11	0.31	0	0	1
	November	0.10	0.31	0	0	1
	December	0.08	0.27	0	0	1

Table 2: Deal Categories on Platforms

	N	%	Price Mean	Price SD	Sales Mean	Sales SD
Groupon						
Beauty	24,657	19.2%	91.7	78.2	135.7	448.5
Family activities	4,700	3.7%	57.8	66.8	222.2	561.2
Fitness	8,377	6.5%	48.0	30.3	139.4	199.9
Goods	14,994	11.6%	40.9	48.1	394.9	1,434.0
Home and automobile services	16,830	13.1%	65.4	55.4	144.7	485.1
Life skill classes	7,262	5.6%	69.9	51.3	97.1	206.0
Live events	6,190	4.8%	29.4	25.5	419.5	2,783.4
Outdoor activities	9,083	7.1%	67.7	64.1	226.2	476.8
Personal care	8,838	6.9%	58.9	38.2	151.8	215.3
Restaurants	20,226	15.7%	22.5	24.0	456.7	535.2
Sports	3,371	2.6%	55.1	53.2	224.3	275.2
Travel	4,221	3.3%	121.9	94.4	197.8	334.5
LivingSocial						
Beauty	12,562	18.1%	67.9	54.9	144.4	992.0
Family activities	7,927	11.4%	56.9	52.1	150.1	879.9
Fitness	7,524	10.9%	36.5	22.4	123.1	225.1
Goods	3,292	4.8%	31.9	50.8	1,577.1	26,580.4
Home and automobile services	9,597	13.8%	60.9	51.5	163.2	667.5
Life skill classes	3,893	5.6%	54.0	46.5	152.2	274.9
Live events	4,148	6.0%	36.0	39.7	367.0	967.6
Outdoor activities	3,270	4.7%	56.1	59.1	460.6	1,079.0
Personal care	4,288	6.2%	51.0	30.9	179.7	273.9
Restaurants	10,763	15.5%	20.3	28.2	451.0	665.3
Sports	1,249	1.8%	42.5	40.7	267.0	419.2
Travel	827	1.2%	56.0	69.2	439.4	793.8

Table 3: Platform Shares by Month and Census region

	Groupon only	LivingSocial only	Multi-homing
User distribution across platform choices per month			
January	70.9%	14.7%	14.4%
February	54.6%	16.3%	13.4%
March	57.9%	19.2%	15.5%
April	54.6%	21.6%	15.1%
May	55.6%	24.2%	16.0%
June	56.1%	20.2%	15.5%
July	60.3%	22.5%	15.4%
August	57.8%	20.1%	14.6%
September	46.2%	20.5%	14.6%
October	50.5%	21.4%	14.4%
November	45.8%	26.5%	13.1%
December	45.3%	21.4%	13.4%
Average	54.6%	20.7%	14.6%
User distribution across platform choices per region			
region 1: New England	5.3%	11.1%	10.4%
region 2: Mid-Atlantic	15.4%	13.9%	12.5%
region 3: East North Central	15.5%	11.1%	12.5%
region 4: West North Central	6.1%	4.2%	6.3%
region 5: South Atlantic	23.0%	19.4%	14.6%
region 6: East South Central	2.3%	5.6%	6.3%
region 7: West South Central	7.7%	8.3%	12.5%
region 8: Mountain	6.4%	9.7%	12.5%
region 9: Pacific	18.2%	16.7%	12.5%
Total	100%	100%	100%

Note: The number of unique visitors for Groupon, LivingSocial, and both sites were acquired from Compete, Inc. The numbers in the top panel are the percentages of active users in each month of 2012. The numbers in the bottom panel are the percentages of active users across US census regions for each platform choice. We acquired these data from comScore, Inc.

Table 4: Average Deal Prices on Groupon and LivingSocial

	Platform	N	Mean	SD	Min	Max	2-sample t test
All deals	Groupon	128,749	59.3	61.1	1	400	<0.001
	LivingSocial	69,340	48.3	48.1	1	400	
Deals with a low face value	Groupon	28,561	13.5	4.4	1	40	<0.001
	LivingSocial	18,925	12.4	4.9	1	40	
Deals with a medium face value	Groupon	75,986	48.3	25.6	6	205	0.005
	LivingSocial	42,254	47.6	24.9	5	250	
Deals with a high face value	Groupon	24,202	147.7	84.6	10	400	<0.001
	LivingSocial	8,161	135.0	76.8	10	400	

Note: Low face value is less than $45, medium value is between $45 and $220, and high face value is higher than $220.

