Multi-Homing and Platform Competition: A Natural Experiment in the Daily Deals Market

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Abstract

Platform competition is shaped by the likelihood of multi-homing (i.e., some complementors or consumers adopt more than one platform). To take advantage of multi-homing, platform owners often attempt to motivate their rivals' complementors or consumers to adopt their own platforms, or attempt to prevent their current complementors or consumers from multi-homing. In this study, we empirically evaluate the effectiveness of such strategies. Using data from the U.S. online daily deals market, we study the impact of an exogenous policy change of Groupon that reduced LivingSocial's ability to identify popular Groupon deals and poach corresponding merchants. We find that after the policy change, LivingSocial copied fewer deals from Groupon. It also increased its efforts to source new deals; consequently, deal variety in the market increased. We also identify a seesaw effect in that reduced merchant-side multi-homing led to increased consumer-side multi-homing, thereby strengthening LivingSocial's position on the consumer side. Our results show that information sharing facilitates multi-homing. They also illustrate a challenge that platform firms face when multi-homing takes place on both sides of their markets: weakening a competitor's market position on one side of the market may strengthen its market position on the other side, thereby making it difficult for one platform to dominate the market.

Keywords: platform competition, multi-homing, daily deals, Groupon, LivingSocial

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1 Introduction

Platforms have become increasingly influential in our economy. They create value by facilitating interactions and transactions among firms and individuals (Iansiti and Levien, 2004; Parker et al., 2016; McIntyre and Srinivasan, 2017; Rochet and Tirole, 2006). In June 2018, of the top 10 most valued public companies, 7 based their growth on their platform ecosystems. In contrast, in June 2010, only 2 out of the top 10 were platform firms. In addition to their presence in technology-intensive industries, such as the video game industry and the smartphone industry, platforms have emerged in many traditional industries, such as transportation (Uber and Lyft), accommodation (Airbnb and HomeAway), restaurants (GrubHub and UberEats), local daily deals (Groupon and LivingSocial), and home services (TaskRabbit and Thumbtack).

Because of the low adoption cost, a common feature of many platform markets is that consumers and complementors (those providing complementary services or products, such as app developers, service providers, or advertisers) frequently adopt multiple platforms, a phenomenon known as multi-homing. Consumers may multi-home to access non-overlapping complementors, and use features that are unique to an individual platform (e.g., Gabszewicz and Wauthy, 2004; Armstrong and Wright, 2007). Similarly, complementors multi-home to access non-overlapping user bases, spread fixed costs, or reduce dependence on any one platform (Clements and Ohashi, 2005; Kretschmer and Claussen, 2016; Corts and Lederman, 2009). For example, many riders use multiple ride-sharing apps such as Uber and Lyft, and many drivers offer services on both apps. Similarly, many merchants offer deals on Groupon and LivingSocial, and many consumers subscribe to the mailing lists of both platforms.

Multi-homing presents an attractive strategy for platform owners to grow their businesses. First, it reduces the cost of searching for complementors and consumers that might be interested in using their platforms. For example, not all drivers are interested in becoming freelance drivers for Uber or Lyft and not all merchants are interested in offering deals on Groupon. Similarly, not all consumers are interested in ride-hailing services or the type of deals offered by deal sites. Second, the experiences that complementors and consumers have gained from working with rival platforms help lower the cost of working with a new platform. Third, to build trust between complementors and consumers, many platforms are transparent regarding the performance of their complementors (and occasionally consumers). For example, Uber provides ratings for its drivers, Airbnb provides ratings for its hosts and travelers, Amazon provides sales ranks for its products, and daily deal sites provide deal performance information and consumer ratings for individual merchants. While such transparency facilitates better matching between the two sides and may generate herding through observational learning (e.g., Zhang, 2010; Li and Wu, forthcoming), which leads to more transactions, it makes it easy for a rival platform to selectively poach high-quality complementors and consumers from the focal platform. Finally, when many complementors and consumers of a focal platform are also available on its rival's platform, the reduced exclusivity makes the indirect network effects between the two sides of the focal platform less effective in attracting new complementors or consumers (e.g., Bresnahan et al., 2015; Bakos and Halaburda, 2018). Hence, a rival platform's multi-homing can slow down the focal platform's ability to grow and dominate the market.

To take advantage of multi-homing tendencies, platform owners often attempt to motivate their rivals' complementors or consumers to adopt their own platforms, or attempt to prevent their current complementors and consumers from multi-homing. Uber and Lyft actively encouraged each other's drivers to serve on their own platforms or asked their own drivers not to multi-home.[1] eBay claimed that Amazon had attempted to lure its top sellers to sell on Amazon's marketplace by exploiting its internal messaging system to contact its sellers.[2] Game console providers have offered incentives to top-ranked game publishers for signing exclusive contracts with them. To grow the sales of Windows Phones, Microsoft reportedly offered \$100,000 or more to many popular developers in an attempt to persuade them to port their apps from iOS or Android to its Windows Phone system.[3] Alibaba, the top e-commerce player in China, discouraged its merchants from adopting its rival's marketplace by designing its ranking algorithm to favor single-homing merchants.[4]

Despite the fact that platform owners use a variety of strategies to influence multi-homing in practice, empirical evidence on how firms leverage multi-homing as a competitive weapon and its effectiveness is limited. The theoretical literature (e.g., Armstrong, 2006; Rochet and Tirole, 2003, 2006; Armstrong and Wright, 2007; Jeitschko and Tremblay, 2017; Belleflamme and Peitz, forthcoming) has treated multi-homing extensively. However, in most of these studies, complementors are assumed to make the decisions on whether or not to multi-home, and platform firms are assumed to use price as the only tool to influence such decisions.

We use data from the U.S. online daily deals market to study the impact of an exogenous policy shift from Groupon that reduced LivingSocial's ability to identify popular Groupon deals and poach the corresponding merchants. We find that after the policy shift, LivingSocial's deals that multi-homed Groupon had greater sales, on average, because LivingSocial copied fewer Groupon deals with moderate popularity. This effect is more pronounced when there is greater uncertainty around deal demand. LivingSocial also increased its efforts to source new deals. As a result of LivingSocial's responses, deal variety in the market increased. In addition, we identify a seesaw effect in that reduced merchant-side multi-homing led to increased consumer-side multi-homing, thereby strengthening LivingSocial's market position on the consumer side. Overall, our results show that information sharing facilitates multi-homing. They also illustrate a challenge that platform firms

[1]Source: https://n.pr/2AoehAa and https://money.cnn.com/2014/08/04/technology/uber-lyft/index.html, accessed August 2018.

[2]Source: https://www.nytimes.com/2018/10/03/technology/ebay-amazon-poaching.html, accessed October 2018.

[3]Source: https://www.theverge.com/2013/6/15/4433082/microsoft-paying-companies-100k-windows-phone-apps, accessed September 2018.

[4]Source: http://www.sohu.com/a/193871212_109973, accessed August 2018.

face when multi-homing takes place on both sides of their markets: weakening a competitor's market position on one side of the market may strengthen its market position on the other side, thereby making it difficult for one platform to dominate the market.

Our study is related to several streams of literature. First, our study is related to the literature on multi-homing. Multi-homing has been comprehensively examined through theoretical models (Armstrong, 2006; Rochet and Tirole, 2003, 2006; Armstrong and Wright, 2007). Very often, when multi-homing is considered, it is restricted to one side of the market (e.g., Armstrong, 2006). Athey et al. (2018) and Ambrus et al. (2016) study endogenous multi- or single- homing in media markets on the ad-side (keeping the consumer side exogenously fixed). Gabszewicz and Wauthy (2004) and Armstrong and Wright (2007) allow for multi-homing on both sides of the market, but find that in equilibrium, multi-homing takes place only on one side of the market. The intuition is that when all agents multi-home on one side of the market, agents on the other side do not gain from multi-homing. Jeitschko and Tremblay (2017) provide a model with heterogeneous agents on both sides of the market and show that it is possible to have a mix of multi-homing and single-homing on both sides of a market in equilibrium. They argue that this equilibrium is the most common allocation actually observed in platform markets. We observe this allocation in our daily deal context. Choi (2010) finds that exclusive content on a platform could induce more consumer multi-homing. Unlike in these studies in which agents make multi-homing decisions, platform owners in our setting actively source deals and influence merchant multi-homing. We highlight the impact of the platform's strategy in determining the multi-homing tendencies on both the merchant and consumer sides. We empirically show that, consistent with Choi (2010), as more merchants on one side of the market single-home, more consumers on the other side will choose to multi-home.

A small number of empirical studies have investigated multi-homing behavior (e.g., Corts and Lederman, 2009; Landsman and Stremersch, 2011; Rysman, 2007; Bresnahan et al., 2015; Venkataraman et al., 2018). Many of these studies focus on the video game industry. Landsman and Stremersch (2011) find that in the video game console industry, the (negative) effect of video game multi-homing on consoles sales is larger than the (positive) effect of the number of video game titles on console sales. This research supports the idea that platform owners need to prevent their users from multi-homing. Corts and Lederman (2009) show that within the video game industry, multi-homing reduces the likelihood that one platform will become dominant in the market. Lee (2013) studies exclusive contracts used by video game console manufacturers with game publishers to prevent multi-homing and finds that such exclusivity favors the entrant platforms. Cennamo et al. (forthcoming) find that multi-homing cost to the video game industry depends on the complexity of the console technology. Outside the video game industry, Rysman (2007) shows that in the payment card industry, consumers tend to concentrate their spending on a single payment network, though many maintain unused cards that allow the ability to use multiple networks. The research shows that affiliation with multiple platforms differs from the actual usage of these platforms. In our study, we use actual consumer usage data to identify their multi-homing behavior. Kim et al. (2017) study daily deal platforms and document significant multi-homing behavior in this industry. They find no meaningful inter-platform differences in deal terms for comparable deals. They also find that merchants that had successful experiences tend to remain with the same platform. Because their studies are based on descriptive statistics and correlation analysis, what drives merchants' multi-homing behavior and the impact of such behavior remain unclear. Unlike these extant studies, our study explores how information sharing serves as a driving force for multi-homing behavior.

