How Users Drive Value in Two-sided Markets: Platform Designs That Matter

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Abstract

One of the deepest platform challenges is understanding how users create network value for each other and which investments provide leverage. Is more value created by advertising to attract users, discounting to subsidize users, or investing in architecture to connect and retain users? Having grown a user network, which promotes "winner-take-all" dominance, why do platforms with large user bases fail? To address these challenges, we build a theoretical and empirical model to simultaneously measure *within* and *across* period network effects for two-sided markets. This yields three main results. First, we extend the customer lifetime value (CLV) literature to network markets, allowing us to measure how different interventions drive CLV on both sides of two-sided markets. Second, we apply our model to the case of Groupon and empirically estimate the strength of within period and across period attraction. We find significant within period attraction between merchants and consumers that does not persist through time. This offers one explanation for the puzzle that even strong network effects might not yield market dominance. Third, we find that users attract users more strongly in experience than search goods markets, as user input drives CLV more than price does. Together these results provide numerous points of leverage for understanding and boosting CLV in order to increase platform value.

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1 Introduction

If the world's first trillion-dollar businesses are platforms based on network effects (Cusumano et al., 2020), why might firms with strong networks falter? Stronger network effects drive platforms toward greater market dominance (Katz and Shapiro, 1985, 1986; Shapiro and Varian, 1998; Schilling, 1999; Park, 2004; Dubé et al., 2010). This encourages platforms to invest in user growth, hoping that jump-starting a user base leads to self-propagating growth. Empirically, however, platforms with large user bases have both succeeded and failed (McIntyre and Srinivasan, 2017; Hagiu and Rothman, 2016). Firms such as Apple, Amazon, Google, and Facebook have grown large user bases, and with high margins and market shares, their valuations have followed. On the other hand, platforms such as Uber, DiDi, Lending Club, and Groupon have grown large user bases yet their valuations have fallen. Venture capitalists have subsidized such firms, despite an absence of profits, under the belief that investing in user growth until network effects achieve critical mass can lead to market dominance. Success simply takes patient capital. Central questions for both platform investors and managers are: When is a large user base insufficient for a "winner-take-all" market, and which user investments create the most value? Answering these questions informs both investment and strategy.

Focusing on platforms, this research explores the role network effects play in creating long term customer value. Current models of customer lifetime value (CLV), however, omit network effects (Gupta et al., 2004; Pfeifer and Farris, 2004; Zhang et al., 2012; McCarthy and Fader, 2018), missing the positive externalities they create for each other. Standard models of network effects are static (Rochet and

Tirole, 2003; Parker and Van Alstyne, 2005; Armstrong, 2006), missing the chain of value creation over time. The main contribution of this research is to build a dynamic within and across period model of two-sided network effects, from which we develop a two-sided model of customer lifetime value, CLV2. We validate this empirically, then show how it applies across different users, goods, and locations. Our theoretical question is how to properly measure network effects over time in order to understand CLV2. Using this model, our empirical question is to measure the strength of attraction in a two-sided market, accounting for time and transacting across various goods and services. Our point of leverage is to use time, within and across periods, to see if we can observe attraction, spillovers, and stickiness. Observing these factors, we also identify precursors that moderate CLV2. Answers thus provide not only investment advice but also insight into odd market behaviors such as low market values despite strong network effects. In the case of Groupon, for example, we find significant cross-side attraction but not stickiness suggesting that better platform design and investment strategies are warranted.

We take "network effect" to mean that a product or service has the property of rising in value as more parties consume it (Katz and Shapiro, 1985; Liebowitz and Margolis, 1994; Shapiro and Varian, 1998). This rise in value naturally attracts consumers whose usage then naturally creates value. Interaction of these properties creates the flywheel investors hope lead to market dominance. This conventional definition of a network effect, however, has several nuances worth clarifying. One is that how users create value can be intentional or unintentional (Parker et al., 2016). The explicit case is represented by reviews, user generated content, and users actively

linking to other users. The implicit case arises when machine learning algorithms observe users' behavior and improve the experience of other users or offer value adding recommendations. The latter requires no intentional act to create value for other users. Network effects can also exhibit strength or weakness based on whether they are local or non-local (Sundararajan, 2008; Parker et al., 2016). Rideshare, home services, and food delivery, for example, give rise to stronger local than non-local attraction as it makes no sense to match a rider in New York to a driver in Paris. By contrast, e-commerce, operating systems, and social networks have stronger non-local network effects because a match need not be location specific.

Further, network effects can be classified based on whether they are "same-side" versus "cross-side" (Eisenmann et al., 2006; Rochet and Tirole, 2006) meaning that the effect operates within group or across groups respectively.[1] In our context, a same-side network effect is represented by the value that consumers create for other consumers or the value that merchants create for other merchants. A cross-side effect is represented by the value that consumers create for merchants and vice versa. Thus a two-sided market can exhibit up to four network effects – two same-side and two cross-side – with no requirement that these necessarily exist or have equivalent strengths. For example, competition among online merchants or among rideshare drivers could eliminate positive spillovers and attraction among them. Adding the time dimension, representing within and across periods, doubles this count to eight possible factors. We will find it convenient to simplify this complexity in the analysis that follows.