Table 5: Merchant Characteristics on Groupon and LivingSocial

		Groupon			LivingSocial			2-sample t test
		N	Mean	SD	N	Mean	SD	
Merchant Size	Low to medium face value	7,900	23.6	48.5	5,039	18.4	42.8	0.002
	High face value	3,118	12.6	30.8	1,211	15.1	42.2	<0.001
Chain	Low to medium face value	8,007	0.12	0.33	5,084	0.08	0.27	<0.001
	High face value	3,124	0.07	0.26	1,223	0.09	0.29	0.052

Note: The variables *merchant size* and *chain* measure the number of employees per merchant and whether it belongs to a chain, respectively. Currently, the merchant-level dataset has 17,470 observations. The smaller sample size is due to data-processing constraints; we are working on data cleaning and matching to increase the sample size.

Table 6: Linear Parameter Estimates for Deal Demand

	(1) Homogeneous logit without IV		(2) Homogeneous logit with IV		(3) Random-coefficient logit with IV	
Variable	Est	SE	Est	SE	Est	SE
Price	-0.834***	0.005	-2.875***	0.061	-3.952***	0.064
Face value	0.013***	0.002	0.296***	0.012	0.311***	0.013
Beauty	0.064***	0.012	0.209***	0.016	0.168***	0.017
Family activities	-0.462***	0.016	-0.755***	0.025	-0.811***	0.026
Fitness	-0.070***	0.015	-0.537***	0.022	-0.513***	0.023
Goods	-1.378***	0.015	-2.353***	0.035	-2.280***	0.037
Life skill class	-0.143***	0.017	-0.215***	0.023	-0.240***	0.023
Live events	-0.036**	0.018	-1.125***	0.040	-1.177***	0.042
Outdoor activities	0.397***	0.016	0.297***	0.022	0.273***	0.024
Personal	0.458***	0.016	0.451***	0.017	0.511***	0.018
Restaurants	0.623***	0.014	-1.224***	0.054	-1.314***	0.057
Sports	0.410***	0.024	0.047	0.032	0.083**	0.034
Travel	-0.642***	0.023	0.020	0.036	0.182***	0.038
Market medium	1.559***	0.008	1.411***	0.011	1.634***	0.011
Market small	2.340***	0.009	2.108***	0.014	2.648***	0.015
January	-0.207***	0.019	-0.281***	0.024	-0.304***	0.026
March	-0.119***	0.018	-0.149***	0.023	-0.106***	0.024
April	-0.219***	0.018	-0.227***	0.023	-0.205***	0.025
May	-0.314***	0.018	-0.248***	0.023	-0.224***	0.024
June	-0.294***	0.018	-0.244***	0.023	-0.224***	0.024
July	-0.453***	0.018	-0.428***	0.023	-0.416***	0.024
August	-0.397***	0.017	-0.378***	0.023	-0.338***	0.024
September	-0.173***	0.017	-0.176***	0.022	-0.159***	0.024
October	-0.475***	0.017	-0.451***	0.022	-0.432***	0.023
November	-0.590***	0.017	-0.532***	0.022	-0.504***	0.024
December	-0.604***	0.017	-0.508***	0.023	-0.468***	0.024
N	198,089		198,089		198,089	

*** p<0.01; ** p<0.05; * p<0.10

Table 7: Nonlinear Parameter Estimates for Deal Demand

	σ		Income		Household size		Age	
Coefficient	Est	SE	Est	SE	Est	SE	Est	SE
Intercept	0.943***	0.011	-0.459***	0.088	-0.980***	0.194	0.497***	0.059
Price	0.354***	0.004	0.456***	0.023	0.587***	0.047	0.388***	0.015

