Dynamic Platform Competition in a Two-Sided Market: Evidence from the Online Daily Deals Promotion Industry*

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Abstract

We empirically study a dynamic platform competition in the online daily deals promotion industry characterized by intense rivalry between two leading promotion sites, Groupon and LivingSocial, that broker between local merchants and local consumers. We find that, for a comparable deal, the incumbent Groupon enjoys a significant advantage in performance measured in the number of coupon sales, which appears largely attributable to its greater network size in the consumer side. Yet LivingSocial successfully enters and quickly increases penetration in this market. We find no evidence that LivingSocial offers consumers more favorable terms on their deals than Groupon. Instead, on the merchant side, we find that LivingSocial poach merchants from Groupon, aided by the publicly available information on individual merchants and deal performance. Poached deals generate greater and more predictable coupon sales than the deals developed internally. While information-based poaching provides a foothold for the entrant in overcoming the initial size disadvantage, over time it turns into a competition-intensifying channel, as Groupon reacts by the same poaching strategy. Our study shows how platforms compete dynamically in a two-sided market with open information structure, thereby complements prior theoretical developments for multi-sided markets.

Keywords: two-sided market, platform competition, online daily deals, merchant poaching

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1 Introduction

Platforms are, in their classical meaning, where trains and passengers meet each other to fulfill travels. In many of today's businesses, especially those mediated by information technologies, platforms are where multiple, interested parties meet each other to fulfill transactions. Examples of platform-mediated businesses abound: Internet search engines, auctioneers, credit cards, and dating services, to name only a few. Reflecting the growing importance of platforms in market competition, there have been significant theoretical developments in the study of multi-sided markets (Armstrong, 2006; Caillaud and Jullien, 2003; Hagiu, 2006; Hagiu and Jullien, 2011; Rochet and Tirole, 2003, 2006; Weyl, 2010). The main focus of these studies has been on the optimal pricing and payment structures that induce participation from both sides of the platform (Rochet and Tirole, 2006; Rysman, 2009).

Despite these theoretical progresses, however, there is a general paucity of empirical investigations that seek answers to "How do platforms compete dynamically in a multi-sided market and how does such competition affect their performance?"[1] This gap in the literature is not surprising, considering major challenges to any empirical study toward this direction. Researchers have found it difficult to obtain detailed data at transaction level for either group of agents. Furthermore, a majority of platforms (e.g., on-line auction sites, video games, search engines) compete in one aggregate market so that strategic responses between platforms can be analyzed only to a limited extent. Our empirical setting, the online daily deals promotion industry, has favorable industrial characteristics that help overcome these obstacles.

The availability of deal outcomes such as sold quantity is a significant advantage of our study because a key limitation of public data gathered from the Internet is lack of systemically organized information on sales quantities (Edelman, 2012). Moreover, unlike most two-sided markets, the daily deals industry involves *local* merchants to which *local* consumers pay physical visits to redeem the purchased coupons.[2] This implies that the eventual match between a consumer and a merchant is necessarily constrained by the local-level competitive environment. Since both platforms, particularly LivingSocial as a second mover in this industry, have exhibited staged entries into regional markets, the variation in the entry timing across different geographic markets allows

[1]In fact, Roson (2005) argued that, in terms of dynamic platform competition, even theoretical developments are in need, let alone empirical investigations thereof.

[2]Platforms typically compete in a single national market without involving local agents. Consider, for instance, the videogame console market (e.g., Zhu and Iansiti, 2012) and the television advertising and viewing market (Wilbur, 2008).

us to identify the strategic action-reaction by these platforms and analyze their impact on the relative performance over time and across regions.

Given this empirical context, we investigate how the two promotion sites compete dynamically in this two-sided market. We start by comparing between the performances of deals offered through these sites, as measured by the number of coupons sold in each deal after accounting for other likely determinants of sales. Theories on two-sided platforms would generally predict that the advantage accrues to the platform that commands a larger network size. Indeed, we find that the incumbent Groupon enjoys a considerable advantage in deal performance: on average, deals offered through Groupon sold 23% more coupons than the comparable deals offered through LivingSocial. Groupon's lead in the merchant-side performance appears largely attributable to its greater network size in the consumer side.

Despite this size advantage that accrues to the incumbent platform, this industry has witnessed a fairly significant catch-up by LivingSocial, a late entrant. In a two-sided market, an entrant could use a "divide and conquer" strategy (Jullien, 2011) by attacking either the consumer side or the merchant side to ignite positive feedback from the other side. We thus first examine if LivingSocial offers to potential buyers more favorable terms than those of Groupon for a similar deal. We find little difference in the deal terms in general, although there is some indication of inter-temporal variations presumably initiated by the incumbent response.

Given the lack of noticeable differences in deal terms, we turn to examine what strategic actions might take place on the merchant side. A distinct feature of this industry is that, for each deal, the identity of the deal-offering merchant and the deal outcomes are all available on the web. This information can thus provide a convenient, and extremely accurate, basis for building effective market intelligence in general. In particular, the promotion sites may use this information to solicit the merchants with prior deal experience; doing so would, all else equal, help the sites to lower the cost of developing the merchant side because these merchants have already revealed their preference for daily deals and are familiar with the business model. The promotion sites could go even further to identify and solicit the merchants that attracted greater demand in prior deals, thereby improving their overall performance. The information availability is likely to work especially in favor of the entrant who has to overcome the initial disadvantage in a relatively short period of time. Consistent with this insight, we find that, on average, about 20% of new LivingSocial deals come from merchants that have previously promoted through Groupon. The proportion of these "poached" deals increases over time, reaching 25% toward the end of our data period. We further find that these poached deals, on average, generate about 9% more coupon sales than the deals developed internally. Our quantile regressions indicate that this performance improvement through poaching comes from both the reduction in the left-tail of the sales distribution and the increase in the right-tail outcome. Thus, the availability of merchant-level information appears to facilitate entries and business development by late movers into this industry.

The entrant's strategic exploitation of the incumbent business, however, does not go unnoticed; Groupon responds to this by also poaching merchants from LivingSocial. Though, due to its larger size, the proportion of poached deals remains below 10% for most of the period, the speed by which Groupon picks up on poaching is noticeable: the proportion starts at less than 5% but reaches 15% by the end of our data period. For Groupon, the poached deals prove even more successful (i.e., 18% higher sales) than the internally developed deals, primarily helped by significant reductions in left-tail outcomes. This indicates that the information-based poaching, which provides a foothold for the entrant, becomes increasingly ineffective as an instrument for catching up with the incumbent and, in fact, turns into a competition-intensifying channel over time.

These findings suggest a fundamental dilemma embedded in the open information structure of Internet-based platforms. On the one hand, the provision of detailed deal information to the public helps alleviate consumers' concern about the quality of their choices while functioning as an effective marketing tool for attracting potential merchants. On the other hand, such public information facilitates entries and competitive chasing by rival platforms who can identify merchants with good track records and "poach" them away. The difficulty of retaining profitable agents exclusively to own turf may, at least partially, explain the recent financial struggles that plague this industry. More broadly, our study sheds a new light on how the information-enabled action-reactions between platforms would perpetuate into intense competition.

1.1 Related Literature

Our study complements and extends recent empirical studies on two-sided platforms. Rysman (2004) demonstrates the importance of network effects in the market for Yellow Pages directories. He finds that advertisers appreciate consumer usage and that consumers also value advertising, which suggests the existence of network effects. Zhu and Iansiti (2012) develop a formal model of entry in platform-based markets in which the relative strength of an entrant's indirect network effects is important to its success. They confirm this insight with data on Xbox's entry into the videogame industry. While our study also confirms the role of network size on platform performance, we focus on how *transaction-level* information affects the dynamic platform competition.

Our paper is closely related to Seamans and Zhu (2012) who investigate the entry effect of Craigslist, a popular website for classified advertisement services, on the U.S. local newspapers. They find that, upon Craigslist's entry, local newspapers with their own ads manager cut ads rates more sharply than those without such manager. Our study complements theirs in that we, too, examine the effects of a new platform's entry on competitive market outcomes. A critical difference is that, while in Seamans and Zhu the competition occurs between a new type of platform (i.e., an online ads site) and a traditional type of platform (i.e., local newspapers), in our set-up two online platforms with an almost identical business model compete in a head-to-head fashion.

Our study is also related to the literature of customer poaching and behavior-based price discrimination (Caminal and Matutes, 1990; Chen, 1997; Fudenberg and Tirole, 2000; Kim and Choi, 2010; Taylor 2003, 2004, etc.). The extant literature on behavior-based price discrimination has primarily focused on firms' strategic discriminations against different consumers depending on purchase history. In contrast, we study the information-based merchant poaching by the platforms that seek to attract more agents on the consumer side. Our paper provides a rationale for a value of merchant list, distinct from Taylor (2004) who theoretically examines the value of customer list that plays a basis for dynamic price discrimination. To the best of our knowledge, we are first to empirically study merchant poaching in a two-sided platform market.[3]

More narrowly, our study joins a series of recent works on the online daily deals market. Despite the fast diffusion of the business model, research on this experimental market remains scanty and has mostly relied on case studies or survey methods. For instance, Edelman, Jaffe, and Kominers (2011) offer a theoretical model in which price discrimination and advertising can improve merchant profitability. Gupta, Weaver, and Rood (2011) conduct a comprehensive case study of Groupon and the daily deals market, and Norton et al. (2012) provide a similar case study of LivingSocial. Dholakia (2011) presents a survey of over 300 merchants across five major daily deal sites including Groupon and LivingSocial. We improve upon these studies by exploiting the full data of daily deals from two leading promotion sites to provide systematic analyses of the effects of multi-level market competition on the terms and performances of these deals. By doing so, we seek to identify the sources of a platform's competitive advantages and thereby provide a dynamic view of the platform competition in a two-sided market such as this one.

[3]It should be noted that we define "poaching" more broadly as a case in which an entrant approaches a merchant who ran a promotion through an incumbent and thus platform switching occurs, regardless of any different treatment in contracts.

2 The Daily Deals Promotion Market

2.1 Two Market Leaders: Groupon and LivingSocial

Groupon is the current market leader with more than 11,000 employees as of June 2012. Only after three years of its first-ever deal, the 50%-discounted pizza coupon in Chicago, Groupon went public in November 2011, instantly raising $700 million that valued the company at close to $13 billion. The first mover's phenomenal success and the almost non-existent entry barriers prompted numerous followers who entered the market with similar services. By early 2011, there were more than 500 online sites that offered discounted daily deals in the U.S. (Norton et al., 2012). Among these, LivingSocial is considered as the only serious competitor of Groupon (Gupta et al., 2011) in terms of size and coverage of deal offers.[4]

LivingSocial sold its first discounted coupons in the U.S. in July 2009 for a restaurant in D.C.'s Chinatown. Since then, LivingSocial has rapidly expanded to reach 330 cities in North America (mostly in the U.S.) by August 2011. With a sequence of investments including Amazon's $175 million, LivingSocial was valued at more than $3 billion as of early April 2011, less than two years after its startup.