[1]Certain literature also uses the terms "direct" and "indirect" for same-side and cross-side network effects respectively (Clements, 2004; Church et al., 2008).

To give precision to these eight factors, we introduce the following conventions. Let "IJ_t" designate network attraction from the class of user i to the class of user j with the subscript representing time from t to the present. Thus, CM_0 represents a cross-side network attraction from consumers to merchants within the current period and CC_{-1} represents a same-side network attraction from consumers to consumers from the prior period to the present. This also generalizes. We can use SS_0 to represent a Same-Side within period network effect for both consumers CC_0 and merchants MM_0 or use CS_{-1} to represent a Cross-Side network effect from prior period for both consumers to merchants CM_{-1} and vice versa MC_{-1} collectively. We summarize nomenclature in Table 1, which also illustrates how attraction occurs.

Table 1: Different Dimensions of Network Effects

	Within-period	Across Period
Same-side	Within-period same-side network effect (SS_0: CC_0, MM_0) *E.g., Gamers interacting with gamers*	Inter-temporal same-side effect (SS_{-1}: CC_{-1}, MM_{-1}) *E.g., Customers learning from prior customer reviews*
Cross-side	Within-period cross-side network effect (CS_0: CM_0, MC_0) *E.g., Customers transacting with current period merchants*	Inter-temporal cross-side effect (CS_{-1}: CM_{-1}, MC_{-1}) *E.g., Merchants learning from prior customer reviews*

Measuring network effects faces special challenges due to the well-known "reflection problem" (Manski, 1993, 1999; Rysman, 2019) and represents one reason empirical research is underdeveloped (Jullien et al., 2021). The adoption choice of an individual depends on the adoption choice by the group yet the group's choice depends on the collective choices of the individuals that comprise it. This simultaneity of decisions has led much of the theoretical literature to embrace fulfilled expectations equilibria where group members correctly anticipate the behavior of other members (Katz and Shapiro, 1985; Cabral, 1990; Krugman, 1991; Economides, 1996). The fact that internal expectations within period are not externally observable confounds

empirical measurement because even use of instruments treats all members of that group the same. Much of this work, however, predates development of two-sided network models (Parker and Van Alstyne, 2000; Rochet and Tirole, 2003; Caillaud and Jullien, 2003) that allow choices of one group to depend on those of a matched but different group. We therefore follow Rysman (2019) and identify instrumental variables that treat only one side of our two-sided network. Further, by introducing the time dimension, choices within group may depend on group choice in the *prior* period, which is externally verifiable (Zhang et al., 2012; Chu and Manchanda, 2016).[2] Careful measurement thus motivates our focus on same-side prior-period network effects and on cross-side within-period network effects. Using our notation, these are SS_{-1} and CS_0 respectively. This focus not only reduces complexity but also avoids the reflection problem.

Different factors modulate product attraction. User generated content (UGC), for example, is more valuable for products with higher uncertainty (Li et al., 2011). Prior sales information also has a greater impact on a customer's choice of an experience good than of a search good (Li and Wu, 2018). In the same vein, we hypothesize that same-side attraction for experience goods is stronger than that for search goods based on peer to peer learning effects (Hagiu and Wright, 2020). Greater information asymmetry renders accumulated information more valuable for goods that must be tried in order to know their value than for goods whose price is the deciding factor. Distance might also matter (Sundararajan, 2008). Since Groupon customers trans-

[2]Another way to resolve the reflection problem is to shrink the time interval of the observation window. This can shift observation of a specific behavior from the current to a prior period, avoiding a simultaneous choice. We thank an anonymous referee for this insight, which also motivates a focus on SS_{-1} rather than SS_0.

act with Groupon merchants in their local markets, we expect local network effects to prove stronger than non-local network effects. Using our model of inter-temporal attraction, we explore both factors and find that both matter. Among customers, same side attraction CC_{-1} is estimated to be positive and significant for experience goods but insignificant for search goods. For both experience and search goods, however, the cross side effect of merchants on customers MC_0 is estimated to be positive and significant. Among merchants, same side MM_{-1} and cross side CM_0 effects are estimated to be positive and significant for both experience goods and search goods, but MM_{-1} for experience goods is approximately 2.5 times as large as that for search goods while CM_0 is qualitatively similar across these categories.

Using model coefficients, we can also account for two-sided market spillovers and explore marketing and information systems interventions to boost customer and merchant lifetime value CLV2 and MLV2. For example, does CLV2 rise more based on adding another customer, another merchant, increasing consumption, or increasing retention? Marketing interventions might add same or cross side market participants. Information systems interventions might capture and present user data or use data to boost stickiness. Interestingly, in the extreme where same side effects SS_{-1} are absent on the platform, strong cross-side effects CS_0 only create value in one period, and CLV2 is equal to the value created in the current period. However, when SS_{-1} is significant and positve, users continue creating value in future periods.

