Information Transparency, 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., complementors or consumers adopt more than one platform). To take advantage of multi-homing, platform firms often attempt to motivate their rivals' high-performing complementors to adopt their own platforms, or attempt to prevent their current complementors or consumers from multi-homing. In this paper, we study the effectiveness of such strategies in the context of the online daily deals market. We first develop a game-theoretical model that takes into account multi-homing on both sides of the market and strategic behavior of all participants—consumers, platform firms, and merchants. We then derive hypotheses and empirically test them. The empirical analysis leverages a policy change of Groupon that reduced information transparency and weakened LivingSocial's ability to identify popular Groupon deals and poach the corresponding merchants. Our results show that limiting information transparency reduced multi-homing: after the policy change, LivingSocial copied fewer deals from Groupon and increased its efforts to source new deals. Consequently, industry-wide deal variety increased. We also observe 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, after accounting for changes in both lifetime value of the customer base and acquisition cost of merchants, Groupon's policy change reduced LivingSocial's profitability.

Keywords: platform competition, multi-homing, information transparency, seesaw effect, 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 January 2020, of the top 10 most valued public companies, seven based their growth on their platform ecosystems. 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; Corts and Lederman, 2009; Cennamo et al., 2018; Venkataraman et al., 2018; Park et al., 2020). 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 consumers and complementors, many platforms are transparent regarding the performance of their complementors (and sometimes consumers), displaying information such as their ratings and past sales information to the public. For example, Uber provides ratings of its drivers, Airbnb provides ratings for its hosts and travelers, Amazon provides sales ranks for its products, and daily deal sites provide sales information for individual deals. While such information transparency has shown to attract more consumers and improve matching (e.g., Lynch and Ariely, 2000; Tucker and Zhang, 2011), it makes it easy for a rival platform to selectively poach high-quality complementors and consumers from the focal platform. For instance, Groupon's deal sales information allows LivingSocial to identify popular merchants and source deals from Groupon. In a similar vein, eBay claimed that Amazon attempted to lure its top sellers to sell on Amazon's marketplace by exploiting its internal messaging system to contact eBay sellers.[1] 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, Forthcoming). Hence, a rival platform's multi-homing can slow down the focal platform's ability to grow and dominate the market.

Empirical research on how firms leverage multi-homing as a competitive weapon and its effectiveness is limited. In this paper, we address this gap by analyzing the U.S. online daily deals market. Our analysis takes advantage of an exogenous policy shift from Groupon that limited the accuracy of the deal sales information displayed in its deal counter. The change in the level of information transparency reduced LivingSocial's ability to identify popular Groupon deals and poach corresponding merchants. We first develop a game-theoretical model that takes into account multi-homing on both sides of the market and strategic behavior of all parties—consumers, platform firms, and merchants. We then derive hypotheses concerning Groupon's policy shift and empirically test them. Our results show that limiting information transparency reduced the multi-homing of rivals on the merchant side. We find that after the policy shift, LivingSocial copied fewer Groupon deals and 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

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

multi-homing led to increased consumer-side multi-homing, thereby strengthening LivingSocial's market position on the consumer side. This result illustrates 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. Therefore, it might become more difficult for one platform to sufficiently reduce its rival's user bases on both sides to dominate the market. Overall, although LivingSocial benefited from increased consumer-side multi-homing, the cost of acquiring new merchants dominated this gain so that LivingSocial's profitability decreased after the policy change.

Our results have important managerial implications. First, we show that platform owners need to be cautious regarding the amount of information they disclose to the public, because rivals can use this information to improve their ability to multi-home or, more generally, to compete. Second, we show that when multi-homing takes place on both sides of the market, reducing multi-homing on one side may not be very effective in reducing competitors' market shares because it induces a seesaw effect. Thus, a platform owner may have to find ways to reduce multi-homing on both sides of the market simultaneously to gain market dominance. Third, we show that how rivals are affected by limiting information transparency on a focal platform should account for changes on the consumer side and for the cost of merchant acquisition, which may vary by industry and by market. The focal platform needs to consider the trade-offs before adopting this strategy.

Our study contributes to the literature on multi-homing, which is often considered one of the most important forces driving the competitive outcomes among platforms (e.g., Armstrong, 2006). We contribute to the literature in three ways. First, the literature on multi-homing usually abstracts from a platform's role or assumes that it uses price as the only tool to influence multi-homing (e.g., Armstrong, 2006; Rochet and Tirole, 2003, 2006; Armstrong and Wright, 2007; Jeitschko and Tremblay, Forthcoming; Belleflamme and Peitz, 2019; Liu et al., 2019). In practice, platform owners are well aware of the importance of multi-homing and are designing strategies to change complementors' or consumers' multi-homing behavior to their advantages. For example, Uber and Lyft actively encouraged each other's drivers to serve on their own platforms or asked their own drivers not to multi-home.[2] Game console providers have offered incentives to top-ranked game publishers for signing exclusive contracts with them. 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, reportedly discouraged its merchants from adopting its rival's marketplace by designing its ranking algorithm to favor single-homing merchants.[4] Our study focuses on a platform's role in influencing multi-homing tendencies on both the merchant and consumer sides by limiting information transparency.

Second, multi-homing in the literature is often restricted to one side of the market (e.g., Armstrong, 2006; Kaiser and Wright, 2006; Athey et al., 2018; Ambrus et al., 2016), potentially because of the complexity of the problem. 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.[5] We allow for multi-homing on both the consumer and merchant sides in the theoretical model and show that multi-homing can exist on both sides in equilibrium. As argued by Jeitschko and Tremblay (Forthcoming), this equilibrium is the most common allocation observed in reality. Importantly, our theoretical model allows all parties—platforms, merchants, and consumers—to be strategic in a competitive setting. We also provide empirical evidence that more single-homing on the merchant side can induce more multi-homing on the consumer side, which is consistent with the theoretical finding in Choi (2010).

Third, much of the multi-homing literature is theoretical. The only few empirical studies mostly focus on the video game industry; these studies find that platform owners need to prevent their users from multi-homing because multi-homing can hurt their sales (Landsman and Stremersch 2011) and make it less likely for one platform to dominate (Corts and Lederman 2009). They also show that exclusive contracts can reduce the entry barrier for entrant platforms (Lee 2013). We contribute to the literature by leveraging a unique natural experiment setting and empirically

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

[5]The intuition here is that when all agents multi-home on one side of the market, agents on the other side do not gain from multi-homing.

documenting how the ease of multi-homing affects various aspects of the market, including platform strategy, consumer adoption, and industry-wide variety.

Our paper is also related to the vast amount of literature on information transparency, particularly, how firms can design new mechanisms that reveal, conceal, bias, and distort information regarding product, price, popularity, and inventory levels to their advantages (e.g., Tapscott and Ticoll, 2003; Granados et al., 2010). Information transparency can have a wide range of effects. Most of the studies focus on how information transparency can affect consumers and focal firms (e.g., Chen and Xie, 2008; Tucker and Zhang, 2011). Some show that transparency can increase sales (e.g., Zhang, 2010; Li and Wu, forthcoming; Lynch and Ariely, 2000; Wagner et al., 2018), while others find that full transparency is not always beneficial (e.g., Gal-Or, 1988; Zhu, 2004; Schultz, 2005; Hotz and Xiao, 2013; Jiang et al., 2017) and that firms may benefit from the manipulation of information through distortion, opaqueness, and bias (e.g., Ellison and Ellison, 2009). A few theoretical studies focus on how information transparency can affect rival firms. For example, Dewan et al. (2007) find that the information intended for consumers on available stock can be used by competitors to dynamically set prices to their advantage. However, empirical work in this area is quite limited. We contribute to the literature by highlighting how information transparency can affect consumers, rival firms, and the industry, both theoretically and empirically. Consistent with prior studies (e.g., Ellison and Ellison, 2009; Zhang, 2010), we find that the simple manipulation of information transparency can result in significant changes in the behavior of market participants.

Finally, our paper adds to the literature on the daily deals market (e.g., Gupta et al., 2011, 2012; Norton et al., 2012; Edelman et al., 2016; Song et al., 2016; Li et al., 2018, forthcoming; Zhang and Chung, forthcoming). In particular, the deal counter has received a great deal of attention in the literature as an important strategic tool of the platforms in this industry. Early research has shown that displaying a minimum limit of deal sales for the deal to be valid can affect sales through group buying (e.g., Jing and Xie, 2011; Chen and Zhang, 2015; Hu et al., 2013; Wu et al., 2014). Other works have shown that displaying deal sales can impact deal sales by triggering herding on the consumer side (Li and Wu, forthcoming) and signaling high-quality on the merchant side (Subramanian and Rao, 2016). We contribute to the literature by studying how displaying deal sales information can affect rivals, consumers, and the industry. Regarding multi-homing, Dholakia (2011) surveys merchants and finds a significant interest in multi-homing. Kim et al. (2017) document significant multi-homing behavior in this industry. Because their studies are based on descriptive statistics and correlation analysis, however, what drives merchants' multi-homing behavior and the impact of such behavior remains unclear. Our study explores how information transparency serves as a driving force for multi-homing behavior.

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 from local merchants online 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 and persuade them to offer deals on their sites, usually with a split of revenue close to 50/50 between the platform and the merchants (Dholakia, 2011). The merchants' negotiation power is highly limited: the deal terms (e.g., discount rate and duration) are usually proposed by the platform based on the terms of similar deals in the past; the merchants are rarely able to negotiate the deal terms (Agrawal, 2011). If a merchant agrees to offer deals, it signs a contract with the platform, which includes the specific product or service offered in the deal, the deal terms, and the commission rate to the platform. Merchants' and consumers' adoption decisions are mainly driven by the classic indirect network effect on two-sided platforms: merchants value the size of the consumer base, and consumers care about the deal variety on a platform.

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. Because of contractual agreements, a merchant often offers deals on one site at a time. Thus, we 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 offer exactly the same deal multiple times.

Groupon is the leading daily deal website in this industry. The company 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 in a blog post a change that it made to its deal counter:[6] "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 stated 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." The change was immediately reported by major media such as the Wall Street Journal, CBS News, and Chicago Tribune.