Figure 1 provides the geographic distributions of the two sites' business operation in the U.S. over time. The comparison between Panel (a) and Panel (c) illustrates Groupon's initial dominance, stemming from its first-mover status. The contrast between Panel (a) and Panel (b), and that between Panel (c) and Panel (d) show the rapid growth of both platforms that have penetrated numerous cities and states in less than two years. Lastly, Panel (b) and Panel (d) together illustrate the two platforms' head-to-head competition.

2.2 The Business Model

Despite some differences in origins, features and target consumers, promotion sites have several common cores in their business model. There are three parties involved in this market: consumer, promotion site, and merchant. A promotion site contacts a merchant (or, much less frequently, a merchant contacts a site) and presents the promotion proposal at specific terms including value, price, discount rate, expiration date, etc. Once both agree to the terms, the site informs their registered users ("subscribers") of the negotiated deal via email. Subscribers receive these offers

[4]There are some sizable players that specialize in certain types of deals, e.g., *Restaurant.com* (restaurants) and *TravelZoo.com* (travel). However, none of these rivals compete with Groupon in a way that LivingSocial does, particularly in terms of the geographic coverage and the variety of deal types.

on a daily basis, which they can also forward to their contacts through emails or social networking services. No consumer pays any usage or membership fees to the promotion site to receive deal information. There are even websites (called "aggregators") such as *Yipit.com* that specialize in aggregating and providing various daily deal promotions, free of charge. On receiving the deal offer, consumers make the purchase decision before the offer expires, typically within two days from the notification. Consumers who purchase the coupon are charged for the listed price in advance, unless the deal is nullified due to, for instance, insufficient demand. Some promotion sites such as Groupon set a minimum quantity called "tipping point," below which the deal is automatically revoked. Consumers then take the coupon to the offering merchant to redeem it for the product or service as specified in the promotion. Some coupons are reportedly left unclaimed even after the expiry, which is normally six months to one year from the issuance date (Gupta et al., 2011).

The promotion site earns a portion of the total revenue (= deal price × sold quantity), according to the pre-determined sharing rule. Dholakia (2011) reports that the merchant share ranges between 30% and 50%. The specific revenue sharing rule is unknown to the public and can vary across deals. However, a 50-50 rule seems to be the norm in this industry. Our own estimation of the split rule based on Groupon's IPO prospectus (SEC, 2011)[5] gives around 46% as the site's average share of the revenue. Figure 2 illustrates the flow of this business model.

2.3 Industry Characteristics

The daily deals promotion market has several distinctive features that provide an attractive context for our empirical investigation. First of all, this is a novel example of two-sided markets. Merchants value the number of subscribers, assuming a constant ratio of buyers to informed subscribers. Considering that consumers can feed the deal information to other potential buyers through various Internet channels, the value of adding one more registered user may increase more than linearly. Similarly, all else equal, consumers may prefer a site that offers a greater variety of deals.[6] Thus, promotion sites must develop many appealing deals in the merchant side to stay attractive to the consumer side. Groupon and LivingSocial as market leaders have stayed far ahead of other promotion sites in attracting merchants due to their size advantage in the consumer base, which in turn enabled them to appeal to a greater number of consumers.

Another notable feature is that market participants are exposed to uncertainty about their

[5] http://www.sec.gov/Archives/edgar/data/1490281/000104746911005613/a2203913zs-1.htm.

[6] Initially, Groupon maintained a single-deal-per-day rule in a given local market. Now it frequently offers multiple "daily" deals.

expected surplus from the transaction. Clearly, each party has an incentive for participation: the consumer gets a steep discount that is otherwise rarely obtained, the merchant advertises the business to a large, targeted audience without bearing any upfront cost, and the promotion site earns a decent cut of the revenue generated from the deal. However, these returns are in no way guaranteed. A merchant's eventual profit of running a promotion may well depend on various factors such as contracted sharing rule, costs of providing the promoted product or service, rate of consumer redemption, the number of coupons sold at the specified terms, composition among buyers between new and existing consumers, and "upside spending" at redemption.[7] Consequently, merchants running a promotion face uncertainty about ultimate profits. Dholakia (2011) reports that 26.6% of the surveyed merchants lost money in daily deal promotions and 17.9% just broke even.[8] Promotion sites are not immune to this uncertainty because the revenue of the sites are completely tied to the merchants' sales performance. Consumers also take risks by paying in advance for an advertised deal to grab the high discount rate. For instance, the consumer may find the restaurant too crowded with many other coupon users, which could ultimately ruin her dining experience. The consumer may also feel that the advertised value was set too high for the food and thus the "perceived" discount rate was in fact low. Since there are many of these factors that render the daily deal quite experimental, we suspect that the performance history such as popularity of the promotion site and the deal-offering merchant can play an important role in facilitating market transactions.

Fortunately, the sites in our dataset make public their deal performance such as the number of coupons sold, from which we can also compute the exact sales revenue from each deal. This fine-grained information is not available for most data that are scraped from the Internet (Edelman, 2012). In fact, most Internet-based businesses have little incentive to make their sales information publicly available. However, in the daily deals market, promotion sites publish the number of coupons sold, among others, for every deal. Doing so helps these sites to establish their credibility to potential consumers, thereby creating positive feedback from the consumer side, as well as to demonstrate the effectiveness of their promotion to potential merchants when developing deals.

We further notice that there is relatively little room for differentiation between promotion sites.

[7] For example, a customer redeeming a restaurant coupon may order drinks or desserts that are not covered by the coupon. Likewise, a dental patient redeeming a coupon for teeth whitening may opt for additional services if the dentist finds out some teeth problems and recommends a treatment.

[8] One may argue that the promotion aims at maximizing long-term profits rather than seeking profits in the current deal, as the advertising slogan goes: "sell at a discounted price and expect consumers to return for a full price." However, given the low predictability of various factors, the uncertainty about the deal performance appears to be a legitimate concern for the merchants.

The merchant exclusivity is rarely achieved as merchants can choose any site to offer their deals through. Establishing the consumer loyalty is also hard as consumers can multi-home and switch almost instantly at no cost. According to Dholakia (2011), 48% of the merchants indicated a willingness to repeat promotion but 73% of them considered a different daily deal site for their next trial. If this were true, the promotion sites might increasingly claim lower shares of revenue as the competition on the merchant side to attract deals gets intensified. The survey revealed another challenge for the promotion sites: the need to cultivate own loyal customers. In the survey, less than 20% of the daily deal buyers returned to the merchant later for a full-price purchase, indicating a fairly low customer loyalty formed through the daily deal promotion. Low differentiations between sites and generally weak loyalties from both sides of the market seem to be causing some industry observers to cast doubts on the market's overall prospect (e.g., Dholakia, 2011). In our data, we also observe frequent changes in the merchant-site matching. Moreover, because the two sites started business in different regions (i.e., Groupon in Chicago vs. LivingSocial in D.C.), the incumbent-entrant relationship also varies across geographic regions, which provide a variation that we can exploit to cross-check the estimated effect of an incumbent status.

3 Data

3.1 Data Sources

Our data came directly from the websites of Groupon and LivingSocial. We downloaded and parsed the entire population of deals that have been offered by these two promotion sites through the end of November 2011, beginning from the Groupon's first pizza deal in Chicago in November 2008. For each deal, we collect all available information such as product and service descriptions, terms of the offer, merchant information, and deal outcomes.

At the time of our data collection, both platforms provided a web-based interface in which a searcher could query with integer identifiers that these platforms had uniquely assigned to deals.[9] Using an automated web crawler written in Python, a computer programming language, we progressively scanned deals beginning from the integer one until no further query returned a result. Owing to this search method, we believe that our dataset is close to being exhaustive.

Each of the promoted deals contains detailed information about the deal such as the content

[9] The last access date to these sites was February 24, 2012, after which LivingSocial seems to have blocked the web-based lookup of past deals using the numeric identifiers.

(e.g., title, subtitle, tags (Groupon only), description of deal), terms of the offer (e.g., value, price, discount rate, start date (Groupon only), end date, expiration date, tipping point (Groupon only)), offering merchant (e.g., physical address, business name (Groupon only)) and others (e.g., sold quantity). Many of these information fields are common between the platforms, which enables the comparison of deal terms and performance across deals and between platforms. Figure 3 illustrates the sources of this information, annotated on typical deal promotions from these websites.

We augmented our dataset with several more variables that may reflect local socio-economic factors. From U.S. Census 2010, we used the county-level population, median household income and the proportion of population whose age ranges from 20 to 29. The inclusion of this particular age group and income was based on a survey by Accenture reporting that the primary consumers using daily deals are "young and affluent people."[10] In addition, to account for the possible impact of Internet accessibility on the demand for daily deals, we used the county-level high-speed Internet access data that the Federal Communications Commission publishes biannually since 2008. Each of these county-level variables was matched to individual deals according to the deal-offering merchant's physical address. Since the data were collected from two different sources, we went through a number of steps to ensure the comparability between the deals from each platform. Appendix A provides the details of the data integration process.

3.2 Sample

For the analysis, we constructed a sample from the raw data by the following procedure. We first excluded the deals that were offered outside the U.S. Since both platforms are operating globally, we chose only domestic deals to enhance comparability across deals. We also eliminated some obvious dummy deals that seemed to have been created for initial test purposes, such as those with negative prices or sold quantities.[11] Along with these dummies were dropped the deals that appeared to have obvious data errors such as zero quantity, zero or missing price and value, and discount rates outside the range of 0-100%. Together, these deals accounted for less than 2% of the observations.

We only included deals that were actually transacted. The Groupon data have a field that shows if a particular deal has been "tipped," which is to indicate if the deal coupons were sold more than the pre-set threshold (called the "tipping point"). Any deal that sells below this minimum purchase volume becomes void. About 7% of the Groupon deals were not tipped and hence were excluded.

[10]Wong, W. (2011, October 24) "Study finds daily deal websites limited to younger, more affluent users." *Chicago Tribune.*

[11]All of these dummy deals were clustered around the initial startup period of these platforms.

We further restricted the time window to the period from July 2009 to October 2011. July 2009 was the month that LivingSocial began to offer daily deals (Norton et al. 2012).[12] We ended the sample period at October 2011 to minimize potential truncation due to the timing of our data collection. Finally, we removed the deals that lacked information on merchant location. About 20% of the deals did not show the physical address of the merchant. Groupon had relatively more deals of this type (about 22% of its total deals) than LivingSocial (about 16%). These deals typically allow for redemption at any store and hence may confound the effect of local competition that we are interested in. Hence, we dropped these deals from the sample.[13]

The final sample used for our analysis had a total of 143,525 observations. Among these, 73% (104,764) were Groupon deals. Table 1 shows the breakdown of deals by platform and category. Overall, the *Arts & Entertainment* represented the largest category (22.4%). Other popular categories included *Beauty & Spas* (20.5%), *Restaurants* (20.0%), and *Health & Fitness* (15.4%). However, the two platforms seemed to differ somewhat in their focus of the deal portfolio: Groupon put a relatively greater emphasis on *Restaurants* while LivingSocial's portfolio was more heavily weighted towards *Arts & Entertainment*, *Beauty & Spas*, and *Health & Fitness*.