In practical terms, these tools allow investment analysis of different options such as methods to enhance user participation (Huang et al., 2019; Chen et al., 2019) or to alter user behaviors that drive differences in platform value (McIntyre and Srinivasan,

2017). Amazon was among the first platforms to invest in recommender systems and UGC to make their undifferentiated books more valuable (Dellarocas, 2003). Using information systems data to present consumers with their own "best value" ranking can drive adoption (Ghose et al., 2012). In SAP's enterprise software ecosystem, independent software vendors (ISVs) compete for contracts and initially hid their expertise from one another. The launch of SAP's developer network, however, rewarded partners for sharing ideas and answering each other's questions in a public forum, which also boosted adoption and retention. ISVs have increased each other's sales, and thus customer value, at statistically significant levels (Ceccagnoli et al., 2012). Airbnb's host forum, likewise, helps hosts solve problems, deal with unruly guests, and share tips for improved ratings (Hardy and Dolnicar, 2017). Platforms can also design information systems to simplify user adoption and avoid disintermediation (Zhu and Iansiti, 2012; Halaburda et al., 2016). For example, platforms can schedule bookings, process payments, and handle logistics to drive platform adoption and retention. As platform users and merchants become stickier due to these value-added services, customer and merchant lifetime value increase, such that user (and/or merchant) acquisition strategies become cost-effective. Parameter estimates for strengths of these relationships help target investments.

This research offers theoretical and practical insights. First, we develop a model of inter-temporal network effects and within-period network effects to complement the static models of two-sided markets in extant literature. Strong within-period attraction does not necessarily imply strong inter-temporal attraction across periods. When the inter-temporal network effect is weak, the within-period network effect

may not persist, and a user growth strategy is not effective. Given this model, we further propose a framework to estimate the customer and merchant lifetime values, CLV2 and MLV2, in two-sided markets. Existing CLV models do not capture the value created through network effects and underestimate that of platforms such as Amazon and eBay (Gupta and Mela, 2008; Zhang et al., 2012). Our innovation extends this literature to a pair of joint calculations accounting for spillovers across time and across sides of two-sided markets. To the best of our knowledge, this is the first study that proposes a theory-driven customer and merchant value calculation that can be adopted easily by practice.

Second, this paper empirically distinguishes and estimates different network effects based on time, location, and type of good. In our context, the inter-temporal network effect is weak overall, yielding poor user stickiness. A user growth strategy is less effective for such platforms. All else equal, $CLV2$ and $MLV2$ are higher in markets with higher same side inter-temporal attraction SS_{-1}. For markets with weak SS_{-1}, we show that platform design interventions that enhance stickiness and spillovers can increase lifetime value, whereby acquisition strategies through marketing interventions become cost-effective. Overall, these findings remind platform managers not to overemphasize user growth when user or merchant stickiness and spillovers are poor and, instead, to focus on platform designs that enhance stickiness and spillovers as well as attraction.

Our paper proceeds as follows. Section 2 reviews related literature. Section 3 introduces our theoretical and empirical models. Section 4 then describes our data set and identification strategies. We present empirical findings in Section 5. Follow-

ing coefficient estimation, Section 6 analyses strategic responses when a platform's user stickiness is poor. Section 7 offers commentary on limitations and directions for future research. Finally, Section 8 concludes with managerial and investor implications, and highlights research contributions.

2 Related Literature

Our research builds on contributions from four research streams including two-sided markets, market dynamics, customer lifetime value, and platform design. Research extensions and contrasts for each stream appear below.

2.1 Static Models of Two-sided Markets

Static models have developed to study the price structure of two-sided markets, how they lead to free goods markets, and which side merits a subsidy (Rochet and Tirole, 2003; Caillaud and Jullien, 2003; Parker and Van Alstyne, 2005; Armstrong, 2006). These theoretical models highlight how one side of a market attracts the other side, requiring use of a coordination mechanism, such as free pricing or a price stimulus to one side, in order to get both sides on board. Empirical works in this context have focused on estimating network effect size and discussing implications for platform competition (Rysman, 2004). Due to the intrinsicly dynamic nature of platform growth, however, static models are insufficient for understanding time dependent aspects of user adoption on a platform's net present value. Our paper extends the static two-sided market framework by adding time. Although the per-

sistence of network effects plays a critical role in platforms' user growth strategies, little empirical work has investigated their inter-temporal durability (McIntyre and Srinivasan, 2017). Considering market entry, Biglaiser et al. (2019) discuss how incumbents maintain a profit advantage via network effects even as entrants match or exceed price and quality. In this research, we control for factors such as platform quality, the presence of a competitor, and how users themselves contribute to persistent network effects.

