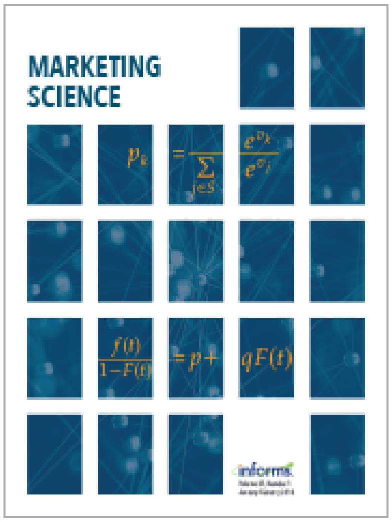


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# Price Bargaining and Competition in Online Platforms: An Empirical Analysis of the Daily Deal Market

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**Abstract.** The prevalence of online platforms opens new doors to traditional businesses for customer reach and revenue growth. This research investigates platform competition in a setting in which prices are determined by negotiations between platforms (specifically, their salespeople) and businesses. We compile a unique and comprehensive data set from the U.S. daily deal market, where merchants offer deals to generate revenues and attract new customers. We specify and estimate a two-stage supply-side model in which platforms and merchants bargain on the wholesale price of deals. Based on Nash bargaining solutions, our model generates insights into how bargaining power and bargaining position jointly determine price and firm profits. By working with a bigger platform, merchants enjoy a larger customer base, but they are subject to lower margins because of less bargaining power. Counterfactual results reveal that, in the absence of platform competition, merchants are worse off owing to their weaker bargaining position, but consumers experience lower prices, thus leading to an increase in total demand.

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

## 1. Introduction

Platform companies such as Amazon, eBay, and Groupon have gained notable growth momentum and attracted considerable attention from researchers and practitioners. The prevalence of these platforms has opened new markets for traditional businesses. Understanding the dynamics of working with platforms is essential for the ongoing success of many businesses.

Platforms in two-sided markets serve two groups of users: individual consumers and business users (e.g., content publishers, music labels, restaurants, and consumer packaged goods brands). Compared with traditional intermediaries, platforms tend to facilitate a larger number of business users with more heterogeneous characteristics. Because they often operate online, the cost of switching platforms is typically lower than in offline settings. Other than these characteristics, in many markets, platforms and businesses negotiate and split the control over transactional terms. A well-known example is the contentious dispute between Amazon and Hachette, the fourth-largest publisher in the United States, that the two businesses settled in 2014 by agreeing to split the profits for e-books (Streitfeld 2014). Despite the practice of price bargaining in platform settings, most extant literature in this domain assumes that platforms (or their suppliers) exert full control over the price-setting process. Only a small stream of research has recently started to relax this assumption and explicitly model the effect of bargaining in platform competition (Hagiu and Lee 2011, Crawford and Yurukoglu 2012).

In this research, we study price bargaining and platform competition in a two-sided market. We ask two questions. (1) What are the determinants of price setting and profit splitting between platforms and suppliers? (2) To what extent does price bargaining affect competition and market outcomes?

We answer these questions using data from the U.S. daily deal market. Deal platforms such as Groupon and LivingSocial sell a daily assortment of discounted goods and services, and by doing so, they connect local merchants with consumers. Merchants use deal sites both to generate revenues and to attract potential consumers for marketing purposes. 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 the interactions between platforms (specifically, their salespeople) and merchants. Second, the daily assortment of deals provides data variation in the number and variety of merchants within a short period of time, helping model identification. Third, because the market is largely a duopoly competition between two deal sites—Groupon and LivingSocial—it is relatively straightforward to examine merchants' tradeoffs in their platform choices. Fourth, the daily deal business is a multibillion-dollar market in the United States alone, and it is even more profitable in developing economies, making it an important market to study in its own right (IBISWorld 2014).

Despite the importance of this context, the research setting presents several modeling challenges. On the demand side, consumers make a multistage decision: they first choose the deal platform(s) and then choose which deal to purchase. Furthermore, for platform choices, consumers may engage in single homing (using one platform) or multihoming (using more than one platform). On the supply side, both platforms and merchants act strategically and negotiate to set terms. During the negotiation, a platform considers not only how much revenue can be generated from each deal but also, the extent to which the deal can help grow its customer base. Similarly, a merchant evaluates both the current deal revenue and the future payoff from retaining the customers acquired through the deal. Thus, the demand and supply systems need to account for many moving parts that jointly determine the equilibrium outcome. It is important to note that this market structure goes beyond the daily deal market, and therefore, insights from this study can be generalized to other markets in which prices are negotiated between the intermediary (platform) and the supplier (merchant).

Taking these challenges into account, we specify a structural model using unique and comprehensive data compiled from multiple sources. The demand-side model includes a nested structure to specify how consumers choose platforms and deals. The supply-side model involves two stages. First, platforms and merchants negotiate through an independent bargaining process to set the price charged to the platform (i.e., a deal's wholesale price). The platform then sets the deal price (i.e., the retail price), and sales are realized. We model price negotiation using the Nash bargaining solution developed by Horn and Wolinsky (1988), which has been increasingly used in recent empirical studies (Crawford and Yurukoglu 2012; Grennan 2013; Gowrisankaran et al. 2015; Lewis and Pflum 2015, 2017). The extent to which each player can influence the negotiation is determined by its respective bargaining position and bargaining power. The bargaining position resolves from competition, which incorporates both the network effect of deals growing the platform and the cannibalization effect among deals within a platform. After controlling for competition, bargaining power is estimated as the additional ability of each party to influence the share of surplus.

The results reveal the underlying primitives that determine pricing and the surplus split between the platforms and merchants. Platforms' differentiating bargaining power and position create a tradeoff: by working with the larger platform (Groupon), merchants have access to more consumers, but they are subject to weaker bargaining power in negotiating the share of profits. However, the lack of bargaining power for the underdog platform, LivingSocial, helps compensate for its smaller customer base when competing for merchants. After controlling for the platform, there is variation among merchants: larger merchants have higher bargaining power than smaller ones, and restaurants and merchants offering physical goods also have higher bargaining power. Furthermore, when offering repeated deals, merchants enjoy higher payoffs on Groupon than on LivingSocial.

Merchants in this market leverage the existence of a competing platform during price negotiation. When platforms consolidate, merchants can have access to more consumers but are subject to a weaker bargaining position. Two counterfactual analyses are conducted to gain insights into these effects. In the first counterfactual, we eliminate a platform from the competition one at a time and thus, essentially quantify the economic value of the platform to merchants. In the second counterfactual, platforms form a single entity that bargains together and makes joint pricing decisions. In both counterfactuals, the merchants can no longer use a competing platform as a threat during negotiation and thus, end up in a weaker bargaining position. The increased buyer power enables the platform to obtain more favorable terms from the merchants (i.e., a lower wholesale price), and thus, merchants' net profits decrease. The consolidated platform passes some of the lower wholesale price on to the market and charges a lower retail price, resulting in an increase in demand. All things combined, the results reveal the important role of price bargaining on platform competition: when prices are negotiated, higher buyer (platform) power can suppress merchants' welfare but can increase consumers' welfare with lower prices and greater demand.

This research makes several contributions. First, it adds to the empirical work on price bargaining in business-to-business (B2B) interactions. Although the pricing decision has received considerable attention in marketing, extant research tends to assume that, for each pricing decision, one party dictates and makes a take-it-or-leave-it offer to the other party. We examine price bargaining and identify the factors that influence the distribution of bargaining power between the negotiating parties. The counterfactual results indicate that, in a market with bilateral price negotiation, larger buyer (platform) power can result in lower prices for consumers, which is contrary to the classic effect of market concentration. Second, our research empirically examines platform competition in a two-sided market. Our model captures both the network effect of merchants to attract consumers and the cannibalization effect among merchants to compete for demand. By doing so, we examine how the competitive effect and the bargaining effect jointly determine the market outcome for the consumers, merchants, and platforms. Third, this research generates important insights for the daily deal market, which has become an interesting area to study owing to its popularity among consumers and small businesses.

The rest of the paper proceeds as follows. Section 2 reviews the related literature. Section 3 describes the empirical setting and data, reports summary statistics, and provides model-free evidence. Section 4 specifies the model, and Section 5 presents the estimation and identification arguments. Section 6 reports the parameter estimates and the counterfactual results. Section 7 concludes.

## 2. Selected Literature

This research builds primarily on two streams of literature. It relates to the empirical literature on pricing involving downstream and upstream firms. The pricing process in B2B settings has been well studied in both empirical industrial organization and marketing research, which have generated important insights into the economic value of channels in various settings (e.g., the personal computer industry (Chu et al. 2007) and the sports drink market (Chen et al. 2008a). Much of the extant literature assumes that one party dictates the pricing decision. For example, in retailing, the upstream firm sets the wholesale price, and the downstream retailer sets the retail price (Sudhir 2001, Chen et al. 2008a). However, price bargaining is a reality in many environments in which neither party has enough market power to dictate the terms (Chen et al. 2008b).

Empirical work has started to formally model how prices are set through negotiations. Crawford and Yurukoglu (2012) advanced the bilateral Nash bargaining model proposed by Horn and Wolinsky (1988) to study the pricing decision between content distributors and conglomerates in the cable television industry. The Nash solution has since become the workhorse for bargaining models in predicting the payoff split 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. In a similar setting, Lewis and Pflum (2015, 2017) offer empirical evidence on how bargaining power varies with hospitals' and managed care organizations' characteristics.

There is limited marketing research that empirically examines price bargaining. The exceptions include Chen et al. (2008b), Draganska et al. (2010), and Meza and Sudhir (2010), all of which have examined price bargaining in a retailing setting. Chen et al. (2008b) simultaneously model consumer brand choice and price negotiation in the automobile market and by doing so, account for price endogeneity related to unobserved consumer preference. Draganska et al. (2010) and Meza and Sudhir (2010) model bilateral price bargaining between manufacturers and retailers, with the former examining retailer competition and the latter focusing on the impact of private labels on retailer bargaining power. In contrast to these studies, our research focuses on bargaining in a two-sided market, which is distinct from retailing in some respects. First, the network effect tends to be a prominent feature of a two-sided market. Thus, it is critical to capture the externality value of a merchant to a platform and to allow it to enter price negotiations. Second, compared with retailers, platforms usually have suppliers with more heterogeneous characteristics. Thus, because our research incorporates merchant heterogeneity, the findings have managerial implications for different types of merchants.