Second, our study is related to the literature documenting the importance of high-performing complementors in driving platform success. With the exception of a few papers, theoretical and empirical studies in the platform literature typically assume that all complementors are of the same quality. Rochet and Tirole (2003) show that the existence of "marquee" buyers (sellers) increases the desirability of the platform for sellers (buyers). In the context of video games, Binken and Stremersch (2009) and Lee (2013) show that the presence of blockbuster video games is a significant factor that drives console purchases. In the crowdfunding context, Doshi (2015) shows that high-performing projects positively affect the platform's subsequent growth and liquidity. Bresnahan et al. (2015) show that multi-homing of superstar apps on mobile operating systems drives the co-existence of iOS and Android. Consistent with these results, LivingSocial is particularly interested in merchants offering popular deals on Groupon. Thus, our study provides additional evidence related to the importance of high-performing complementors in such markets.

Finally, the online daily deals market itself has received a great deal of attention in the literature. Edelman et al. (2016) provide a theoretical model showing that merchant profitability improves when a platform exercises successful price discrimination. Hu et al. (2013) and Wu et al. (2014) study group buying as a selling mechanism. Gupta et al. (2012) find that merchants on Groupon profit from only about half of all vouchers sold, and the return on investment varies widely. Gupta et al. (2011) and Norton et al. (2012) conduct case studies of Groupon and LivingSocial, respectively. Dholakia (2011) conducts a survey of merchants across five major daily deal sites and finds that a significant number of them are interested in multi-homing. Song et al. (2016) study consumers' shopping and redemption behavior on a major Korean daily deals site. Subramanian and Rao (2016) use a theoretical model to show that while daily deals cannibalize a merchant's revenue from experienced consumers, by displaying the number of deals sold, the platform can leverage discounted sales to experienced consumers to help a high-quality merchant signal its type and acquire new consumers at a higher margin. Li and Wu (forthcoming) show that both the herding effect from displaying deal sales and Facebook-mediated word of mouth directly impact Groupon's deal sales. Li et al. (2018) show that on Groupon, local characteristics have a significant impact on both deal demand and the supply side. Zhang and Chung (2018) find that merchants enjoy access to a larger customer base by working with a bigger platform, but they are subject to lower margins due to lower bargaining power during negotiations.

2 Empirical Setting

Daily deals platforms are online marketplaces that connect consumers with offline stores in local markets by offering deep discounts for a variety of products and services. Consumers purchase deals online from local merchants and later redeem them offline. Platforms such as Groupon and LivingSocial play an active role in determining the type of deals offered. They selectively approach local merchants, usually with a 50/50 split of revenue between the platform and the merchants, and persuade them to offer deals on their sites (Dholakia, 2011). Multi-homing behavior exists on both sides of the platform: merchants can offer deals on more than one site and consumers can visit and purchase deals on multiple sites. Due to contractual agreements, a merchant often offers deals on one site at a time. We thus define a deal as a multi-homing deal if the merchant offering a deal on one site has previously listed deals in the same category on other sites. Further, multi-homing is defined at the category level, not at the deal level, because merchants rarely put up exactly the same deal multiple times.

Groupon is the leading daily deal website in this industry. It filed for an IPO in June 2011. Financial analysts used Groupon's deal counter to infer Groupon's revenue and raised concerns regarding the viability of Groupon's business model. Consequently, Groupon amended its IPO documents several times, with one of the revisions containing a major restatement of revenue. On October 9, 2011, Groupon announced a change that it made to its deal counter in a blog post.[5] "Instead of showing the exact number of Groupons purchased, the counter is now reduced by a random percentage that will change over time in a way that makes it impossible to see trending by counting the units. Additionally, we are capping and rounding the counter from time to time. We now precede the Groupon count with the word 'over' to reflect that the actual number is always actually larger than what's being displayed." According to the same blog post, the intention was to prevent outsiders from estimating Groupon's revenue, which could hurt the company on its journey to going public. The blog post said that "some clever people are using the counter to make (consistently incorrect) estimates of our total company sales, which we don't like for the same reason you probably wouldn't like if people tried to guess your weight all day."

Immediately after this announcement, Sucharita Mulpuru, an analyst with Forrester Research, said the company should have eliminated its deal counter a long time ago since it only benefitted Groupon's competitors, who could tell which deals were most popular and copy them.[6] At its IPO on November 4, 2011, the company was valued at $12.7 billion.

Groupon's change to its deal counter is ideal for our research design. Because the policy change was not motivated by a desire to deter competitors' multi-homing, it was likely to be

[5] Source: https://www.groupon.com/blog/cities/about-the-deal-counter, accessed July 2018.
[6] Groupon Gives Up Disclosure, 10 October 2011, Dow Jones News Service.

exogenous to factors that drive competitors' multi-homing behavior. Our analysis focuses on how Groupon's policy change affected its largest rival, LivingSocial. We expect that LivingSocial would be significantly impacted by the policy change, as it was likely to rely on Groupon's deal counter, rather than other sites', to identify new merchants to poach. During our sample period, there were 628 other deal sites in existence and 97.6% of them did not have a deal counter. Moreover, among the ones that provided deal sales information, the size of the largest site is only 8.7% that of Groupon in terms of total cumulative number of deals offered. Therefore, Groupon was likely to be the main source of deal popularity information for LivingSocial. Consequently, Groupon's policy change was likely to have a significant impact on LivingSocial's multi-homing behavior.

3 Hypothesis Development

3.1 Impact on LivingSocial's Multi-Homing Behavior

The impact on LivingSocial's multi-homing behavior depends on LivingSocial's multi-homing strategy before the policy change. Note that while multi-homing helps LivingSocial lower its deal discovery and acquisition cost and reduce the uncertainty of deal popularity, multi-homing reduces the differentiation between the two platforms, thereby resulting in more intense competition. This trade-off suggests that there is an optimal multi-homing level for LivingSocial, and LivingSocial always has incentives to source a few unique deals.

In the first scenario, if LivingSocial only multi-homed the most popular deals on Groupon before the policy change, its impact would be limited. A major reason LivingSocial uses Groupon's deal sales information is to reduce sales uncertainty. For the most popular deals on Groupon, however, LivingSocial could use a variety of information (e.g., the number of consumer reviews of these deals posted on Groupon, or the amount of discussion about these deals on other online forums and on social media) to determine their popularity in a reliable manner. In addition, in our setting, for these deals, even after Groupon's manipulation of its deal counter, the counter could still convey sufficient signal regarding deal popularity because the number in the counter presented the lower bound. Hence, LivingSocial's ability to identify these popular deals is unlikely to be affected much by the policy change. In a similar vein, Zhu and Zhang (2010) show that online reviews for popular products are less effective in influencing consumers' purchase decisions because consumers have many other channels to obtain information on product quality.

In the second scenario, if LivingSocial not only multi-homed the most popular deals on Groupon but also the moderately popular deals before the policy change, the policy change would have an impact on LivingSocial's multi-homing strategy. In practice, LivingSocial may still be interested in copying a Groupon deal even if it is not very popular because the cost of working with an additional merchant is small, and the loss of differentiation from one more overlapping deal is likely to be negligible when LivingSocial offers numerous deals. Because of limited information from other channels, accurate sales information on these deals from Groupon is valuable for LivingSocial. The policy change would therefore make it difficult for LivingSocial to identify such deals. As a result, LivingSocial might copy fewer such deals after the policy.

Overall, if LivingSocial multi-homed both the most popular and the moderately popular deals on Groupon before the policy change, we expect that the policy change would reduce the number of Groupon deals that LivingSocial multi-homed.

Hypothesis 1 *After Groupon's policy change, LivingSocial would multi-home fewer Groupon deals.*

Given that the policy limited the amount of information on Groupon's deal popularity, the moderately popular deals would be more affected than the most popular deals, as discussed earlier. Therefore, we expect LivingSocial to continue to copy Groupon's most popular deals, but reduce its multi-homing on deals with moderate popularity after the policy change. As a result, the average sales of the deals that LivingSocial copied from Groupon was likely to increase.

Hypothesis 2 *After Groupon's policy change, the average sales of deals that LivingSocial copied from Groupon would increase.*

Groupon's policy change affected LivingSocial because it made information regarding deal popularity ambiguous. If LivingSocial's multi-homing behavior is indeed influenced by information from Groupon, we expect the effect of the policy change on multi-homing deal sales in Hypothesis 2 to be stronger when Groupon's sales information is more valuable to LivingSocial.

The value of sales information from Groupon can vary by market and by deal category. First, if there is a larger demand uncertainty in deal sales in a particular market, it is more difficult for LivingSocial to predict the sales of a particular deal; thus the information on deal sales from Groupon becomes more important. Second, if there is intrinsic uncertainty in deal sales for a particular type of deal, the information on past deal sales from Groupon becomes more valuable.

Hypothesis 3 *The effect hypothesized in Hypothesis 2 would become more pronounced when uncertainty regarding deal popularity was greater.*

3.2 Impact on Deal Variety

Following Hypotheses 1 and 2, if LivingSocial no longer copied as many Groupon deals as earlier, to compensate for the reduced deal variety on its site, we expect it to devote more efforts to source new deals. As a result, the deal variety in each market would increase and most of this increase would result from LivingSocial's new deals.

Hypothesis 4 *The deal variety in each city became greater after the policy change, and LivingSocial contributed more to this variety after the policy change.*

3.3 Impact on Consumers' Multi-Homing Behavior

Consumers' responses to changes in merchant-side multi-homing and in industry variety could be mixed. On the one hand, as LivingSocial and Groupon became more differentiated in terms of their deal offerings, the benefit from multi-homing would increase for consumers, as suggested by theoretical studies (e.g., Gabszewicz and Wauthy, 2004; Armstrong and Wright, 2007; Choi, 2010). Therefore, consumers were more likely to visit both Groupon and LivingSocial after the policy change. On the other hand, although LivingSocial provided more deal variety, the quality of these new deals was not guaranteed. If the new deals offered on LivingSocial were not attractive, consumers might not find it worthwhile to incur the multi-homing cost, particularly given that there was still a great overlap of popular deals between Groupon and LivingSocial.