*** p<0.01; ** p<0.05; * p<0.10

Table 8: Parameter Estimates for Platform Choices

Variables	Est	SE
Beauty	0.0048***	0.0007
Family activities	0.0016***	0.0004
Fitness	0.0003	0.0005
Goods	0.0003	0.0004
Home and automobile services	0.0020***	0.0006
Life skill classes	0.0013***	0.0004
Live events	0.0006	0.0004
Outdoor activities	0.0002	0.0004
Personal care	0.0001	0.0005
Restaurants	0.0108***	0.0008
Sports	0.0009***	0.0003
Travel	0.0009***	0.0003
February	-0.0963***	0.0044
March	0.0397***	0.0059
April	0.0551***	0.0068
May	0.1251***	0.0074
June	0.0539***	0.0078
July	0.1397***	0.0079
August	0.0706***	0.0078
September	-0.0129*	0.0074
October	0.0297***	0.0068
November	0.0401***	0.0059
December	-0.0290***	0.0044

*** $p<0.01$; ** $p<0.05$; * $p<0.10$

Table 9: Supply Parameter Estimates

Parameter	Est	SE
Intercept	2.363***	0.009
Groupon	-1.444***	0.010
Merchant size	0.016**	0.006
Merchant size X Groupon	-0.020**	0.010
Chain	0.638***	0.008
Chain X Groupon	-0.0539***	0.010
Merchant annual sales	0.208***	0.017
Voucher face value	0.046***	0.012
κ		
Groupon	-0.139***	0.010
Beauty	0.293***	0.007
Family activities	0.340***	0.004
Fitness	0.330***	0.010
Goods	0.349***	0.004
Home and automobile services	0.324***	0.015
Life skill classes	0.338***	0.003
Live events	0.343***	0.002
Outdoor activities	0.342***	0.002
Personal care	0.339***	0.003
Restaurants	0.341***	0.006
Sports	0.344***	0.009
Travel	0.350***	0.004

*** $p<0.01$; ** $p<0.05$; * $p<0.10$

Note: Estimates are from a subset of observations (N=17,470) for which we have an exact match of merchant names with the OneSource dataset. As calculating the disagreement payoffs is very computational intensive, using a sub-sample helps ease the computation burden.

Table 10: Counterfactual Results on Price and Sales Changes

	5% Increase in bargaining power		10% Increase in bargaining power		20% Increase in bargaining power		50% Increase in bargaining power	
% changes in	Groupon	LivingSocial	Groupon	LivingSocial	Groupon	LivingSocial	Groupon	LivingSocial
Price	4.4	4.3	8.5	8.1	15.8	14.9	34.6	29.8
Demand	-11.3	-10.7	-20.1	-19.1	-33.1	-31.3	-55.5	-50.6
Profits	2.3	15.5	3.1	26.0	3.4	38.2	13.0	48.0

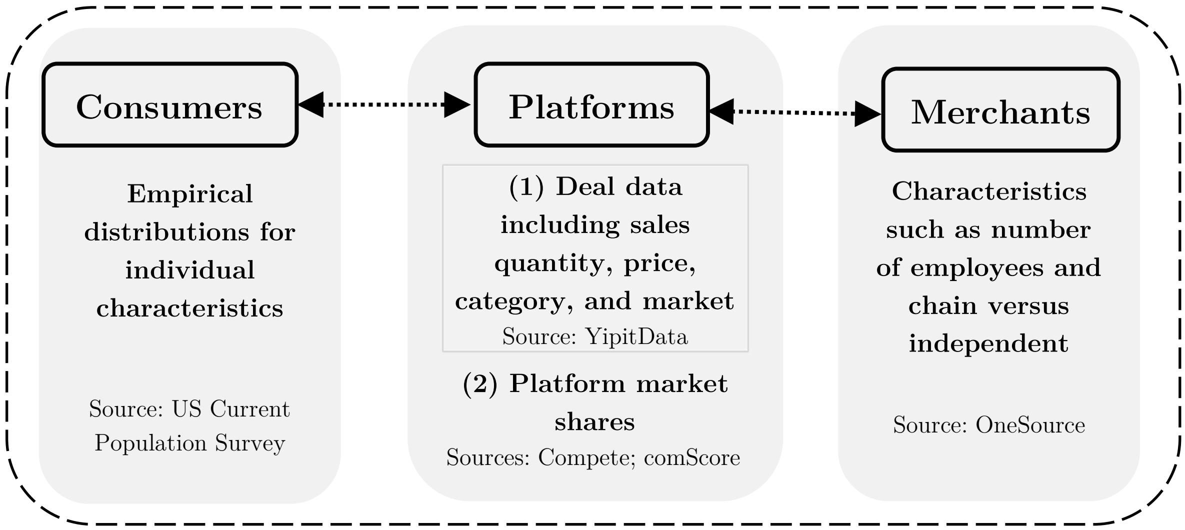
Note: When computing the counterfactual price and demand with a 5% increase in Groupon's bargaining power, we take LivingSocial's bargaining power as given. The same is done for the calculation for LivingSocial. The numbers are percentage changes relative to the value with the current true bargaining power.