This research also generates important insights for the daily deal market. Early studies in this domain conducted surveys to provide descriptive analysis of the profitability of daily deals (Dholakia 2011). A few recent theoretical papers have examined how daily deals can help merchants attract new customers through advertising (Edelman et al. 2016) and through signaling service quality (Subramanian and Rao 2016). In empirical work, Li et al. (2018) identify how local market characteristics, such as travel cost and store density, affect the demand and growth of deal platforms. Luo et al. (2014) find that social influence and observational learning among consumers also influence the popularity of deals and the likelihood of redemption. By using intertemporal purchase data, Wu et al. (2014) identify the effect of a threshold design on promoting deal sales. Although much of the extant empirical work focuses on the demand-side competition, our research incorporates the supply-side decisions and analyzes how competition and platform-merchant bargaining jointly determine the price and profit sharing in this market.

## 3. Data and Model-free Evidence

### 3.1. Empirical Setting

Daily deal sites emerged around 2008 as a marketplace connecting merchants to consumers and selling discounted deals. They offer a unique opportunity to match customers and merchants in a local market: consumers enjoy a wide variety of goods and services with deep discounts, whereas merchants use the deal platforms to build awareness and generate extra revenue.

The business model has attracted many players ranging from small local deal aggregators to large national sites. However, by and large, two companies—Groupon and LivingSocial—dominate the market. In 2013, Groupon and LivingSocial made up 59.1% and 16.6%, respectively, of the total revenue in the U.S. market.[1]

We compile a unique data set involving Groupon and LivingSocial, the two leading platforms. Specifically, we collect the transactions from all of the deal categories that appeared on each platform for a year, enabling us to comprehensively examine platform competition. Our variables fall into three groups: (1) deal data, including sales, price, and other deal-level characteristics; (2) platform-level market share; and (3) merchant characteristics.

### 3.2. Deal and Merchant Characteristics

We acquire sales data from a premium data aggregator in the daily deal market. Our sample includes all of the deals offered by Groupon and LivingSocial in 2012. For each observation, we obtain the deal description, 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)" on June 27th in New York City. In this case, the price is $79, and the original face value of the voucher is $189, with a discount depth of 58%.

Table 1 presents the summary statistics. In 2012, Groupon promoted roughly 129,000 deals, with an average price of $59.3 (standard deviation (SD) = $61.2) per deal and average sales of 244.2 (SD = 886.0). Deals were evenly distributed throughout the year, with slightly more deals in the third quarter. LivingSocial offered approximately 69,000 deals. The average price was $48.3 (SD = $48.1), and the average sales were 274.4 (SD = 1,259.8).

Deals are from 12 categories: the largest category is beauty followed by home, automobile services, and restaurant deals. Table 2 presents the distribution of categories on each platform. The relative sizes of the categories are largely comparable between platforms except that Groupon offers more deals on goods than LivingSocial does, but the latter has more family and fitness deals.

Deal prices vary substantially across categories. Travel, home and auto services, and beauty deals tend to be more expensive than others. The average deal price is higher on Groupon than on LivingSocial for all categories except live events. Sales also vary across categories and platforms. Groupon has higher average sales than LivingSocial for the family, fitness, live events, and restaurants categories. LivingSocial has higher average sales for the other categories. However, directly comparing sales could be misleading owing to the price differences between the platforms.

We obtain merchant profiles from OneSource, a comprehensive database of business and company data. For each merchant, we collect the number of employees, the annual sales, and whether the merchant belongs to a chain.

### 3.3. Market Definition and Platform Share

We acquire platform usage data from two premium data sources that track the web-browsing behaviors of internet users across the United States. From Compete, the industry's leading consumer behavior database, we obtain the number of unique visitors to www.Groupon.com and www.LivingSocial.com for each month (including those visiting both) in 2012.[2] Compete updates daily clickstream data from a panel of 2.3 million U.S. consumers. From the comScore Media Metric database, which has a representative U.S. consumer panel of roughly 47,000 members, we retrieve the geographical distribution of active

**Table 1.** Summary Statistics of Deal Characteristics and Sales

| Platform and characteristics | Mean | SD | Min | Median | Max |
|---|---|---|---|---|---|
| Groupon ($N$ = 128,749) | | | | | |
| Sales | 244.19 | 885.97 | 1 | 90 | 100,000 |
| 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 |
| LivingSocial ($N$ = 69,340) | | | | | |
| Sales | 274.41 | 1,259.82 | 1 | 92 | 94,226 |
| 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 |

**Table 2.** Deal Characteristics and Sales by Platform and Category

| | | | Price | | Sales | |
|---|---|---|---|---|---|---|
| | *N* | % | Mean | SD | Mean | 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 | 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 | 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 |

users of Groupon, LivingSocial, and both. Combining these two data components, we compute the number of active users for each platform per market per month and use these numbers to define the aggregate platform choices in the subsequent analyses.[3]

Groupon and LivingSocial divide the U.S. market into "divisions" that largely correspond to the metropolitan statistical areas (MSAs) defined by the Office of Management and Budget.[4] A typical MSA centers 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 serves 156 markets, and LivingSocial serves 166 markets, with 131 markets served by both.

For each market, the "market size" for platform choices is defined as the total number of users who could use one or both deal platforms. Because anyone with internet access can use a deal site, we use the number of internet users as the measure of market size. The data are retrieved from the "October 2012 School Enrollment and Internet Use Survey," a supplement to the Current Population Survey (CPS) by the U.S. Census Bureau.

The total number of active users for Groupon and LivingSocial is computed by combining the monthly platform-level usage data and the distribution of users across regions. For example, the total number of active Groupon users was 18 million in July 2012, 15.4% of whom lived in the mid-Atlantic region. From the CPS data, we also know that the internet users in the New York market make up 17.3% of the mid-Atlantic region total. Therefore, the number of active Groupon users from the New York market in July 2012 is calculated as 17.3% $\times$ 15.4% $\times$ 18 million $\approx$ 480,000. Dividing the number of active users by the market size (i.e., the number of internet users) gives us the market share for each platform choice in that market. During our data collection period, approximately 6.5% of the internet users used Groupon exclusively, 2.5% used LivingSocial exclusively, and 1.7% used both. The remaining 89.3% chose the outside option: they either purchased daily deals from other platforms or did not participate in this market.

### 3.4. Model-free Evidence

In this section, we summarize how merchants choose a platform to offer deals and provide some model-free evidence on price bargaining.

**3.4.1. The Merchant's Platform Choice.** In our data, merchants tend to transact with only one platform in a market (defined as the combination of "division" and "month"), but they may have multiple (repeated) deals over time. We first look at the extent to which merchants have multiple deals (see Table 3). On Groupon, 68.8% of the deals are from merchants with one deal, and 31.2% are from those with repeated deals. The proportions for LivingSocial are 77.1% and 22.9%, respectively.[5]

When zooming in on repeated deals, we find substantive differences between the platforms (see columns 4 and 5 in Table 3). For Groupon, 85.2% of the repeated deals are from returning merchants—those that have offered a previous deal(s) on Groupon—and 14.8% are from merchants that have worked with LivingSocial but then switched to Groupon. On LivingSocial, the proportion of deals from returning merchants is much smaller (56.4%), suggesting that merchants working with Groupon are more likely to return than those working with LivingSocial. We find that this pattern is not driven by deal categories. Li et al. (2018) also find that merchants who previously offered deals on Groupon are more likely to offer deals again.

New and returning merchants could potentially expect different marketing effects on a platform. Thus, the data variation related to returning merchants could help explain the merchants' pricing decision. In the estimation section, we will discuss how this observed data pattern helps identify the parameters in our structural model.

**3.4.2. Merchant and Platform Bargaining.** At the core of this research is the price-setting process between merchants and platforms. Based on our knowledge of the daily deal market, deal terms are determined through negotiations between the two parties. The imminent questions here are as follows. (1) Is there evidence of bargaining? (2) If so, what is bargained over? The two critical deal features are the deal price charged to consumers (i.e., the retail price of a deal) and the price paid by the platform to the merchant (hereafter the wholesale price). The deal price determines the discount depth and thus, the consumer reach. Attracting customers is the reason why many merchants offer deals in the first place. The wholesale price is also important because it determines the profit margin for both parties. The difference between the deal price and the wholesale price determines the platform's commission rate.

For direct evidence of bargaining, we need to observe the wholesale price, which is typically unknown to researchers. Fortunately, we were able to obtain a propriety data set containing wholesale prices from one of the leading platforms in this industry. If the pricing process involves negotiation, one would expect systematic variation in the deal terms among merchants with different characteristics. To examine this, we turn to the platform's commission rate (i.e., one minus the wholesale-to-retail price ratio) and plot it against merchant size (see Figure 1(a)). The plot shows a clear trend of decreasing commission rates with an increase in merchant size. In other words, larger merchants can charge relatively higher wholesale prices than smaller merchants can on this platform. Figure 1(a) provides evidence that the platform does not have full discretion over the commission rate. Thus, the common belief that platforms in this market pay a flat rate of 50% of the revenue to merchants is far from the truth. Survey responses also confirm variation in commission rates. The self-reported numbers range from roughly 30% to 50% demanded by the deal platforms (Dholakia 2011).

A key objective of this research is to investigate how platforms and merchants negotiate to determine the level of profit sharing. To determine what is negotiated, we plot the ratio between the retail price and the voucher's face value as shown in Figure 1(b). If the retail price is jointly determined as much as the wholesale price, one would expect that the variation is related to the merchants' characteristics. However, Figure 1(b) shows similar average ratios among merchants of different sizes, suggesting that it is the wholesale price rather than the retail price that is being negotiated. Building on this model-free evidence, our model formally specifies the bargaining process between platforms and merchants.

## 4. Model

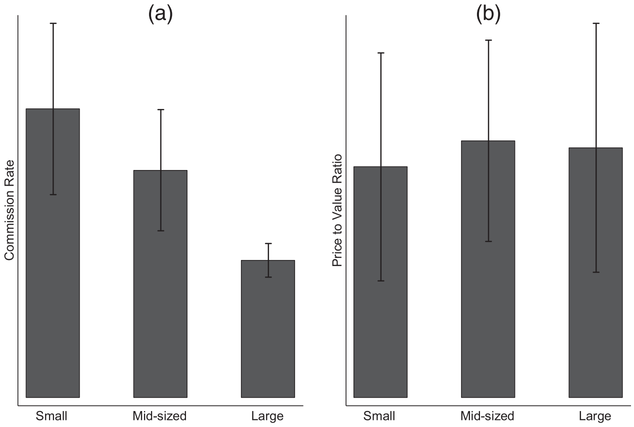
Based on the model-free evidence, we model consumer choices and the price-bargaining decisions

**Table 3.** Patterns of Deal Offerings

| | Merchants | | From merchants with repeated deals | |
|---|---|---|---|---|
| | Single deal | Multiple deals | Different platforms | Same platform |
| Groupon | 53,882 (68.8%) | 24,461 (31.2%) | 6,189 (14.8%) | 35,616 (85.2%) |
| LivingSocial | 36,412 (77.1%) | 10,800 (22.9%) | 7,701 (43.6%) | 9,971 (56.4%) |

*Notes*. This table presents the patterns of deal offerings. In columns 2 and 3, we report the proportions of merchants that offer only one deal and those that offer multiple deals. Columns 4 and 5 report, for merchants with multiple deals, the percentages of deals offered on different platforms vs. on the same platform.