4 Empirical Strategy

We begin our empirical analysis by examining the determinants of platform performance. Given the two-sidedness of the deal promotions industry, we expect that the network size on the consumer side should significantly impact the performance on the merchant side in terms of coupon sales. We notice that, to effectively isolate the effect of network size, we should properly control for the performance variation arising from multi-level competition. That is because Groupon and LivingSocial not only compete on a national scale in terms of area coverage, advertisement, and strategic alliance formation, but they also involve local merchants and local consumers in their business transactions. Moreover, as both platforms have regional bases, each of which is responsible for the business development within the region, strategic decisions made at the regional level may also influence competitive outcomes. Hence, in the corresponding analysis we construct several variables measured at the national, regional and local levels to capture potential variations in deal performance across levels of competition between platforms.

[12] Despite this truncation, we included the entire period prior to July 2009 when constructing the variables that, by definition, traced back to the initial period such as entry timing and cumulative performance of platforms.

[13] Including these deals did not materially change the results reported in this paper.

We then move on to look at LivingSocial's strategy to overcome the initial disadvantage in network size. We first focus on the consumer side and analyze how LivingSocial compares with Groupon in deal terms such as discount rate, price and value, because these deal terms are most important for consumers' purchase decisions; all else equal, providing more attractive terms will help the entrant to win consumers. We are also interested in potential changes in Groupon's deal terms upon LivingSocial's entry, as a plausible indicator of incumbent reactions to entry threats. This is empirically feasible because the platforms enter multiple disaggregated local markets (i.e., divisions) at different points in time (i.e., year-month) with different product offerings (i.e., categories). For a meaningful comparison across different deals, we control for division-category-year-month-fixed effects in addition to local demographics and other deal characteristics.

Next we turn to the merchant side to examine the strategic actions taking place between the platforms, especially following the entries by LivingSocial into Groupon's territory. According to a survey on daily deals (Edison Research, 2012)[14], 69% of LivingSocial subscribers also use Groupon and 37% of Groupon users also subscribe to LivingSocial. By contrast, our data show that only 20.2% (8.4%) of merchants that have run a promotion with Groupon (LivingSocial) run another promotion with the other platform. Given the prevalent multihoming (i.e., subscribing to both sites) on the consumer side and the relatively lower frequency of multi-homing on the merchant side, the merchant side appears to be a "competitive bottleneck" (Armstrong, 2006) in this industry. Hence, the search for attractive new merchants becomes a critical part of the platforms' competitive strategies.

A distinctive characteristic of our setting is that the information on the merchant identity and their sales performance in a particular deal is publicly available. The availability of this detailed information allows the promotion sites to identify the merchants that have previously used a rival site to promote daily deals and use that information for developing new deals and thereby improving their overall performance. Thus, we investigate the changes in the platform-merchant combination that are likely induced by the platforms' use of past transaction information to poach merchants from the rival site. We also examine the performance implication of such tactic by comparing coupon sales between the deals from merchants that are developed internally and those from merchants that are poached. We expect this analysis to provide a new and general insight on the competitive dynamics in the flourishing Internet-based platforms that involve local agents with open information structures.

[14]http://www.edisonresearch.com/wp-content/uploads/2012/04/Edison-Research-Daily-Deals-Report-2012.

5 Determinants of Deal Performance

In this section we examine the determinants of deal performance, focusing on the effect of network size. Notice that, because platform revenues are a fixed percentage of merchant revenues, examining the merchant performance in a deal is equivalent to analyzing the platform performance. For a meaningful comparison of deal performance, we defined the variables as follows.

5.1 Construction of Variables

Deal Performance We used the sold quantity, q_i, to capture the sales performance of a deal i. One could alternatively use the gross revenue but, since revenue is equal to deal price times sold quantity, regressions of log-transformed revenue with a control of logged price produce almost identical coefficient estimates on the regressors but that of price. Hence, we keep the sold quantity for our primary performance measure.

Measures of Competition We defined measures of competition at three different levels: local market, geographic division and national market. Note that deal i contains a number of different characteristics such as geographic division (d_i), deal category (c_i), deal date (t_i), mediating platform (w_i), and merchant location (l_i).

Our definition of the local market is a time-varying space that covers m months prior to the focal deal i, $0 < t_i - t_j \leq m$, within r miles of radius surrounding the focal merchant, $\|l_j - l_i\| \leq r$. Thus, the local market reflects the dynamic nature of competition among merchants and between platforms without being tied to a particular geographic boundary. We then defined *Local Density* (LD_i) as the total counts of daily deals offered by either of the platforms in the same deal category as that of deal i. This variable thus measures the "crowdedness" of the local market in the vicinity of deal i during the most recent period. Figure 4 illustrates how our definition of local market matches with the contour of the map of deals in the case of New York City. We used $m = 3$ and $r = 3$ for our main specification.[15]

At the division level, we defined *Competitive Intensity* (CI_i) as the difference between the (log) number of deals of all categories offered by LivingSocial and the (log) number of deals of all categories offered by Groupon. This variable thus measures the closeness of the entrant's deal-

[15] A more narrowly defined local market reduces an overlap with that of the geographic division, but contains fewer deals and tends to produce many zero values for *Local Density*. We experimented with alternative definitions of the local market by varying the time window (e.g., 1 month, 3 months, and all preceding months) and the radius (e.g., 3 miles, 5 miles and 10 miles). The results were robust to these variations.

offering capacity to that of the incumbent. Note that CI_i covers all historical deals offered in a division so as to capture "cumulative" competitive outcomes in a given region. Because LivingSocial generally offered fewer deals, CI_i took a negative value for more than 95% of the observations.

At the national level, we used *Groupon Deal* dummy as the indicator of deals offered by Groupon. Given that our sample covers the entire U.S. regions in which both platforms operate, this variable is expected to capture the incumbent advantage over the entrant in the performance of individual merchant deals. This is obviously a crude measure as it only dichotomizes between platforms and hence fails to capture possible effects due to, for instance, changes in the relative size of consumer network over time. Hence, we also defined *Relative Platform Reputation* (RPR_i), a more sophisticated measure of incumbent advantage in the national market, as the difference between Groupon and LivingSocial in the total number of coupon sales cumulated up to $t_i - 1$ where t_i indicates the year-month of deal i.[16] This variable is thus a continuous and time-varying proxy of the size-based advantage of incumbent in the national market.[17]

Other Variables We also included a number of potential covariates of deal performance. *Prior Performance*, measured by the gross revenue from the immediate prior deal of the focal merchant, controls for cross-merchant differences in quality (e.g., popularity, convenience, attractiveness of deal terms). Note that, by construction, this variable is defined only for the merchants that offer more than one daily deals during the sample period. For the merchants that offer a deal for the first time, we assigned zero to this measure. To isolate the effect of this treatment, we separately included *First Deal*, a dummy indicating the deals offered for the first time by the same merchant. *Distance to Division Centroid* measures the geographic distance (in miles) between the deal-offering merchant and the division centroid which is the geo-center of the division as indicated by Groupon (Groupon, Application Programming Interface). This variable controls for differences in other demand-side characteristics associated with merchant locations. *Price* controls for the effect of this important deal term on the demand for deal i. *20's Ratio* represents the proportion of people whose age is between 20 and 29 in the corresponding county. *Median Household Income* measures the average purchasing power of people living in a county. Lastly, *High-Speed Internet Access*,

[16] We also tried total dollar amount instead of sold quantity. Results were very similar.

[17] To more precisely measure the relative size of consumers, we would ideally like to count the number of "subscribers" who regularly receive deal offers from each platform at each point in time during the study period. However, such data are not available. Instead, we used the "realized" demand for the deals to proxy for the size of the consumers who are affiliated with the platform. To the extent that the consumer's propensity of purchasing a deal given the deal offer is comparable between two platforms, the actual number of coupon sales should be proportional to the size of the consumers affiliated with each platform.

coded as one of zero to six, captures Internet accessibility in the region.[18] Appendix B presents the descriptive statistics of the variables in our data.

5.2 Estimation

We assume that the deal performance is a linear function of the national-, regional-, and local-level competition measures, in addition to deal terms and local demographics. We interacted the measures of competition with *Groupon Deal* dummy to identify potential incumbent advantages at each level of competition. We additionally controlled for temporal effects by including dummies for calendar year and month as well as for location-deal category-fixed effects by including division-category dummies. We used the ordinary least squares (OLS) for estimation. To reduce the problem of heteroskedasticity, we logged all skewed variables and used robust standard errors, clustered by division-category. The regression equation is given by

$$\log(q_{idcym}) = \alpha + \beta_0 \cdot Groupon_i + (\beta_1 + \beta_2 \cdot Groupon_i) \times RPR_i + \boldsymbol{X}_{idcym}\boldsymbol{\gamma} + \delta_{dc} + \tau_y + \tau_m + u_{idcym} \quad (1)$$

where q_{idcym} is the sold quantity of deal i in division d, category c, calendar year y and month m; $\mathbf{X}$ is the matrix of competition measures such as CI and LD including demographic variables, first deal dummy, deal terms (price, discount rate), prior performance, and distance to division centroid; δ_{dc}, τ_y, and τ_m are respective fixed-effect terms for division-category, year and month; and u_{idcym} is an error term. Note that, for this estimation, we separately control for calendar year and month because RPR_i is defined at the national level and hence is perfectly correlated with year-month fixed effects.

5.3 Results

Table 2 presents the results on the determinants of deal performance. Column 1 shows that, for a comparable deal, promotions through Groupon on average leads to 23.1% more coupon sales than those through LivingSocial, as indicated by the significantly positive coefficient on the *Groupon Deal* dummy. Thus it appears that the incumbent platform enjoys a considerable advantage over the entrant in terms of the national market-level demand. This performance premium is less likely

[18]The measure counts the number of residential fixed connections faster than at least 768 kilobits per second (kbps) downward and 200 kbps upward. The original data are coded, based on the percentage, for each county into one of six categories including zero: less than 20% is coded as 1, 20% to 40$ as 2, 40% to 60% as 3, 60% to 80% as 4, and above 80% as 5.

to be due to selection (i.e., high quality merchants choose to place their deals with the incumbent) because we explicitly controlled for the prior merchant performance, which was a positive predictor of the current deal performance. Note also that we included local demographic variables to control for socio-economic factors that might influence entry decision and deal performance.