Given that the multi-homing cost for consumers in this industry only involves visiting another website, the benefit from multi-homing is likely to be greater than the cost. As a result, we expect more consumers to multi-home after the policy change. In addition, we expect that consumers who were already multi-homing both platforms before the policy change will visit Living Social more frequently, given a greater number of unique deals offered by LivingSocial after the policy change.

Hypothesis 5 *After Groupon's policy change, consumers were more likely to multi-home by visiting both Groupon and LivingSocial, and existing multi-homing consumers visited LivingSocial more frequently.*

4 Data

We obtain data from two sources, which provide information on both merchant-side and consumer-side multi-homing behaviors. We obtain the first data set from Yipit, a market research company that tracks all deal sites in the U.S.. The data set contains deal offerings and sales information for most of the daily deals websites for deal offerings made between January 2010 and December 2012. The policy change took place in October 2011, which is the 22nd month of our sample period, leaving us with 21 pre-policy months and 15 post-policy months. For each deal offering, we observe its category, price, discount, starting date, ending date, the market and website on which the deal was offered, and merchant information such as zip code and address. We focus on the top 100 cities in terms of the cumulative number of deals offered during our sample period. We remove non-U.S. cities and cities that Groupon and LivingSocial entered after the policy change, and focus on the cities that have experienced both pre- and post-policy periods. The final data set contains 82 cities, 160,876 merchants and 618,258 deal offerings. Among all deals, 44% are Groupon deals, 13% are LivingSocial deals, and 43% are deals from other sites.[7]

[7]During our sample period, Groupon and LivingSocial moved beyond the "one-deal-a-day" stage and offered more than one deal per day per city.

Table 1 provides the summary statistics for deal offerings across daily deal sites. Groupon deals have, on average, higher prices, and longer durations than deals on LivingSocial and other sites. LivingSocial has the highest average deal sales, while discount rates are comparable across sites. We also examine the multi-homing behavior of merchants in terms of their past experiences with each site before they offered a focal deal. For each deal, we calculate the number of deals that the merchant offered on each site before this focal deal. We find that multi-homing behavior is relatively common during our sample period. A typical Groupon merchant has, on average, offered 0.94 Groupon deals, 0.54 LivingSocial deals, and 0.50 deals on other sites in the past. A typical LivingSocial merchant has, on average, offered 0.29 Groupon deals, 0.36 LivingSocial deals, and 0.29 deals on other sites in the past.

Table 2 provides summary statistics for the merchants. Among the 160,876 unique merchants, 59.4% have offered Groupon deals, 50.7% have offered LivingSocial deals, and 75.0% have offered deals on other sites. The sum of these percentages is greater than 1 due to merchants' multi-homing behavior. On average, each merchant offers 3.84 deals during our sample period, including 1.69 Groupon deals, 0.5 LivingSocial deals, and 1.65 deals on other sites.

The second data set contains consumers' website browsing records, collected by comScore, from January 2011 to December 2012, which covers 9 pre-policy months and 15 post-policy months. For each website visit, we observe the machine ID, starting and ending time stamps, website visited, last website visited before the focal visit, and household information such as zip code, income, and age. We focus on consumers who had at least one website visit to Groupon or LivingSocial and who live in the same set of cities included in the first data set. The final data set contains 5,839 consumers and 12,981 records of visits to Groupon and LivingSocial's websites. A typical consumer visits Groupon 1.62 times per month on average, with a standard deviation of 3.00, and visits LivingSocial 0.89 times per month, with a standard deviation of 2.28.

5 Methods and Empirical Results

5.1 Impact on LivingSocial's Multi-Homing Behavior

We first explore LivingSocial's multi-homing behavior before the policy change, and examine whether it only multi-homed popular deals on Groupon. Within each city-category, we first rank the Groupon deals by their sales. As the total number of deals varies across cities and categories, we normalize the ranking by the total number of deals in a city-category and use the normalized ranking for the analysis. The normalized ranking ranges from 0 to 100. Second, we identify the deals that were multi-homed by LivingSocial and record their normalized rankings. Specifically, for each merchant that was multi-homed by LivingSocial at time t, we identify the deal it offered on Groupon before time t; if a particular merchant offered more than one deal on Groupon before time t, we use the deal with the maximum sales as it represents the merchant's best potential. Finally, we calculate the probability that merchants on Groupon were multi-homed by LivingSocial, given their normalized sales rankings, which is the proportion of multi-homed merchants among all merchants with the same normalized sales ranking. As depicted in Figure 1, the probability of being multi-homed decreases with the normalized rankings for all categories, yet it is not 1 for the most popular deals and not 0 for the least popular deals. The result suggests that LivingSocial multi-homed more popular deals in general, but it also multi-homed other deals.[8] Overall, we find that LivingSocial multi-homed both popular and moderately popular deals before the policy change. Therefore, we expect the policy change to have an impact on LivingSocial's multi-homing behavior.

We next examine the change in LivingSocial's multi-homing behavior after the policy change. For each city in our data sample, we calculate the percentage of LivingSocial deals that multi-homed Groupon in a particular month. We then average across the cities in each month, and plot the averages in Figure 2. To ensure that our results are not driven by different cities in different stages of growth, we separately plot the percentages for cities Groupon entered before the 10th month and for cities Groupon entered between the 11th and the 19th month.[9]

We find that after the policy change (the 22nd month), the percentage of multi-homing deals decreased substantially for both types of cities, suggesting that our finding is not driven by different stages of industry life cycle. Note that this result cannot be driven by merchants' switching behavior. As Groupon adjusted the counter downwards, which may adversely affect its merchants' performance, more merchants should be switching from Groupon to LivingSocial, resulting in greater multi-homing for LivingSocial.

We next conduct regression analysis to test our hypothesis. We regress the percentage of LivingSocial deals that multi-homed from Groupon in category j in city m in month t ($PctMultihome_{jmt}$) on a dummy variable that indicates post policy ($Post\ Policy_t$), a city-specific linear time trend (t_m), the interaction between these two variables to detect any shift in trend after the policy change, and a set of control variables:

$$\begin{aligned} PctMultihome_{jmt} &= \beta_0 + \beta_1 PostPolicy_t + \beta_2 PostPolicy_t \times t_m + \beta_3 t_m + \gamma_1 Category_j \\ &\quad + \gamma_2 X_{jmt} + \gamma_3 D_m + \gamma_t T_t + \varepsilon_{jmt}, \end{aligned} \tag{1}$$

[8] This may be because the most popular merchants have benefited enough from offering deals on Groupon and do not need to offer deals on LivingSocial again; for moderately popular deals, they have strong incentives to offer deals on LivingSocial again in the hope of gaining additional exposure to consumers. For several categories, when the number of merchants in a market is small, LivingSocial might have to offer overlapping deals regardless of the deal ranks.

[9] Among all the cities we study, 92.8% of the time Groupon entered in the same month as or earlier than LivingSocial did. As the market of daily deals for a particular city began growing after the first major deal site entered, we use Groupon's entry month to define the cities' growth stage. Using LivingSocial's entry month yields the same growth stage definition (e.g., if Groupon entered in the 17th month and LivingSocial entered in the 18th month, using either entry timing yields the same categorization of entry, which is between the 11th and 19th month). Finally, for 7.2% of the cities where LivingSocial entered earlier, we excluded the months when LivingSocial was present and Groupon was not because LivingSocial was not able to multi-home Groupon in these months.

where $Category_j$ represents category fixed effects; X_{jmt} represents average deal characteristics such as logged price, discount rate, and duration; D_m represents market demographics such as population, percentage of female, age, income, and education; and T_t represents month-of-the-year fixed effects that capture potential seasonality. The city-specific linear time trend (t_m) represents the number of months since Groupon entered the city and captures the city-specific growth stage. The error terms are clustered at the city level. As shown in Model 1 of Table 3, there is a positive linear time trend and a positive post-policy main effect. The coefficient of the interaction term is negative and greater than the main effect of the time trend, suggesting that the percentage of multi-homing deals actually decreased after the policy change. The results are robust if we replace the market demographics with city fixed effects in Model 2. These results support Hypothesis 1 that LivingSocial multi-homed Groupon deals less frequently after the policy change.

Besides evaluating the change in the proportion of multi-homing deals, we examine the sales of LivingSocial's multi-homing deals before and after the policy change. We use LivingSocial's deals that did not multi-home Groupon, which included LivingSocial's unique deals or deals LivingSocial multi-homed from other sites, as a benchmark to control for the overall change in the popularity of LivingSocial deals. We first show model-free evidence of the change in the sales of multi-homing deals before and after the policy change. Figure 3 plots the average logged sales for deals LivingSocial multi-homed from Groupon and its other deals over time based on city types. We find that there is consistently a larger gap between these two types of deals after the policy change.

We further use a difference-in-differences approach to demonstrate the change in the sales of multi-homing deals on LivingSocial after the policy change. We run a deal-level regression using logged deal sales ($\log Sales_{it}$) as the dependent variable:

$$\begin{aligned}\log Sales_{it} &= \beta_0 + \beta_1 Post\,Policy_t + \beta_2 Post\,Policy_t \times Multi\text{-}Homing_{it} + \beta_3 Multi\text{-}Homing_{it} \\ &\quad + \gamma_0 Own\,Existence_{it} + \gamma_1 Category_i + \gamma_2 X_i + \gamma_3 D_m + \gamma_t T_{mt} + \varepsilon_{it}, \qquad (2)\end{aligned}$$

where $\log Sales_{it}$ is the logged unit sales of deal i on LivingSocial, and $Multi\text{-}Homing_{it}$ is a dummy variable that takes the value of 1 if the merchant has previously offered deals on Groupon. We control for the merchant's past experience with LivingSocial by including a dummy variable $Own\,Existence_{it}$ that equals 1 if the merchant has worked with LivingSocial before. We further control for category fixed effects $Category_i$, deal characteristics X_i (e.g., logged price, discount, and duration), market demographics D_m (e.g., population, percentage of females, age, income, and education), and time fixed effects T_{mt} (e.g., month-of-the-year fixed effects; city-specific linear and quadratic time trends in terms of the number of months since daily deal sites entered a city). In particular, the city-specific time trends can control for different growth stages of daily deals in each city.