**Figure 1.** Commission Rates and Price-to-Value Ratios Among Merchants




*Notes.* We depict in panel (a) the platform's commission rate and in panel (b) the ratio between the retail price and voucher face value. The summaries are from a proprietary data set from a leading daily deal platform. Because of a confidentiality agreement, we cannot disclose the ratios and thus, leave the $y$-axis scale blank. The length of the whisker is one standard deviation. The $x$ axis corresponds to merchant size. The difference in commission rates between the three groups of merchants is highly significant: analysis of variance $F(2, 11{,}671) = 4{,}323.7$, $p < 0.001$. The proprietary data are from one deal category but across multiple markets. Dividing the data by market yields similar patterns.

between platforms and merchants. We first describe the demand-side specification and then present the supply-side model.

## 4.1. Demand

In a daily deal setting, consumers follow a two-stage process. First, they choose which platform(s) to use, and second, given the available deals on the chosen platform(s), they consider which deal to purchase. This nested structure is similar to the way in which consumers choose intermediaries in vertical markets, such as choosing an insurance policy and then selecting a healthcare provider in the insurance network. Following this convention, we present the model for deal demand followed by that for platform choices.

**4.1.1. Deal Demand.** A consumer derives utility from deal $j$ that belongs to category $c$ on platform $k$ in division $m$ at time $t$. The consumer's utility is specified as

$$u_{jkmt} = \alpha + \alpha_c p_{jkmt} + \beta x_{jkmt} + \xi_{jkmt} + \varepsilon_{jkmt}. \tag{1}$$

Because each deal uniquely belongs to category $c$ on platform $k$ in a market (defined as a combination of $m$ and $t$), subscripts for the category, platform, and market are omitted for expositional simplicity. Here, $p_j$ is the price to consumers (i.e., retail price); $x_j$ is the set of observable characteristics; $\xi_j$ is deal platform-specific shocks that are unobserved by the econometrician but observed by the consumers, platforms, and merchants; and $\varepsilon_j$ is the idiosyncratic utility shock.

We make two assumptions concerning consumers' deal choices. First, a consumer chooses up to one deal per category per month from the platform(s) on which he or she is active.[6] Second, the consumer treats different categories independently. These assumptions help capture the competition among deals within the same category, but they avoid assuming that different categories are complements or substitutes.[7] Not purchasing a deal in a category yields the outside option, which can be understood as the best alternative to purchasing any deal from that category. The utility of the outside option for each category is defined as $u_0 = \delta_0 + \varepsilon_0$, where $\delta_0$ is a constant that sets the utility scale.

We assume that $\varepsilon_j$ is independently and identically distributed (i.i.d.) from a type I extreme value distribution. For consumers who single home on $k$, the market share for deal $j$ is given by

$$s_j^{SH} = \frac{\exp(\delta_j)}{\sum_{j' \in J_{ck}} \exp(\delta_{j'}) + \exp(\delta_0)}, \tag{2}$$

where $\delta_j = u_j - \varepsilon_j$, and $J_{ck}$ is the collection of all deals belonging to category $c$ on platform $k$ in the market.

There are also consumers who multihome on both platforms for whom the consideration set becomes the collection of deals across Groupon and LivingSocial. The market share becomes

$$s_j^{MH} = \frac{\exp(\delta_j)}{\sum_{j' \in J_{c,k=1}} \exp(\delta_{j'}) + \sum_{h \in J_{c,k=2}} \exp(\delta_h) + \exp(\delta_0)}, \tag{3}$$

where $k = 1$ for Groupon and $k = 2$ for LivingSocial. Therefore, the realized sales for deal $j$ equal the sum of purchases by single-homing and multihoming consumers.

**4.1.2. Platform Choices.** Next, we model a consumer's decision to choose the platform(s). Two main considerations lead to our model formulation. First, we assume that, when consumers choose a platform(s), they have not yet realized the idiosyncratic demand shocks. Therefore, they form expectations on the utility of each platform (Ho 2006). Second, the consumer may choose single homing or multihoming. Based on our empirical evidence, some consumers use only Groupon or LivingSocial, and some use both. Our model incorporates this pattern and does not treat platforms as mutually exclusive. Indeed, the segment of multihoming consumers is important for platform competition. If the proportion of multihoming consumers is sufficiently large, platforms would become substitutes, and neither would have a competitive advantage over the other. We regroup the platform choices so that each consumer may fall into one and only one of the four groups: Groupon only, LivingSocial only, both platforms, and neither (the outside option).

For a consumer who is single homing on platform $k$ ($k = 1$ for Groupon and $k = 2$ for LivingSocial), the ex ante expected utility for category $c$ on that platform equals the expected maximum utility across all of the deals in that category given by $EU_c^k = E_\varepsilon(\max_{j\in J_{ck}}(u_j))$. Assuming i.i.d. type I extreme value distribution for $\varepsilon_j$, the expected utility becomes

$$EU_c^k = \log\left(\sum_{j\in J_{ck}} \exp(\delta_j)\right), \tag{4}$$

where the log sum term is the logit inclusive value of category $c$ and represents the expected utility for the choice of deals within that category as opposed to the outside option.

For a multihoming consumer, the ex ante expected utility for category $c$ should equal the expected maximum utility across all of the deals in that category from both platforms: that is,

$$\begin{aligned} EU_c^{MH} &= E_\varepsilon\left(\max_{j\in\{J_{c,k=1},J_{c,k=2}\}}(u_j)\right) \\ &= \log\left(\sum_{j\in J_{c,k=1}} \exp(\delta_j) + \sum_{h\in J_{c,k=2}} \exp(\delta_h)\right). \end{aligned} \tag{5}$$

Let $r \in R \equiv \{1,2,3,0\}$ denote the set of platform choices. A consumer's choice is coded as $r = 1$ if choosing only Groupon, $r = 2$ if choosing only LivingSocial, and $r = 3$ if choosing both (i.e., multihoming). Option $r = 0$ denotes the outside option when the consumer chooses a platform other than Groupon or LivingSocial or does not use any deal platform. Because single homing on one platform and multihoming on both are not independent options, we allow the error terms to be correlated by $\sigma$ (Berry 1994). Thus, the utility for platform choice $r$ is specified as

$$\begin{aligned} u_r^{pf} &= I(r\in\{1,2\})\cdot\sum_c \gamma_c EU_c^r + I(r=3)\cdot\sum_c \gamma_c EU_c^{MH} \\ &\quad + \omega_t + \eta_r + \Gamma_{rt} + (1-\sigma)\varepsilon_r^{pf}, \end{aligned} \tag{6}$$

where *I(r)* is an indicator function for single homing or multihoming. In Equation (6), the first two terms capture the total expected utility across all available categories for platform set $r$, where $\gamma_c$ is the taste parameter for deal category $c$, $\omega_t$ is the fixed effect for month $t$ that captures the time-specific shocks at the industry level (e.g., mass media may broadcast stories about daily deals that boost or diminish consumers' overall interest), $\eta_r$ represents the time-invariant fixed effects that capture the overall preference for option $r$ across consumers, and $\Gamma_{rt}$ absorbs the unobserved time-varying structural errors for platform choices. Note that the fixed effect of platform choice, $\eta_r$, is after controlling for the deals being offered and could be a manifestation of several things, including a positive attitude about the platform's reputation or the quality of customer services, such as shipping speed and return policy. It also absorbs the information processing costs or other nonmonetary costs of using deal platforms, such as the disutility of having to receive frequent email alerts that deal platforms typically send out. Without such costs, one would expect consumers to always multihome on platforms because more deal options would always yield higher expected total utility. In reality, however, many consumers choose to single home, suggesting the existence of such costs.

Lastly, a consumer chooses whichever set $r$ maximizes her platform utility. We scale the platform utility by restricting the outside option utility as $u_0^{pf} = 0 + \varepsilon_0^{pf}$. The three platform choices ($r \in \{1,2,3\}$) are correlated with the nesting parameter $\sigma$ ($0 < \sigma < 1$), with a higher value implying greater within-nest substitution. Assuming that the idiosyncratic error $\varepsilon_r^{pf}$ follows a type I extreme value distribution, the estimating equation of the aggregated share takes on the form

$$\begin{aligned} \log(s_r^{pf}/s_0^{pf}) &= I(r\in\{1,2\})\cdot\sum_c \gamma_c EU_c^r + I(r=3) \\ &\quad \cdot\sum_c \gamma_c EU_c^{MH} + \omega_t + \eta_r + \sigma s_{r|r\in\{1,2,3\}}^{pf} + \Gamma_{rt}, \end{aligned}$$

where $s_0^{pf}$ is the outside option share and $s_{r|r\in\{1,2,3\}}^{pf}$ is the within-nest share in each market (Berry 1994). The rest of the estimation directly follows the generalized method of moments (GMM) procedure.

### 4.2. Supply Model

The model-free evidence shows that the rate of transfer from platform to merchant (i.e., wholesale price) is nonuniform and varies among merchants. The industry practice is that platforms use salespeople to recruit merchants, and wholesale prices are determined by negotiations between merchants and platforms on a deal-by-deal basis. Both merchants and platforms are incentivized to influence the price to their advantage. We formally capture this process using a two-stage game. First, a platform-merchant pair bargains to set the wholesale price. Second, the platform sets the retail price, and the sales are realized.

**4.2.1. Platform Price Setting.** The objective of the platform is to maximize the market-level total profits—that is, $\max_{\vec{p}} \sum_{j\in J_k} (p_j - w_j)\cdot q_j$—across all deals in the market. Here, $w_j$ is the wholesale price. Note that the division and time subscripts are again omitted for expositional simplicity.

For every focal deal $j$, the remaining deals on platform $k$ in the same market belong to two groups: in the same category and in different categories. We distinguish between these two groups because deal $j$ directly competes with other deals in the same category ($h \in J_{c,k}, \forall h \neq j$), whereas it affects the demand of the deals in different categories ($h' \in J_{c' \neq c,k}$) only by influencing the customer base of the platform (Equation (6)).