Column 2 additionally included *Relative Platform Reputation*, our proxy for the relative size between the platforms in the national market, along with its interaction with the *Groupon Deal* dummy. With the inclusion of this variable, the coefficient on *Groupon Deal* lost significance. We have just interpreted the positive coefficient on the *Groupon Deal* dummy as evidence of an overall incumbent advantage. In two-sided markets such as this one, the incumbent platform typically enjoys a greater positive feedback effect due to the larger network size in the consumer side. Reflecting this correlation, including a more fine-grained measure of the incumbent advantage in size completely absorbed the effect previously born by the incumbent dummy variable. Estimates on other variables remained nearly unchanged.

This incumbent advantage, however, was reduced by the entrant's penetration into regional markets: a higher competitive intensity at the division level boosted the performance of LivingSocial deals relative to that of Groupon deals. A greater local density also undermined the industry-wide incumbent advantage: all else equal, Groupon deals performed worse than LivingSocial deals in local areas where deals of the same category had been more densely offered.[19]

Coefficients on demographic variables were generally consistent with intuition: population, income, and the proportion of 20's in population were all positively related to sold quantity, though high-speed Internet accessibility was insignificant. First-time deals performed significantly better than subsequent deals on sold quantity. Consistent with the *law of demand*, a higher price led to lower sales. Merchants that were farther from the division centroid seemed to exhibit location disadvantage.

6 Competition on the Consumer Side

The previous section's result demonstrates the size advantage that accrues to the incumbent platform and hence a disadvantage for late entrants. However, as Figure 5 shows, LivingSocial was able to capture a fast-increasing share of the market since its entry. Though having begun as a small marginal player, LivingSocial quickly grew in size and, by the end of our data period, claimed over

[19]Since Groupon deals are, on average, more frequently offered in any given local market, this could reflect intra-platform competition in Groupon deals.

a third of the combined sales of the two platforms. Then, how did LivingSocial, a late entrant, mitigate the initial disadvantage? Given the two-sidedness of the industry, there are two ways that an entrant can quickly build up its business and thereby overcome the initial disadvantage. That is, the entrant could either attack the consumer side by offering more favorable terms for a similar deal, thereby triggering positive feedback on the side of merchants who are attracted by a large consumer network. Or, the entrant could try developing many attractive deals from the merchant side in order to attract consumers who actively search for such deals.

6.1 Comparison of Deal Terms

Based on this logic, we first examined the actions on the consumer side by comparing the terms of deals offered by the two platforms. Three deal terms, among others, collectively influence a consumer's purchase decision: value, discount rate, and price where the relationship is governed by $price = value \cdot (1 - discount\ rate)$. Each deal is unique in its own way. Also, platforms exhibit different deal mixes in terms of geographic regions, product category and timing. Thus, to ensure a fair comparison, we controlled for division-category-year-month-fixed effects. As a result, we estimated the following equation:

$$\varphi_{idcym} = \alpha + \beta \cdot Groupon_i + \delta_{dcym} + v_{idcym} \tag{2}$$

where φ_{idcym} is one of three deal terms, $\varphi \in \{discount\ rate, value, price\}$, offered for deal i in division d, category c, calendar year y, and month m; Groupon dummy takes on value one for a deal offered by Groupon and zero otherwise; δ_{dcym} denotes the full set of division-category-year-month dummies; v_{idcym} is an error term. Hence, the baseline group consists of the deals offered through LivingSocial in the same division, category, year and month as those through Groupon. Note that here we did not take logarithm of the deal terms in order to facilitate the interpretation of coefficients. To avoid possible bias due to extreme values, we excluded outliers (i.e., top 1% in each deal term) from estimation.[20]

6.2 Results

Table 3 shows the comparison of deal terms. Coefficients on the constant terms indicate that, on average, LivingSocial offered a 55.8% discount on deals with a value of $95.2, selling them for a price

[20] The criteria for the outliers were either over $1,000 in value, or over 90% in discount rate, or over $200 in price.

of \$34.3 to consumers.[21] This steep discount is one of the salient features of daily deal promotions. Surprisingly, however, Groupon generally offered slightly greater discounts on deals offered in the same region, category and month as those of LivingSocial. Groupon deals were also of somewhat higher value. But the differences in discount rate (0.44%p) and value (\$2.2), albeit statistically significant, did not appear economically meaningful. As a result, consumers of both platforms ended up paying virtually the same price for a comparable deal. Hence, we found no evidence that the entrant was able to turn on the charm on the consumer side through more favorable deal terms. If at all, it was the incumbent, not the entrant, that seems to have tried grabbing consumer attention, at least by offering more valuable deals at a greater discount, even though marginally.

Could it be that these differences in deal terms were a result of Groupon's strategic response to LivingSocial's entry? To examine this possibility, we performed the deal comparison on two separate time windows: (i) deals offered within the first 12 months of LivingSocial's entry into a division, and (ii) those offered after one year and beyond of the entry. Table 4 clearly demonstrates that the differences in deal terms almost entirely came from the initial 12 months following LivingSocial's entry. During the first year of the entry, the incumbent Groupon offered a significantly greater discount (0.71%p) on deals of higher value (\$3.85) than the entrant LivingSocial did for competing deals. These differences, however, disappeared after more than a year since the entry. In neither of the time windows was there a price differential between platforms. The sharp inter-period contrast in deal terms suggests that, upon LivingSocial's entry, Groupon has systemically responded by increasing discount rates and deal values while keeping the consumer price unchanged.[22] Most likely, such deal design reflects the incumbent's strategic action to make its deals look more appealing to the consumers who can now access highly substitutable deal promotions in the local market. However, this strategy seems to have been imitated fairly quickly by the entrant. The erosion of the gap in the second period was not because Groupon reverted to its previous deal term structure but because LivingSocial matched Groupon deals by increasing discounts (0.7%p) and values (\$13) of its own deals. This strategic action-reaction between the platforms led to a gradual convergence in deal terms over time. The average coupon price increased by about \$3.5 between the periods, but the increment was considerably smaller than the increase in the average deal value. As a consequence, consumers were able to purchase more valuable goods and services at relatively lower prices as the competition between the platforms intensified. Clearly, the duopoly competition initiated by

[21] Deals of higher value often come with greater discounts but the relationship is not generally linear. Thus, the formula of $price = value \cdot (1 - discount\ rate)$ may not hold on the averages.

[22] Changing the time cutoff to six months produced qualitatively equivalent results.

LivingSocial's entry has benefited consumers. Any advantages attained through favorable deal terms seem relatively short-lived as imitative reactions of the rival platform quickly erode such advantages.

To check the robustness of this result, we further controlled for other variables might also affect deal terms. These variables are the ones used in the previous section's performance analysis. The results, summarized in Tables 5 and 6, generally confirm the basic findings. On average, Groupon offered marginally higher discounts than LivingSocial, while deals of both platforms had similar value and price. But even this difference in deal terms disappeared as entry effects phased out over time, leaving absolutely no difference in deal terms between the platforms after one year of LivingSocial's entry.

Looking at the effects of competition on deal terms (Table 5), platforms offered greater discounts where local deals were more densely offered. Deals offered for the first time appeared more lucrative as they commanded a significantly lower discount rate and a much higher value or price than subsequent deals by the same merchant did. Merchants with a good track record generally commanded higher prices and lower discounts on their deals. A longer distance from the division centroid was associated with a slightly higher discount rate and a higher value or price. Among the demographics, both population and household income were positively associated with discount rates, but other variables had no effect on deal terms. Interestingly, prices were significantly lower in areas with greater population and higher income, suggesting that platforms may compete more fiercely in local markets with greater demand.

7 Competition on the Merchant Side: Information-Based Merchant Poaching

The previous section's result indicates that LivingSocial's increased penetration in this market is unlikely to have come through more aggressive deal terms on the consumer side. Thus, we turn to the merchant side to examine possible strategic actions that the entrant used to ignite positive feedback thereby overcoming the initial disadvantage in network size. In fact, the prevalent multi-homing by consumers, coupled with the rapid convergence in deal terms over time, is likely to render the merchant side to become a competitive bottleneck. It thus becomes critical for the promotion sites to continually search for new merchants and offer novel deals in order to remain competitive. Recall that the open information structure in this industry allows the sites to identify the merchants with prior deal experience and obtain detailed information on individual deals. This information availability can be particularly helpful for new entrants who lack experience in deal development in a local market. Given the situation, the entrant might find it profitable to approach the merchants who already had a business relationship with the incumbent. In at least three ways, utilizing such information will help the entrant to build its business relatively quickly and/or improve over performance. First, it reduces the cost of searching for merchants who might be interested in offering daily deals because these merchants have already revealed a preference for this novel online marketing channel. Second, the learning that took place in prior deals also helps minimize the cost of executing the deals. Third, past performance in deals by these merchants provides a reasonable reference point and hence reduces uncertainty about the expected outcome of a deal.

7.1 The Use of Merchant Poaching as Entry Strategy

Given these benefits, developing deals from the merchant that had prior experience with the incumbent (i.e., "merchant poaching" in our definition) may appear to be a dominant option for the entrant as opposed to developing new merchants on their own. However, switching to another platform may incur some cost to the merchant as it may have to negotiate with a new salesperson and perhaps learn new rules. To ease the switching, the poaching platform may offer the merchant a more attractive revenue-sharing formula. Such private contracts, of course, are not available to outsiders such as us. We can only conjecture that the entrant makes a trade-off between developing new merchants on their own at some marketing cost and soliciting the incumbent platform's merchant with some concessions on the revenue split. Our data show that they mix these two. On average, 20.2% of LivingSocial's new deals were with the merchants that had run at least one prior promotion through Groupon. The proportion of these poached deals among the new LivingSocial deals continued to increase over time, reaching over 25% by the end of our data period, which is about a 10%p increase in the initial stage of entry (Figure 6). Thus it appears that LivingSocial aggressively took advantage of the available information on the merchant side to overcome initial disadvantages for late entrants and thereby quickly build up business.

7.2 Performance Implication of Merchant Poaching for the Entrant Platform

How, then, do these poached deals contribute to the performance of the entrant? Recall that poaching can help improve the entrant performance at least by lowering the cost of merchant development or by reducing the variance in deal outcomes. Although we do not observe the cost of merchant development, we have data that allow us to examine the outcome variation across deals. In particular, we can measure the effect of poaching on the entrant performance by directly comparing the outcomes of poached deals with those of deals developed internally. For a meaningful comparison between heterogeneous deals, we used the residuals recovered from the performance equation in Section 5. That is, we constructed the residuals in the following manner:

$$\widehat{u^k}_{idctm} = \log(q^k_{idctm}) - \widehat{\log(q^k_{idctm})} \tag{3}$$

where the superscript $k \in \{\text{poached}, \text{own}\}$. By this construction, $\widehat{u^k}$ for a deal can only differ in the way it was developed, i.e., poached from Groupon ("poached") versus developed internally ("own"). With this transformed measure of performance, we first examined the performance distribution between deal types.