As shown in Table 4, the main effect of the policy change is negative, suggesting that deal sales on LivingSocial decreased on average after the policy change. The main effect of the multi-homing dummy is positive, suggesting that multi-homing deals had higher sales than non-multi-homing deals in general. The positive coefficient of the interaction term of post policy and multi-homing suggests that multi-homing deals had 27.6% higher sales on average after the policy change, which supports Hypothesis 2. The results are robust if we replace the market demographics with city fixed effects.[10]

Note that the change in sales is driven by merchant popularity on LivingSocial rather than changes in specific deal characteristics such as price, discount rate or duration. To verify this, we run the following regression using deal price, discount rate, and duration as the dependent variables (in logarithm):

$$\begin{aligned}\log X_{it} \;=\;& \beta_0 + \beta_1 Post\,Policy_t + \beta_2 Post\,Policy_t \times Multi\text{-}Homing_{it} + \beta_3 Multi\text{-}Homing_{it} \\ & + \gamma_0 Own\,Existence_{it} + \gamma_1 Category_i + \gamma_3 d_m + \gamma_t T_{mt} + \varepsilon_{it}, \qquad (3)\end{aligned}$$

where d_m represents city fixed effects. As shown in Table 5, the coefficients on the interaction term are all insignificant, suggesting that the deal characteristics did not systematically change after the policy change and, thus, are unlikely to be the drivers of the change in deal sales.

5.1.1 Moderators

To test Hypothesis 3, we examine two moderators that capture uncertainty in deal sales.

Moderator 1: Market-category level demand variation. When demand is more variant and uncertain in a particular market-category, Groupon's sales information about a particular deal becomes more valuable to LivingSocial, and the effect in Hypothesis 2 should be more pronounced. We thus include the variance of deal sales in a particular category-city, $Demand\ Variation_{jm}$, as a moderator to the original difference-in-differences regression.

$$\begin{aligned}\log Sales_{it} \;=\;& \beta_0 + \beta_1 Post\,Policy_t + \beta_2 Post\,Policy_t \times Multi\text{-}Homing_{it} \\ & + \beta_3 Post\,Policy_t \times Demand\,Variation_{jm} + \beta_4 Multi\text{-}Homing_{it} \times Demand\,Variation_{jm} \\ & + \beta_5 Post\,Policy_t \times Multi\text{-}Homing_{it} \times Demand\,Variation_{jm} \\ & + \beta_6 Multi\text{-}Homing_{it} + \beta_7 Demand\,Variation_{jm} + \gamma_0 Own\,Existence_{it} \\ & + \gamma_1 Category_i + \gamma_2 X_i + \gamma_3 D_m + \gamma_t T_{mt} + \varepsilon_{it}. \qquad (4)\end{aligned}$$

As shown in Table 6, the coefficient on the triple interaction term is positive and significant. The coefficient estimate suggests that if the variance of deal sales increases by 0.1, the sales of

[10]As a robustness check, we use a continuous variable of multi-homing intensity, $Multi\text{-}Homing\ Intensity_{it}$, in place of the dummy variable $Multi\text{-}Homing_{it}$. The continuous variable represents the number of times (in logarithm) that the merchant has previously offered deals on Groupon. Similarly, we use $Own\ History_{it}$, which represents the number of times (in logarithm) the merchant has previously offered deals on LivingSocial, in place of the dummy variable $Own\ Existence_{it}$. We obtain similar results.

multi-homing deals would increase by 8.5% after the policy change. The results are robust if we replace market demographics with city fixed effects.

Moderator 2: Deal category. An alternative approach to evaluating uncertainty is to examine the variation in uncertainties across deal categories. Deals of different categories may intrinsically differ in terms of how consumers decide to buy the deals and, in turn, may have different sales uncertainty. We adopt an exploratory approach. We first include category fixed effects, $Category_i$, as a moderator to the original difference-in-differences regression.

$$\begin{aligned}\log Sales_{it} \;=\;& \beta_0 + \beta_1 Post\,Policy_t \times Category_i + \beta_2 Multi\text{-}Homing_{it} \times Category_i \\ & + \beta_3 Post\,Policy_t \times Multi\text{-}Homing_{it} \times Category_i + \gamma_0 Own\,Existence_{it} \\ & + \gamma_1 Category_i + \gamma_2 X_i + \gamma_3 D_m + \gamma_t T_{mt} + \varepsilon_{it}, \end{aligned} \tag{5}$$

where the coefficients on the main effect and the triple interaction term can be interpreted as category-specific effects relative to the baseline category "other." As shown in Table 7, the estimated coefficient on the triple interaction term is positive for three categories: Beauty, Entertainment, and Home and Family, suggesting that LivingSocial's response to Groupon's policy change is stronger in these three categories. The coefficient estimates suggest that the sales of multi-homing deals in Beauty, Entertainment, and Home and Family increase by 20.2%, 72.1%, and 26.0%, respectively, after the policy change.

To explain why there is a difference in LivingSocial's multi-homing strategy across categories, we tabulate the average price, discount, and duration across categories. As shown in Table 8, the three categories do not systematically differ from other categories in terms of deal discount or duration, but their deal prices are substantially higher than those of other categories. The price of a deal may affect uncertainty in deal sales: consumers may be more hesitant to buy a high-priced deal, so there is more uncertainty in deal sales. Groupon's sales information thus became more valuable to LivingSocial in categories with higher prices. LivingSocial's response to Groupon's policy change is therefore likely to be stronger in these categories.

To further test whether category price is the main driver of the effect, we use the average logged category-city level price, $Category\,Price_{jm}$, as the moderator in place of $Demand\,Variation_{jm}$ in Equation (4) and repeat the analysis. As shown in Table 9, the coefficient on the triple interaction term is positive and significant, suggesting that Hypothesis 2 is more pronounced when the category price is higher.

Overall, the results using these two moderators support Hypothesis 3 and boost our confidence that LivingSocial indeed leveraged Groupon's sales information when deciding which deals to source.

5.2 Impact on Deal Variety

We next examine how the industry-wide (i.e., including Groupon, LivingSocial, and other sites) deal variety changed after the policy change. Intuitively, consumers value unique deals that appear on the websites during a specific time period. We therefore count a deal toward industry-wide variety if the merchant did not offer deals in the same category on any of the websites in the past three months.[11] We measure deal variety at the city level ($Variety_{mt}$), which is the number of such "variety" deals, normalized by the total number of deals in city m in month t. We define the contribution of each deal site to this variety ($Groupon\ Contribution_{mt}$ and $LivingSocial\ Contribution_{mt}$) as the number of variety deals on the deal site, normalized by the total number of variety deals in city m in month t.

To examine how deal variety changed after the policy change, we first plot the average percentage of variety deals across cities in Figure 4. We find that the industry variety decreased before the policy change, which might be due to an exhausting merchant pool, but started to increase after the policy.

We further regress $Variety_{mt}$ on $Post\ Policy_t$, a linear city-specific time trend, the interaction between $Post\ Policy_t$ and the time trend, city fixed effects, and month-of-the-year fixed effects:

$$Variety_{mt} = \beta_0 + \beta_1 Post\,Policy_t + \beta_2 Post\,Policy_t \times t_m + \beta_3 t_m + \gamma_m d_m + \gamma_t T_t + \varepsilon_{mt}. \tag{6}$$

As shown in Table 10, there is a negative linear time trend and a negative post-policy main effect, suggesting that variety decreased over time in general: as the platforms grow, there remain fewer merchants who have not worked with any platform or who have only worked with one site. However, the coefficient of interest on the interaction term is positive, suggesting that the policy change increased industry variety.

To test whether LivingSocial contributed more to the variety after the policy change, we run a similar regression by replacing the dependent variable with $Groupon\ Contribution_{mt}$ and $LivingSocial\ Contribution_{mt}$, respectively. As shown in Table 10, there is a positive post-policy main effect and a positive interaction effect for LivingSocial, suggesting that LivingSocial contributed more variety after the policy change. At the same time, the coefficients of the post-policy main effect and the interaction term are insignificant for Groupon, suggesting that Groupon's contribution remains unchanged after the policy change.

Overall, these results provide support for Hypothesis 4.

5.3 Impact on Consumers' Multi-Homing Behavior

To examine how consumer behavior changed after the policy change, we utilize comScore data on individual consumer online website visits. The data span years 2011 and 2012, which corresponds

[11] Results are robust when we use other time windows such as two months and six months.

to Yipit data from the 13th month to the 36th month. We focus on the cities that we studied in the Yipit data and only use observations taken after both Groupon and LivingSocial entered a given city. Further, we do not examine consumers' visits to other daily deals sites as those visits are too sparse and there was no one site, among the 628 sites in our data, that obtained sufficient visits to be comparable to Groupon or LivingSocial.

For each city, we count the number of unique customers who visited only Groupon, only LivingSocial, and both Groupon and LivingSocial in a particular month. We calculate the percentages of the three types of consumers, and plot the average percentages across markets in Figure 5.

First, we find that the percentage of consumers who exclusively visited LivingSocial decreased before the policy change, while it increased after the policy change. This shift is consistent with the explanation that because LivingSocial contributed more to deal variety after the policy change through its unique deals, it attracted more exclusive consumers. Although LivingSocial copied fewer deals from Groupon after the policy change, the average popularity of these multi-homed deals increased, suggesting that LivingSocial's exclusive consumers could still access the most popular Groupon deals.

Second, we find that the percentage of consumers who exclusively visited Groupon decreased after the policy change, while the percentage of multi-homing consumers who visited both sites increased after the policy change. This result suggests that a few consumers who exclusively visited Groupon before perceived greater value in the increasing variety on LivingSocial and began visiting LivingSocial as well.