The total profits of the platform equal the sum of profits across the two groups and across single-homing ($r \in \{1,2\}$) and multihoming ($r = 3$) customers. That is,

$$\begin{aligned}\frac{1}{M}\pi_k = {} & (p_j - w_j)s_j^{r=k}s_{r=k}^{pf} + (p_j - w_j)s_j^{r=3}s_{r=3}^{pf} \\ & + \sum_{h \in J_{c,k}, h \neq j}\left[(p_h - w_h)s_h^{r=k}s_{r=k}^{pf} + (p_h - w_h)s_h^{r=3}s_{r=3}^{pf}\right] \\ & + \sum_{h' \in J_{c',k}}\left[(p_{h'} - w_{h'})s_{h'}^{r=k}s_{r=k}^{pf} + (p_{h'} - w_{h'})s_{h'}^{r=3}s_{r=3}^{pf}\right],\end{aligned} \tag{7}$$

where $M$ is the total market size in division $m$ at time $t$; $s_j^{r=k}$ is the market share of deal $j$ among single-homing customers, $s_j^{r=3}$ is the market share among multihoming customers, and $s_r^{pf}$ is the platform market share for option $r$.

By taking the first-order condition (FOC) of Equation (7), we derive the optimal price $p_j$ as a function of $w_j$ (see Online Appendix I for details).

**4.2.2. Nash Bargaining of the Wholesale Price.** The wholesale price is modeled as the equilibrium outcome of a bilateral Nash bargaining problem in the sense that neither the platform nor the merchant deviates from the determined price point. The Nash bargaining model, developed by Horn and Wolinsky (1988), is applied to bilateral negotiations in several empirical settings (Chen et al. 2008b; Draganska et al. 2010; Crawford and Yurukoglu 2012; Grennan 2013; Lewis and Pflum 2015, 2017). In our application, a negotiated wholesale price maximizes the Nash product of the payoffs to the platform and the merchant with an agreement relative to the payoffs without an agreement. The outcome solves

$$w_{jk} = \arg\max\left[\pi_k(\vec{\boldsymbol{p}}, \vec{\boldsymbol{w}}) - d_k\right]^{b_k}\left[\pi_{jk}(p_{jk}, w_{jk}) - d_{jk}\right]^{b_j}, \forall j \in J_k. \tag{8}$$

A useful way to understand the bargaining process is to decompose Equation (8) into the bargaining position and bargain power (Lewis and Pflum 2015). The bargaining position determines how much each party can threaten to withdraw from the negotiation. Thus, for merchant $j$, its bargaining position is the incremental value of an added deal to platform $k$—that is, $\pi_k(\vec{\boldsymbol{p}}, \vec{\boldsymbol{w}}) - d_k$. Similarly, the bargaining position for platform $k$ is the incremental value that merchant $j$ can achieve by working with $k$—that is, $\pi_{jk}(p_{jk}, w_{jk}) - d_{jk}$. Note that the bargaining position is determined by competition.

Bargaining power, denoted as $b_k$ for the platform and $b_j$ for the merchant, describes the ability of each party to extract a share from the overall surplus after accounting for the competitive effect. Because the bargaining power parameters are not separately identifiable, we normalize them by setting $b_k + b_j = 1$. In the extreme case in which $b_j = 1$, the merchant sets the wholesale price and makes a take-it-or-leave-it offer to the platform (Sudhir 2001, Chen et al. 2008a) or vice versa when $b_k = 1$. Thus, our bargaining model nests the special scenario when either the merchant or the platform has full discretion over setting prices. Next, we describe our specifications for the net payoffs.

***4.2.2.1. The Platform's Net Payoffs.*** For platform $k$, deal $j$ affects the demand via two mechanisms: (1) it cannibalizes the sales of the deals from the same category (i.e., a cannibalization effect), and (2) it contributes to the overall market share of the platform (i.e., a network effect) and thus, affects sales of the other categories. These two mechanisms are explicitly modeled in our demand system. In the negotiation process, the platform rationalizes both effects, and the payoff is determined at the platform level rather than at the deal level. Formally, deal $j$'s bargaining position with respect to platform $k$ equals the total profit $\pi_k$ with the agreement minus the disagreement payoff $d_k$ without the agreement.

For the disagreement payoff, we adopt the approach of Horn and Wolinsky (1988), and assume that other contracts—especially those between platform $k$ and other merchants—would not be renegotiated if the focal agreement failed. This assumption has been widely adopted to make the bargaining model tractable (Grennan 2013, Lewis and Pflum 2015). In the daily deal market, merchants operate independently, and platforms typically assign specific salespeople to different merchant accounts. Thus, it is reasonable to assume that bargaining occurs independently. As a result, the disagreement payoff for the platform becomes $d_k = \pi_k(\vec{\boldsymbol{p}}, \vec{\boldsymbol{w}}; J_k|\{-j\})$, the total profit given the prices of all remaining deals, which is implied by our demand-side model.[8]

***4.2.2.2. Merchant's Net Payoffs.*** For merchant $j$, the net payoff from the negotiation equals the profit with the agreement $\pi_{jk}$ minus the disagreement payoff $d_{jk}$. For $\pi_{jk}$, it is important to note that, in this empirical setting, merchants are interested in deals not only because they bring current revenues but also, because some deal customers may return to the business in the future. The marketing effect is a salient feature of the daily deal market (Edelman et al. 2016, Li et al. 2018). Therefore, we capture merchant $j$'s profits in two parts: (1) the profits from selling and serving the customers with deals, $q(p_{jk})(w_{jk} - c_j)$, where $c_j$ is the merchant's marginal cost of serving a deal, and (2) a future flow of revenues from customers who are acquired through deals but return as regular customers (without deals).[9] For future transactions, we assume that the acquired deal customers return with a rate that may potentially vary by merchant and platform, denoted by $\lambda_{jk}$, and that, on average, they consume goods or services worth the face value of the deal, $FV_j$, which is the actual price that a consumer would pay without a deal. Thus, the recurring sales attributable to a deal promotion follow an exponential decay, and a merchant's expected future profit is represented by

$$\sum_{t=1}^{\infty} \lambda_{jk}^{t} q(p_{jk})(\mathrm{FV}_j - c_j) = (1 - \lambda_{jk})^{-1} q(p_{jk})(\mathrm{FV}_j - c_j).$$

Note that this term captures the important "marketing effect" from running a deal. Without the revenue from potential returning customers, the economics of giving out heavy discounts in daily deals is not justified (Edelman et al. 2016).

During negotiations, merchant $j$ considers the payoff that it can extract from the other platform $k'$, which specifies the merchant's disagreement payoff if the agreement fails:

$$d_{jk} = q_{jk'} \cdot \left(w_{jk'} - c_j + (1 - \lambda_{jk'})^{-1}(\mathrm{FV}_j - c_j)\right),$$

which can be thought of as the second-best option given that the merchant decides to offer a deal. It is important to specify the merchants' disagreement as the payoff from the competing platform. As shown in the FOC for Equation (8), if the merchant's disagreement payoff is underspecified (for example, set to zero because merchants choose not to participate in the daily deal market), the platform's bargaining power would be underestimated (or equivalently, the merchant's bargaining power would be overestimated).[10] Working with the other platform is a credible threat in this market because the switching cost between platforms is low.

***4.2.2.3. Implied Wholesale Price.*** To better understand the negotiation process, we insert the profits and disagreement payoffs into Equation (8) and solve the first-order condition of the Nash bargaining problem with respect to $w_{jk}$. The following equation is obtained:

$$\left(w_{jk} - c_j + \frac{FV_j - c_j}{1 - \lambda_{jk}}\right) - \frac{q_{jk'}}{q_{jk}}\left(w_{jk'} - c_j + \frac{FV_j - c_j}{1 - \lambda_{jk'}}\right)$$
$$= \frac{b_j}{b_k} \frac{\pi_k - d_k}{-\partial \pi_k / \partial w_{jk}} \left(1 + \frac{\partial q_{jk}}{\partial w_{jk}} \frac{1}{q_{jk}} \left(w_{jk} - c_j + \frac{FV_j - c_j}{1 - \lambda_{jk}}\right)\right). \tag{9}$$

The left-hand side of Equation (9) can be understood as the merchant's markup adjusted for future payoffs and the opportunity cost from working with the other platform. It is straightforward to show that the equilibrium wholesale price is decreasing with regard to future payoffs: with higher expected future returns, a merchant would agree to a lower wholesale price because future payoffs would compensate for the reduced markup. All else being equal, the wholesale price would also increase if the merchant expects better returns from the other platform. The right-hand side of the equation specifies how competition and bargaining power jointly determine the markup of the merchant. The comparative statics analysis shows that the negotiated wholesale price $w_{jk}$ is increasing in the merchant-to-platform bargaining power ratio $b_j/b_k$ and in the "externality value" of the deal to the platform $\pi_k - d_k$. These relationships exist because of the incentive compatibility behavior of the merchants (Online Appendix II provides a detailed analysis of the comparative statics).

## 5. Estimation and Identification

### 5.1. Demand-side Parameters

We use the GMM to minimize an objective function based on a set of moment conditions (Hansen 1982).

**5.1.1. Deal Demand.** The vector of observable deal characteristics $x_j$ includes the face value of the voucher, the month of the deal (to capture any seasonal variation), the deal categories, the interactions between the price and category, and the market fixed effects. We use the logarithm of prices in the estimation to address the skewness of this variable.

When estimating the price parameter $\alpha_c^p$, we need to account for a potential nonzero correlation between $p_j$ and $\xi_j$. Because a deal with a higher demand shock, $\xi_j$, may be priced higher but still incur more sales, failing to account for endogeneity could bias the estimate toward zero. A valid price instrument should be correlated with $p_j$ but be exogenous to $\xi_j$. We use two price instruments: (a) the average price of similar deals from the same category during the same month in other markets of the focal platform and (b) the average price similarly defined for the other platform.[11] These instruments are in the spirit of Hausman (1996) and Nevo (2001). They are averaged across similar deals of the same category around the same time, and therefore, they should be correlated with $p_j$ because of common cost shifters at the category level. Because the average is 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. Note that the instruments would be invalid if they were only weakly correlated with $p_j$ (causing a weak instrument problem) or if the unobservable demand shocks were correlated across markets (violating the exogenous requirement). In the results section, we provide diagnostic statistics for the strength of the instruments.

**5.1.2. Platform Demand.** Equation (6) specifies the utility that a consumer expects to derive from each platform choice. The taste parameters for deal categories, $\gamma_c$, are identified through variations in the platform share and deal offers in different categories across platforms over time. In a specific market, if the change in the market share of a platform is related to a change in the offerings in a category (e.g., restaurant deals), the taste parameter for that category would be estimated as substantial. The identification for the remaining platform demand parameters is straightforward. For platform fixed effect $\eta_r$, we use single homing on LivingSocial as the reference level and estimate the preference difference for single homing on Groupon and for multihoming, respectively. These fixed effects are identified by the variation in platform shares across market and time after controlling for the quantity and quality of deal offerings.