2.2 Dynamic Models of Network Effect Markets

Network effects have attracted a long-standing interest in market coordination and evolution. The adoption decision is often modeled as a function of users' expectations of network size (Katz and Shapiro, 1994; Shapiro and Varian, 1998; Cabral, 2011; Krugman, 1991; Farrell and Klemperer, 2007). Empirical contributions in this domain have estimated the magnitude of different cross-side network effects. For example, Chu and Manchanda (2016) quantified the extent to which current consumers attract future suppliers (and vice versa) in online retail. Zhang et al. (2012) examined how UGC contributors created value for UGC consumers. Importantly, these models use only lagged prior period terms, and not within period terms, omitting measures of current period attraction. We include current period attraction and use an instrumental variables approach to address the reflection problem.

Li et al. (2020) further studied user growth across multiple categories of goods and across different time periods in a two-sided market. Insights from these studies show how to optimize investments in user growth conditional on the effectiveness of

different cross-side network effects.

The assumption that cross-side network effects depend on user beliefs of network size is reasonable when user switching costs are high. Platform research has shown that switching cost is an important determinant of user value (Farrell and Klemperer, 2007; Metcalfe, 2013; Katz and Shapiro, 1985). At present, however, user switching costs are low on many digital platforms. In search, rideshare, group-buying, and e-commerce, for example, users can easily observe competing platform offers and switch without lock-in. The possibility of platform switching can dissipate rents and intensify competition (Rysman, 2009). A large supplier base in one period does not necessarily guarantee consumer adoption in the next period. Cross-side attraction in existing papers, often cast as an inter-temporal effect (Chu and Manchanda, 2016), corresponds to the mixture of SS_{-1} and CS_0 in our model. Since different types of user effects correspond to different mechanisms and imply a need for different platform strategies, we distinguish them and estimate them separately. Our model shows that platform user stickiness plays a critical role: when user stickiness is poor, no user growth strategies can generate high returns on investment (ROI) because the network is just a "leaky bucket." In contrast to conventional wisdom, investing in either side or in different categories of goods might not be cost effective. Rather, we suggest that a platform should improve its design so as to enhance user stickiness. Our user-value strategy is particularly relevant when switching costs are low, as is the case for many digital platforms.

2.3 Network Effect Design

The importance of network effects is such that they imply changes in the structure of the firm. Parker et al. (2017) show that product firms transition to platform firms as the strength of network effects increase. Because network effects scale faster among external users than among internal employees, the firm "inverts" in the sense that value creation shifts from inside to outside. Network effects, however, are not simply exogenous environmental factors but might instead be the consequence of conscious design (Schrage, 2012).

Platforms can enhance network effects through investments in connecting users to one another, enabling file sharing, creating complements, and hacking compatibility (McIntyre and Subramaniam, 2009). Piggybacking on social media to promote word-of-mouth (WOM) can generate social influence. Capturing and presenting user-generated-content (UGC) builds engagement. Extant research has shown that reviews, ratings, and other UGC affect the attractiveness of a platform over time (Dellarocas, 2003; Forman et al., 2008; Li et al., 2011). Several recent studies also model network effects as a learning mechanism because UGC sheds light on product/service quality, which reduces uncertainty as customers make their purchase decisions (Hagiu and Wright, 2018; Wu et al., 2015). Firms also give away reference designs and system developer toolkits (Boudreau, 2010), or open application programming interfaces (Benzell et al., 2017). These design choices attract developers who improve platform quality, which attracts users, creating platform value (Tellis et al., 2009; Zhu and Iansiti, 2012). Of particular importance for our paper, network size alone might not be the best predictor of value, which might instead depend more

on network density or topology (Suarez, 2005).

Complementing these works, our paper proposes a framework to manage user stickiness modeled as different categories of same-side and cross-side network ties . We show that investments in network designs can make current users more valuable for future users, magnifying each user's lifetime value, and raising the value of the platform. This is consistent with investing for the purpose of "making customers better to make better customers" (Schrage, 2012). As a further illustration, Airbnb trained hosts to take more attractive photos of their homes, which increased guest bookings, which inn turn increased guest listings. Network effects need not be assumed, they may be designed.

2.4 Customer Lifetime Value

An important stream of research that is closely related to firm value is the concept of CLV in marketing (Gupta et al., 2004; McCarthy and Fader, 2018). This line of research emphasizes user stickiness and explicitly incorporates user retention in CLV calculation (Gupta et al., 2004; Pfeifer and Farris, 2004; Gupta, 2005). However, extant literature is largely restricted to businesses without network externalities. Despite its popularity, the extant CLV calculation is insufficient to estimate the true value of users on digital platforms. One primary objective of our research is to explicitly model how network externalities create value across groups and across time. We thus extend the CLV framework to two-sided markets. Furthermore, extant CLV research does not distinguish how different factors contribute to user value. Following Zhang et al. (2012) and Li et al. (2020), we control for factors such

as platform quality and focus on analyzing how different types of network effects affect value creation.

Our study is distinct from extant studies that also addressed network effects (Tucker and Zhang, 2011; Chu and Manchanda, 2016; Li et al., 2020). Whereas those studies focus on choosing a preferred investment side or within versus cross-category investment, our research explicitly provides a framework that not only quantifies CLV2 for both sides in a two-sided markets but also sheds light on the relative contributions of network effects and net margin in boosting user value. This makes a comparison of advertising, discounting, and architectural design investments feasible.