Table 11: Counterfactual Results on Difference between Platforms

			LivingSocial bargaining power			
	Face value	Merchant size	True	10% increase	20% increase	40% increase
Price	Low	Small	-9.6%	-8.5%	-7.3%	-4.8%
		Large	-10.1%	-9.0%	-7.8%	-5.4%
	High	Small	-7.8%	-6.7%	-5.6%	-3.4%
		Large	-8.2%	-7.1%	-6.1%	-3.9%
Purchase likelihood	Low	Small	32.6%	28.0%	23.5%	14.8%
		Large	34.4%	29.9%	25.5%	16.9%
	High	Small	25.5%	21.5%	17.6%	10.0%
		Large	27.6%	23.0%	19.1%	11.7%

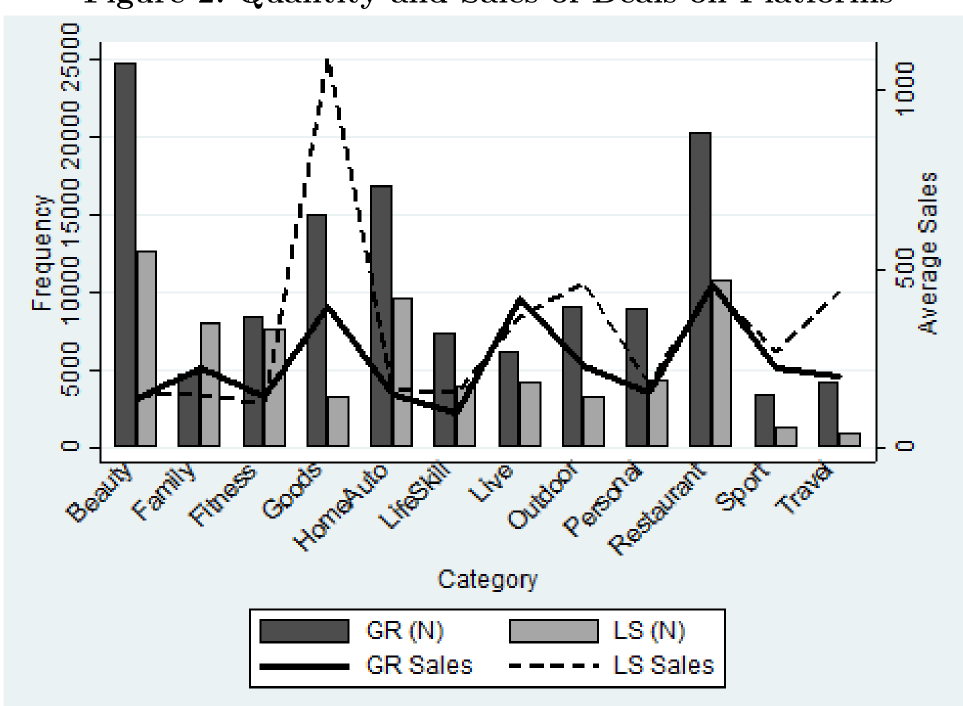
Note: Deal share is the estimated likelihood of purchase for each deal. Small and large merchants correspond to those with 2 and 40 employees, respectively. Similarly, low and high face values are defined according to the 25% and 75% percentiles of the variable, which correspond to $58 and $173, respectively. The numbers are the percentage differences compared to Groupon values. For example, for a typical small merchant offering a low-face-value voucher, its price on LivingSocial is lower than that on Groupon by 9.6% and the likelihood of purchase is higher by 32.6%.