Panel (a) in Figure 7 illustrates the kernel densities of $\widehat{u^k}$ for LivingSocial deals. The solid line represents 'poached' deals and the dotted line 'own' deals. Two observations stand out. First, there is little difference in the median outcome between poached deals and own-developed deals. Second, poached deals have a fatter right-tail and a thinner left-tail than own deals, through these are partially offset by the lower density in the middle-right part of the outcome distribution. Clearly, through selective poaching based on prior deal information, LivingSocial was able to screen out in advance poorly performing merchants while improving the chance of outperforming deals among its offering. This pattern of performance contrast seemed to have remained steady throughout the post-entry period; as shown in panels (b) and (c), the kernel densities of both deal types were quite similar between the two time periods (i.e., within 12 months of the entry vs. after 12 months of the entry).

A set of statistical analyses confirms these patterns. Table 7 shows the result of two-sample t-test (with equal variances) of $\widehat{u^k}$ between poached deals and own deals for LivingSocial. The test strongly rejected the null hypothesis of equal means between the two groups (t-stat = -5.45, p-value = 0.000), indicating that, on average, poached deals sold significantly greater numbers of coupons than internally-developed deals did. Clearly, poached deals seem to have boosted the overall performance of LivingSocial as it strove to increase penetration. Quantile regressions, reported in Table 8, show that the performance improvement primarily came from the curtailment of poor outcomes (at or below 25% in the distribution) as well as a sharp increase in the right-tail outcome (over 95%). Inter-quantile regressions suggest that poached deals were also more predictable in performance, which unconditionally reduced the overall variance in outcomes of LivingSocial deals.

7.3 Incumbent Response to Merchant Poaching

If merchant poaching was so frequently used by the entrant and doing so significantly helped it increase penetration and improve overall performance, such strategy would likely trigger an incumbent response. We already saw in the previous section that, facing LivingSocial's entry, Groupon aggressively responded with greater discounts and higher value deals, at least during the first year of the entry. We observe similar incumbent reactions to the entrant poaching. As seen in Figure 6, Groupon has quickly increased the frequency of poached deals among new deals it offered in the regional market that experienced LivingSocial entry. The proportion of poaching stayed around 7-8% during the first year of the entry but continued to increase up to 15% by two years after the entry. The mean proportion (8.4%), however, remained lower than that of LivingSocial, largely because Groupon offered many more deals during the period.

Interestingly, merchant poaching turned out to be relatively more profitable for the incumbent. The kernel densities of $\widehat{u^k}$ for Groupon deals, depicted in Panel (a) of Figure 8, show a statistical dominance of poached deals over own-developed deals for most of the left-side of the performance distribution. That is, the deals poached from LivingSocial were much less likely to generate a below-median sales performance among Groupon's new deals. Moreover, the distribution had a fat right-tail, suggesting that some of the poached deals delivered outstanding performance. This pattern held consistently throughout the period since LivingSocial entry, as illustrated in Panels (b) and (c) of Figure 8. On average, poached deals generated 18% greater coupon sales for Groupon than the internally developed deals did, and this difference was statistically significant (Table 9). Our quantile regressions, presented in Table 10, suggest that this performance improvement through poached deals came from a general upward shift in the outcome distribution, except at the points around 75 percentile. As in the case of LivingSocial, merchant poaching helped Groupon as well to significantly reduce the variance in performance, as indicated by the inter-quantile regressions (Table 10). The availability of merchant and deal information allowed the incumbent to curtail the uncertainty of deal outcome by selectively soliciting merchants from the entrant platform.

8 Concluding Remarks

The last decade has witnessed many insightful scholarly works that shed light on the platform competition in two-sided markets with direct and/or indirect network effects. The focus of these works has generally been on the optimal price structures and competitive outcomes. Nonetheless, we recognize a general dearth of empirical studies that address intriguing questions on these markets: How do platforms compete dynamically? In particular, how does a new platform overcome initial disadvantages associated with a smaller network size in either side of the platform? How does an incumbent platform respond to the challenges by the entrant? Addressing these questions, we believe, is an important step toward a better understanding of the two-sided platform competition, especially from the dynamic standpoint. Our study is an attempt to fill this void in the literature.

We notice that the fast-growing deal-of-the-day market provides an ideal environment for our empirical investigation. Not only has the market been characterized by a stable, *de facto* duopoly between Groupon and LivingSocial that compete head-to-head in numerous regional markets in the U.S., but it also provides detailed transaction-level data with objective outcome measures such as the number of coupons sold and sales revenue per deal. Thus, we construct a comprehensive dataset from their websites and study the dynamic competition between the two promotion sites on the sides of consumers and merchants.

We find that, on average, the incumbent Groupon enjoys a significant advantage in deal performance over the rival platform LivingSocial. We further find that this incumbent advantage is primarily attributable to the greater network size on the consumer side. On the consumer side, however, we do not find the evidence of aggressive actions by LivingSocial, the most successful entrant to this industry; both platforms offer similar deal terms to the consumers, though there is some evidence that Groupon responds with more favorable terms, at least in early stages of the entry. More salient, and perhaps more interesting, strategic actions seem to be occurring on the side of merchant in the form of merchant poaching. Since its entry, LivingSocial actively solicits merchants that previously promoted through Groupon, thereby quickly increasing penetration into the regional markets. These poached deals also positively contribute to the overall performance through higher coupon sales and lower variability in sales. Groupon, however, follows suit to counter the entrant threat, while improving its own performance through poached deals.

The open information structure in this Internet-based industry allows the promotion sites to identify the merchants with prior deal experience and obtain detailed information on individual deals. This is particularly helpful for new entrants as it reduces the costs associated with searching, negotiating and contracting with merchants and the uncertainty surrounding deal performance. Clearly, this open information structure facilitates entries of new platforms into this industry, which then generally increases consumer welfare by making a greater variety of deals at more favorable terms. At the same time, the open information structure, coupled with the already low switching cost for the merchants, seems to make it harder for the platforms to build merchant loyalty. Thus, the information availability turns into a competition-intensifying channel over time, particularly as the incumbent fights back with an increased poaching of the new merchants that the entrant manages to develop at their own cost.

The phenomenal advances in the information technology have dramatically reduced the cost of matching between different groups or agents. As a result, we observe a burgeoning of various web-based intermediary platforms that link between online and offline economic activities. We believe that our study will play a guiding role for future studies on these platform-mediated markets. Consider, for instance, the online vacation rental market. A number of websites (e.g., *Airbnb.com*, *VRBO.com*, and *Vacationrentals.com*) connect between homeowners who seek to rent out their places and travelers who look for short-term stays in lieu of hotels. This market exhibits most of the characteristics found in the daily deals market such as the heavy reliance on information technology, the critical involvement of local agents, low entry barriers, and considerable uncertainty associated with transactions. Intermediating platforms have strong incentives to publicize their transaction records to attract agents from both sides as the market is still deemed experimental and the transactional uncertainty that agents face is relatively high. Given the similarity in market conditions, we surmise that most of our findings on platform competition may easily apply to this emerging two-sided market. More generally, we hope that our study will encourage further fruitful research on the dynamic platform competition.

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Tables

Table 1: Deals by Platform and Category

Category	Groupon	Share	LivingSocial	Share	Total (G+L)	Share
Arts and Entertainment	22,103	21.1%	9,969	25.7%	32,072	22.4%
Automotive	2,707	2.6%	751	1.9%	3,458	2.4%
Beauty & Spas	20,672	19.7%	8,771	22.6%	29,443	20.5%
Education	4,029	3.9%	1,711	4.4%	5,740	4.0%
Food & Drink	4,102	3.9%	1,971	5.1%	6,073	4.2%
Health & Fitness	14,735	14.1%	7,432	19.2%	22,167	15.4%
Home Services	215	0.2%	146	0.4%	361	0.3%
Nightlife	359	0.3%	601	1.6%	960	0.7%
Pets	288	0.3%	110	0.3%	398	0.3%
Professional Services	1,576	1.5%	702	1.8%	2,278	1.6%
Restaurants	24,023	22.9%	4,668	12.0%	28,691	20.0%
Shopping	7,892	7.5%	1,815	4.7%	9,707	6.8%
Travel	2,063	2.0%	114	0.3%	2,177	1.5%
Total	104,764	100.0%	38,761	100.0%	143,525	100.0%

Table 2: Determinants of Deal Performance

	1 (Log) Sold quantity	2 (Log) Sold quantity
(Dummy) Groupon deal	0.231**	0.029
	(0.030)	(0.040)
Relative platform reputation		-0.153**
		(0.020)
Groupon dummy × Relative platform reputation		0.132**
		(0.018)
Competitive intensity	0.070**	0.054**
	(0.012)	(0.012)
Groupon dummy × Competitive intensity	-0.097**	-0.074**
	(0.014)	(0.014)
Local density	0.080**	0.079**
	(0.011)	(0.012)
Groupon dummy × Local density	-0.256**	-0.253**
	(0.018)	(0.018)
(Log) County population	0.082**	0.079**
	(0.013)	(0.013)
(Log) Median household income	0.443**	0.453**
	(0.084)	(0.084)
Ratio of household with highspeed Internet	-0.042†	-0.046*
	(0.022)	(0.022)
Ratio of 20's population	0.028**	0.029**
	(0.005)	(0.005)
(Dummy) First deal	2.028**	2.021**
	(0.093)	(0.093)
(Log) Price	-0.361**	-0.359**
	(0.013)	(0.013)
Discount rate	0.001	0.001
	(0.001)	(0.001)
(Log) Prior performance	0.251**	0.251**
	(0.010)	(0.010)
(Log) Distance to division centroid	-0.076**	-0.078**
	(0.008)	(0.008)
Constant	-2.414*	-1.962*
	(0.947)	(0.955)
N	143,210	143,210
F-stat	166.70	161.81
Adj. R^2	0.319	0.320

Note: Division-category, year and month fixed effects are included in all models. Robust standard errors, clustered by division-category, are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

Table 3: Comparison of deal terms between platforms

	Discount rate	Value	Price
Groupon	0.436**	2.160*	-0.047
	(0.077)	(0.895)	(0.244)
Constant	55.787**	95.199**	34.337**
	(0.056)	(0.653)	(0.177)
N	142,121	142,173	142,140
Adj. R^2	0.265	0.230	0.272

Note: Division-category-year-month fixed effects are included in all models. Robust standard errors clustered by division-category are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

Table 4: Comparison of deal terms over time since entry

	Discount rate		Value		Price	
	(Within 1 year)	(After 1 year)	(Within)	(After)	(Within)	(After)
Groupon	0.707**	0.175	3.854**	0.511	0.069	-0.160
	(0.099)	(0.114)	(1.225)	(1.276)	(0.336)	(0.345)
Constant	55.479**	56.178**	90.274**	103.198**	33.018**	36.558**
	(0.071)	(0.081)	(0.877)	(0.903)	(0.240)	(0.244)
N	70,784	62,869	71,042	62,626	70,997	62,640
Adj. R^2	0.280	0.250	0.253	0.215	0.287	0.262

Note: Division-category-year-month fixed effects are included in all models. Robust standard errors, clustered by division-category, are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