### 5.2. Supply-side Parameters

After regrouping the terms, we rewrite Equation (9) to separate out the bargaining power, marginal cost, and retention rate parameters such that

$$\frac{b_j}{b_k}\frac{\pi_k - d_k}{-\partial\pi_k/\partial w_{jk}}\frac{1}{q_{jk'}}\left(\frac{\partial q_{jk}}{\partial w_{jk}}\left(w_{jk} - c_j + \frac{FV_j - c_j}{1-\lambda_{jk}}\right) + q_{jk}\right)$$
$$= \frac{q_{jk}}{q_{jk'}}\left(w_{jk} - c_j + \frac{FV_j - c_j}{1-\lambda_{jk}}\right) - \left(w_{jk'} - c_j + \frac{FV_j - c_j}{1-\lambda_{jk'}}\right). \tag{10}$$

The parameters to be estimated in this bargaining equation are the bargaining power ratio $b_j/b_k$, the marginal cost $c_j$, and the platform-specific retention rate $\lambda_{jk}$. The rest of the terms are either observed or fully determined by the demand model and the pricing equations. Note that, for our research interest, it is sufficient to identify the net effect of the marginal cost and future payoff through retention. In addition, to fully capture these two sets of parameters—the bargaining power ratio and the joint effect of $c_j$ and $\lambda_{jk}$—one needs to specify each set in terms of data, parameters, and unobservables. Therefore, it is not feasible to identify $b_j/b_k$ and the joint effect of $c_j$ and $\lambda_{jk}$ separately, and one of the sets must be specified without unobservables. We follow a strategy similar to that of Grennan (2013) and allow the joint effect of $c_j$ and $\lambda_{jk}$ to be entirely determined by the data and parameters without unobservables, allowing us to specify the full distribution of bargaining power (in terms of data, parameters, and unobservables), which is of particular interest for this research.

**5.2.1. Bargaining Parameters.** After taking the logarithm transformation on both sides of Equation (10), we separate the bargaining parameters and the marginal cost/marketing effect parameters into their respective terms. We relate the bargaining power ratio to the platform and merchant characteristics (Grennan 2013, Lewis and Pflum 2015) and parameterize the ratio as a function of observables, $\chi^{(1)}_{jk}$, and unobservables, $\varsigma_{jk} : b_j/b_k = e^{f(\chi^{(1)}_{jk};\theta_1)+\varsigma_{jk}}$. Several considerations guide our choice of $\chi^{(1)}_{jk}$. First, recent empirical papers provide strong evidence that bargaining power can vary substantively across pairs of players in negotiations, such as across pairs of hospitals and managed care organizations (Gowrisankaran et al. 2015; Lewis and Pflum 2015, 2017). We use the platform dummy variable to capture the variation in bargaining power related to platforms and the category dummy variables to absorb the variation among merchants from different service categories.

Second, the theoretical bargaining literature suggests that bargaining power may depend on the amount of knowledge and information available to one negotiating party versus the other (Sobel and Takahashi 1983). Lewis and Pflum (2017) find suggestive evidence that a larger hospital system has higher bargaining power. Because having an information advantage could be related to the amount of resources available, we hypothesize that merchants' bargaining power relative to the platform's bargaining power would depend on the merchant's size (measured by the number of employees) and on whether it belongs to a chain.

Third, merchants may also exert different bargaining power owing to the importance of local competition intensity (Li et al. 2018). Note that the competition effect because of demand is already captured through the bargaining position term in our model. Here, we use the number of merchants within the same category in the same market to capture any competition effects on bargaining power that are beyond the merchant's bargaining position on the platform.

**5.2.2. Net Marketing Effect and Cost Parameters.** Under the assumption that marginal cost is a percentage of face value (i.e., a merchant's original markup is proportional to cost) $c_j = \kappa_j FV_j\,(0 < \kappa_j \leq 1)$, the net of the future payoffs and marginal cost (referred to as the *net gain* hereafter) can be shown as

$$\frac{FV_j - c_j}{1 - \lambda_{jk}} - c_j = \left(\frac{1 - \kappa_j}{1 - \lambda_{jk}} - \kappa_j\right) FV_j = \rho_{jk} FV_j.$$

The coefficient associated with the face value $\rho_{jk}$ is bounded between −1 and infinity (i.e., $-1 \leq \rho_{jk} < \infty$) (see Online Appendix III for more details). The minimum occurs when $\kappa_j = 1$ and $\lambda_{jk} = 0$ (i.e., when the marginal cost equals the face value and the retention rate is 0), and the maximum occurs when $\lambda_{jk} = 1$ (i.e., 100% retention rate). The range of $\rho_{jk}$ with regard to the values of $\kappa_j$ and $\lambda_{jk}$ makes intuitive sense; thus, given this range, we parameterize net gain as a function of merchant and platform characteristics using the following parametric form: $(e^{\psi(\chi^{(2)}_{jk};\theta_2)} - 1) \cdot FV_j$.

Next, we consider the factors $\chi^{(2)}_{jk}$ that could influence a merchant's net gain. First, the marginal cost of a deal depends on the nature of the goods/services, which we capture by the deal category. We also include the merchant's total annual sales to capture a potential economies-of-scale effect. Second, the net gain may also vary between Groupon and LivingSocial for two reasons. (1) The platforms may have different operational efficiency, and therefore, merchants may incur different costs for setting up deals. (2) Groupon and LivingSocial may also attract different types of customers, and therefore, the propensity to return as a regular customer could vary. We use a Groupon indicator to absorb the net effect of these two considerations. It is also important to consider how the net gain relates to whether the merchant has used the platform before. If the merchant has done so, some current deal buyers may have purchased deals before—that is, the so-called "deal hunters." All else being equal, it is reasonable to postulate that merchant $j$ would expect a lower retention rate because these deal hunters are less likely to return as regular customers. Meanwhile, a returning merchant may enjoy a reduced operation cost to set up the deal because much of the information needed to run the deal is already in place. To capture the combined effect of these possibilities, we include an indicator for whether merchant $j$ has transacted with platform $k$ in the past. We also include an interaction term between this indicator and the platform dummy to capture the systematic difference between platforms as motivated by our model-free evidence. It is important to note that, after we control for other merchant characteristics and the competition effect, merchants' returning status and their economies scale should not be directly related to their bargaining power, and hence, they serve as exclusive variables to help identify the parameters related to net gain. Lastly, the merchant's size and whether it is a chain business may also matter for the net gain of the deal and thus, are also included in $\chi^{(2)}_{jk}$.[12]

For the estimation equation, we use the logarithm transformation, and therefore, the unobservables enter the equation linearly such that

$$\begin{aligned} & f\left(\chi^{(1)}_{jk};\theta_1\right) + \varsigma_{jk} + \log\left(\frac{\pi_k - d_k}{-\partial\pi_k/\partial w_{jk}}\frac{1}{q_{jk'}}\right) \\ & + \log\left(\frac{\partial q_{jk}}{\partial w_{jk}}\left(w_{jk} + \left(e^{f\left(\chi^{(2)}_{jk};\theta_2\right)} - 1\right)FV_j\right) + q_{jk}\right) \\ & = \log\left(\frac{q_{jk}}{q_{jk'}}\left(w_{jk} + \left(e^{f\left(\chi^{(2)}_{jk};\theta_2\right)} - 1\right)FV_j\right) \right. \\ & \left. - \left(w_{jk'} + \left(e^{f\left(\chi^{(2)}_{jk'};\theta_2\right)} - 1\right)FV_j\right)\right). \end{aligned} \tag{11}$$

We use a linear specification for function $f(.)$, where the parameters of interest are $\theta_1$ and $\theta_2$. The variables related to bargaining power ($\chi^{(1)}_{jk}$) enter the pricing equation as main effects, whereas those associated with net gain ($\chi^{(2)}_{jk}$) enter the equation as interactions with the face value.

Although our bargaining model has imposed a substantial amount of structure, the parameters associated with net gain and bargaining power are also identified because they utilize different variations in the data. In particular, to facilitate the identification of the net gain parameters, we use the repeated deals per merchant (see Section 3.4.1) (roughly 31% of Groupon merchants and 23% of LivingSocial merchants had repeated deals). As can be seen from Equation (11), the bargaining parameters ($f(\chi^{(1)}_{jk};\theta_1)$) are constant within merchants, and they are linearly separable from the net gain parameters. Thus, the variation across the repeated deals from the same merchant contains only the net gain parameters and thus, provides the identification for $\theta_2$. This identification approach requires reasonable within-merchant data variation: in our sample, 86% of the repeated deals varied in face value (i.e., the same merchant set different face values when offering a repeated deal(s) on the same platform). Thus, our data provide the

**Table 4.** Parameter Estimates for Deal Demand

| | (1) | | (2) | |
|---|---|---|---|---|
| Variable | Estimate | SE | Estimate | SE |
| *Price* | −0.852*** | 0.011 | −1.648*** | 0.048 |
| *Price* × *Beauty* | 0.102*** | 0.014 | −0.572*** | 0.071 |
| *Price* × *Family* | −0.002 | 0.017 | 0.271*** | 0.100 |
| *Price* × *Fitness* | −0.075*** | 0.023 | −0.410*** | 0.074 |
| *Price* × *Goods* | −0.027* | 0.016 | 0.516*** | 0.064 |
| *Price* × *LifeSkill* | −0.003 | 0.021 | −1.023*** | 0.102 |
| *Price* × *LiveEvents* | 0.189*** | 0.021 | 2.410*** | 0.106 |
| *Price* × *Outdoor* | −0.016 | 0.017 | −0.503*** | 0.096 |
| *Price* × *Personal* | −0.345*** | 0.026 | −1.407*** | 0.117 |
| *Price* × *Restaurants* | 0.177*** | 0.015 | 0.079 | 0.057 |
| *Price* × *Sports* | 0.139*** | 0.027 | 0.319*** | 0.087 |
| *Price* × *Travel* | −0.025 | 0.021 | 0.184*** | 0.067 |
| *Voucher value* | 0.014*** | 0.002 | 0.189*** | 0.007 |
| *Beauty* | −0.279*** | 0.056 | 2.459*** | 0.281 |
| *Family* | −0.270*** | 0.066 | −1.383*** | 0.374 |
| *Fitness* | 0.182** | 0.085 | 1.200*** | 0.277 |
| *Goods* | −0.088 | 0.057 | −2.168*** | 0.228 |
| *LifeSkill* | −0.133 | 0.081 | 3.755*** | 0.398 |
| *LiveEvents* | −0.659*** | 0.070 | −8.023*** | 0.350 |
| *Outdoor* | 0.402*** | 0.065 | 2.207*** | 0.365 |
| *Personal* | 1.776*** | 0.101 | 5.880*** | 0.456 |
| *Restaurants* | 0.157*** | 0.051 | −0.225 | 0.204 |
| *Sports* | −0.138 | 0.101 | −0.896*** | 0.321 |
| *Travel* | 0.340*** | 0.091 | −0.304 | 0.269 |
| *January* | −0.157*** | 0.017 | −0.214*** | 0.019 |
| *March* | −0.107*** | 0.016 | −0.125*** | 0.018 |
| *April* | −0.224*** | 0.016 | −0.244*** | 0.018 |
| *May* | −0.310*** | 0.016 | −0.301*** | 0.018 |
| *June* | −0.306*** | 0.016 | −0.298*** | 0.018 |
| *July* | −0.424*** | 0.016 | −0.418*** | 0.018 |
| *August* | −0.393*** | 0.015 | −0.392*** | 0.017 |
| *September* | −0.217*** | 0.015 | −0.226*** | 0.018 |
| *October* | −0.505*** | 0.015 | −0.522*** | 0.017 |
| *November* | −0.568*** | 0.015 | −0.551*** | 0.018 |
| *December* | −0.592*** | 0.015 | −0.574*** | 0.018 |
| Intercept | −7.409*** | 0.045 | −4.766*** | 0.041 |
| Market fixed effects | Included | | Included | |
| Instruments | No | | Yes | |
| $R^2$ | 0.972 | | 0.958 | |
| *N* | 185,032 | | 185,032 | |