Figure 1: Illustration of Data Components



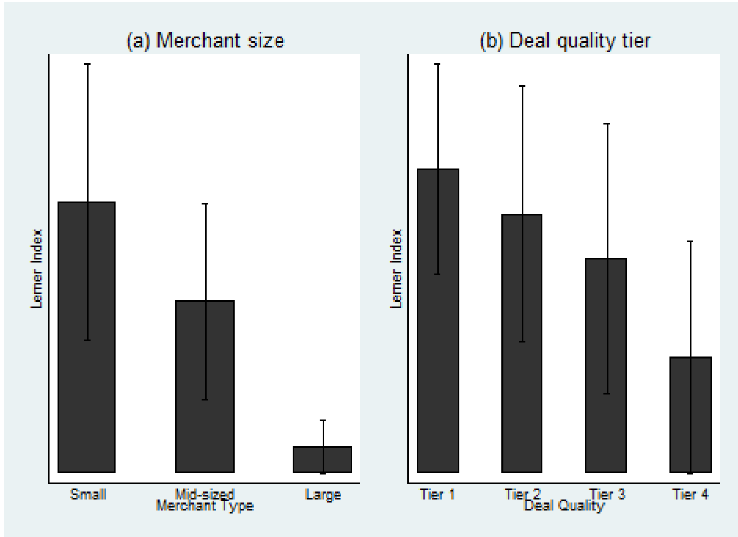
Note: Data components related to consumers and platforms are for year 2012. Merchants' characteristics are retrieved from the OneSource database in 2015. We assume that the characteristics of interest—number of employees and whether a merchant belongs to a chain or is independent—are the same between 2012 and 2015.

Figure 2: Quantity and Sales of Deals on Platforms



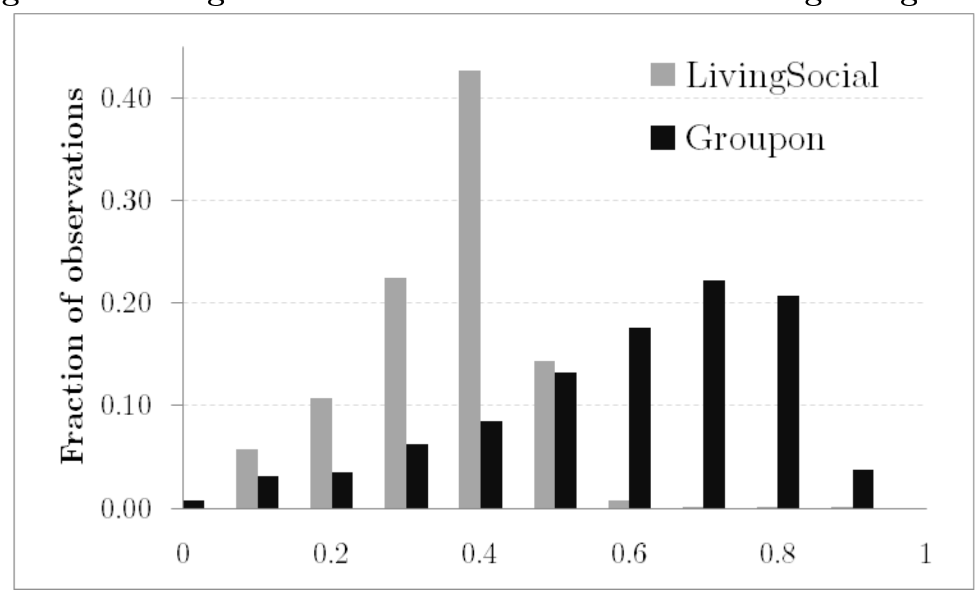
Note: The bars correspond to the number of deals by category for Groupon ("GR") and LivingSocial ("LS"). The lines depict the average sales quantity per category on each platform.

Figure 3: Average Lerner Index by Merchant Size and Deal Tier



Note: We plot the Lerner index using a proprietary dataset from one of the two deal sites. The height of the bar corresponds to the average index and the error bars indicate one standard deviation above and below the mean. The left panel depicts the average index by merchant type: small, mid-sized, and large. The right panel presents the average index by deal quality; the higher the tier, the better the perceived quality.

Figure 4: Histogram of Platforms' Relative Price-bargaining Power



	N	Mean	SD	Min	Max
Groupon	9,865	0.61	0.18	0.09	0.99
LivingSocial	4,671	0.36	0.10	0.09	0.86

Note: The table summarizes the estimated relative bargaining power for Groupon and LivingSocial.