3 Modeling Approach

This section presents our model specification. First, we explain how different types of network effects influence the dynamics of two-sided markets and specify an aggregate-data discrete-choice model to study users' participation choices (Berry et al., 1995). Second, based on the estimates of network effect sizes, we develop a model to calculate consumer and merchant lifetime values, $CLV2$ and $MLV2$, in two-sided markets. We discuss platform heterogeneity and demonstrate how the strength of SS_{-1} affects the effectiveness of the user growth strategy.

3.1 Demand Dynamics in Two-sided Markets

Built upon the static model of Parker and Van Alstyne (2005) and the dynamic model of Chu and Manchanda (2016), we incorporate the time dimension and study

demand dynamics in two-sided markets. Figure 1 describes the demand evolution on the two sides of a online market, which allows consumers (merchants) in the pervious period to influence consumers (merchants) in the current period. To illustrate market evolution, consider a shock to consumer base at $t-1$ and its dynamic effect, as shown in Figure 1. First, the shock to consumer base at $t-1$ affects the consumer base at t via SS_{-1}. Second, an increase in the current consumer base would lead to growth in the current merchant base via the CS_0. The prices and sizes of each user group combinedly determine the profit during each period in the dynamic system. Here n_t, m_t, p_t^n, p_t^m correspond to the consumer base, merchant base, price for consumers, and price for merchants, respectively, in period t. The same logic applies to a shock to the merchant base. Next, we present how these different network effects are modeled empirically. For exposition, we refer to the two sides as the "consumer side" and the "merchant side", although our modeling framework can be applied to a two-sided market beyond the retailing setting.

3.1.1 Consumer Side

On the consumer side, several factors jointly determine the utility that a representative buyer i derives from using the platform in market j week t. First, the utility is related to the platform's attractiveness, which is further decomposed into four components: (1) consumer $i's$ intrinsic preference for the focal platform α_j^n (in subsequent analysis, superscript 'n' denotes the consumer side), which is assumed to be varying by market but constant over time; (2) the number of consumers in the previous period $n_{j,t-1}$, to capture CC_{-1} that is attributable to word-of-mouth and

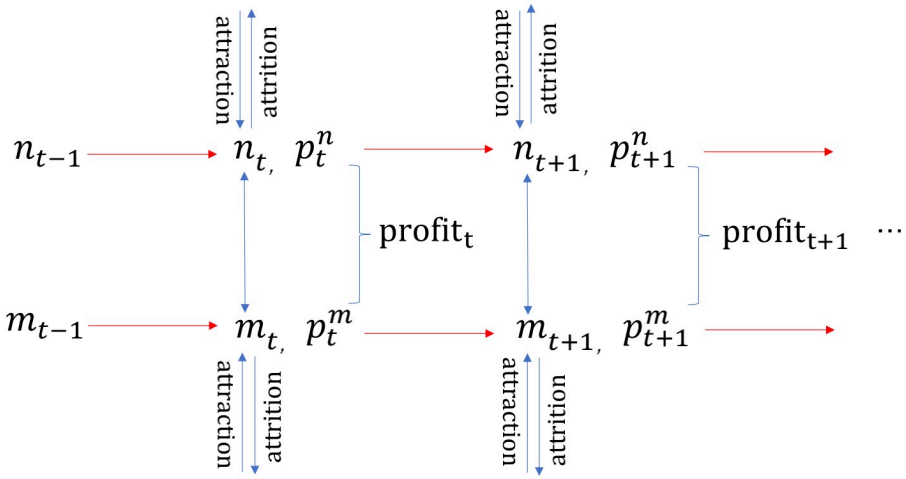


Figure 1: Each period shows dynamic participation of consumers (n_t) and merchants (m_t). Link $n_{t-1} \rightarrow n_t$ represents CC_{-1} while link $n_t \rightarrow m_t$ represents CM_0. Links anchored at m_{t-1} and m_t are symmetric in network effects MM_{-1} and MC_0 respectively.

UGC; (3) the number of merchants m_{jt}, to capture MC_0 that is due to the amount of supply;[3] and (4) average price p_{jt} and other product characteristics X_{jt}. Furthermore, the utility depends on (i) the attractiveness of the rival platform R_{jt} (Rochet and Tirole, 2003; Armstrong, 2006), which includes rivals' user base in market j at t, ii) the macro-economic trends of the industry and seasonalities that are common to all markets and unobserved to researchers T_t^n, (iii) the unobserved market and time specific shocks to the demand ξ_{jt}^n, and (iv) the idiosyncratic error ε_{ijt}^n. Formally, the net indirect utility is specified as follows:

$$U_{ijt}^n = f(\alpha_j^n, n_{j,t-1}, m_{jt}, p_{jt}, X_{jt}) f(R_{jt}) f(T_t^n, \xi_{jt}^n, \epsilon_{ijt}^n). \tag{1}$$

[3]The lags of merchant base are excluded from Equation 2 because we model a setting with trivial switching cost. In such a context, consumers make decisions after observing current supply on competing platforms, and thus, they do not need to form expectations about current supply based on past supply.