LivingSocial's gain on the consumer side is also reflected in site-visiting behaviors of multi-homing consumers. In Figure 6, we plot the proportion of visits to a particular site by a typical multi-homing consumer, measured as the ratio of the number of visits to a particular site to the total number of visits per month. Interestingly, besides gaining more exclusive and multi-homing consumers, we find that LivingSocial enjoyed a higher share of multi-homing consumers' attention after the policy change. The proportion of site visits to LivingSocial decreased before the policy change and increased after the policy change, while the fraction of site visits to Groupon increased before the policy change and decreased after the policy change.

We also observe that the change in the consumers' multi-homing behavior appeared to occur a few months after the policy change, while the change in the merchants' multi-homing behavior happened immediately after the policy change. This result seems to suggest that while the policy change immediately limited LivingSocial's ability to leverage sales information, it took time for consumers to learn about the change in deal variety across multiple platforms. We use a supremum likelihood ratio test to test whether there is a structural change in the percentage of multi-homing consumers and, if yes, where the breakpoint is. We use bi-weekly percentages of multi-homing consumers for this test because of a lack of sufficient observations to perform the test using monthly data (i.e., 24 observations). The p-value is 0.0658, thereby rejecting the null hypothesis of no breakpoint at the 10% level. The empirically estimated breakpoint is the 25th month, which is consistent with our observation from the graph.[12]

We further test whether consumer multi-homing increased after the policy change by regressing the percentage of multi-homing consumers in market m in month t ($Consumer\ Multi_{mt}$) on $Post\ Policy_t$, city fixed effects, and month-of-the-year fixed effects:

$$Consumer\, Multi_{mt} = \beta_0 + \beta_1 Post\, Policy_t + \gamma_m d_m + \gamma_t T_t + \varepsilon_{mt}, \tag{7}$$

where we redefine $Post\ Policy_t$ using the empirically identified breakpoint. As shown in Table 11, there is a positive and significant post-policy main effect, suggesting that the percentage of multi-homing consumers increased by 4.93 percentage points after the policy change.

Finally, we test whether the site-visiting frequency of multi-homing consumers increased for LivingSocial and decreased for Groupon after the policy change by regressing the percentage of site visits to LivingSocial ($Multi\ LivingSocial_{mt}$) for multi-homing consumers in market m in month t on $Post\ Policy_t$, a linear city-specific time trend, the interaction between $Post\ Policy_t$ and the time trend, city fixed effects, and month-of-the-year fixed effects:

$$\begin{aligned} Multi\ LivingSocial_{mt} &= \beta_0 + \beta_1 Post\, Policy_t + \beta_2 Post\, Policy_t \times t_m \\ &\quad + \beta_3 t_m + \gamma_m d_m + \gamma_t T_t + \varepsilon_{mt}, \end{aligned} \tag{8}$$

where $Post\ Policy_t$ is again defined using the empirically identified breakpoint. As shown in Table 12, there is a positive post-policy main effect and a positive interaction effect for LivingSocial, suggesting that multi-homing consumers visited LivingSocial more after the policy change. As the proportion of site visits to Groupon and to LivingSocial sums up to one, the results also suggest that multi-homing consumers visited Groupon less after the policy change.

Overall, consistent with Hypothesis 5, we find that while the policy change reduced multi-homing on the merchant side, it increased multi-homing on the consumer side.

6 Robustness Checks

We conduct robustness checks to ensure that our findings with regard to the changes in LivingSocial's multi-homing strategy are caused by Groupon's policy change, and not by other factors. First, if the reduction in LivingSocial's multi-homing behavior toward Groupon is due to Groupon's policy change, we should not observe a reduction in LivingSocial's multi-homing behavior toward other deal sites. In other words, Hypothesis 1 should not hold when we consider how LivingSocial multi-homed deals on other sites. We plot the percentage of LivingSocial deals that multi-homed other deal sites in Figure 7. There appears to be no reduction in the percentage of LivingSocial

[12] Using a supremum Wald test yields the same result.

deals that multi-homed from other sites after the policy change. Regression analysis suggests the same pattern.

Second, if Groupon's policy change affects LivingSocial's multi-homing behavior, it should also affect the behavior of other sites. In other words, Hypothesis 1 should also hold when we consider how other sites multi-homed deals on Groupon. To test this hypothesis, we calculate the site-city-month level percentage of deals that multi-homed Groupon deals in our data. As there were site entries and exits during our sample period, we focus on the sites that existed during both the pre- and post-policy periods. We also remove the site-city pairs if the number of deals offered by a particular site in a particular city is too small, which may produce very large (e.g., 50%, 100%) or zero percentages and bias the results. Figure 8 shows a plot of the average percentage of deals that multi-homed Groupon deals across sites. We find that other sites also copied Groupon less frequently after the policy change. Regression analysis finds similar results.

7 Conclusion

In this paper, we show that a policy change on Groupon, which limits the sharing of information of deal popularity, reduces the multi-homing behavior of its rival, LivingSocial. The impact of this policy change is moderated by the value of the information to LivingSocial. We also show that this policy change leads to an increase in product variety in the market because of an increased effort by LivingSocial to source new deals independently. As a result, consumers are more likely to multi-home. We contribute to the empirical literature on multi-homing by providing evidence on how information sharing influences the multi-homing behavior of rivals.

Because of the pervasiveness of multi-homing behavior in many platform markets, our findings offer managerial implications for many platform owners. First, our research suggests that multi-homing is not a static feature of a market, nor is it entirely determined by consumers and service providers' decisions. A platform owner can strategically influence multi-homing to its advantage.

Second, we show that platform owners need to be cautious regarding the amount of information they disclose to the public, because rivals can use such information to improve their ability to multi-home, or more generally, to compete. In our setting, disclosing the actual deal sales is beneficial to Groupon as it helps reduce consumers' uncertainty and generate herding behavior, which leads to more deal sales. However, it allows LivingSocial to free-ride and source deals from the popular merchants on Groupon. Platform owners thus face trade-offs in terms of whether and how they disclose such information. Outside the daily deal market, many websites provide similar information to consumers. For example, Amazon provides sales rank information on its website, and Apple and Google publish download rankings for mobile apps on their smartphone operating systems. Such information enables their rivals to target the best-selling items.

Third, when multi-homing takes place on both sides of the market, reducing multi-homing on one side of the market may not be very effective in weakening competitors because it induces a seesaw effect. In our setting, although the policy change reduced multi-homing on the merchant side, it increased multi-homing on the consumer side, which may have strengthened LivingSocial's market position on the consumer side. A platform owner thus needs to find ways to reduce multi-homing on both sides of the market simultaneously to gain market leadership or reduce competitive intensity. Amazon provides fulfilment services to third-party sellers and charges them higher fees when their orders are not from Amazon's marketplace to incentivize them to sell exclusively on its platform. It also uses Amazon Prime, a paid subscription service for free two-day shipping for most of its products, to retain customers and reduce their tendency to multi-home. As another example, manufacturers of video game consoles such as Microsoft and Sony frequently sign contracts with game publishers to make their best games available exclusively for their consoles. On the player side, the high prices of consoles and their associated subscription services such as Xbox Live and PlayStation Plus reduce players' incentives to multi-home. The reduced competitive intensity allowed both console makers to be profitable.

Our study has several important limitations. First, our data set comes from a third-party market research company. As a result, after Groupon's policy change, we do not have accurate sales data for Groupon deals and could not evaluate the impact of its policy change on deal performance on Groupon. Second, although we find that consumers are more likely to visit both sites, we are not able to examine whether consumers ultimately purchased more deals as a result of greater deal variety. Finally, our study examines one approach platform owners can consider in reducing multi-homing. As we have discussed, in practice, platform owners can employ many other strategies to reduce rivals' multi-homing or to encourage users of rival platforms to multi-home. Evaluating these strategies and comparing their effectiveness can be possible avenues for future research.

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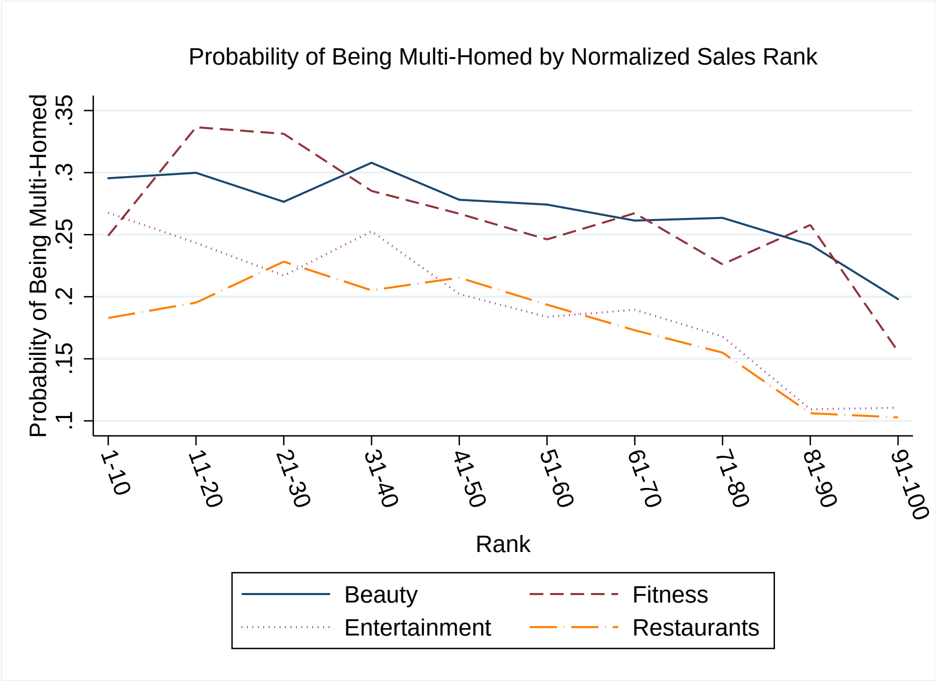