Table 5: Comparison of deal terms between platforms

	Discount rate	Value	Price
(Dummy) Groupon deal	0.293**	0.807	-0.384
	(0.105)	(0.976)	(0.300)
Relative platform reputation	-0.109	0.575	0.550†
	(0.098)	(0.738)	(0.287)
Competitive intensity	0.034	-0.117	-0.062
	(0.038)	(0.406)	(0.123)
Local density	0.683**	2.234**	0.100
	(0.067)	(0.836)	(0.218)
(Log) County population	0.513**	-0.283	-1.455**
	(0.084)	(1.042)	(0.328)
(Log) Median household income	1.052*	-9.606†	-3.649*
	(0.431)	(5.790)	(1.819)
Ratio of household with highspeed Internet	0.063	0.714	0.049
	(0.117)	(1.495)	(0.426)
Ratio of 20's population	-0.047†	-0.370	-0.074
	(0.025)	(0.314)	(0.102)
(Dummy) First deal	-3.492**	8.040*	5.441**
	(0.394)	(3.902)	(0.929)
(Log) Prior performance	-0.359**	2.091**	0.996**
	(0.047)	(0.461)	(0.108)
(Log) Distance to division centroid	0.316**	3.583**	0.691**
	(0.050)	(0.578)	(0.166)
Constant	41.538**	175.045*	81.598**
	(4.741)	(68.666)	(21.541)
N	141,806	141,861	141,835
F-stat	16.21	10.87	17.85
Adj. R^2	0.248	0.239	0.269

Note: Division-category, year and month fixed effects are included in all models. Robust standard errors, clustered by division-category, are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

Table 6: Comparison of deal terms within and after 1 year of entry

	1 Discount rate (Within 1 year)	2 Discount rate (After 1 year)	3 Value (Within 1 year)	4 Value (After 1 year)	5 Price (Within 1 year)	6 Price (After 1 year)
(Dummy) Groupon deal	0.535**	-0.027	2.254†	0.449	-0.362	-0.075
	(0.097)	(0.176)	(1.208)	(1.427)	(0.362)	(0.404)
Relative platform reputation	0.094	-0.019	-0.422	-8.822**	0.226	-2.417**
	(0.080)	(0.261)	(0.831)	(2.955)	(0.268)	(0.792)
Competitive intensity	0.071	0.262*	0.247	-0.786	0.137	-0.650†
	(0.048)	(0.104)	(0.530)	(1.240)	(0.158)	(0.389)
Local density	0.707**	0.672**	1.051	2.486**	-0.322	0.178
	(0.081)	(0.097)	(1.303)	(0.916)	(0.275)	(0.269)
(Log) County population	0.573**	0.459**	-1.009	0.680	-1.900**	-0.935*
	(0.104)	(0.109)	(1.130)	(1.504)	(0.368)	(0.435)
(Log) Median household income	1.802**	0.244	-18.323*	-2.920	-7.939**	-0.563
	(0.568)	(0.575)	(7.651)	(7.383)	(2.215)	(2.437)
Ratio of household with highspeed Internet	-0.090	0.295†	0.132	2.596	0.271	0.325
	(0.181)	(0.160)	(2.365)	(2.108)	(0.628)	(0.617)
Ratio of 20's population	-0.016	-0.058	-0.295	-0.422	-0.112	-0.073
	(0.024)	(0.036)	(0.342)	(0.401)	(0.104)	(0.134)
(Dummy) First deal	-4.231**	-2.741**	2.525	13.288**	5.273**	5.982**
	(0.524)	(0.474)	(6.553)	(3.315)	(1.345)	(0.982)
(Log) Prior performance	-0.485**	-0.239**	1.328†	2.747**	0.986**	1.029**
	(0.063)	(0.056)	(0.801)	(0.428)	(0.160)	(0.122)
(Log) Distance to division centroid	0.341**	0.292**	4.351**	2.336**	0.959**	0.243
	(0.052)	(0.086)	(0.725)	(0.891)	(0.195)	(0.225)
Constant	31.656**	48.698**	301.228**	120.137	139.611**	53.368†
	(6.304)	(6.483)	(87.542)	(86.696)	(25.505)	(29.712)
N	70,683	62,656	70,944	62,413	70,900	62,433
F-stat	12.84	10.70	7.49	5.56	11.55	7.50
Adj. R^2	0.272	0.240	0.259	0.220	0.282	0.260

Note: Division-category, year and month fixed effects are included in all models. Robust standard errors, clustered by division-category, are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

Table 7: Two-sample t-test with equal variances for merchants poached by LivingSocial

Group	Obs.	Mean	Std. Err.
Own	24,825	-0.0531	0.0077
Poached	6,232	0.0413	0.0159
Difference (=Own−Poached)		-0.0945**	0.0173

Note: ** denotes statistical significance at 1%.

Table 8: Quantile and inter-quantile regression using poach dummy for LivingSocial (N=31,057)

	Quantile regression					Inter-quantile regression	
	0.05	0.25	0.50	0.75	0.95	0.95-0.05	0.75-0.25
(Dummy) Poached by LS	0.239**	0.080**	0.017	-0.022	0.356**	0.118*	-0.102**
	(0.044)	(0.025)	(0.020)	(0.022)	(0.033)	(0.050)	(0.022)
Constant	-2.174**	-0.804**	0.016†	0.793**	1.813**	3.987**	1.597**
	(0.020)	(0.011)	(0.009)	(0.010)	(0.015)	(0.022)	(0.012)

Note: †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

Table 9: Two-sample t-test with equal variances for merchants poached by Groupon

Group	Obs.	Mean	Std. Err.
Own	52,710	0.1423	0.0053
Poached	4,408	0.3217	0.0177
Difference (=Own−Poached)		-0.1794**	0.0189

Note: ** denotes statistical significance at 1%.

Table 10: Quantile and inter-quantile regression using poach dummy for Groupon (N=57,118)

	Quantile regression					Inter-quantile regression	
	0.05	0.25	0.50	0.75	0.95	0.95-0.05	0.75-0.25
(Dummy) Poached by GP	0.385**	0.228**	0.128**	-0.018	0.226**	-0.159	-0.246**
	(0.057)	(0.029)	(0.023)	(0.021)	(0.021)	(0.104)	(0.023)
Constant	-2.098**	-0.590**	0.299**	1.079**	1.719**	3.817**	1.669**
	(0.016)	(0.008)	(0.007)	(0.006)	(0.006)	(0.012)	(0.008)

Note: †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

Figures

Figure 1: Geographic Distribution of Groupon and LivingSocial in the U.S.

(a) Groupon, December 2009

(b) Groupon, October 2011

(c) LivingSocial, December 2009

(d) LivingSocial, October 2011

Note: Each panel of (a)-(d) is a snapshot of deals distributed across the U.S. territory. Each green bubble represents a Groupon deal and each blue a LivingSocial deal. Each red dot indicates the center of a Groupon-designated geographic division (see Section 3 for the details).

Figure 2: A Schematic Illustration of the Daily Deals Promotion Market

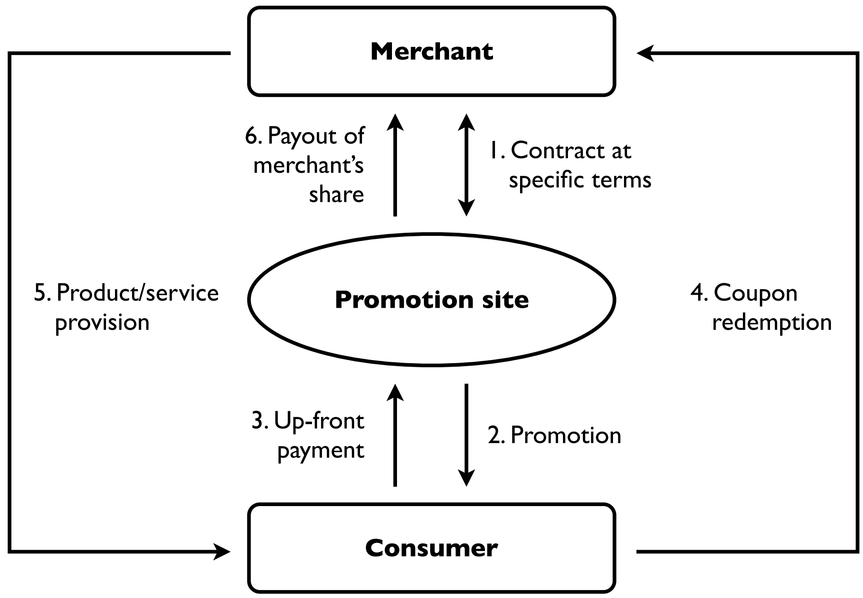
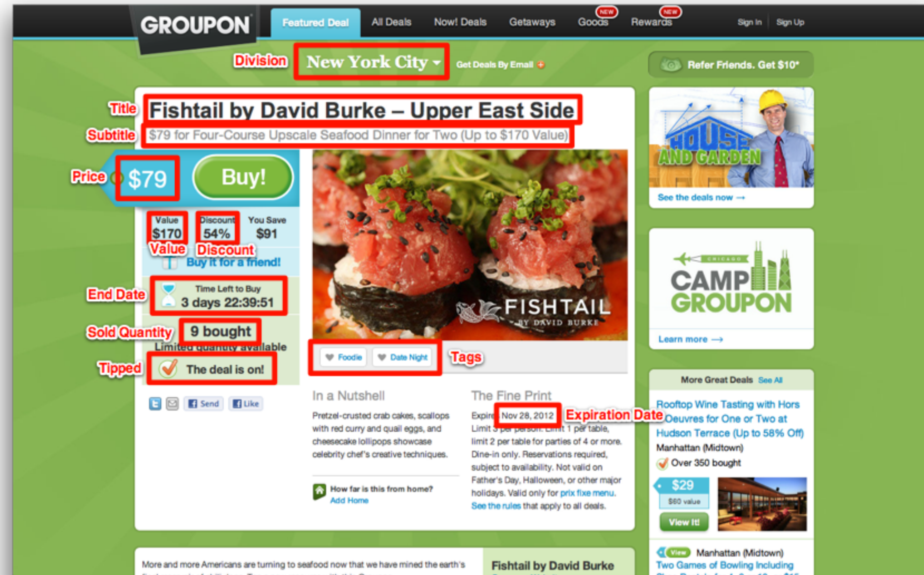
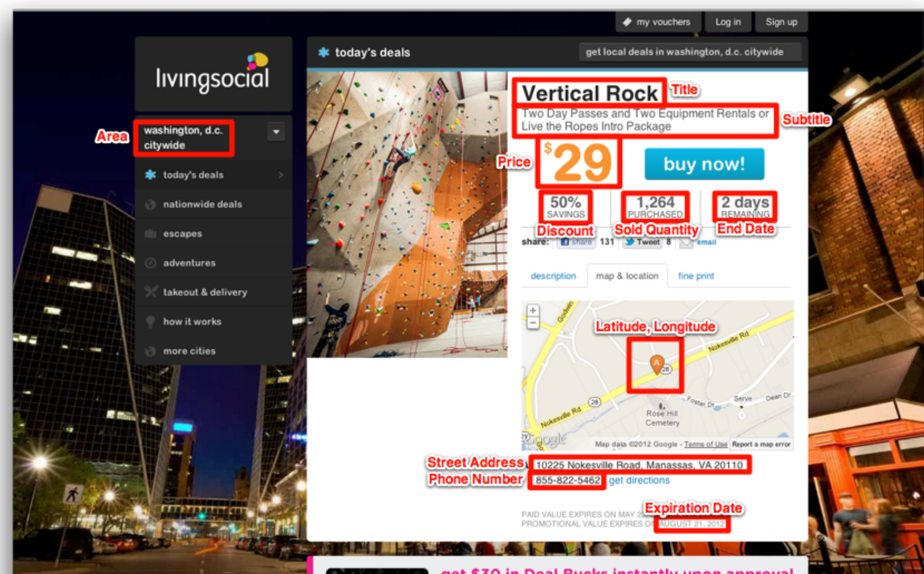