*Notes.* The dependent variable is the log share ratio between the deal and the outside option. For the categories, the reference level is home and auto. For month, February is the reference level. The first specification is without the price instruments, and the second is with the instruments. The market fixed effect is included. SE, standard error.

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

necessary within-merchant variation to identify the net gain parameters.

In sum, our identification argument goes as follows. Imagine a similar deal (with the same face value) from merchants with the same characteristics on each platform, but the observed deal prices are different. Through our pricing equation, we can infer the wholesale price and thus, the surplus that the platform captures (the deal price minus the wholesale price). The difference in each platform's surplus for a similar deal from a merchant with the same characteristics would identify the bargaining parameters—the more surplus the platform captures, the higher the bargaining power the specific platform would have over the merchant. Now, suppose that the same merchant on the same platform (and thus, with the same bargaining power) has the same deal price but products with different face values (e.g., a restaurant agrees to a deal with a face value of $100 once and with $150 another time but with an identical deal price of $75 on both occasions). The fact that the merchant has settled for a deeper discount price (face value minus deal price) means that the higher face value deal would be justifiable only with a higher net gain. Hence, the interaction with the face value would identify the parameters associated with the net gain. In addition, the exclusive variables help with identification.[13]

# 6. Results

## 6.1. Demand-side Parameter Estimates

**6.1.1. Deal Demand.** Table 4 shows two specifications of deal demand. The first specification is a logit model that does not account for price endogeneity. This is simply an ordinary least squares (OLS) estimate, with the dependent variable being the logarithm of the deal share minus the logarithm of the outside share. For the second specification, we use the Hausman-type price instruments discussed in Section 5.1. With these instruments, the main effect of the (retail) price is much stronger: −1.648 with instruments versus −0.852 without instruments. The direction of the change is as expected when the price and the unobserved demand shock are positively correlated; when popular deals are priced high and unpopular ones are priced low, the OLS estimate of the price coefficient attenuates toward zero, such as in our case.

To assess the strength of the instruments, we run the first-stage regression and find the *F* statistic to be 3,987.6 ($p < 0.001$). The partial adjusted $R^2$ is 4.2%, indicating a modest but satisfactory correlation between the price and the instrumental variables after partialling out the effect of the other variables in the model (including the market fixed effects). We also run the Stock and Yogo (Stata 2013) test for weak instruments: our *F* statistic is higher than the test-critical value of 19.93, rejecting the null hypothesis of weak instruments.

The results show substantial variation in price elasticity across categories. Consumers are most price sensitive to deals in the personal care category (−3.055) followed by life skill classes (−2.671) and beauty services (−2.220). Among the 12 categories, the four categories that are the least price elastic are live events (e.g., concerts or other entertainment events: 0.762, $p > 0.05$), goods (−1.132), family activities

(−1.377), and sports (−1.329), most of which are related to social and entertainment consumption. To put these numbers into perspective, the average price elasticity for consumer-packaged goods is around −2.50 (Tellis 1988). For example, soft drinks are typically considered elastic goods: Coca Cola has an elasticity of −3.8, whereas Mountain Dew has an elasticity of −4.4 (Ayers and Collinge 2003). Alcoholic beverages typically have an elasticity of between −1.0 and −1.5.

**6.1.2. Platform Demand.** Table 5 shows consumer preferences for different deal categories when choosing platforms. The higher the estimate for $\gamma_c$, the more attractive the category is in terms of drawing consumers to the platform. The results reveal heterogeneity in the capacity of categories to grow the customer base. Beauty deals have the highest appeal (0.023, $p < 0.01$) followed by restaurant deals (0.019, $p < 0.01$), family activity deals (0.011, $p < 0.01$), fitness deals (0.007, $p < 0.01$), live events (0.004, $p < 0.01$), and outdoor activity deals (0.004, $p < 0.01$). Sports deals, home and auto deals, and personal care deals (e.g., massages and facials) are also effective in growing a platform but less so than the categories mentioned. Three categories—life skill classes, travel deals, and physical goods—exert only minimal influence on consumers' 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 5.** Parameter Estimates for Platform Demand

| Parameter | Estimate | SE |
|---|---|---|
| *Beauty* | 0.023*** | 0.008 |
| *Family* | 0.011*** | 0.002 |
| *Fitness* | 0.007*** | 0.003 |
| *Goods* | 0.0001 | 0.0009 |
| *Home and auto* | 0.002*** | 0.001 |
| *LifeSkill* | 0.0001 | 0.0001 |
| *LiveEvents* | 0.004*** | 0.001 |
| *Outdoor* | 0.004*** | 0.001 |
| *Personal* | 0.001*** | 0.0002 |
| *Restaurants* | 0.019*** | 0.005 |
| *Sports* | 0.002* | 0.001 |
| *Travel* | 0.001 | 0.001 |
| *Groupon Only* | 0.471*** | 0.043 |
| *Multihoming* | −0.757*** | 0.022 |
| *Intercept* | −3.885*** | 0.120 |
| $\sigma$ | 0.421*** | 0.055 |
| Month fixed effects | Included | |

*Notes.* The dependent variable is the log share ratio between the platform choice and the outside option. The multihoming dummy variable is the fixed effect to capture the utility change in using both platforms. $\sigma$ is the nesting parameter to capture the correlation between the three platform choices. The standard errors (SEs) are obtained through bootstrapping.

*$p < 0.10$; ***$p < 0.01$.

The estimates for platform choice fixed effects show that, after controlling for other factors, consumers' overall preference for Groupon is higher than that for LivingSocial (0.471, $p < 0.01$). The multihoming fixed effect is negative and significant (−0.757, $p < 0.01$), confirming that there is a cost associated with being affiliated with both platforms. This helps explain the relatively small market share of multihoming consumers. Lastly, the nesting parameter, which captures the level of substitution between the platform choices, is estimated to be positive and significant (0.421, $p < 0.01$), indicating a substantial degree of correlation.

## 6.2. Supply-side Parameter Estimates

Table 6 reports the estimates for the supply-side model: columns 2 and 3 for parameters associated with bargaining power ($\theta_1$) and columns 4 and 5 for those with net gain ($\theta_2$). We start by presenting the results related to bargaining power. Note that larger estimates here indicate a higher merchant-to-platform bargaining power ratio. The parameter for the Groupon dummy is estimated as negative and significant (−1.472, $p < 0.01$), indicating that, holding everything else constant, merchants have lower bargaining power on Groupon than on LivingSocial. When relating bargaining power to merchant characteristics, larger merchants (measured in terms of the number of employees) have higher bargaining power than smaller ones (0.375, $p < 0.01$), but after

**Table 6.** Parameter Estimates for the Supply-side Model

| | Bargaining ratio ($\theta_1$) | | Net gain ($\theta_2$) | |
|---|---|---|---|---|
| | Estimate | SE | Estimate | SE |
| Intercept | 0.683*** | 0.225 | −0.378 | 0.257 |
| *Groupon* | −1.472*** | 0.266 | −0.129** | 0.054 |
| *SizeEmployees* | 0.375*** | 0.038 | 0.169*** | 0.026 |
| *Chain* | −0.218 | 0.150 | −0.121 | 0.173 |
| *Number of Competitors* | 0.0001 | 0.001 | NA | |
| *SalesScale* | NA | | 0.062*** | 0.010 |
| *RepeatedDeals* | NA | | −0.140** | 0.068 |
| *Groupon* × *RepeatedDeals* | NA | | 0.268** | 0.136 |
| *Beauty* | 0.357 | 0.255 | 0.131 | 0.486 |
| *Family* | 0.198 | 0.177 | −0.097 | 0.215 |
| *Fitness* | −0.119 | 0.155 | −0.248 | 0.356 |
| *Goods* | 0.662*** | 0.139 | −0.173** | 0.384 |
| *LifeSkill* | 0.256 | 0.171 | −0.354** | 0.288 |
| *Outdoor* | 0.174 | 0.144 | −0.160 | 0.378 |
| *Personal* | 0.013 | 0.267 | −0.229 | 0.458 |
| *Restaurants* | 0.410* | 0.221 | 0.044 | 0.332 |
| *Sports* | 0.156 | 0.158 | −0.117 | 0.072 |
| *Travel* | −0.417*** | 0.122 | −0.124*** | 0.104 |

*Notes.* Estimates are from a subset of observations ($N$ = 17,080) for which the merchant names can be matched with the OneSource database. Standard errors (SEs) are obtained through bootstrapping. NA, not applicable.

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

controlling for merchant size, chain status is insignificant (−0.218, $p > 0.10$). The estimate for the number of competitors turns out to be close to zero and insignificant, suggesting that our model has sufficiently captured competition and that the remaining competition effect is no longer substantial. Lastly, there is also variation in bargaining power across categories: compared with the home and automobile deals (the reference category), restaurants and merchants selling physical goods have higher bargaining power, with the estimated differences in the bargaining power ratio being 0.410 ($p < 0.10$) and 0.662 ($p < 0.01$), respectively. Merchants offering travel deals have the lowest bargaining power (−0.417, $p < 0.01$).