Figure 1: LivingSocial's Multi-Homing Strategy Before the Policy Change

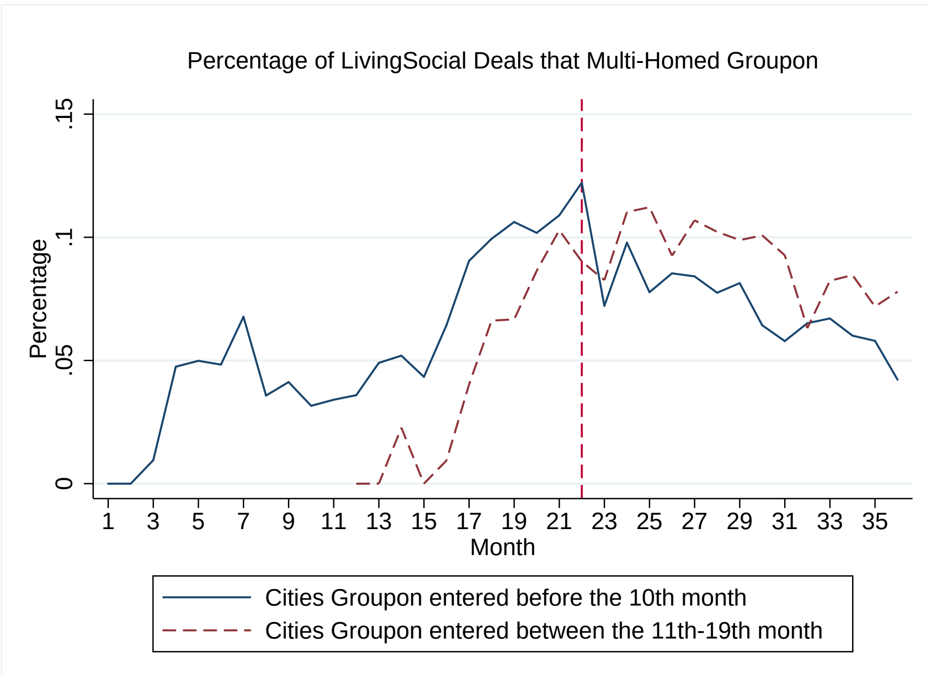


Figure 2: LivingSocial's Multi-Homing Strategy. The dotted vertical line indicates the month in which Groupon changed its counter.

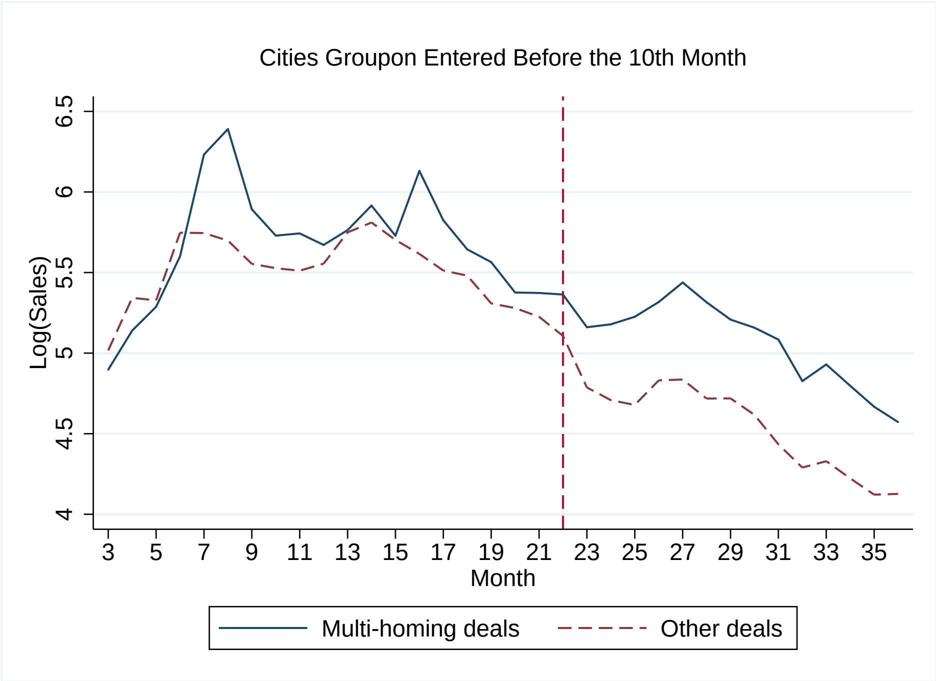


Figure 3: Average Logged Deal Sales

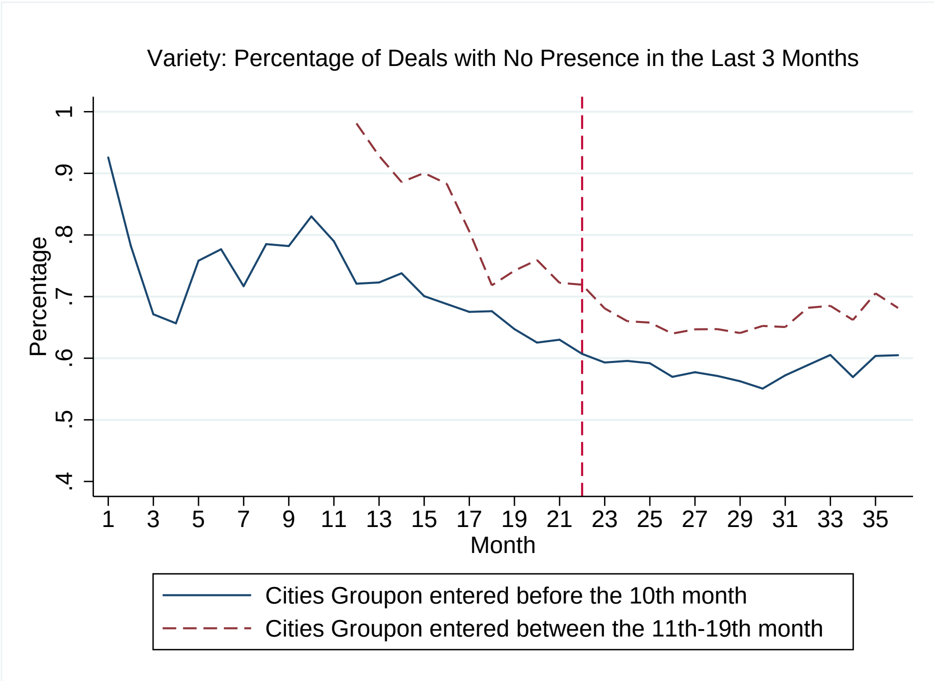
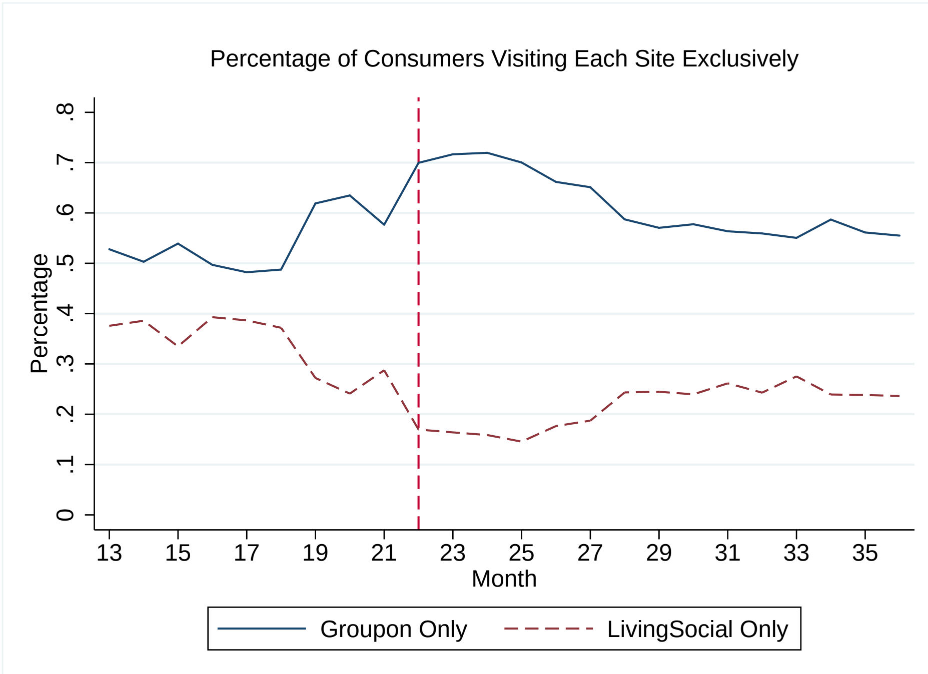