Right after this announcement, Sucharita Mulpuru, an analyst with Forrester Research, said the company should have eliminated its deal counter a long time ago because it only benefitted Groupon's competitors, who could tell which deals were the most popular and then copy them.[7]

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 exogenous to factors that drive competitors' multi-homing behavior. In addition, if Groupon indeed used this policy change to deter multi-homing, it should have also changed other strategies related to multi-homing. In particular, Groupon could have offered more favorable deal terms (e.g., deal discount and duration) and commission rates to the merchants when negotiating with them, which could have incentivized the merchants to work exclusively with Groupon and, hence, reduce multi-homing. We test this possibility and do not find evidence that the deal terms or commission rates changed during that time. Section 6.1 includes details of this test along with a set of robustness checks regarding

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

the assumption that the counter change is exogenous, which arrive at the same conclusion. This boosts our confidence that the policy change was not aimed at deterring multi-homing.

Our analysis focuses on how Groupon's policy change affected its largest rival, LivingSocial. 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 was 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 when it comes to identifying popular deals to source. Consequently, Groupon's policy change was likely to have a significant impact on LivingSocial's multi-homing behavior. The change in the platform's multi-homing strategy can further impact consumers' multi-homing behavior and the industry.

3 Hypothesis Development

We first use a theoretical model to derive testable hypotheses regarding the policy impact on platforms' multi-homing decisions, and merchants' and consumers' adoption decisions. As with many theoretical models on platforms,[8] we build our model specifically for the daily deal market so that we could use features of this market to inform our modeling assumptions.

The model captures multi-homing incentives for the platforms, the consumers, and the merchants. For the platforms, although multi-homing helps reduce the uncertainty of deal popularity and potentially lowers deal discovery and acquisition costs, multi-homing reduces the differentiation between the two platforms, thereby intensifying the competition. This trade-off suggests that platforms have incentives to both multi-home and search for new, unique deals. Consumers' and merchants' adoption decisions are mainly driven by the classic indirect network effect on two-sided platforms, here with an additional consideration of multi-homing. Consumers are attracted by deal variety and popularity on a platform. They are more likely to multi-home if the two platforms are more differentiated and provide fewer overlapping deals. Merchants are attracted by the consumer base of a platform and will adopt a platform if the revenue from the consumer base is large

[8]For example, Rochet and Tirole (2003) are inspired by the credit card industry, Hagiu (2009) and Lee (2013) study the video game industry, and Halaburda et al. (2018) are motivated by the matching market.

enough to cover the cost of adopting the platform. In addition, merchants take into account that multi-homing consumers and single-homing consumers may generate different revenues.

The timing of the model is as follows: At the beginning, there are a set of merchants that have worked with Groupon before. Their popularity is known to the public because Groupon disclosed their past sales information. The two platforms, Groupon and LivingSocial, can choose to approach some of them (i.e., "copy") or search for new merchants (i.e., "search") with uncertain popularity.[9] We assume that Groupon is the Stackelberg leader because it is a first mover in most markets. Merchants who are approached by either platform then decide whether to accept the offer, and they do this by accounting for the number of consumers on each platform. At the same time, consumers decide which platform(s) to use, and they do this by accounting for the number of merchants that will offer deals on each platform. We solve for the equilibrium platform strategies and merchant and consumer adoption decisions. Then, we derive how the deal counter change affects the equilibrium through raising LivingSocial's cost of copying merchants.

The merchants have heterogeneous popularity. The most popular merchants are known to the public and will always be approached by both platforms, regardless of whether Groupon discloses their sales information. Hence, we focus on solving the platforms' copying and searching strategies of the moderately popular merchants. We make this modeling assumption for the following reasons: First, popular merchants can be easily identified,[10] and they could potentially bring great revenue to the platforms. Hence, the benefit of approaching them is likely to exceed the cost. Second, the moderately popular merchants are more relevant for our analysis of the policy impact. Because of limited information from other channels, accurate past sales information on the moderately popular

[9] We focus on modeling platforms' copying and searching strategies as their strategic decisions because, as discussed in Section 6.1 of the paper, Groupon's deal terms (discount and duration) and commission rates did not change after the policy change. This finding is consistent with Kim et al. (2017) who find no meaningful inter-platform differences in deal terms for comparable deals in the daily deals industry. It is consistent with the wisdom from industry experts that platforms in this industry did not use deal terms or commission rates as a competitive tool during this period.

[10] 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 discussions 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 a sufficient signal regarding deal popularity because the number in the counter presents 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 about product quality.

merchants from Groupon is more valuable. The deal counter change makes it difficult to identify such merchants.

Importantly, the model allows for both the consumer and the merchant sides to multi-home. Given the complexity of the problem, we present a baseline model where we solve for LivingSocial's strategy given a fixed Groupon's strategy, assuming that all the merchants that are approached will accept the offers. In the appendix, we present two model extensions. The first extension allows Groupon to strategically choose its strategy and anticipate LivingSocial's optimal response. The second extension further relaxes our assumption to allow the merchants to strategically choose whether to accept the offers. In all cases, consumers are allowed to strategically choose which platform(s) to use. As shown in the appendix, the hypotheses derived from the baseline model continue to hold when allowing all parties—platforms, merchants, and consumers—to be strategic.

3.1 Model Setup

In the baseline model, we assume that Groupon's strategy is fixed and derive LivingSocial's best response to the policy change. We also assume that the merchants are in a competitive market and will always accept the offers if the platform(s) approach them.

There are N merchants that have worked with Groupon before and each merchant has one deal to offer. We use subscript G and L to denote Groupon and LivingSocial, respectively. As in Choi (2010), we assume that there is a binding upper bound for the total number of merchants offering deals on either platform $(\bar{N}_G, \bar{N}_L)$, so the platform needs to trade off between copying existing merchants versus searching for new merchants.[11] Groupon copies N_G past merchants and searches for $\bar{N}_G - N_G$ new merchants. LivingSocial copies N_L past merchants and searches for $\bar{N}_L - N_L$ new merchants. The cost of copying a merchant from the existing pool is $C_{G,C}$ for Groupon and $C_{L,C}$ for LivingSocial. The cost of searching for a new merchant is $C_{G,S}$ for Groupon and $C_{L,S}$ for LivingSocial.

Consumers are uniformly distributed along a Hotelling line of length 1, with Groupon at 0, LivingSocial at 1, and a unit transportation cost of t.[12] Consumers value deal variety and receive an

[11] The upper bound captures consumers' cognitive limitations of going through many deals.

[12] We use the Hotelling model to capture the differentiation between the two platforms. Besides differences in site layouts, Groupon and LivingSocial also differed in policies. For example, at that time, unlike Groupon, LivingSocial

expected utility of u_s from each searched merchant and u_c from each copied merchant. The utilities of a consumer with location $x \in [0, 1]$ from using Groupon exclusively, LivingSocial exclusively, and multi-homing are, thus, the following:

$$
\begin{aligned}
U_G &= u_s(\bar{N}_G - N_G) + u_c N_G - tx, \\
U_L &= u_s(\bar{N}_L - N_L) + u_c N_L - t(1 - x), \\
U_{GL} &= bu_s(\bar{N}_G - N_G) + bu_s(\bar{N}_L - N_L) + bu_c(N_G + N_L - \frac{N_G N_L}{N}) - t. \qquad (1)
\end{aligned}
$$

For multi-homing consumers, the expected utility from each merchant is further multiplied by $b \in \left(\frac{1}{2}, 1\right)$. On the one hand, the per-merchant expected utility is smaller for a multi-homing consumer than for a single-homing consumer because of the consumer's limited attention or the cost of visiting two platforms, as captured by $b < 1$. On the other hand, for multi-homing to take place, there has to exist a consumer who obtains greater expected utility from multi-homing than from single-homing on either platform, which yields $b > \frac{1}{2}$.[13] Note that N_G and N_L represent the number of merchants copied from the same pool, and may contain overlapping merchants. We subtract the average number of overlapping merchants ($\frac{N_G N_L}{N}$) from the expected utility of multi-homing consumers so they only value overlapping merchants once.[14] Setting $U_G = U_{GL}$ and $U_L = U_{GL}$ yields the locations of consumers who are indifferent between exclusively visiting Groupon and multi-homing, x_1, and indifferent between multi-homing and exclusively visiting LivingSocial, x_2:

$$
\begin{aligned}
x_1 &= 1 + \frac{(1 - b)u_s(\bar{N}_G - N_G) + (1 - b)u_c N_G - bu_s(\bar{N}_L - N_L) - bu_c(N_L - \frac{N_G N_L}{N})}{t}, \\
x_2 &= \frac{bu_s(\bar{N}_G - N_G) - (1 - b)u_s(\bar{N}_L - N_L) + bu_c(N_G - \frac{N_G N_L}{N}) - (1 - b)u_c N_L}{t}.
\end{aligned}
$$

had no minimum number of people required to participate for the deal to start. Therefore, we assume the transportation cost, t, is large enough so that each platform will capture some exclusive consumers in equilibrium. This is also consistent with our comScore data on consumer website visits.

[13]For multi-homing to take place, there has to exist a consumer with location $\tilde{x}$ such that $U_{GL}(\tilde{x}) > U_G(\tilde{x})$, and $U_{GL}(\tilde{x}) > U_L(\tilde{x})$. Substituting the expressions of U_{GL}, U_G, and U_L into the inequalities yields $b > \frac{1}{2}$.

[14]We assume that the merchants separately searched by the two platforms do not overlap. However, because the two platforms copy from the same set of past merchants, there are potentially overlapping merchants. Given that there are N past merchants and that Groupon copied N_G of them, the average probability of being copied by Groupon is $\frac{N_G}{N}$. When LivingSocial copies N_L from the same pool of past merchants, $N_L \times \frac{N_G}{N}$ of them would be approached by Groupon as well. Therefore, the number of overlapping merchants is $\frac{N_G N_L}{N}$.

The numbers of exclusive Groupon consumers, multi-homing consumers, and exclusive LivingSocial consumers are x_1, $x_2 - x_1$, and $1 - x_2$, respectively, as shown in Figure 1.