We assume that the utility takes the Cobb-Douglas form (Chu and Manchanda, 2016) and rewrite the indirect net utility as:

$$\begin{aligned} u_{ijt}^n = \alpha_j^n + \beta_1 \ln n_{j,t-1} + \gamma_1 \ln m_{jt} + \rho_1 \ln p_{jt} + \eta_1 X_{jt} \\ + \theta_1 \ln R_{jt} + \phi_1 T_t^n + \xi_{jt}^n + \varepsilon_{ijt}^n. \end{aligned} \tag{2}$$

The inter-temporal and within-period network effect parameters are our primary interest in Equation 2. There are also market-specific demand shocks ξ_{jt}^n that make the platform more or less attractive across different markets over time. These shocks are observed by platforms and users but unobserved to researchers, causing an endogeneity concern. All other factors are absorbed in the idiosyncratic errors ε_{ijt}^n.

We now denote the utility as $u_{ijt}^n = \delta_{jt}^n + \varepsilon_{ijt}^n$ and normalize the utility of the outside option as zero, which corresponds to consumers choosing the rivals or not participating in the market. Assuming that ε_{ijt}^n follows independent and identically distributed (i.i.d.) Type-I extreme value distribution, we derive the market share of the focal platform as:

$$s_{jt}^n = \frac{e^{\delta_{jt}^n}}{1 + e^{\delta_{jt}^n}}. \tag{3}$$

Thus, the platform's relative market share is:

$$\begin{aligned} \ln \frac{s_{jt}^n}{s_{0jt}^n} &= \ln \frac{n_{jt}/N_{jt}}{\big(N_{jt} - n_{jt}\big)/N_{jt}} \\ &= \alpha_j^n + \beta_1 \ln n_{j,t-1} + \gamma_1 \ln m_{jt} + \rho_1 \ln p_{jt} + \eta_1 X_{jt} \\ &+ \theta_1 \ln R_{jt} + \phi_1 T_t^n + \xi_{jt}^n, \end{aligned} \tag{4}$$

where s^n_{0jt} is the market share of the outside option and N_{jt} is the market size for buyers in market j time t. Estimating the parameters of interest based on Equation 4 poses challenges due to endogeneity and market heterogeneity. We discuss our identification strategy in detail in Section 6.

3.1.2 Merchant Side

The utility specification for the merchants is similar to that of the consumer side. For a representative merchant (seller) l in market j at time t, its utility of working with the platform is related to the following factors: (1) merchants $l's$ preference for the focal platform α^m_j (in subsequent analysis, superscript 'm' denotes the merchant side), which is assumed to be varying by market but constant over time; (2) the number of existing merchants $m_{j,t-1}$ to capture MM_{-1}; (3) the number of current consumers n_{jt} to capture CM_0; (4) product price P_{ljt}; and (5) whether the merchant has experiences with the platform X_{ljt}, which captures the switching cost on the platform.

Note that the merchant base in the past, the MM_{-1}, can affect the participation decision for a current merchant for several reasons. Existing merchants could create a word-of-mouth effect, which helps the platform to attract new merchants. Too many merchants, however, could increase competition and deter future entry, causing a negative same-side network effect. Thus, the MM_{-1} on the merchant side could be positive or negative, depending on which effect dominates. The CM_0 from consumers to merchants is expected to be positive, because more consumers would bring higher

sales and profits, increasing the attractiveness of the platform to merchants [4]. For specific platforms such as Groupon, the consumer base helps increase the consumer reach and awareness for the merchant's brand, creating a marketing effect (Dholakia, 2011; Edelman et al., 2016). Nevertheless, the CM_0 term in our model captures the cross-side effect of consumers on both the current profits and future profits.

The merchant's utility further depends on (i) the attractiveness of the rival platform R_{jt}, (ii) the macro-economic trends of the industry that are common to all markets and unobserved to researchers T_t^m, (iii) the unobserved market and time specific shocks to the demand ξ_{jt}^m, and (iv) the idiosyncratic error ε_{ljt}^m. Formally, the net indirect utility for a merchant is specified as follows:

$$\begin{aligned} u_{ljt}^m = \alpha_j^m + \beta_2 \ln m_{j,t-1} + \gamma_2 \ln n_{jt} + \rho_2 \ln p_{ljt} + \eta_2 X_{ljt} \\ + \theta_2 \ln R_{jt} + \phi_2 T_t^m + \xi_{jt}^m + \varepsilon_{ljt}^m. \end{aligned} \tag{5}$$