Figure 3: Examples of Deal Promotions at Groupon and LivingSocial

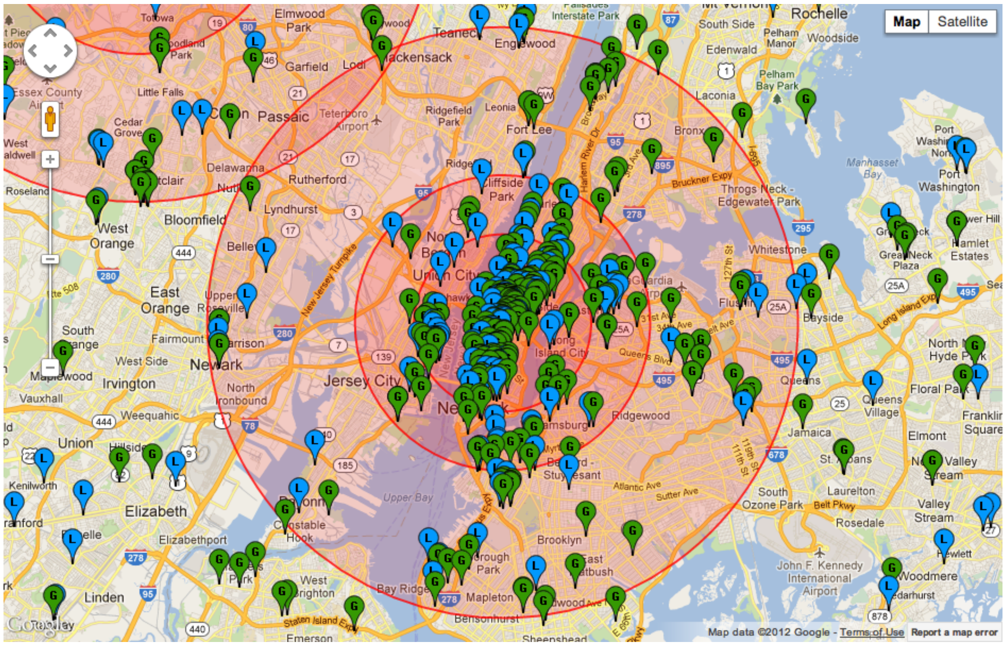


(a) Groupon



(b) LivingSocial

Figure 4: Boundaries of Local Market in New York City (October 2011)



Note: The radii of the three concentric circles, from the smallest to the largest, are 3, 5, and 10 miles.

Figure 5: Trend of market share in sold quantity between two platforms

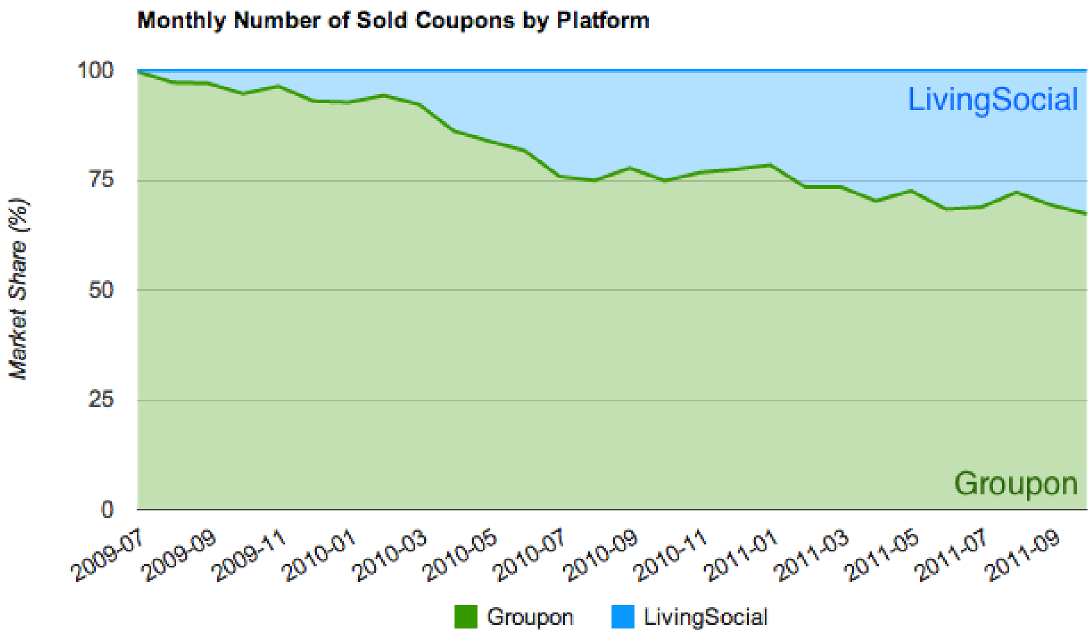


Figure 6: The proportion of poached deals by platform

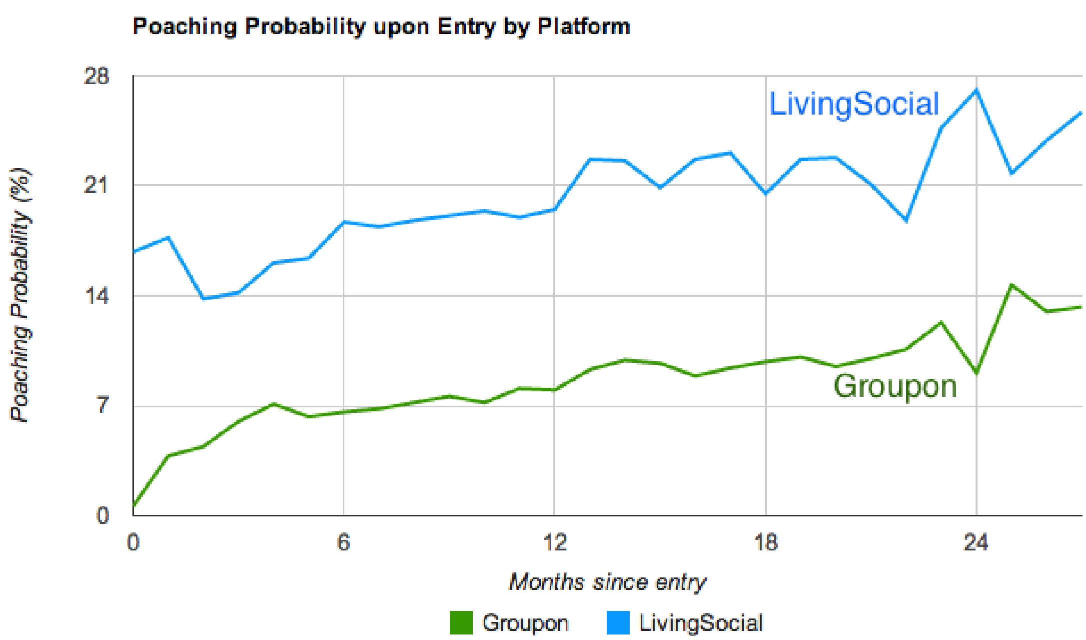
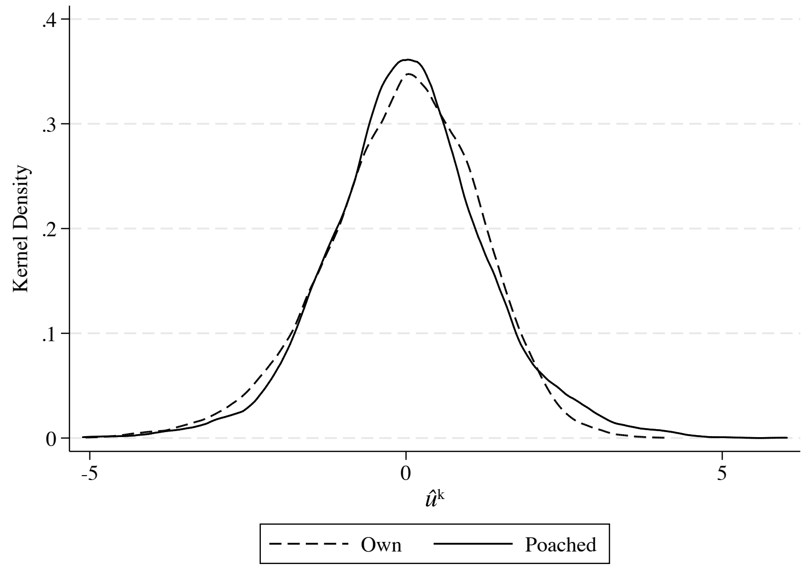
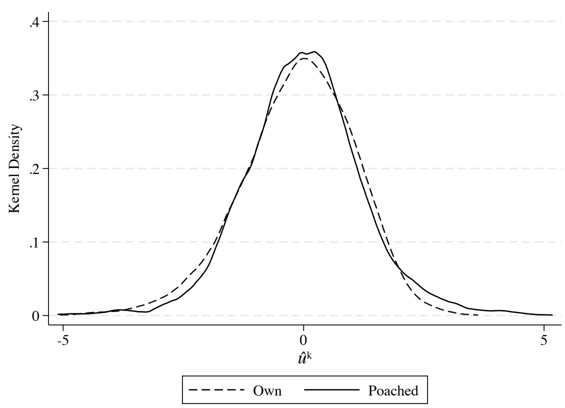


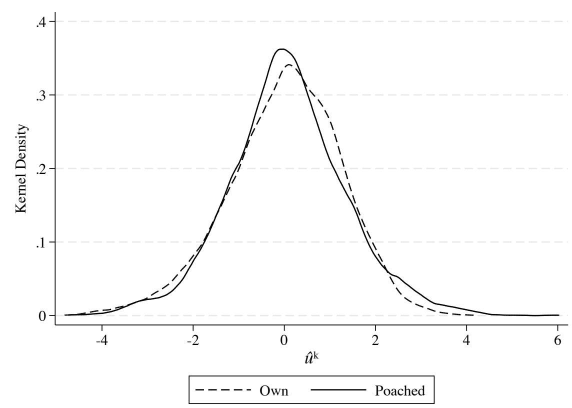
Figure 7: Performance comparison: New vs. Poached by LivingSocial