Given Groupon's choice of N_G, LivingSocial chooses N_L to maximize its profit:

$$\pi_L = b_1(1 - x_2) + \frac{b_2}{2}(x_2 - x_1) - \frac{N_L^2}{2} C_{L,C} - \frac{(\bar{N}_L - N_L)^2}{2} C_{L,S},$$

where we use a quadratic cost function to capture the increasing cost of acquiring merchants. b_1 is the revenue generated by each single-homing consumer, and b_2 is the revenue generated by each multi-homing consumer (assuming the revenue is evenly split between the two platforms).[15] We assume that a multi-homing consumer can generate more revenue than a single-homing consumer because multi-homing consumers are likely to be avid deal seekers, $b_1 < b_2$.[16] The first-order condition with respect to the number of copied merchants for LivingSocial is

$$N_L^* = \frac{\bar{N}_L C_{L,S} + b_1 \frac{(1-b)u_c - (1-b)u_s}{t} - \frac{b_2}{2} \frac{(1-2b)u_c - (1-2b)u_s}{t} + \frac{(b_1 - b_2)bu_c}{N} N_G}{C_{L,C} + C_{L,S}}, \tag{2}$$

which decreases with $C_{L,C}$, increases with $C_{L,S}$, and decreases with N_G and u_s. Intuitively, if the cost of copying is small and/or the cost of searching is large, LivingSocial will copy more. If Groupon copies more, the two platforms are potentially less differentiated, so LivingSocial would then prefer to copy less and search more. Finally, if the searched deals are attractive, LivingSocial would prefer to copy less and search more.

3.1.1 Policy Impact on LivingSocial's Multi-Homing Behavior

The deal counter change made it more difficult for LivingSocial to copy Groupon's past merchants. In our model, it suggests that $C_{L,C}$ increased after the policy change. According to Equation (2), N_L^* would decrease in this case (i.e., $\frac{\partial N_L^*}{\partial C_{L,C}} < 0$). That is, LivingSocial would copy fewer Groupon deals and search for more new deals after the policy change.

[15] Athey et al. (2018) study multi-homing and make a similar assumption. In particular, they assume that consumers are endowed with two units of attention. If consumers multi-home, they devote one unit to each platform.

[16] We also empirically test this assumption using consumers' website browsing records from comScore. During our sample period, a typical single-homing consumer generated 1.8 site visits in a month on average, while a typical multi-homing consumer generated 7.1 site visits in a month. Assuming that revenue generated per site visit is relatively constant, we can conclude that a multi-homing consumer can generate more revenue than a single-homing consumer.

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

The hypothesis suggests that as it became more costly to acquire merchants through copying, LivingSocial began to reduce copying and increase searching. Given that LivingSocial continued to copy Groupon's most popular deals, but reduced its multi-homing on deals with moderate popularity after the policy change, the average sales of the deals that LivingSocial copied from Groupon would increase.

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

3.1.2 Policy Impact on Deal Variety

The change in LivingSocial's multi-homing behavior also led to a change in industry-wide deal variety in terms of the number of deals offered. Because LivingSocial copied fewer past merchants and searched for more new merchants, LivingSocial contributed more to the deal variety after the policy change. Therefore, we have the following hypothesis:

Hypothesis 3 *LivingSocial contributed more to the deal variety after the policy change.*

3.1.3 Policy Impact on Consumers' Multi-Homing Behavior

After LivingSocial reduced its number of copied merchants after the policy change, consumers' responses to changes on merchant-side multi-homing 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. Therefore, consumers were more likely to visit both Groupon and LivingSocial after the policy change. On the other hand, the popularity of LivingSocial's 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 some overlap of popular deals between Groupon and LivingSocial.

To examine how the policy change affected consumers' homing behavior, we take derivatives of the numbers of multi-homing, LivingSocial-exclusive, and Groupon-exclusive consumers with respect to N_L. For multi-homing consumers, we have the following:

$$\frac{\partial\left(x_2-x_1\right)}{\partial N_L}=\frac{(1-2b)(u_s-u_c)-\frac{2bu_cN_G}{N}}{t}.$$

Note that $\frac{1}{2}<b<1$. If $u_s>u_c-\frac{2bu_cN_G}{(2b-1)N}$ (i.e., the expected utility from the searched merchants is sufficiently large), we have $\frac{\partial(x_2-x_1)}{\partial N_L}<0$. That is, the number of multi-homing consumers would increase after the policy change. The result indicates that as the two platforms became more differentiated in terms of deals offered, if the searched merchants were attractive enough, consumers became more willing to multi-home.

Hypothesis 4 *If $u_s>u_c-\frac{2bu_cN_G}{(2b-1)N}$, after Groupon's policy change, consumers were more likely to multi-home by visiting both Groupon and LivingSocial.*

For LivingSocial's exclusive consumers, we have the following:

$$\frac{\partial\left(1-x_2\right)}{\partial N_L}=\frac{\frac{bu_cN_G}{N}-(1-b)(u_s-u_c)}{t}.$$

If $u_s>u_c+\frac{bu_cN_G}{N(1-b)}$, the derivative is negative, indicating that LivingSocial had more exclusive consumers after the policy change. Intuitively, because there were more searched merchants on LivingSocial after the policy change, if these merchants were attractive, the exclusive consumers on LivingSocial would increase.

Hypothesis 5 *If $u_s>u_c+\frac{bu_cN_G}{N(1-b)}$, after Groupon's policy change, there were more exclusive consumers on LivingSocial.*

For Groupon's exclusive consumers, we have the following:

$$\frac{\partial x_1}{\partial N_L}=\frac{b(u_s-u_c)+\frac{bu_cN_G}{N}}{t}.$$

If $u_s>u_c-\frac{u_cN_G}{N}$, the derivative is positive, indicating that Groupon had fewer exclusive consumers after the policy change.

Hypothesis 6 *If $u_s>u_c-\frac{u_cN_G}{N}$, after Groupon's policy change, there were fewer exclusive consumers on Groupon.*

In sum, if the expected utility from LivingSocial' searched merchants was sufficiently large, after Groupon's policy change, consumers were more likely to multi-home by visiting both Groupon and LivingSocial. In the meantime, the number of exclusive LivingSocial consumers increased, while the number of exclusive Groupon consumers decreased. Figure 1 illustrates Hypotheses 4-6 graphically.

In the appendix, we present two model extensions. One allows Groupon to strategically choose its strategy and anticipate LivingSocial's optimal response. The other one further allows the merchants to strategically choose whether to accept the offers. In all cases, consumers are allowed to strategically choose which platform(s) to use. We find that the hypotheses derived from the baseline model continue to hold when allowing all parties—platforms, merchants, and consumers—to be strategic. In the next section, we use data on deals and consumer visit behavior to test these hypotheses.

4 Data

We obtain data from two sources that provide information on both the merchant-side and consumer-side multi-homing behavior. We obtain the first data set from Yipit, a market research company that tracks all deal sites in the United States. 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 to focus on the cities that experienced both the 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.[17]

Table 1 provides the summary statistics for deal offerings across the daily deal sites. Groupon

[17] 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.

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 the 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 the analyzed 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 the 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 one because of the merchants' multi-homing behavior. On average, each merchant offered 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 nine 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 were 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 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, as shown 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 the cities Groupon entered before the 10th month and for the cities Groupon entered between the 11th and the 19th months.[18]

We find that after the policy change (the 22nd month), the percentage of multi-homing deals decreased substantially for both types of cities, indicating that our finding is not driven by different stages of the industry life cycle.

We next conduct a 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:

$$\begin{aligned} PctMultihome_{jmt} \quad = \quad & \beta_0 + \beta_1 PostPolicy_t + \beta_2 PostPolicy_t \times t_m + \beta_3 t_m + \gamma_1 Category_j \\ & + \gamma_2 D_m + \gamma_t T_t + \varepsilon_{jmt}, \end{aligned} \tag{3}$$

where $Category_j$ represents category fixed effects; D_m represents the 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, capturing 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, indicating 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,

[18]Among all the cities we study, 92.8% of the time, Groupon entered in the same month as or earlier than LivingSocial did. Because 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 exclude the months when LivingSocial was present and Groupon was not because LivingSocial was not able to multi-home Groupon for these months.

showing 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's 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:

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

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 experiences 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 and 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, indicating that deal sales on LivingSocial decreased on average after the policy change. The main effect of the multi-homing dummy is positive, indicating 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.[19]

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):

$$\begin{aligned}\log X_{it} \quad &= \quad \beta_0 + \beta_1 Post\, Policy_t + \beta_2 Post\, Policy_t \times Multi\text{-}Homing_{it} + \beta_3 Multi\text{-}Homing_{it} \\ &\quad + \gamma_0 Own\, Existence_{it} + \gamma_1 Category_i + \gamma_3 d_m + \gamma_t T_{mt} + \varepsilon_{it}, \qquad (5)\end{aligned}$$

where d_m represents city fixed effects. As shown in Online Appendix Table A.1, the coefficients on the interaction term are all insignificant, indicating 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.

5.2 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 deal websites during a specific time period. Therefore, we 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.[20] We measure deal variety at the city level ($Variety_{mt}$), which is the number of "variety" deals normalized by the total number of deals in city m in month t. We define the contribution of LivingSocial to this variety ($LivingSocial\ Contribution_{mt}$) as the number of variety

[19] As a robustness check, we also 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.

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

deals on LivingSocial, 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, as shown in Figure 4. We find that the industry variety decreased before the policy change, which might be because of 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, as follows:

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

As shown in Table 5, there is a negative linear time trend and a negative post-policy main effect, indicating 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, indicating 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 $LivingSocial\ Contribution_{mt}$.

As shown in Table 5, there is a positive post-policy main effect and a positive interaction effect, indicating that LivingSocial contributed more to the variety after the policy change.

Overall, these results provide support for Hypothesis 3.

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 the years 2011 and 2012, corresponding 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 the observations taken after both Groupon and LivingSocial entered a given city. Further, we do not examine consumers' visits to other daily deals sites because 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, as shown in Figure 5.

First, we find that the percentage of consumers who exclusively visited LivingSocial decreased before the policy change but 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, indicating 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. This result indicates that some 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 the site-visiting behavior of multi-homing consumers. In Figure 6, we plot the proportion of visits to a particular site by a typical multi-homing consumer, which is 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, while the fraction of site visits to Groupon increased before the policy change and decreased after.

We also observe that the change in the consumers' multi-homing behavior appears to have occurred 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 indicate that although 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 check if there is a structural change in the percentage of multi-homing consumers and, if yes, where the breakpoint is. We use the 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.[21]

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 6, there is a positive and significant post-policy main effect, indicating that the percentage of multi-homing consumers increased by 4.93 percentage points after the policy change.