Following a similar step as for the consumer side, we denote the utility as $u_{ljt}^m = \delta_{jt}^m + \varepsilon_{ljt}^m$ and normalize the utility of outside option as zero. Assuming that ε_{ijt}^m is i.i.d. Type-I extreme value distributed, we derive the relative market share of merchants choosing the platform as follows:

$$\begin{aligned} \ln \frac{s_{jt}^m}{s_{0jt}^m} &= \ln \frac{m_{jt}/M_{jt}}{\big(M_{jt} - m_{jt}\big)/M_{jt}} \\ &= \alpha_j^m + \beta_2 \ln m_{j,t-1} + \gamma_2 \ln n_{jt} + \rho_2 \ln p_{jt} + \eta_2 X_{jt} \\ &+ \theta_2 \ln R_{jt} + \phi_2 T_t^m + \xi_{jt}^m, \end{aligned} \tag{6}$$

[4]Following Li et al. (2017), the lags of the consumer base are excluded from Equation 5 because merchants have correct expectations about future demand.

where s^m_{0jt} is the market share for merchants choosing the outside option and M_{jt} is the market size for potential merchants. Variables p_{jt} and X_{jt} are the average deal price and characteristics in market j week t. Our estimation and identification strategy is discussed in Section 6.

Table 2 provides a summary of all variable and parameter definitions used in our model.

Table 2: Variable and Parameter Definitions

Notation	*Definition*	*Notation*	*Definition*
n	consumer base	β_1, β_2	CC_{-1}, MM_{-1}
m	merchant base	γ_1, γ_2	MC_0, CM_0
N	consumer market size	α^n_j, α^m_j	user preference
M	merchant market size	s^n_{jt}, s^m_{jt}	market share
R	rival user base and price	θ_1, θ_2	competitive effect
p	price	ρ_1, ρ_2	price elasticity
X	product features	η_1, η_2	product attractiveness
T	industry-level common trend	ϕ_1, ϕ_2	time effects
		ξ^n_{jt}, ξ^m_{jt}	unobserved shocks

3.2 Customer Lifetime Value in Two-sided Markets

In their classic work, Gupta et al. (2004) define the CLV as the expected sum of discounted future earnings generated by a customer. Following their definition, we develop a model to estimate the $CLV2$. Take the consumer's $CLV2$ as an example. We assume a one-unit increase in the consumer base and quantify the increase of user bases on both sides of the market. To compute the $CLV2$, we transform the estimated elasticity of the market share into a marginal effect of the user base using

the standard relationship: $\Delta Y/\Delta X = \bar{Y}/\bar{X} \times \Delta \ln Y/\sigma_{\ln X} \times (1-\bar{s}^Y)$, where s^Y is the average market share of Y (Berry et al., 1995; Trusov et al., 2009). Thus, the marginal effects of inter-temporal user attraction are $\tilde{\beta}_1 = \beta_1 \times (1-\bar{s}^n)$ and $\tilde{\beta}_2 = \beta_2 \times (1-\bar{s}^m)$, and the marginal effects of within-period user attraction are $\tilde{\gamma}_1 = \frac{\bar{n}}{\bar{m}} \times \gamma_1 \times (1-\bar{s}^n)$ and $\tilde{\gamma}_2 = \frac{\bar{m}}{\bar{n}} \times \gamma_2 \times (1-\bar{s}^m)$. The marginal effects of deal price on the consumer and merchant bases are $\tilde{\rho}_1 = \frac{\bar{n}}{\bar{p}} \times \rho_1 \times (1-\bar{s}^n)$ and $\tilde{\rho}_2 = \frac{\bar{m}}{\bar{p}} \times \rho_2 \times (1-\bar{s}^m)$, respectively.

In the long term, a one-unit increase in the consumer base leads to $\frac{1}{1-\tilde{\beta}_1}$ additional consumers via CC_{-1}, and $\frac{\tilde{\gamma}_2}{1-\tilde{\beta}_1}$ additional merchants via the CM_0 of consumers on merchants. Furthermore, $\frac{\tilde{\gamma}_2}{1-\tilde{\beta}_1}$ merchants lead to $\frac{\tilde{\gamma}_2}{1-\tilde{\beta}_1} \times \frac{1}{1-\tilde{\beta}_2}$ total merchants via the MM_{-1} of merchants. For each consumer and merchant, we use π^n and π^m, respectively, to denote the value they generate in one period. We use the discounted cash flow approach to compute value perpetuity (Brealey et al., 2012). Thus, the consumer value is represented by the total increased profits associated with a one-unit increase in the consumer base.[5] Formally, the consumer's $CLV2$ is computed as follows:

$$CLV2 = \underbrace{\frac{1}{1-\tilde{\beta}_1} \times \pi^n}_{\text{consumer side value}} + \underbrace{\frac{\tilde{\gamma}_2}{1-\tilde{\beta}_1} \times \frac{1}{1-\tilde{\beta}_2} \times \pi^m}_{\text{merchant side value}}. \tag{7}$$

Based on the same logic, the merchant's $MLV2$ is:

$$MLV2 = \underbrace{\frac{1}{1-\tilde{\beta}_2} \times \pi^m}_{\text{merchant side value}} + \underbrace{\frac{\tilde{\gamma}_1}{1-\tilde{\beta}_2} \times \frac{1}{1-\tilde{\beta}_1} \times \pi^n}_{\text{consumer side value}}. \tag{8}$$

We can then examine the effectiveness of a user growth strategy by comparing

[5] To simplify the calculation, we assume there is no discount of profits across periods.

the $CLV2$ and the consumer acquisition cost, and the $MLV2$ and the merchant acquisition cost, respectively. We denote the consumer acquisition cost and merchant acquisition cost as AC^n and AC^m, respectively. A user growth strategy is effective only when $CLV2 > AC^n$ or $MLV2 > AC^m$.