The intercept in Table 6 (under "bargaining ratio") corresponds to the logarithm of the merchant-to-platform bargaining power ratio on LivingSocial for an independent merchant with the average merchant size and number of competitors in the category of home and auto deals. To better illustrate the bargaining power distribution, we compute the bargaining power for all of the merchants given their category and characteristics and report the summary statistics in Table 7. The average bargaining power for merchants is around 0.368 on Groupon (SD = 0.106) and 0.689 on LivingSocial (SD = 0.089). The bargaining power estimates dispute the common belief that platforms dictate the share of surplus during the pricing process. On average, merchants can exert higher bargaining power on LivingSocial, the smaller platform. Even on Groupon, merchants' bargaining power is lower but significantly higher than zero. The bargaining power also indicates that merchants do not have full discretion in setting the wholesale price, making the daily deal market different from many vertical industries in which the suppliers have full control over wholesale prices. In this market, the negotiation power split plays an important role, which will be further discussed in the counterfactual analysis section.

Next, we discuss the parameter estimates associated with net gain parameters: larger estimates correspond to higher net payoff (i.e., the future payoff net of the cost). As mentioned in Section 5.2, our data do not permit separate identification of marginal cost and future payoff, and thus, the estimates here represent the combined effect of the two. First, note that the net gain parameter for returning merchants on LivingSocial is negative (−0.140, $p < 0.05$). This indicates that, on LivingSocial, returning merchants would expect a lower net gain than new merchants would expect, perhaps because they are more likely to attract deal hunters and thus, have a lower marketing effect. Interestingly, returning merchants on Groupon do not experience the reduced marketing effect, with a positive estimate for the difference between returning and new merchants on Groupon (0.268 − 0.140 = 0.128). This helps explain why merchants on Groupon are more likely than those on LivingSocial to return as shown in the model-free evidence. The main effect of Groupon is estimated to be negative (−0.129, $p < 0.05$), indicating that the deals on Groupon, on average, expect a lower net gain rate than those on LivingSocial, perhaps because of the different customer characteristics on different platforms.

Second, capturing the level of economies of scale, the estimate for merchants' annual revenue is positive and significant (0.062, $p < 0.01$), which is expected because large-scale merchants are associated with low marginal cost. Merchant size is positive and significant (0.169, $p < 0.01$), indicating that the future payoff net of marginal cost (net gain) is higher for larger merchants.

**Table 7.** Summary of Merchant Bargaining Power

| | $N$ | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Groupon | 10,325 | 0.368 | 0.106 | 0.144 | 0.856 |
| LivingSocial | 6,755 | 0.689 | 0.089 | 0.481 | 0.944 |

*Notes.* The table summarizes the estimated bargaining power for merchants relative to platforms after controlling for bargaining position. The difference in the mean ratio between Groupon and LivingSocial is statistically significant ($t$ = 39.28, $p < 0.001$).

### 6.3. Bargaining Power vs. Bargaining Position

A key objective of this research is to disentangle the effect of bargaining power and bargaining position for the merchants. On the one hand, a merchant's bargaining power represents its ability to influence the split of the surplus, which can be attributed to the characteristics of the platform-merchant pair. The merchant's bargaining position, on the other hand, corresponds to the net payoff that it can bring to the platform, and hence, it captures the competitive effect of the deal. The relative effects of bargaining power and bargaining position are empirical issues that we are interested in investigating.

Table 8 reports the effect of a merchant's bargaining power and bargaining position on negotiating the wholesale price. Following a similar approach as in Lewis and Pflum (2017), we look at the pairs with low bargaining power for the merchant (the 25th percentile) and those with high bargaining power (the 75th percentile) and report the average wholesale price, retail price, and the ratio between the two. Higher ratios correspond to a higher margin for merchants.

As predicted by our bargaining equation, an increase in a merchant's bargaining power would be associated with a higher margin (i.e., a higher share

**Table 8.** Summary of Deals Wholesale-to-Retail Price Ratio

| | By merchant bargaining power | | By merchant bargaining position | |
|---|---|---|---|---|
| | 25th Percentile | 75th Percentile | 25th Percentile | 75th Percentile |
| Wholesale price, $ | 8.2 | 27.7 | 10.6 | 34.7 |
| Retail price, $ | 17.3 | 52.5 | 23.2 | 66.0 |
| Wholesale-to-retail price ratio (%) | 46.5 | 53.0 | 45.3 | 52.2 |

*Notes*. The bargaining position of a merchant is the expected incremental payoff that it can bring to the platform. The numbers are the averages across the merchants in the corresponding percentiles.

of the total surplus). When a merchant's bargaining power increases from low to high, the wholesale-to-retail price ratio rises from 46.5% to 53.0% (a difference of 6.5 percentage points)—that is, a higher surplus for the merchant and lower commission for the platform.

In the same vein, we look at the merchants with low and high bargaining positions. When a merchant has a higher bargaining position, it is in a better position to threaten to withdraw, and hence, it is better able to obtain a larger share of the surplus. When the merchant's bargaining position increases from low to high, the wholesale-to-retail price ratio increases by 6.9 percentage points. The finding that the markup attributable to bargaining power and that attributable to bargaining position are somewhat comparable suggests that bargaining power is, perhaps, as important a factor in the daily deal market as the competitive effect. Thus, empirical research should not ignore bargaining power when studying such markets.

### 6.4. Counterfactual Analyses

In this section, we conduct counterfactual analyses to answer the main question of interest: how does price bargaining affect competition and market outcomes? Specifically, in the presence of price negotiation, what are the market consequences with the formation of a larger and stronger platform? The classic results for market concentration predict high prices and low market demand. However, in an intermediary market in which (wholesale) prices are negotiated, buyer power may enable the platforms to obtain sufficient discounts from merchants (suppliers). This could lead to lower prices charged to consumers, thus increasing total market demand (Dobson and Inderst 2007, Inderst and Wey 2007). To examine such effects, we perform two counterfactual analyses. The first considers platform consolidation, and the second examines a buyer alliance whereby platforms form a single entity to negotiate prices.

In a competitive platform market (e.g., the daily deal market), an important source of merchants' bargaining position comes from the option of working with a competing platform. Merchants can leverage the existence of a competing platform and threaten to work with the competitor if the negotiation fails. Therefore, the absence of a competing platform weakens the merchant's power to threaten, which would lead to less favorable negotiated terms. To assess the magnitude of this effect, we eliminate platforms one at a time so that a single platform covers the entire market, and then, we compute the merchants' counterfactual payoffs.[14] By doing so, we are effectively quantifying each platform's economic value to the merchants.

The absence of a competing platform affects merchants in ways beyond the reduction in the disagreement payoff. Two other factors also affect merchants' bargaining position. On the one hand, the consolidated (remaining) platform would have a larger market share of consumers, leading to a higher promotional effect (i.e., an increased customer base exposed to the deal).[15] On the other hand, because a single platform offers all deals, the deal-level competition would become more intense. All of these effects jointly determine merchants' bargaining position.

Taking LivingSocial as an example, its economic value to merchants is computed using the following procedure. First, we eliminate LivingSocial from the market and let all of the current LivingSocial merchants consider using Groupon together with all of the current Groupon merchants. The merchants' disagreement payoff is then set to zero (i.e., the outside option of not offering deals), reduced from the counterfactual payoff of working with the other platform. Second, under the same deal characteristics (e.g., face value, category), we compute the newly negotiated wholesale price and the resulting retail price for all of the deals in the market. Note that two elements jointly determine the wholesale price: the merchant's bargaining power (relative to the remaining platform, Groupon) and its bargaining position (as in Equation (8)). Merchants' new bargaining power is the counterfactual bargaining power given the merchants' characteristics, which can be directly computed based on the bargaining power parameter estimates. Merchants' updated bargaining position is determined by the counterfactual sales quantity from the demand estimation and the counterfactual net gain of serving the deal on the remaining platform given the merchants' characteristics related to net gain. Online Appendix IV summarizes the counterfactual procedure in detail.

Table 9 reports the results of this counterfactual analysis. If LivingSocial were eliminated from the market, merchants would have a weaker bargaining position in negotiating with Groupon and thus, settle for a lower wholesale price. The platform passes some of the discount on to the retail price, and the demand increases. The increase in demand, however, is not enough to offset the drop in the wholesale price, leading to a reduction in merchants' profits. For merchants currently on Groupon, eliminating LivingSocial initiates 21.4% and 26.8% decreases in wholesale and retail prices, respectively, resulting in a 33.5% increase in demand. For merchants on LivingSocial, eliminating LivingSocial results in an 18.6% decrease in wholesale prices and a 35.0% increase in demand.

Columns 4 and 5 of Table 9 show the results when Groupon is eliminated. Merchants again settle for a lower wholesale price and make lower profits. The wholesale price would fall by 14.6% and 13.4% for the current Groupon merchants and LivingSocial merchants, respectively.

The changes in merchants' profits essentially represent the economic value of platforms. The existence of Groupon in a competitive market can account for 18.8% of the profits for Groupon merchants and 22.0% of the profits for LivingSocial merchants, whereas LivingSocial accounts for 43.6% of the profits for the former and 51.8% of the profits for the latter. The finding that the economic value of Groupon is smaller than that of LivingSocial is, perhaps, for the following reason. A competing platform contributes to the merchants' bargaining position because they can threaten to work with this competitor if negotiation fails. Such a bargaining point is more important when merchants bargain with Groupon than with LivingSocial because the former has higher bargaining power over merchants. Thus, LivingSocial is more valuable to the merchants not because it can sell more deals, but because the merchants can use it as a threat during negotiation.

**Table 9.** Counterfactual Results on the Platform Value to Merchants

| | Value of LivingSocial | | Value of Groupon | |
|---|---|---|---|---|
| | Mean | SD | Mean | SD |
| Groupon merchants | | | | |
| Change in wholesale price | −0.214 | 0.164 | −0.146 | 0.120 |
| Change in retail price | −0.268 | 0.148 | −0.253 | 0.154 |
| Change in demand | 0.335 | 0.257 | 0.293 | 0.195 |
| Change in merchant profits | −0.436 | 0.269 | −0.188 | 0.147 |
| LivingSocial merchants | | | | |
| Change in wholesale price | −0.186 | 0.144 | −0.134 | 0.105 |
| Change in retail price | −0.248 | 0.125 | −0.235 | 0.139 |
| Change in demand | 0.350 | 0.207 | 0.320 | 0.183 |
| Change in merchant profits | −0.518 | 0.220 | −0.220 | 0.129 |

*Notes.* A platform's economic value to merchants is computed as the fractional difference between the observed merchant profit and the counterfactual profit if the focal platform is eliminated from the market. We assume that deal characteristics remain the same.