Finally, to check if the site-visiting frequency of multi-homing consumers increased for LivingSocial, we regress 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 7, there is a positive post-policy main effect and a positive interaction effect for LivingSocial,

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

indicating that multi-homing consumers visited LivingSocial more after the policy change. Because the proportions of site visits to Groupon and to LivingSocial sum up to one, the results also suggest that multi-homing consumers visited Groupon less after the policy change.

Overall, the results support Hypotheses 4, 5, and 6 that multi-homing and LivingSocial-exclusive consumers increased and Groupon-exclusive consumers decreased after the policy. Although the policy change reduced multi-homing on the merchant side, it increased multi-homing on the consumer side.

5.4 Impact on LivingSocial's Profit

Our analysis shows that the policy change affected LivingSocial in several ways. After the policy change, (1) LivingSocial multi-homed fewer Groupon deals, yet the average deal sales of multi-homing deals increased; (2) LivingSocial increased variety by searching for more new deals; and (3) there were more multi-homing and LivingSocial-exclusive consumers. In particular, increased variety and a larger user base can have a positive impact on LivingSocial's profitability. However, the increase in the user base may come at a higher cost because it may be more costly for LivingSocial to acquire new merchants compared with copying Groupon's deals. In this section, we examine how these changes jointly affected LivingSocial's profitability.

5.4.1 Impact on Revenue

We first evaluate the impact on LivingSocial's revenue. We sum the sales of all LivingSocial deals in each month, which equals the number of deals multiplied by average per-deal sales in that month, and further multiply this by LivingSocial's commission rate (50%, given the typical 50/50 revenue split between the platform and merchants).[22] We use this as the dependent variable and regress it 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:

$$\begin{aligned} TotRev_{mt} &= \beta_0 + \beta_1 PostPolicy_t + \beta_2 PostPolicy_t \times t_m + \beta_3 t_m \\ &\quad + \gamma_m d_m + \gamma_t T_t + \varepsilon_{mt}, \end{aligned} \tag{9}$$

[22]Our conclusions are unchanged if we use a slightly different commission rate, such as 45%.

where d_m represents city fixed effects, and T_t represents month-of-the-year fixed effects that capture seasonality. The error terms are clustered at the city level.

As shown in Model 1 of Table 8, there is a positive linear time trend and an insignificant post-policy main effect. The key coefficient of interest on the interaction term is negative, indicating that LivingSocial's total revenue increased slower after the policy change, indicating that the policy change **hurt** LivingSocial.

5.4.2 Accounting for Increased Customer Base

The impact on the total revenue in the previous analysis only accounts for deal sales in the current period, not for (1) an increased customer base, which can generate more future revenue and (2) increased merchant acquisition costs because of increased search effort to find new merchants. In this subsection, we first account for an increased customer base to re-evaluate the policy impact. We further account for merchant acquisition costs in the next subsection.

The value associated with LivingSocial's incremental customer base in market m at time t can be described as $\Delta CLV_{mt} = \Delta NumConsumerLS_{mt} \times CLV$, where $\Delta NumConsumerLS_{mt}$ is the incremental number of LivingSocial consumers in market m at time t, and CLV is the customer lifetime value (CLV) of a typical consumer, which can be proxied by the cumulative deal sales generated by each consumer. We obtain the average cumulative deals sold per customer for Groupon from its 10-K filings, which is 3.5 per customer, and use this as the value of CLV in our analysis.[23] This number is consistent with industry observations that a typical Groupon or LivingSocial customer has a lifetime value between \$100 and \$140 and that each deal generates \$25 revenue on average.[24] As shown later, the results are robust when varying this assumption on CLV. To obtain $\Delta NumConsumerLS_{mt}$, we combine the comScore data and Groupon's 10-K reports and leverage the number of consumers in these two data sets. Note that the analysis is

[23]See https://d18rn0p25nwr6d.cloudfront.net/CIK-0001490281/e745556f-46ec-4f05-b0f5-63f337d287d6.pdf, accessed March 2019. Groupon reports the average cumulative number of deals sold per customer from 1/1/2009 through the end of June 2010, December 2010, and June 2011, which are 3.0, 3.5, and 4.0, respectively. We take the average and use 3.5 in our analysis.

[24]The lifetime value estimates are from the co-founder and CEO of Yipit, based on his conversations with industry insiders (https://www.quora.com/What-is-the-lifetime-value-of-a-Groupon-or-LivingSocial-subscriber, accessed March 2019). The average revenue generated per deal is \$25, according to Groupon's 10-K filings (https://d18rn0p25nwr6d.cloudfront.net/CIK-0001490281/e745556f-46ec-4f05-b0f5-63f337d287d6.pdf, accessed March 2019).

conducted using data from the years 2011 and 2012 when comScore data are available.

In particular, we observe the incremental number of consumers in market m at time t for both Groupon and LivingSocial in the comScore sample and need to scale them up to the full population. Because LivingSocial is not public, we first obtain Groupon's number of customers from its 10-K filings. We calculate its counterpart in the comScore sample and use their ratio as the scale to extrapolate the incremental number of LivingSocial consumers from our sample to the full population. This gives us the values of $\Delta NumConsumerLS_{mt}$.[25]

Second, we calculate the total CLV associated with LivingSocial's incremental customer base as $\Delta CLV_{mt} = \Delta NumConsumerLS_{mt} \times CLV$. To see how the policy change impacted LivingSocial's total CLV, we use ΔCLV_{mt} as the dependent variable to run the regression in Equation (9). As shown in Model 2 of Table 8, there is a negative linear time trend and a negative post-policy main effect. The key coefficient of interest on the interaction term is positive, indicating that LivingSocial's total CLV increased after the policy change; the policy change increased the value of LivingSocial's customer base.

Finally, we add the value associated with the incremental customer base in each city-month to the original total revenue, obtaining $\widetilde{TotRev}_{mt} = TotRev_{mt} + \Delta CLV_{mt}$. We use this as the dependent variable to re-run the main regression in Equation (9). As shown in Model 3 of Table 8, there is a negative (insignificant) linear time trend and a negative post-policy main effect. The key coefficient of interest on the interaction term is positive and is larger than the main effect of the time trend, indicating that LivingSocial's total revenue $\widetilde{TotRev}_{mt}$ increased after the policy. That is, the policy change **helped** LivingSocial when accounting for CLV of an increased customer base.

5.4.3 Accounting for Merchant Acquisition Cost

We further account for the cost of acquiring merchants or sales force expenses, because LivingSocial's increased search may be costly and could have negatively impacted the company's revenue.

[25] Groupon reports its cumulative number of customers by the end of 2011 and 2012, N_{2011}, N_{2012}, in its 10-K filings (see also https://www.statista.com/statistics/273245/cumulative-active-customers-of-groupon/, accessed March 2019). We observe their counterparts in the comScore data, $N_{2011}^{sample}, N_{2012}^{sample}$. The ratio $\frac{N_{2012}-N_{2011}}{N_{2012}^{sample}-N_{2011}^{sample}}$ is used to scale up the in-sample values to population values. For instance, if the incremental number of LivingSocial consumers in the comScore sample is $\Delta NumConsumerLS_{mt}^{sample}$, the total incremental number of LivingSocial consumers is $\Delta NumConsumerLS_{mt} = \Delta NumConsumerLS_{mt}^{sample} \times \frac{N_{2012}-N_{2011}}{N_{2012}^{sample}-N_{2011}^{sample}}$, which we use in our CLV analysis.

To estimate the acquisition cost of each merchant for LivingSocial, we examine how sales force expense changes with the number of merchants. Because LivingSocial does not publish annual financial reports, we use the numbers from Groupon's 10-K and S1 and assume that the same cost holds for LivingSocial. As shown later, our conclusions are robust when we change this assumption.

First, we obtain Groupon's sales force expenses from its 10-K reports and use them as the measure of the merchant acquisition cost $TotAcqCost_t$.[26] We regress the measure on the total number of deals $NumMerchant_t$ and the fraction of new deals $FracNewMerchant_t$ in a given month, as follows:

$$TotAcqCost_t = \beta_0 + \beta_1 NumMerchant_t + \beta_2 FracNewMerchant_t + \varepsilon_t.$$

The coefficients can parsimoniously capture how the acquisition cost changes with the number of merchants, accounting for the potential difference in the cost of acquiring new merchants versus existing merchants. We find that the acquisition cost increases with the number of merchants and that acquiring new merchants is more costly, which is consistent with our intuition. We assume that these values also apply to LivingSocial.

Second, given the estimated $\{\beta_0, \beta_1, \beta_2\}$, we calculate the acquisition cost of merchants for LivingSocial in each city-month as $AcqCost_{mt} = \beta_0 + \beta_1 NumMerchant_{mt} + \beta_2 FracNewMerchant_{mt}$. To see how the policy change impacted LivingSocial's acquisition cost, we use $AcqCost_{mt}$ as the dependent variable to run the regression in Equation (9). As shown in Model 4 of Table 8, the key coefficient of interest on the interaction term is positive and smaller than the main effect of the time trend, indicating that LivingSocial's acquisition cost decreased slower after the policy change.

[26]Groupon's 10-K and S1 are obtained from the following site: https://www.nasdaq.com/markets/ipos/company/groupon-inc-826818-67316?tab=financials, accessed March 2019. Groupon's 10-K contains quarterly sales force size, and we assume that the same size applies to all three months within each quarter. To combine the sales force expense with the $TotRev_{mt}$ in our analysis later, we need to convert the sales force expense to the same units as $TotRev_{mt}$ (measured in deals sold in the Yipit data). In addition, we need to know the sales force expense at the monthly level. This is achieved through the following steps: First, from the Yipit data, we know that the number of total deals sold was 27,976,608 in 2011. From Groupon's S1, we know that the sales force expense as a fraction of total revenue was 27.8% in 2011. Multiplying these two figures yields the sales force expense measured in the number of deals sold: 7,777,497. Second, from Groupon's 10-k, we know that the total size of the sales force was 11,151 in 2011. Therefore, the per-person sales force expense measured in the number of deals sold was 697.5 (=7,777,497/11,151). Finally, the monthly acquisition cost or sales force expense equals the monthly sales force size times the per-person sales force expense.

That is, the policy change increased LivingSocial's acquisition cost.