(a) Entire period

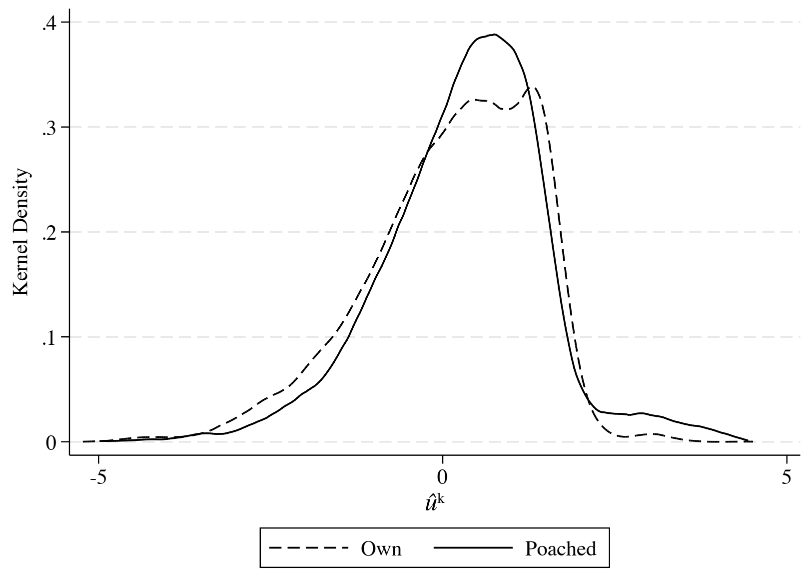


(b) Within 12 months of entry

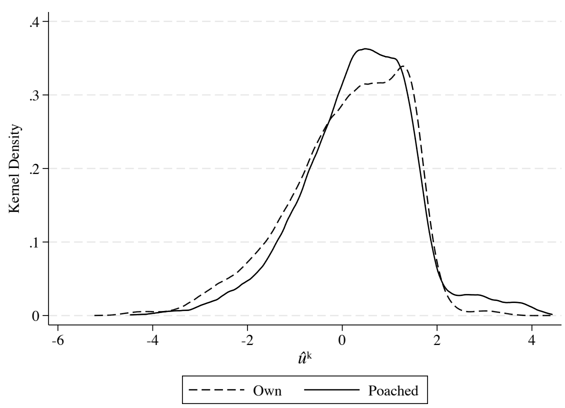


(c) After 12 months of entry

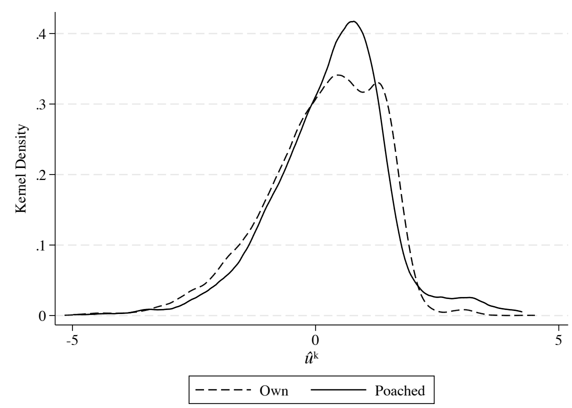
Figure 8: Performance comparison: New vs. Poached by Groupon



(a) Entire period



(b) Within 12 months of entry



(c) After 12 months of entry

Appendix A: Data Integration

First of all, we unified the geographic unit of the deals within the U.S. territory. In the data, each platform utilizes their own way of classifying deals to specific geographic units, which are different from standard administrative units such as city or county. For instance, Groupon uses *divisions* and LivingSocial employs *areas*. These geographic units cluster the deals by broader location. More importantly, these units demarcate the boundary of business activities such as deal development and promotion.[23] Each division or area represents essentially a city-level metropolitan area (e.g., East Bay Area near San Francisco or Long Island in New York State). Though LivingSocial covers a smaller part of the U.S. than Groupon, the number of *areas* (220) is larger than that of *divisions* (155). Given our interest in the competition between platforms and the role of locality in the competition, we need to maintain consistency in matching the geographic unit of decision-making and define the measures at the corresponding level. Since Groupon is the dominant incumbent in this market and its divisions are closer to the boundaries of cities, we adopted Groupon's division system. Thus, we matched each of the LivingSocial deals with the closest division based on the merchant's street address.

We also developed a common deal categorization system. Each deal is, in principle, unique in the deal characteristics but is relatively homogeneous within the category it belongs to (e.g., restaurants, health and fitness, shopping, etc.). At a minimum, we need to control for the variations across deal categories. Groupon utilizes *tags* to characterize deals (e.g., steakhouses, personal trainers, pet stores, etc.). Each Groupon deal thus carries at least one and up to four tags that represent the nature of the deal. There are about 580 unique tags associated with Groupon deals. These tags can be aggregated into 18 broad tags ("categories," hereafter) defined by Groupon. We used these categories to classify the Groupon deals. However, there is no corresponding classification system for LivingSocial deals and hence we had to assign each of the LivingSocial deals into one of the Groupon categories based on the content of the deal. For this assignment, we utilized a machine learning algorithm that applied a Bayesian inference logic to match each deal with a category that best represented the deal content. We used as inputs for training the machine the entire list of vocabularies that appeared in *titles* and *subtitles* of the deals. For the implementation, we utilized the Natural Language ToolKit (Bird, Loper, and Klein, 2009). To ensure consistency in classification, we not only classified all LivingSocial deals but also re-classified each Groupon deal

[23] For instance, subscribers are only notified of deals offered in the geographic units they live in.

to a unique category using the same algorithm. Appendix C provides the details of this Bayesian category classification procedure. This process reduced the effective number of categories to 13, to which all deals in the dataset were uniquely assigned.

Further, we integrated the merchant information from both platforms to uniquely identify the merchants. Though both platforms provide the street addresses of the deal-offering merchants, they use different formats for the address field. More critically, LivingSocial does not state merchant names. These inconsistencies make it challenging to precisely match merchants between the two data sources. Thus, we used as merchant identifiers the geographic coordinates of latitude and longitude, measured to the sixth decimal point. Both platforms provided these coordinates for each deal in numerical forms. The difference of 10^{-6} degrees in latitude or longitude around the mid-point roughly translates into 3 feet. Thus, coordinates at this level of precision reasonably serve as valid identifiers.

To determine the timing of deal offer, we used the *end date*. One could alternatively use the *start date*, but such information was only available for Groupon deals. Moreover, the time gap between the start date and the end date was very short (the median was two days). In addition, we used the month as our time window for analysis. Thus, using the end date for determining the offer timing is unlikely to cause any material bias to our results.

A final note on the data concerns the sold quantity. We used this information, along with the sales revenue, to measure the outcome of a deal. The sold quantity in a Groupon deal was truncated at 1,000, 5,000, 25,000, 100,000 and 1,000,000 such that any deals falling between two marks were set for the lower bound (e.g., 1,001 units was recorded as 1,000). For about 8% of the deals, the sold quantity was reported truncated (about 80% of them were clustered at 1,000). In contrast, LivingSocial reported the actual number of units that the consumers purchased. We computed the sales revenue per deal by multiplying the price with the sold quantity. Hence, the actual sold quantity and the sales revenue for the quantity-truncated Groupon deals should always be greater than or equal to the corresponding figures in our data. This implies that any advantage of Groupon over LivingSocial we may find from our analysis on these outcome measures will be a conservative estimate. Our results hold even if we drop all deals that appear truncated.

Appendix B: Descriptive Statistics

	N	Mean	Std. Dev.	Min	Max
Discount rate	143,525	56.46	10.54	0.00	98.76
Value	143,525	119.82	323.03	1.00	30,000.00
Price	143,525	43.77	138.64	0.99	14,999.00
Sold quantity	143,525	339.58	539.85	1.00	25,000.00
(Dummy) Groupon deal	143,525	0.73	0.44	0.00	1.00
Relative platform performance	143,525	1.81	1.14	1.21	13.23
Competitive intensity	143,525	-1.49	1.14	-5.68	3.99
Local density	143,525	1.33	1.20	0.00	5.43
(Dummy) First deal	143,525	0.68	0.47	0.00	1.00
Prior performance	143,525	2,699.09	10,002.74	0.00	716,782.00
Distance to division centroid	143,525	12.44	14.76	0.00	274.87
County population	143,525	1,358,500	1,851,534	1,175	9,818,605
Median household income	143,525	54,625.10	12,718.48	24,133.00	119,075.00
Ratio of 20's population	143,525	14.77	3.08	5.72	38.72
(Dummy) Poached by LS	31,057	0.20	0.40	0.00	1.00
(Dummy) Poached by GP	57,118	0.08	0.27	0.00	1.00

Appendix C: Bayesian Category Classification Procedure

The procedure for the category classification, summarized in Figure 9, consisted of two steps. In the first step, we used the machine learning algorithm to train Bayesian classifiers for each of the 18 Groupon-designated broad tags (i.e., categories). Training the machine requires as inputs a set of vocabularies that are associated with each category so that, once trained, the classifier can compute using the Bayes' rule the probability that a deal containing a certain set of vocabularies belongs to a given category. Since Groupon assigns each deal to at least one category, we can use the entire deal description-category pairs to build a frequency-weighted vocabulary list for each of the 18 categories. To build these lists, we extracted the words from the titles and subtitles of the deals and tokenized them. For instance, a restaurant deal titled "Mexican food with soda" produces four tokenized title words (i.e., "Mexican," "food," "with," and "soda"). Then, these four words enter the list of vocabulary for the *Restaurants* category. We repeated this process for each and every Groupon deal, obtaining a full list of frequency-weighted vocabularies for each of the 18 categories. These profiles were then used to train the classifiers.

In the second step, we let the trained classifiers compute for each deal the probability that, given the tokenized title and subtitle, the deal belongs to a specific category. This probability is based on aggregated binary inferences (i.e., yes or no) on the tokenized title and subtitle words of the deal. It is thus possible that a deal gets classified into more than one category. In such case, we chose a category with the highest probability. For instance, the classifier recognizes a deal titled "Large pizza with bowling" by four tokenized title words (i.e., "large," "pizza," "with," and "bowling") and determines the probabilities that, given these words, this deal belongs to the *Restaurants* category (e.g., 0.991) or to the *Arts and Entertainment* category (e.g., 0.872). We then uniquely assigned this deal to the *Restaurants* category. We repeated this process for all Groupon and LivingSocial deals to ensure consistency in category classification between platforms. As five of the 18 categories received zero deal assignments, the effective number of categories became 13. For the implementation of this procedure, we used the Python Natural Language ToolKit (Bird et al., 2009).

Figure 9: Conceptual Diagram on How a Bayesian Classifier Assigns a Deal to a Category