Figure 4: Industry Variety Index



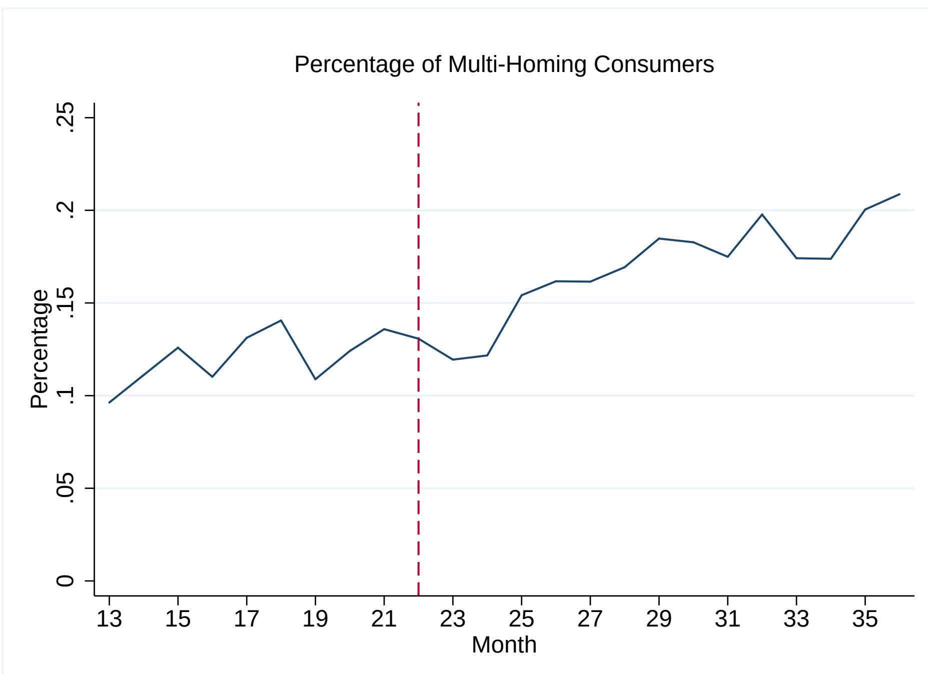


Figure 5: Consumer Site-Visiting Behavior

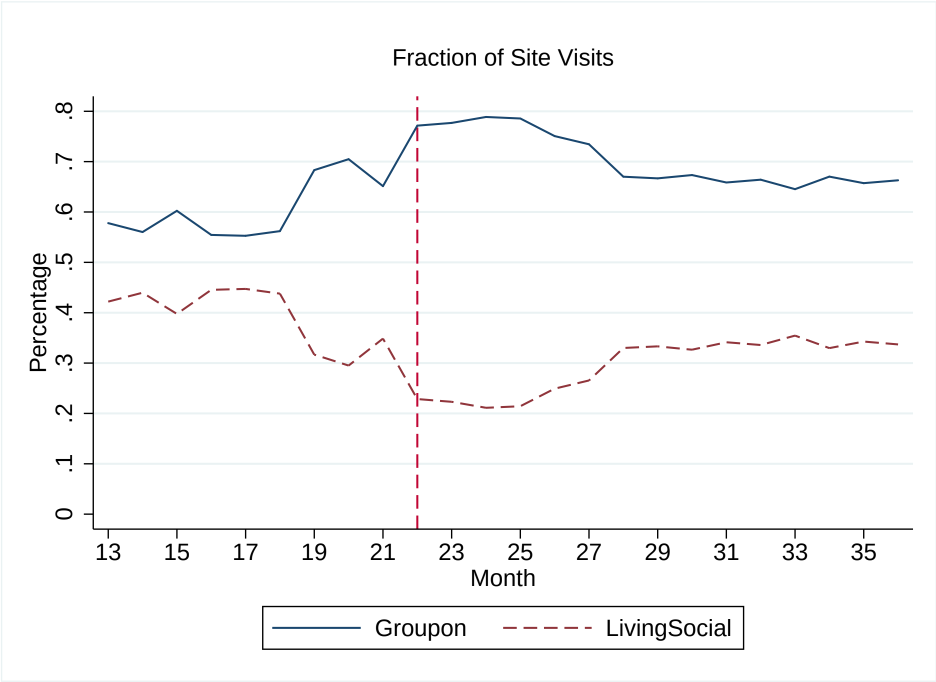


Figure 6: Multi-Homing Consumer Site Visiting Behavior

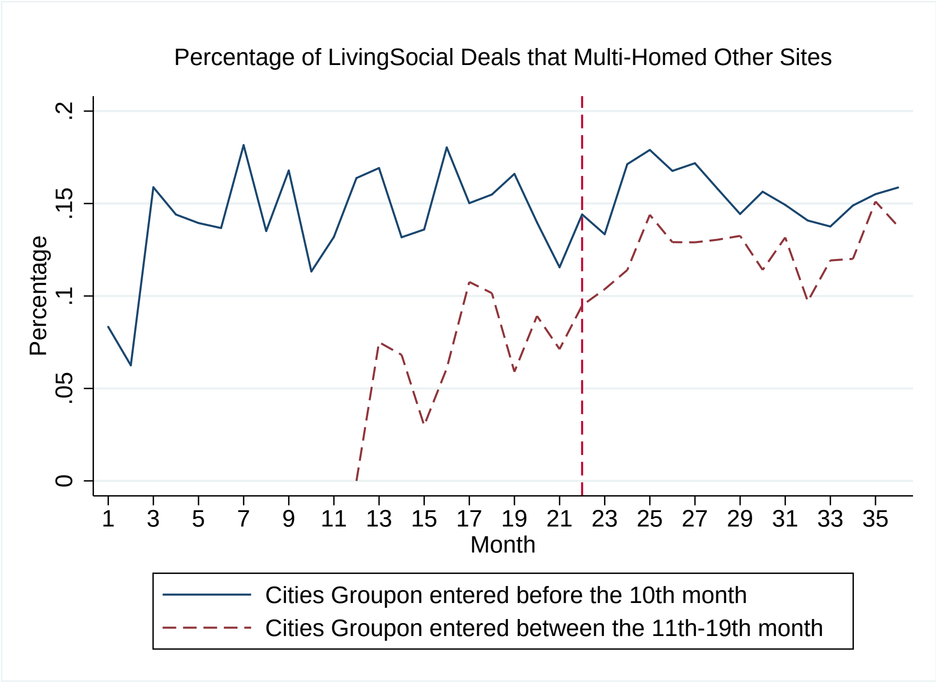


Figure 7: LivingSocial's Multi-Homing Strategy: Other Sites

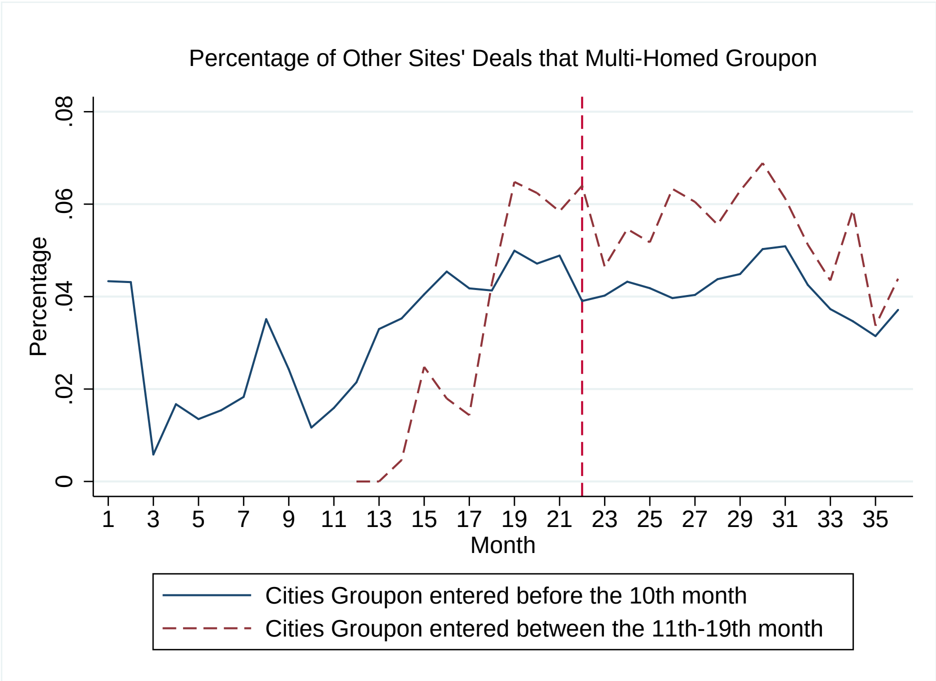


Figure 8: Other Sites' Multi-Homing Strategy

Table 1: Summary Statistics: Deals

	Groupon		LivingSocial		Other Sites	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Price	87.5	(267.5)	58.9	(169.0)	63.9	(344.8)
Discount	58.0	(14.8)	57.2	(11.6)	56.2	(14.1)
Duration	12.4	(24.7)	6.34	(5.33)	6.42	(7.32)
Unit Sales	242.9	(1487.0)	296.7	(1318.9)	108.4	(331.4)
Past Experience: Groupon	0.94	(1.75)	0.54	(1.32)	0.50	(1.23)
Past Experience: LivingSocial	0.29	(0.72)	0.36	(0.94)	0.29	(0.74)
Past Experience: Other Sites	1.02	(3.46)	1.06	(3.20)	2.99	(7.08)
Observations	271,745		80,769		265,744	

Table 2: Summary Statistics: Merchants

	Unique Merchants		Number of Deals Per Merchant	
	Number	%	Mean	Std. dev.
Groupon	95,565	(59.4%)	1.69	(5.73)
LivingSocial	81,550	(50.7%)	0.50	(1.32)
Other Sites	120,733	(75.0%)	1.65	(4.80)

Table 3: Regression Results: LivingSocial's Multi-Homing Deal Volume

DV: Percentage of Multi-Homing Deals	(1)		(2)	
Post Policy	0.0897***	(0.00904)	0.0819***	(0.00898)
Post Policy × Time Trend	−0.00614***	(0.000738)	−0.00614***	(0.000774)
Time Trend	0.00520***	(0.000882)	0.00572***	(0.000929)
Population	$-2.99e{-}09$***	($6.67e{-}10$)	–	
Female	0.00586	(0.00538)	–	
Age	−0.00531	(0.00406)	–	
Income	0.000782	(0.00114)	–	
Education	−0.00177*	(0.000961)	–	
City Fixed Effects	–		YES	
Month-of-the-year Fixed Effects	YES		YES	
Category Fixed Effects	YES		YES	
Observations	10,087		10,087	
R-squared	0.042		0.065	

Notes: Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: Regression Results: LivingSocial's Multi-Homing Deal Popularity

DV: Logged Deal Sales	(1)		(2)	
Post Policy	−0.377***	(0.0516)	−0.199***	(0.0270)
Multi-Homing	0.0692**	(0.0313)	0.0981***	(0.0278)
Post Policy × Multi-Homing	0.244***	(0.0350)	0.207***	(0.0312)
Own Existence	0.326***	(0.0168)	0.323***	(0.0155)
Time Trend: Linear	−0.0107	(0.00692)	−0.0315***	(0.00545)
Time Trend: Quadratic	$-5.61e{-}05$	(0.000151)	0.000217	(0.000139)
Population	$3.64e{-}08$***	($4.00e{-}09$)	–	
Female	−0.0565	(0.0484)	–	
Age	0.0573	(0.0409)	–	
Income	0.0244***	(0.00914)	–	
Education	0.0238***	(0.00759)	–	
City Fixed Effects	–		YES	
Deal Characteristics	YES		YES	
Month-of-the-year Fixed Effects	YES		YES	
Category Fixed Effects	YES		YES	
Observations	81,326		81,326	
R-squared	0.330		0.355	