Finally, we subtract the acquisition cost associated with merchants in each city-month from the total revenue, obtaining $\widehat{TotRev}_{mt} = TotRev_{mt} + \Delta CLV_{mt} - AcqCost_{mt}$. We use this as the dependent variable to re-run the main regression in Equation (9). As shown in Model 5 of Table 8, there is a positive linear time trend and a positive post-policy main effect. The key coefficient of interest on the interaction term is negative and smaller than the main effect of the time trend, indicating that LivingSocial's total revenue increased slower after the policy. Therefore, the policy change **hurt** LivingSocial when accounting for both the CLV of its incremental customer base and acquisition cost of merchants.

5.4.4 Sensitivity Analysis

In our analysis, we assume that the lifetime value of LivingSocial customers is the same as that of Groupon customers, $CLV = 3.5$. We re-run the analysis in Section 5.4.2 and find that the results are robust if we let $CLV = 1$ or $CLV = 5$ (Models 1 and 2 of Online Appendix Table A.2, corresponding to Model 3 of Table 8). Similarly, we assume that LivingSocial's merchant acquisition cost is the same as that of Groupon. We re-run the analysis in Section 5.4.3 and find that the results are robust if we let LivingSocial' acquisition cost estimates to be 1.5 or 0.8 times of Groupon's cost estimates (Models 3 and 4 of Online Appendix Table A.2, corresponding to Model 5 of Table 8).

The sensitivity analysis above also indicates that, consistent with the intuition, the effect of the policy change is more positive (less negative) when CLV is larger (acquisition cost is smaller). In fact, we find that the negative overall policy impact disappears when $CLV = 7$ (twice the default value) and the acquisition cost is 0.5 times of Groupon's cost estimates, as shown in Model 5 of Online Appendix Table A.2.

5.5 Discussion

In sum, we find that the policy change hurt LivingSocial's total revenue. It increased the value of LivingSocial's customer base but also LivingSocial's merchant acquisition cost. Overall, the policy change still hurt LivingSocial when accounting for both the CLV of incremental customer base and acquisition cost of merchants.

The results have implications for other platform firms. In general, when the focal firm adopts a policy that reduces information transparency regarding the performance of its complementors, the impact on the rival's profitability can be mixed. On the one hand, the rival is forced to explore new complementors, which can attract more consumers and generate more revenues. On the other hand, the new complementors may come at a high acquisition cost. Depending on the specific industry and specific market, the benefit from the incremental consumer base may be larger or smaller than the cost of acquisition, resulting in a net gain or loss in the rival's profitability. In our setting, the cost is larger than the gain, so LivingSocial's profitability decreased after the policy change. In other markets or industries, if consumers are particularly valuable and the acquisition costs of merchants are relatively low, the gain may dominate the cost so that the rival's profitability will increase. We provide an example to illustrate the possible consequences of policies that limit information transparency. It is also important to note that for technology startups, if their valuation and ability to attract investors depend more on the sizes of their user bases than their profitability, Groupon's policy change may have made it more difficult for Groupon to drive its rivals out of the market. Our results indicate that in practice, firms need to evaluate different aspects of the potential policy impact before adopting such policies.

6 Robustness Checks

6.1 Exogeneity of Groupon's Deal Counter Change

Our empirical analysis hinges on the assumption that Groupon's counter change is exogenous. Although from Groupon's announcement, the counter change was intended to deter outsiders' estimation of Groupon's financial situation, one might still be worried whether Groupon's true motivation behind the change was to deter multi-homing. In particular, if Groupon indeed launched the policy change to deter multi-homing, we should expect to see changes in Groupon's other strategies related to multi-homing around the same time. The first type of strategy is the deal terms offered to the merchants, and the second type of strategy is the commission rate offered to the merchants. Both strategies affect merchants' homing decisions, as discussed in Section 2, and affect platform competition in this industry. To examine whether the policy change is exogenous to multi-homing-related factors, we examine whether the deal terms and the commission rates changed along with the policy change. The idea is that if these multi-homing-related strategies were not changed after the policy change, the policy change is unlikely to be driven by Groupon's motivation to deter multi-homing.

First, we examine whether the deal terms—discount rate and duration—that Groupon offered changed after the policy change.[27] We focus on Groupon deals six months before and after the deal counter change and run the following regression using the discount rate and deal duration (in logarithm) as the dependent variables:

$$\begin{aligned} \log X_{it} &= \beta_0 + \beta_1 Post\,Policy_t + \beta_2 Post\,Policy_t \times t_m + \beta_3 t_m \\ &\quad + \gamma_1 Category_i + \gamma_3 d_m + \gamma_t T_{mt} + \varepsilon_{it}. \end{aligned} \tag{10}$$

As shown in Online Appendix Table A.3, the main effect and the interaction term of the post-policy effect are all insignificant, indicating that Groupon's deal terms did not systematically change after the policy change. These results are consistent with Kim et al. (2017) who find no meaningful inter-platform differences in deal terms for comparable deals in the daily deals industry. These results suggest that platforms may not strategically manipulate deal terms to compete for the merchants in this industry.

Second, we examine whether the commission rates changed after the policy change. Intuitively, Groupon may have chosen to reduce its commission rates to incentivize merchants to work exclusively with Groupon. Although we do not have data on Groupon's commission rates, we obtain a data set on LivingSocial's commission rates from a market research company that surveyed a large number of LivingSocial's merchants in a few deal categories during our study period. The company provided us with the average commission rates for the three categories (home and family, fitness, and beauty) that they surveyed between May 2011 and June 2012. In each month, the company obtained survey results from more than 10 merchants in each category. If Groupon had reduced

[27]We do not examine deal prices because they represent the face values or regular prices of the deals before discounting, which relate to the nature of the product or service offered and are not part of the negotiation between merchants and platforms.

its commission rates, LivingSocial, as a follower, would likely have reduced its commission rates to stay competitive. Online Appendix Figure A.1 shows the trend of LivingSocial's commission rates over time for the three categories. We find that LivingSocial's commission rates vary slightly across categories[28] but remain stable before and after Groupon's deal counter change.

Furthermore, if the purpose of the policy change was indeed to deter multi-homing, Groupon should have focused on its most popular deals because these deals generate the most revenues and drive the most user traffic. For instance, game console providers have offered incentives to top-ranked game publishers for signing exclusive contracts with them. Similarly, Groupon should have made the information disclosure more limited for its most popular deals than for the moderately popular deals, forcing LivingSocial to multi-home fewer most popular deals and resulting in lower average multi-homing deal sales after the policy change. In contrast, our results indicate that the average multi-homing deal sales increased for LivingSocial after the policy change.

Overall, these results boost our confidence that the deal counter change does not appear to be part of a large strategic initiative to deter LivingSocial's multi-homing at that time.

6.2 Additional Evidence on the Impact of Policy Change on LivingSocial

We also conduct several robustness checks to ensure that our findings regarding the changes in LivingSocial's multi-homing strategy are caused by Groupon's policy change, not by other factors. First, if the reduction in LivingSocial's multi-homing behavior toward Groupon is because of 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 Online Appendix Figure A.2. There appears to be no reduction in the percentage of LivingSocial deals that multi-homed from other sites after the policy change. Regression analysis suggests the same pattern.

Second, if Groupon's policy change affected LivingSocial's multi-homing behavior, it should also have affected 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

[28] Zhang and Chung (forthcoming) also document variation in commission rates across deals.

the site-city-month level percentage of deals that multi-homed Groupon deals. Because 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, hence biasing the results. Online Appendix Figure A.3 shows a plot of the average percentage of the 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.

6.3 Groupon's Deal Counter as the Information Channel

Groupon's deal counter change affected LivingSocial because it made information regarding deal popularity ambiguous. If LivingSocial indeed used Groupon's sales information to guide its decisions on which deals were worth copying, 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. We also expect Groupon's sales information to be more valuable to LivingSocial when LivingSocial faced greater uncertainty in predicting its own deal sales. Thus, we construct two measures on LivingSocial's deal sales uncertainty to test whether uncertainty moderates the relationship in Hypothesis 2.[29]

The first measure of deal sales uncertainty we construct is demand variation of similar deals. When demand is more variant and uncertain for similar deals in a particular market, Groupon's sales information about a particular deal becomes more valuable to LivingSocial, and the effect in Hypothesis 2 should be stronger. We define "similar" deals as those that fall into the same subcategory in our data set. Here, a subcategory is a granularly defined set of deals that are similar in the type of deal offered and deal characteristics.[30] We include the variance of similar deal

[29]We could also derive this moderating effect from our theoretical model. The value of sales information from Groupon can be proxied by the uncertainty in the searched deal quality. Instead of copying Groupon, LivingSocial can search for new deals without pre-existing sales information from Groupon. A larger uncertainty in the searched deal quality makes Groupon's sales information more valuable, leading to a stronger policy impact. In the model, u_s captures the quality of the searched deals. A decrease in u_s can proxy for a higher uncertainty in the searched market. Equation (2) suggests that $\frac{\partial^2 N_L}{\partial u_s \partial C_{L,C}} = \frac{b_1 - \frac{b_2}{2} + b(b_2 - b_1)}{(C_{L,C}+C_{L,S})^2 t} > \frac{b_1 - \frac{b_2}{2} + \frac{1}{2}(b_2 - b_1)}{(C_{L,C}+C_{L,S})^2 t} = \frac{\frac{1}{2} b_1}{(C_{L,C}+C_{L,S})^2 t} > 0$, which indicates that a higher market uncertainty or a smaller u_s would decrease $\frac{\partial N_L}{C_{L,C}}$ (i.e., making it more negative).

[30]To show how granular the definition is, we calculate the number of deals in a particular subcategory-city-month

sales in a particular subcategory-city, $Uncertainty_{km}$, as a moderator to the original difference-in-differences regression.

$$\begin{aligned}
\log Sales_{it} = \; & \beta_0 + \beta_1 Post\,Policy_t + \beta_2 Post\,Policy_t \times Multi\text{-}Homing_{it} \\
& + \beta_3 Post\,Policy_t \times Uncertainty_{km} + \beta_4 Multi\text{-}Homing_{it} \times Uncertainty_{km} \\
& + \beta_5 Post\,Policy_t \times Multi\text{-}Homing_{it} \times Uncertainty_{km} \\
& + \beta_6 Multi\text{-}Homing_{it} + \beta_7 Uncertainty_{km} + \gamma_0 Own\,Existence_{it} \\
& + \gamma_1 Category_i + \gamma_2 X_i + \gamma_3 D_m + \gamma_t T_{mt} + \varepsilon_{it}. \qquad (11)
\end{aligned}$$

As shown in Online Appendix Table A.4, the coefficient on the triple interaction term is positive and significant. The coefficient estimate indicates that if the variance of similar deal sales increases by 0.1, the sales of multi-homing deals would increase by 6.3% after the policy change. The results are robust if we replace market demographics (column 1) with city fixed effects (column 2).