The results from this counterfactual analysis reveal the important role of bilateral price bargaining in the daily deal market. Platform concentration enables the stronger intermediary to obtain higher discounts from merchants. Because daily deals are elastic, the platform passes on the discount to the retail price, and thus, sales quantity increases. This, however, comes at a cost to merchants because they settle for reduced profits. These results are contrary to the classic effect of intermediary merger, whereby suppliers set their own wholesale price.

The first counterfactual treats the platforms' bargaining power as an exogeneous parameter, which does not change after platform consolidation. However, research suggests that the platforms' bargaining power may change with a merger or consolidation owing to factors such as the quantity and quality of information (Grennan 2013, Lewis and Pflum 2017). The second counterfactual analysis further examines the effect of bargaining power after controlling for bargaining position.

In this analysis, the two platforms form a single entity to jointly bargain and maximize profits. Similar to the first counterfactual, the direct consequence of this platform alliance[16] is that merchants can no longer use the competing platform as a negotiation point during bargaining. Thus, merchants' disagreement point is again set to zero. However, deals are still competing under two platform brands for consumer demand.[17] Furthermore, Groupon and LivingSocial jointly maximize their combined profits, which is reflected in two decisions: (1) the incremental payoff for the platform alliance is the combined platform profits with the focal deal minus the profits without the deal, and (2) given the negotiated wholesale prices, the platform alliance jointly sets the retail prices, considering all deals in the market.

To examine the effect of bargaining power, we set the alliance's bargaining power to two sets of values: (1) the average of Groupon's and LivingSocial's bargaining power and (2) Groupon's bargaining power. Given the new market structure, we compute a new equilibrium outcome for negotiated wholesale prices, retail prices, platform share, and deal shares. Merchants' net gain rate, deal characteristics, and total market size are all kept constant. On the demand side, consumers still view the platforms as two brands: they choose to single home on one platform or multihome on both, whereas deals in the same category still compete on the same platform.[18] Table 10 reports the results of this analysis.

When platforms conduct joint bargaining, merchants with a weaker bargaining position negotiate to a lower wholesale price and make lower profits. Platforms charge a lower retail price to consumers, leading to an increase in demand. The extent to which joint bargaining affects merchants' and consumers' outcomes further depends on the bargaining power of the platform alliance. When the alliance's bargaining power is set to the maximum of the members' bargaining power (i.e., Groupon's bargaining power), the merchants receive, on average, a 21.0% reduction in wholesale prices and a 15.2% reduction in profits. The market-level total profits for the platforms increase by an average of 66.7%, which is driven by the increased demand and lower wholesale prices. On average, the market-level total deal demand increases by 48.6%.

When the alliance's bargaining power is set as the average of the members' bargaining power, the effects are qualitatively similar, but the magnitude is smaller. The merchants would settle for an average of an 11.0% reduction in wholesale prices and a 6.4% reduction in profits. There is also large heterogeneity among merchants because the merchants currently on LivingSocial would have lower bargaining power when negotiating with the alliance and vice versa for those currently on Groupon. The effect owing to the change in bargaining power cancels out some of the effect because of bargaining position. Nevertheless, the results from this counterfactual indicate that bargaining power plays an important role in determining the profits for merchants and platforms, making it a critical factor to consider in empirical applications.

**Table 10.** Counterfactual Results on the Platform Joint Bargaining

| | Average bargaining power | | Maximum bargaining power | |
|---|---|---|---|---|
| | Mean | SD | Mean | SD |
| Merchant outcome | | | | |
| Change in wholesale price | –0.110 | 0.127 | –0.210 | 0.168 |
| Change in retail price | –0.241 | 0.145 | –0.276 | 0.141 |
| Change in demand | 0.480 | 0.318 | 0.806 | 0.649 |
| Change in merchant profits | –0.064 | 0.187 | –0.152 | 0.096 |
| Platform outcome (by market) | | | | |
| Change in total profits | 0.407 | 0.276 | 0.667 | 0.397 |
| Change in total deal share | 0.285 | 0.100 | 0.486 | 0.133 |

*Notes*. The results are computed after Groupon and LivingSocial form a single entity and engage in joint profit maximization for each market. Merchants can no longer use the competing platform as the bargaining point, but deals are still offered on two platforms. Under "average bargaining power," the platform alliance's bargaining power is set as the average of the two platforms' bargaining power. Under "maximum bargaining power," the alliance's bargaining power is equal to Groupon's bargaining power.

It is noteworthy to mention that we do not explicitly model the merchants' decision to participate in the daily deal market but rather, assume that merchants have decided to participate in the market for exogenous reasons (e.g., an exogenous shock to the demand of their regular business). The platform would like to have the merchants join its network to increase platform demand, and the merchants would want to offer a deal on the platform because they would otherwise receive zero payoff. Hence, based on the Nash bargaining solution in our model, the platform and the merchant would agree on a wholesale price that generates positive profits for both parties. However, one can imagine that a merchant would decide to exit the daily deal market if terms were overly unfavorable. Furthermore, the merchant's disagreement payoff could be positive (and not zero) under a monopoly platform. By not taking these factors into account, the counterfactual analyses may have overestimated the transfer of surplus from the merchants to the platform.

## 7. Conclusion and Discussion

The prominence of online platforms has presented exciting opportunities for traditional merchants, which can leverage the reach of the platforms to attract new consumers without having to invest heavily in their marketing efforts. However, the effectiveness of this approach depends greatly on the terms that a merchant can negotiate with a platform. Despite the managerial implications, limited empirical research has examined how merchants and platforms negotiate to reach an agreement.

Using a unique and comprehensive data set from the U.S. daily deals market, we specify a structural model that examines consumer demand as well as the strategic interactions between merchants and platforms. This research contributes to the literature by allowing prices to be jointly determined by platforms and merchants, a practice commonly seen in real-world applications but challenging to analyze. The supply-side model formulates how platforms and merchants negotiate to reach a mutually agreed-on wholesale price following the Nash bargaining solution pioneered by Horn and Wolinsky (1988). During this process, the platform internalizes the externality value of a deal in growing its network, and the merchant incorporates not only the current deal profit but also, future payoffs from returning customers.

This study generates insights into the underlying primitives that determine the profit split between platforms and merchants. A tradeoff exists between bargaining power and bargaining position. When working with a larger platform, merchants can potentially have a higher payoff, but they are subject to lower bargaining power. The opposite is true for the smaller platform. A systematic variation in bargaining power exists among merchants. On average, larger merchants, those offering physical goods, and restaurants can negotiate a larger slice of the surplus.

Results from the counterfactual analyses shed further light on the effect of bargaining in platform competition. Merchants benefit from a competitive downstream market because they can leverage the competing platform(s) as a bargaining point during negotiation. In the absence of platform competition, merchants experience a decrease in profits. The lack of a second-best option weakens the merchant's bargaining position, resulting in a decrease in the negotiated wholesale price. The platforms pass some of the lower wholesale price to the consumer by charging a lower retail price, thus increasing overall demand. Combined, in the absence of platform competition, merchants are worse off with reduced profits, and consumers experience lower prices, which increases the total market demand.

There are a few limitations to note. First, the lack of merchant data outside the daily deal domain limits inference about merchants' outside options. This analysis examines the tradeoff between the inside options given that merchants decide to offer a deal; thus, the merchants' payoff can be understood as the additional benefit of offering daily deals after normalizing the outside option to zero. This approach, however, does not allow the outside option to vary across merchants. Second, we do not observe customer retention, and thus, we are unable to directly relate the marketing effect to merchant or deal characteristics. Relatedly, not observing retention and marginal cost limits the nonparametric identification of bargaining power. One can potentially obtain greater insights by collecting better data on retention and costs. Third, we assume that platforms are myopic and bargain with merchants to maximize the joint payoffs of the current transaction, regardless of how the outcome may influence the platform's future returns. Note that we do allow merchants to internalize not only current profits but also, future payoffs. In the same vein, a platform may face a tradeoff between current and future payoffs. If a platform accepts a price that is favorable to merchants, more merchants may be willing to join that platform instead of its competitors. The network effect could increase the platform's customer base and boost profits in the long run. Modeling such dynamic decision making requires a longer time horizon of observations on the platform's pricing decisions. By focusing on the static payoffs, this research generates insights into the way that platforms and merchants internalize price-bargaining power in their strategic interactions, and thus, it lays a foundation for future research on the forward-looking behavior of platforms. Although not addressed in this study, these issues could be exciting venues for future research.

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## Endnotes

[1] See *Statistica* 2015: http://www.statista.com/statistics/322293/groupon-market-share-us/.

[2] Mobile usage was very limited for the daily deal industry during the data collection period for this study.

[3] Active users represent a platform's customer base better than subscribers because a subscriber may use an inactive email account to receive messages and not actively consider making any purchases.

[4] The Office of Management and Budget divides the United States into 388 MSAs.

[5] A small proportion of merchants in the original data transact with both platforms during the same month: approximately 2.3% for Groupon and 4.1% for LivingSocial. We remove these observations because the amount of such data does not permit a reliable analysis. After this step, our sample size becomes 185,032.

[6] The average sales per deal are rather small relative to the platform's user base. Hence, we consider it innocuous to assume that a consumer buys, at most, one deal per category per month per market.

[7] This assumption of deal substitution within a category is in line with Li et al. (2018).

[8] As a robustness analysis, alternative specifications for platforms' disagreement point are also examined: if the negotiation fails, the platform will fill the empty spot with another deal from the focal market, such as an average deal from the local market with sales lower than the focal deal. This corresponds to a typical backup deal that the platform can use from its supply repository. The results with the alternative specification are qualitatively similar. We thank the senior editor for recommending this robustness analysis.

[9] Customers who return and buy deals again would be captured by the bargaining process for the future deal (if any).

[10] See Online Appendix II for a detailed discussion. We thank the senior editor and the associate editor for suggesting this point.

[11] Two deals are considered "similar" if they fall into the same bucket according to discount depth (we split deals into 20 equal-sized buckets per category). Varying the number of groups yielded similar results.

[12] We thank the associate editor and two anonymous reviewers for suggesting some of these factors.

[13] To ensure parameter identification, we checked for robustness using various starting values.

[14] We thank an anonymous reviewer for suggesting this counterfactual analysis.

[15] We assume that merchants work with only one platform during a specific month, which is supported by the data (see Section 3.4.1 for details).

[16] One can think of a platform alliance as a buyer group that engages in joint bargaining or a merged firm that decides to operate on both platforms.

[17] This analysis is managerially relevant because Groupon acquired LivingSocial in 2016, but deals are still offered on the individual platforms.

[18] Note that, in the first counterfactual, deals are offered on only one platform.

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