Notes: Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 5: Robustness: LivingSocial's Multi-Homing Deal Characteristics

Dependent Variable	*Logged Price*	*Logged Discount*	*Logged Duration*
Post Policy	-0.0342^{*}	0.0266^{***}	-0.0543^{***}
	(0.0186)	(0.00413)	(0.0203)
Multi-Homing	-0.0350	0.0197^{***}	-0.0317^{***}
	(0.0238)	(0.00505)	(0.00876)
Post Policy × Multi-Homing	0.0203	0.00189	0.00814
	(0.0196)	(0.00774)	(0.00904)
Own Existence	0.0721^{***}	-0.00598	-0.0396^{***}
	(0.00801)	(0.00940)	(0.00665)
Time Trend: Linear	0.00979^{***}	-0.000493	0.0515^{***}
	(0.00210)	(0.000648)	(0.00436)
Time Trend: Quadratic	$-1.52e{-}05$	$-4.73e{-}05^{**}$	0.000189^{**}
	$(5.76e{-}05)$	$(1.89e{-}05)$	$(7.40e{-}05)$
City Fixed Effects	YES	YES	YES
Month-of-the-year Fixed Effects	YES	YES	YES
Category Fixed Effects	YES	YES	YES
Observations	81,366	81,363	81,366
R-squared	0.297	0.115	0.555

Notes: Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 6: Moderator 1: Demand Variation

DV: Logged Deal Sales	(1)		(2)	
Post Policy	0.613***	(0.129)	0.840***	(0.110)
Multi-Homing	−0.102	(0.177)	−0.119	(0.157)
Demand Variation	0.466***	(0.152)	0.190	(0.135)
Post Policy × Multi-Homing	−0.799***	(0.186)	−0.795***	(0.173)
Post Policy × Demand Variation	−0.780***	(0.0890)	−0.818***	(0.0792)
Multi-Homing × Demand Variation	0.130	(0.138)	0.168	(0.125)
Post Policy × Multi-Homing × Demand Variation	0.816***	(0.148)	0.781***	(0.139)
Own Existence	0.317***	(0.0167)	0.314***	(0.0154)
Time Trend: Linear	−0.0101	(0.00702)	−0.0317***	(0.00548)
Time Trend: Quadratic	−6.01e−05	(0.000157)	0.000234*	(0.000139)
Population	3.55e−08***	(4.02e−09)	–	
Female	−0.0560	(0.0484)	–	
Age	0.0536	(0.0418)	–	
Income	0.0240**	(0.00914)	–	
Education	0.0234***	(0.00765)	–	
City Fixed Effects	–		YES	
Deal Characteristics	YES		YES	
Month-of-the-year Fixed Effects	YES		YES	
Category Fixed Effects	YES		YES	
Observations	81,315		81,315	
R-squared	0.334		0.360	

Notes: Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 7: Moderator 2: Uncertainty

DV: Logged Deal Sales		(1)		(2)	
	Category				
Post Policy	0	−0.353**	(0.137)	−0.153	(0.122)
× Category Fixed Effect	1	−0.450***	(0.0538)	−0.249***	(0.0327)
	2	−0.461***	(0.0673)	−0.285***	(0.0406)
	3	−0.668***	(0.0521)	−0.479***	(0.0327)
	4	0.0276	(0.0669)	0.203***	(0.0568)
	5	−0.528***	(0.0699)	−0.357***	(0.0543)
	6	−0.285***	(0.101)	−0.133	(0.0846)
	7	−0.168	(0.124)	0.0223	(0.112)
Multi-Homing	0	−0.0261	(0.284)	−0.0115	(0.282)
× Category Fixed Effect	1	−0.0211	(0.0404)	0.0153	(0.0387)
	2	0.345***	(0.0748)	0.353***	(0.0736)
	3	0.0726	(0.0651)	0.108*	(0.0623)
	4	−0.0218	(0.0598)	0.0101	(0.0556)
	5	0.295***	(0.102)	0.314***	(0.102)
	6	0.128	(0.111)	0.135	(0.107)
	7	−0.142	(0.326)	−0.121	(0.328)
Post Policy	0	0.239	(0.417)	0.182	(0.416)
× Multi-Homing	1	0.182***	(0.0452)	0.133***	(0.0449)
× Category Fixed Effect	2	0.0305	(0.0796)	0.0199	(0.0764)
	3	0.543***	(0.0687)	0.496***	(0.0653)
	4	0.00123	(0.0660)	−0.0424	(0.0613)
	5	0.231**	(0.110)	0.216**	(0.108)
	6	0.0726	(0.128)	0.0735	(0.126)
	7	0.462	(0.348)	0.429	(0.349)
Own Existence		0.320***	(0.0168)	0.318***	(0.0155)
Time Trend: Linear		−0.00976	(0.00693)	−0.0308***	(0.00543)
Time Trend: Quadratic		$-8.27e{-05}$	(0.000152)	0.000181	(0.000140)
Population		$3.68e{-08}$***	($3.91e{-09}$)	–	
Female		−0.0571	(0.0481)	–	
Age		0.0529	(0.0408)	–	
Income		0.0240***	(0.00906)	–	
Education		0.0238***	(0.00760)	–	
City Fixed Effects		–		YES	
Deal Characteristics		YES		YES	
Month-of-the-year Fixed Effects		YES		YES	
Category Fixed Effects		YES		YES	
Observations		81,326		81,326	
R-squared		0.337		0.362	

Notes: Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Category 0, 1, 2, ..., and 7 represent "Other," "Beauty," "Fitness," "Entertainments," "Restaurants," "Home and Family," "Automobile," "Clothing and Goods," respectively.

Table 8: Summary Statistics: Deal Characteristics by Category on LivingSocial

	Unique Deals		Price		Discount		Duration		Unit Sales	
	Number	%	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Beauty	20,147	(24.8)	101.2	(286.3)	60.6	(12.4)	5.2	(2.6)	184.7	(302.0)
Fitness	9,578	(11.8)	36.7	(33.0)	65.8	(13.2)	5.0	(3.1)	194.9	(325.5)
Entertainments	19,312	(23.7)	56.9	(132.8)	54.9	(11.7)	7.4	(6.4)	327.7	(1840.0)
Restaurants	15,487	(19.0)	17.6	(24.8)	50.8	(5.0)	5.3	(5.9)	534.8	(764.1)
Home and Family	12,144	(14.9)	66.1	(133.7)	56.6	(9.4)	9.4	(8.2)	187.8	(2153.6)
Automobile	2,574	(3.2)	50.4	(44.5)	57.9	(10.2)	5.3	(2.7)	311.3	(1055.8)
Clothing and Goods	1,335	(1.6)	49.8	(80.8)	54.9	(8.8)	6.1	(4.0)	210.8	(581.3)
Other	789	(1.0)	38.5	(81.0)	54.1	(9.1)	5.3	(9.9)	722.8	(1663.9)

Table 9: Moderator 2: Category Price

DV: Logged Deal Sales	(1)		(2)	
Post Policy	0.835***	(0.144)	1.015***	(0.140)
Multi-Homing	−0.111	(0.190)	−0.0841	(0.180)
Category Price	0.735***	(0.124)	0.434***	(0.108)
Post Policy × Multi-Homing	−0.271	(0.217)	−0.341	(0.208)
Post Policy × Category Price	−0.340***	(0.0374)	−0.346***	(0.0369)
Multi-Homing × Category Price	0.0506	(0.0499)	0.0503	(0.0482)
Post Policy × Multi-Homing × Category Price	0.144**	(0.0575)	0.155***	(0.0564)
Own Existence	0.324***	(0.0166)	0.321***	(0.0156)
Time Trend: Linear	−0.0134**	(0.00655)	−0.0320***	(0.00561)
Time Trend: Quadratic	$6.38e{-}06$	(0.000154)	0.000243	(0.000150)
Population	$2.85e{-}08$***	($4.03e{-}09$)	–	
Female	−0.0351	(0.0458)	–	
Age	0.0264	(0.0393)	–	
Income	0.0222**	(0.00862)	–	
Education	0.0233***	(0.00718)	–	
City Fixed Effects	–		YES	
Deal Characteristics	YES		YES	
Month-of-the-year Fixed Effects	YES		YES	
Category Fixed Effects	YES		YES	
Observations	81,326		81,326	
R-squared	0.334		0.358	

Notes: Robust standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 10: Regression Results: Industry Variety

Dependent Variable	*Deal Variety*	*Groupon's Contribution*	*LivingSocial's Contribution*
Post Policy	-0.180^{***}	0.0167	0.0221^{**}
	(0.00862)	(0.0138)	(0.0110)
Post Policy × Time Trend	0.0107^{***}	-0.00129	0.00178^{**}
	(0.000597)	(0.000954)	(0.000760)
Time Trend	-0.0134^{***}	0.0114^{***}	-0.00223^{***}
	(0.000645)	(0.00103)	(0.000822)
City Fixed Effects	YES	YES	YES
Month-of-the-year Fixed Effects	YES	YES	YES
Observations	1,676	1,676	1,676
R-squared	0.754	0.728	0.597

Notes: Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 11: Regression Results: Consumer Site Visit Behavior

DV: Percentage of Multi-Homing Consumers	
Post Policy	0.0493^{***}
	(0.0106)
City Fixed Effects	YES
Month-of-the-year Fixed Effects	YES
Observations	1,375
R-squared	0.268

Notes: Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 12: Regression Results: Site Visit Behavior of Multi-Homing Consumers

DV: Percentage of Visits to LivingSocial		
Post Policy	0.234^{***}	(0.0852)
Post Policy × Time Trend	0.0143^{***}	(0.00318)
Time Trend	-0.0392^{***}	(0.00740)
City Fixed Effects	YES	
Month-of-the-year Fixed Effects	YES	
Observations	1,375	
R-squared	0.214	

Notes: Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.