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. In the online appendix, we show that deal category indeed serves as a moderator of the policy impact. It further supports our conclusion that uncertainty moderates the relationship in Hypothesis 2.

7 Conclusion

In this paper, we show that a policy change made by Groupon, which limited the sharing of information of deal popularity, reduced the multi-homing behavior of its rival, LivingSocial. The policy change also led 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 were more likely to multi-home. The overall policy impact on LivingSocial's profitability was negative when accounting for

and find that 90% of the times, there are at most five deals in the same subcategory in a particular city-month. There are 136 unique subcategories. The major categories in our analysis—beauty, fitness, entertainments, restaurants, home and family, automobile, clothing and goods—each include 14, 11, 15, 5, 5, 3, and 3 subcategories, respectively. For instance, the beauty category includes subcategories such as "skin care," "teeth whitening," "hair salons," "nail care," "massage," "facials," "waxing," and "spa." The fitness category includes subcategories such as "pilates," "boot camp," "bowling," "martial arts," "yoga," "dance classes," and "golf."

changes in the value of the customer base and the cost of merchant acquisition. We contribute to the literature on multi-homing and information transparency by highlighting the trade-off of information transparency in the presence of multi-homing. In our setting, disclosing the actual deal sales was beneficial to Groupon because it helped reduce consumers' uncertainty and generate herding behavior, leading to more deal sales. However, this allowed 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. Because of the pervasiveness of multi-homing behavior and information disclosure in many platform markets, our findings offer managerial implications for many other platform owners. 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. This information enables their rivals to target the best-selling items.

Our results also indicate 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. Because of the seesaw effect we identified between consumer-side and merchant-side multi-homing, an incumbent platform needs to find ways to reduce multi-homing on both sides of the market simultaneously to gain market leadership. For example, to incentivize third-party sellers to sell exclusively on its platform, Amazon provides fulfillment services to them and charges them higher fees when their orders are not from Amazon's marketplace. Amazon also uses Amazon Prime, a paid subscription service for free two-day shipping for many of its products, to reduce its customers' tendency to multi-home (Zhu and Iansiti, 2019).

Entrants can strategically take advantage of the seesaw effect to grow their market shares. For example, the Chinese e-commerce platform Pinduoduo (PDD) strategically differentiated itself on the consumer side from the incumbent, Alibaba, by targeting rural consumers (Zhu et al., 2019). Because of these single-homing consumers, many merchants on Alibaba chose to multi-home and adopt PDD. Alibaba started to restrict its merchants from selling on PDD, but PDD began helping manufacturers to build brands and sell directly on its platform, which introduced differentiation on the merchant side and thus incentivized Alibaba's customers to multi-home and adopt PDD.

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 Groupon's deal performance. The deal counter change may have reduced herding effects on Groupon, resulting in lower profitability for Groupon as well. 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 this greater deal variety. Finally, our study examines one approach (i.e., reducing information transparency) that platform owners can consider in reducing multi-homing. Other approaches that increase the cost of copying a merchant from the existing pool could have similar outcomes as proposed and examined in this paper. 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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Appendix: Theoretical Model Extensions

Extension 1: Allowing Groupon to be Strategic

Next, we allow Groupon to be strategic in its copying and searching decisions and examine whether our hypotheses continue to hold. Groupon anticipated the best response of LivingSocial and solved for the optimal number of copied merchants N_G to maximize its profit:

$$\pi_G = b_1 x_1 + \frac{b_2}{2}(x_2 - x_1) - \frac{N_G^2}{2}C_{G,C} - \frac{(\bar{N}_G - N_G)^2}{2}C_{G,S}.$$

Taking derivative with respect to N_G yields the following:

$$\frac{\partial \pi_G}{\partial N_G} = (b_1 - \frac{b_2}{2})\frac{\partial x_1}{\partial N_G} + \frac{b_2}{2}\frac{\partial x_2}{\partial N_G} - (C_{G,C} + C_{G,S})N_G + \bar{N}_G C_{G,S} = 0.$$

We use the implicit function theorem to show how N_G^* changed after the policy change.[31] First, consider the case in which N_L does not respond to a change in N_G. Applying the implicit function theorem yields the following:

$$\frac{\partial N_G}{\partial N_L} = -\frac{\frac{\partial \pi_G^2}{\partial N_G \partial N_L}}{\frac{\partial \pi_G^2}{\partial^2 N_G}} = \frac{bu_c(b_1 - b_2)}{Nt(C_{G,C} + C_{G,S})} < 0. \tag{12}$$

The expression suggests that if LivingSocial copied less (N_L decreased) after the policy change, Groupon copied more (N_G would increase) and searched less. The intuition is that copying from the same set of past merchants would make the two platforms less differentiated and more competitive. Given that LivingSocial copied less, Groupon would be more willing to copy.

Now, consider the response of LivingSocial. Equation (2) suggests that after the policy change, as $C_{L,C}$ increased, N_L decreased, which caused N_G to increase per Equation (12). A higher N_G would in turn make N_L decrease further. This suggests that Hypotheses 1 and 2 continue to hold when accounting for Groupon's strategic decisions. The intuition is that if Groupon copied more, the merchants that LivingSocial copied would be more likely to multi-home, so LivingSocial would have even less incentive to copy. In equilibrium, after the policy change, LivingSocial copied fewer past merchants and searched for more new merchants, and Groupon copied more past merchants and searched for fewer new merchants. Therefore, LivingSocial contributed more to industry variety. Thus, Hypothesis 3 continues to hold.

Regarding consumers' visiting behavior, the number of multi-homing consumers can be expressed as

$$x_2 - x_1 = \frac{(2b-1)u_s(\bar{N}_G + \bar{N}_L) + (1-2b)(N_G + N_L)(u_s - u_c) - 2bu_c\frac{N_G N_L}{N}}{t} - 1,$$

which depends on the numbers of copied merchants on Groupon and LivingSocial (N_G and N_L). As Groupon copied more and LivingSocial copied less (N_G increased and N_L decreased) after the policy change, the change in the total number of copied merchants ($N_G + N_L$) is ambiguous. If the decrease in N_L dominated the increase in N_G, the total number of copied merchants would decrease, so the number of multi-homing consumers could increase. In general, whether Hypothesis 4 would hold is an empirical question and depends on the relative changes in N_G and N_L after the policy change.

The number of LivingSocial's exclusive consumers can be expressed as follows:

$$1 - x_2 = 1 - \frac{\left[bu_s\bar{N}_G - (1-b)u_s\bar{N}_L\right] + [(1-b)N_L - bN_G](u_s - u_c) - bu_c\frac{N_G N_L}{N}}{t}.$$

Given that N_G increased and N_L decreased after the policy change, $(1-b)N_L - bN_G$ would de-

[31] The explicit solution of N_G is available upon request. The derivation is much more involved.

crease. If u_s was relatively large, the change in the second term would dominate the change in the third term, so the number of exclusive consumers on LivingSocial would increase, meaning that Hypothesis 5 holds. The same intuition behind Hypothesis 5 continues to apply here: as LivingSocial searched more and Groupon searched less after the policy change, if the searched merchants were sufficiently attractive (i.e., u_s was sufficiently large), consumers were more likely to visit LivingSocial exclusively.

The number of Groupon's exclusive consumers can be expressed as follows:

$$x_1 = 1 + \frac{\left[(1-b)u_s\bar{N}_G - bu_s\bar{N}_L\right] + [bN_L - (1-b)N_G](u_s - u_c) + bu_c\frac{N_G N_L}{N}}{t}.$$

Similar to the discussion above, given that N_G increased and N_L decreased after the policy change, $bN_L - (1-b)N_G$ would decrease. If u_s was relatively large, the change in the second term would dominate the change in the third term in the numerator, so the number of exclusive consumers on Groupon would decrease, meaning that Hypothesis 6 holds.

In sum, we find that most of the hypotheses in the previous section continue to hold when allowing Groupon to strategically make its copying and searching decisions. The only exception is Hypothesis 4: whether multi-homing consumers would increase or not remains an empirical question and depends on the relative changes in the numbers of copied merchants for Groupon and LivingSocial.

Extension 2: Allowing for Strategic Merchants

The above analyses are based on the assumption that competitive merchants will accept any offer from the platform(s). In this section, we further allow the merchants to strategically choose whether to accept the offers when they are approached by the platform(s). We highlight an important distinction between the merchants that are approached by the platforms and those that choose to offer deals on the platforms. The platform incurs a cost when approaching a merchant and only earns revenues from merchants that eventually offer deals on the platform.

The platforms first choose the number of merchants to approach through copying and searching. We continue to use N_G and N_L to denote the number of merchants that the two platforms approached from the past pool and $\bar{N}_G - N_G$ and $\bar{N}_L - N_L$ to denote the number of new merchants the platforms approached. We introduce Groupon and LivingSocial's commission rates, r_G and r_L, into the model, as follows:[32]

$$\pi_L = r_L \left[b_1(1-x_2) + \frac{b_2}{2}(x_2 - x_1) \right] - \frac{N_L^2}{2} C_{L,C} - \frac{(\bar{N}_L - N_L)^2}{2} C_{L,S}, \tag{13}$$

$$\pi_G = r_G \left[b_1 x_1 + \frac{b_2}{2}(x_2 - x_1) \right] - \frac{N_G^2}{2} C_{G,C} - \frac{(\bar{N}_G - N_G)^2}{2} C_{G,S}. \tag{14}$$

Not all merchants that are approached will offer deals on the platform. A merchant will accept the offer from a platform if the benefit is greater than the cost:

$$(1 - r_G) \frac{b_1 x_1 + \frac{b_2}{2}(x_2 - x_1)}{N_G^{total}} - c > 0,$$

$$(1 - r_L) \frac{b_1(1 - x_2) + \frac{b_2}{2}(x_2 - x_1)}{N_L^{total}} - c > 0,$$

where N_G^{total} and N_L^{total} denote the total number of merchants that eventually offer deals on Groupon and LivingSocial, respectively. c is the heterogeneous cost of working with a platform, which is drawn from a uniform distribution $c \sim U[0, m]$. Merchants benefit from offering deals on a platform because they can access consumers on that platform and earn revenues at the rate $1 - r_G$ or $1 - r_L$. However, they need to split the total revenues with other merchants on the same platform and incur the cost of c to work with a platform.[33] A merchant will multi-home if it is approached by both platforms and if the benefit exceeds the cost of working with both platforms. We assume that there is no direct interdependence between the merchants' decisions of accepting the offers from Groupon and LivingSocial. However, consumers' decisions of which platform(s) to use account for the interactions between the platforms or multi-homing decisions of the merchants (i.e., consumers only value multi-homing merchants once, as shown in Equation (1)), so the merchants' decisions of accepting offers from Groupon and LivingSocial are indirectly related.

In equilibrium, we can use the individual merchant's conditions above to derive the overall probability of merchants accepting the offer from a platform and the aggregate number of merchants that eventually appear on a platform. In particular, the number of merchants that eventually accept Groupon's offer N_G^{total} satisfies

$$\frac{(1 - r_G) \frac{b_1 x_1 + \frac{b_2}{2}(x_2 - x_1)}{N_G^{total}}}{m} \bar{N}_G = N_G^{total},$$

[32]In the previous sections, because a competitive merchant will accept any commission rate that the platform offers, assuming its marginal costs from offering a deal is zero, it is equivalent to setting $r_G = r_L = 1$. Here, $r_G, r_L \in (0, 1)$ so that merchants can earn some revenues and are incentivized to work with the platforms.

[33]For simplicity, we assume that the merchants equally split the revenues. We conduct a robustness check by allowing the revenue share to be proportional to the attractiveness of the merchants (i.e., u_c and u_s) and find that the results are robust.

from which we obtain $N_G^{total} = \sqrt{\frac{(1-r_G)(b_1 x_1 + \frac{b_2}{2}(x_2 - x_1))\bar{N}_G}{m}}$. As $\bar{N}_G$ merchants are approached and N_G^{total} of them accept the offer, the probability of acceptance is

$$P_G = \frac{N_G^{total}}{\bar{N}_G} = \sqrt{\frac{(1-r_G)(b_1 x_1 + \frac{b_2}{2}(x_2 - x_1))}{m\bar{N}_G}}. \tag{15}$$

The expression shows that merchants are more likely to accept the offer if there are more consumers on Groupon and if the revenue share to the merchant is more favorable. Similarly, we can obtain the probability of merchants accepting LivingSocial's offer as follows:

$$P_L = \frac{N_L^{total}}{\bar{N}_L} = \sqrt{\frac{(1-r_L)(b_1(1-x_2) + \frac{b_2}{2}(x_2 - x_1))}{m\bar{N}_L}}. \tag{16}$$

Consumers only care about how many merchants choose to offer deals on each platform, which equals the number of merchants that are approached times the probability of acceptance. Their expected utility functions become the following:

$$U_G = u_s(\bar{N}_G - N_G)P_G + u_c N_G P_G - tx, \tag{17}$$

$$U_L = u_c N_L P_L + u_s(\bar{N}_L - N_L)P_L - t(1-x), \tag{18}$$

$$U_{GL} = bu_s(\bar{N}_G - N_G)P_G + bu_s(\bar{N}_L - N_L)P_L + bu_c(N_G P_G + N_L P_L - \frac{N_G N_L}{N}\min(P_G, P_L)) - t. \tag{19}$$

We include the min operator in the last equation because the multi-homing merchants need to accept offers from both platforms. P_G and P_L represent the upper bound or the maximum cost for the merchants to accept the offers from each platform, so the smaller one is the binding one. The locations of the indifferent consumers are the following:

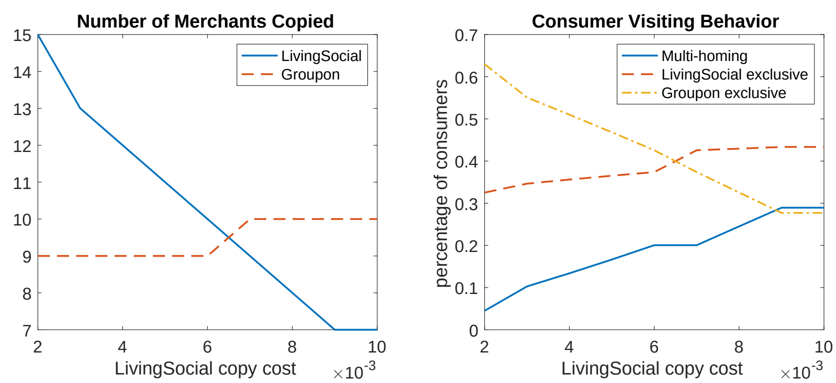
$$x_1 = 1 + \frac{(1-b)u_s(\bar{N}_G - N_G)P_G + (1-b)u_c N_G P_G - bu_s(\bar{N}_L - N_L)P_L - bu_c(N_L P_L - \frac{N_G N_L}{N}\min(P_G, P_L))}{t}, \tag{20}$$

$$x_2 = \frac{bu_s(\bar{N}_G - N_G)P_G - (1-b)u_s(\bar{N}_L - N_L)P_L + bu_c(N_G P_G - \frac{N_G N_L}{N}\min(P_G, P_L)) - (1-b)u_c N_L P_L}{t}. \tag{21}$$

Overall, the equilibrium is defined by the platforms' first-order conditions (derived from Equations (13) and (14)), the merchants' optimal decisions (Equations (15) and (16)), and the consumers' optimal decisions (Equations (20) and (21)). These equations capture that platforms trade off between the revenues generated by the consumers attracted and the cost of approaching merchants;

the approached merchants care about the number of consumers on each platform when deciding whether to accept the offers; and the consumers care about the number of merchants that eventually appear on each platform. As mentioned earlier, an important distinction of this extended model is that the platform incurs the cost of acquiring merchants for each merchant they approach (e.g., N_G enters the cost term of the platform profit function in Equation (13)), while the benefit only comes from the merchants that eventually accept the offers (e.g., $N_G P_G$ affects consumer adoption decisions captured by x_1 and x_2, which in turn enter the platform profit function in Equation (13)).

Because the system contains six highly non-linear equations, it is not possible to derive closed-form solutions. Thus, we numerically solve for it given a set of parameter values. The parameterization is chosen mainly to ensure that $x_1 \in [0, 1]$, $x_2 \in [0, 1]$, and $x_2 > x_1$. The results are robust to alternative parameterization. In particular, we let $u_c = 1.5, u_s = 2.5, b = 0.9, \bar{N}_G = \bar{N}_L = 25, N = 35, r_G = r_L = 0.5, b_1 = 1, b_2 = 1.8, m = 100, t = 50, C_{L,S} = 0.005, C_{G,S} = 0.002, C_{G,C} = 0.001$. Given the parameter values, we solve for the equilibrium numbers of the merchants approached from copying by Groupon and LivingSocial (N_G, N_L), the merchants' probabilities of accepting Groupon and LivingSocial's offers, and the numbers of consumers who visit Groupon exclusively, multi-home, and visit LivingSocial exclusively $(x_1, x_2 - x_1, 1 - x_2)$. We vary the cost of copying for LivingSocial $C_{L,C}$ from 0.002 to 0.010 to illustrate how an increase in $C_{L,C}$ after the policy change affects the equilibrium outcome. The values of N_G and N_L are restricted to take integer values.



Appendix Figure 1: Numerical Solutions: Strategic Merchants

As shown in the two plots in Appendix Figure 1, when $C_{L,C}$ increases, LivingSocial copies fewer merchants, and Groupon copies more merchants, indicating that Hypotheses 1 and 2 continue to hold. Because more searched deals come from LivingSocial, LivingSocial contributes more to deal variety, and Hypothesis 3 holds. Meanwhile, more consumers multi-home and visit LivingSocial exclusively while fewer consumers visit Groupon exclusively, indicating that Hypotheses 4, 5, and 6 hold.

In sum, the numerical solutions suggest that all the hypotheses hold when allowing for all parties—Groupon, LivingSocial, merchants, and consumers—to be strategic.

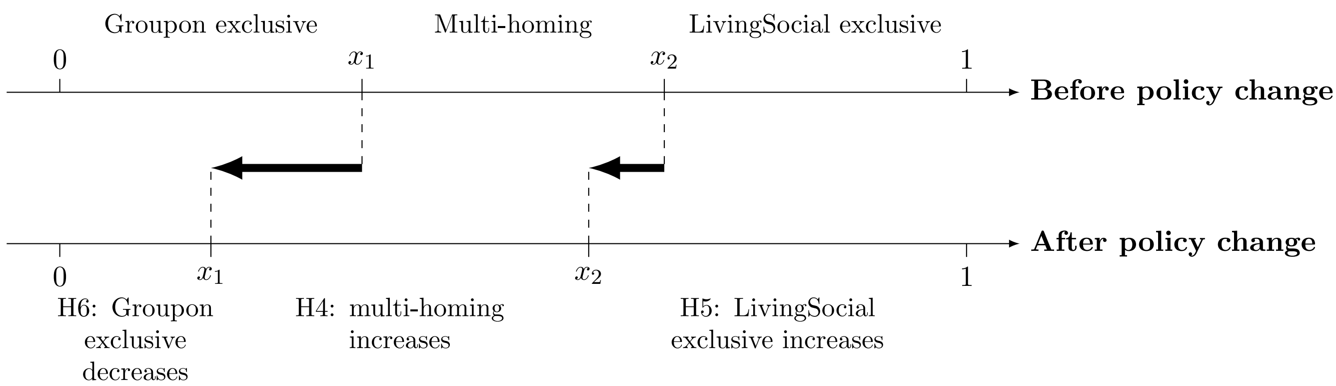


Figure 1: Graphic Illustration of Hypotheses 4-6

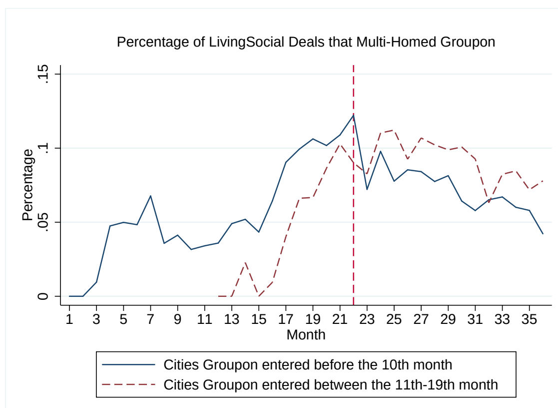


Figure 2: LivingSocial's Multi-Homing Strategy. The dotted vertical line indicates the month in which Groupon changed its counter.

Figure 3: Average Logged Deal Sales

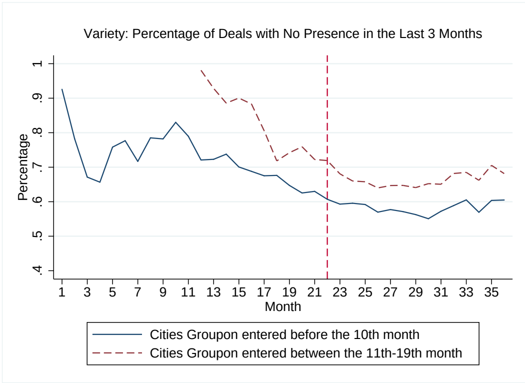
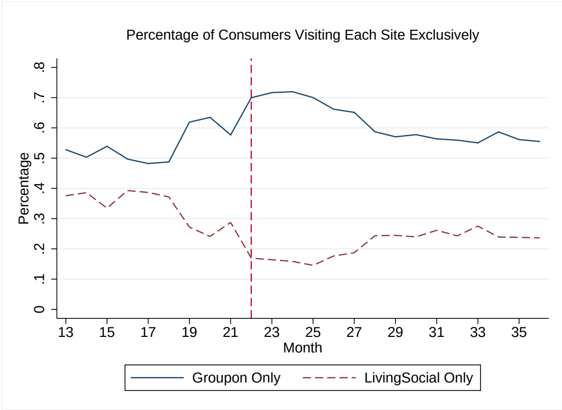


Figure 4: Industry Variety Index



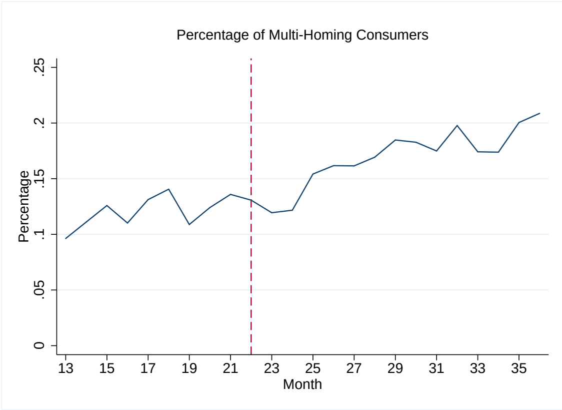


Figure 5: Consumer Site-Visiting Behavior

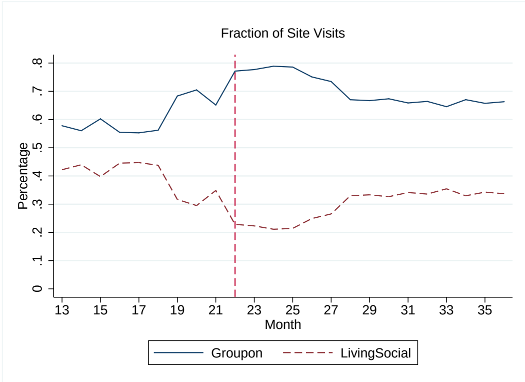


Figure 6: Multi-Homing Consumer Site Visiting Behavior

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: Regression Results: Industry Variety

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

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

Table 6: 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 7: 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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 8: Regression Results: Total Profit Impact on LivingSocial

	(1)	(2)	(3)	(4)	(5)
Post Policy	-1,355	-77,281***	-79,677***	-195,800***	103,892***
	(1,041)	(7,638)	(7,663)	(25,375)	(29,052)
Post Policy × Time Trend	-109.4**	2,128***	2,076***	12,595***	-9,308***
	(47.97)	(705.8)	(693.2)	(2,095)	(1,799)
Time Trend	527.6***	-2,169**	-1,638	-35,891***	32,855***
	(104.5)	(1,069)	(1,147)	(3,226)	(2,747)
City Fixed Effects	YES	YES	YES	YES	YES
Month-of-the-year Fixed Effects	YES	YES	YES	YES	YES
Observations	1,618	1,240	1,240	1,240	1,240
R-squared	0.489	0.664	0.668	0.714	0.705

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

Online Appendix

Deal Counter as the Information Channel: Deal Category as Moderator

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 the category fixed effects, $Category_i$, as a moderator to the original difference-in-differences regression:

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

where the coefficients on the main effect and the triple interaction term can be interpreted as the category-specific effects relative to the baseline category "other." As shown in Online Appendix Table A.5, the estimated coefficient on the triple interaction term is positive for three categories: beauty, entertainment, and home and family, indicating 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 Online Appendix Table A.6, 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. Thus, Groupon's sales information 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 $Uncertainty_{km}$ in Equation (11) and repeat the analysis. As shown in Online Appendix Table A.7, the coefficient on the triple interaction term is positive and significant, indicating that Hypothesis 2 is stronger when the category price is higher.

Overall, the results provide further confidence that LivingSocial indeed leveraged Groupon's sales information when deciding which deals to source.

Figure A.1: LivingSocial's Commission Rates

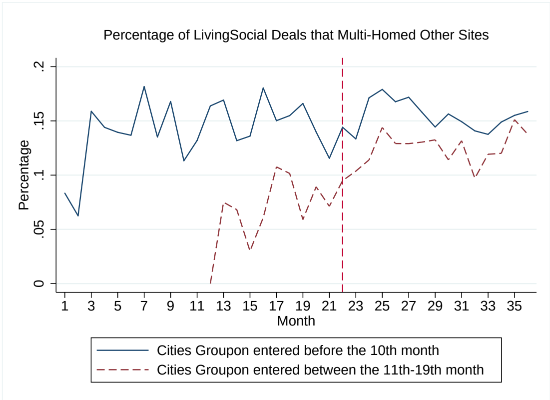


Figure A.2: LivingSocial's Multi-Homing Strategy: Other Sites

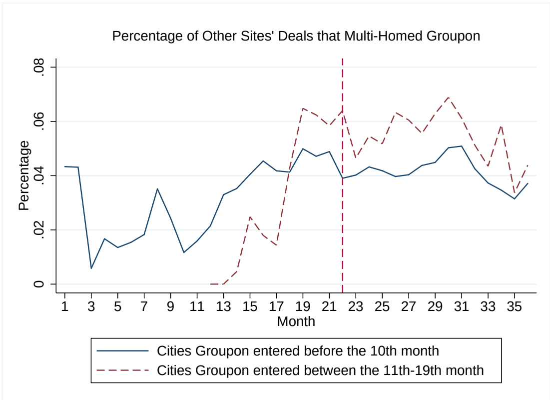


Figure A.3: Other Sites' Multi-Homing Strategy

Table A.1: 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 A.2: Robustness: Total Profit Impact on LivingSocial

	(1)	(2)	(3)	(4)	(5)
Post Policy	-24,477***	-112,798***	195,677***	67,178***	-65,173***
	(2,595)	(10,885)	(43,678)	(23,319)	(18,888)
Post Policy × Time Trend	555.7***	2,988***	-15,000***	-7,032***	-1,489
	(197.0)	(994.8)	(2,846)	(1,393)	(1,109)
Time Trend	-88.60	-2,568	50,102***	25,956***	13,439***
	(395.0)	(1,604)	(4,323)	(2,142)	(1,845)
City Fixed Effects	YES	YES	YES	YES	YES
Month-of-the-year Fixed Effects	YES	YES	YES	YES	YES
Observations	1,240	1,240	1,240	1,240	1,240
R-squared	0.646	0.668	0.712	0.699	0.645

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

Table A.3: Robustness: Groupon's Multi-Homing Deal Characteristics

Dependent Variable	*Logged Discount*	*Logged Duration*
Post Policy	0.00819	0.0322
	(0.00531)	(0.0198)
Post Policy × Time Trend	-0.000495	-0.00161
	(0.000369)	(0.00160)
Time Trend	-0.00307^{**}	-0.00485
	(0.00128)	(0.00382)
Time Trend: Quadratic	$5.38e{-}05$	$-8.16e{-}05$
	$(5.51e{-}05)$	(0.000157)
City Fixed Effects	YES	YES
Month-of-the-year Fixed Effects	YES	YES
Category Fixed Effects	YES	YES
Observations	102,961	102,961
R-squared	0.165	0.229

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

Table A.4: Uncertainty Due to Demand Variation of Similar Deals

DV: Logged Deal sales	(1)		(2)	
Post Policy	0.288^{***}	(0.0919)	0.536^{***}	(0.0566)
Multi-Homing	0.105	(0.0893)	0.143^{*}	(0.0813)
Demand Variation	0.102	(0.0621)	0.0559	(0.0411)
Post Policy × Multi-Homing	-0.474^{***}	(0.117)	-0.534^{***}	(0.109)
Post Policy × Uncertainty	-0.592^{***}	(0.0596)	-0.648^{***}	(0.0498)
Multi-Homing × Uncertainty	-0.0334	(0.0765)	-0.0381	(0.0722)
Post Policy × Multi-Homing × Uncertainty	0.611^{***}	(0.103)	0.626^{***}	(0.0983)
Own Existence	0.314^{***}	(0.0169)	0.310^{***}	(0.0154)
Time Trend: Linear	-0.00813	(0.00697)	-0.0305^{***}	(0.00536)
Time Trend: Quadratic	$-6.76e{-}05$	(0.000154)	0.000249^{*}	(0.000135)
Population	$3.73e{-}08^{***}$	$(4.19e{-}09)$	–	
Female	-0.0586	(0.0498)	–	
Age	0.0570	(0.0428)	–	
Income	0.0251^{***}	(0.00941)	–	
Education	0.0240^{***}	(0.00770)	–	
City Fixed Effects	–		YES	
Deal Characteristics	YES		YES	
Month-of-the-year Fixed Effects	YES		YES	
Category Fixed Effects	YES		YES	
Observations	80,640		80,640	
R-squared	0.336		0.362	

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

Table A.5: Uncertainty Due to Variation Across Categories

DV: Logged Deal Sales	Category	(1)		(2)	
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 A.6: 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 A.7: Using Category Price as the Moderator

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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.