Importantly, Equations 7 and 8 can also be used to answer the question: what is a free customer worth (Gupta and Mela, 2008). The direct effect of π^n in the first equation or of π^m in the second equation could be zero and yet both $CLV2$ and $MLV2$ could be positive due to non-zero cross-side value.

3.3 Platform Heterogeneity in User Growth Strategy

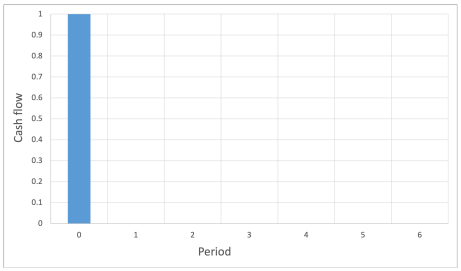
An interesting question to consider is why the effectiveness of a user growth strategy varies by platforms with strong CS_0. According to Equation 7 and 8, the $CLV2$ and $MLV2$ are jointly determined by the strength of both SS_{-1} and CS_0. The existence of SS_{-1} makes the influence of CS_0 persist over time and thus amplifies the impact of CS_0 on $CLV2$ and $MLV2$.

Table 3: How SS_{-1} Amplifies The Impact of CS_0 on $CLV2$.

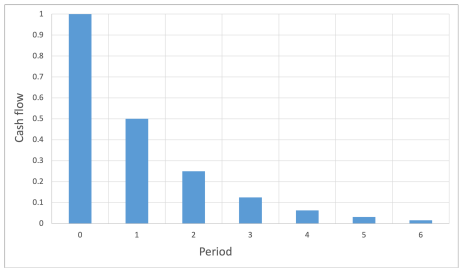
AS_n	1	2	3	4	5	6	7	8	9	10
β_1	0	0.5	0.667	0.75	0.8	0.833	0.857	0.875	0.889	0.9

To illustrate the impact of SS_{-1} on $CLV2$, we vary the value of β_1 while keep other parameters unchanged, then compute the changes in $CLV2$. We use AS_n to denote the amplification size of the consumer's SS_{-1} on $CLV2$. According to our

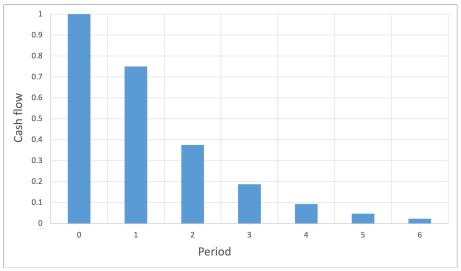
Figure 2: Cash Flow in Each Period When SS_{-1} Changes.



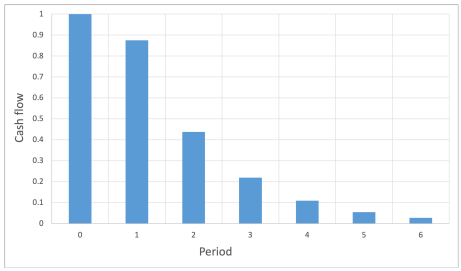
$\text{AS}_n = 1,\ \beta_1 = 0$



$\text{AS}_n = 2,\ \beta_1 = 0.5$



$\text{AS}_n = 4,\ \beta_1 = 0.75$



$\text{AS}_n = 8,\ \beta_1 = 0.875$

model, $AS_n = \frac{1}{1-\tilde{\beta}_1}$. Table 3 shows the correspoding relationship between AS_n and β_1: not only does AS_n increase with β_1, but also the increase in AS_n accelerates when β_1 becomes larger. Figure 2 depicts the impact of various SS_{-1} on cash flow in future periods. In an extreme case when the SS_{-1} is absent on the platform, the CS_0 only creates value in one period, and the $CLV2$ is equal to the value created in the current period. However, when the SS_{-1} exists, users continue creating value in future periods, leading to amplified $CLV2$.

Therefore, a weak SS_{-1} could explain why platforms with strong CS_0 may fail in using a user growth strategy. We theorize that one reason for the heterogeneous SS_{-1} is because of the "product learning" mechanism: product with higher uncertainty would expect a higher SS_{-1}. Using Groupon data, Li and Wu (2018) show that

previous sales information has a greater impact on consumer choices in the category of experience goods than search goods because experienced goods are associated with higher uncertainty. In the same vein, we hypothesize that the SS_{-1} of experienced goods is stronger than that of search goods. In the following sections, we discuss our identification strategies and test this hypothesis.

4 Data and Estimation

This section presents the empirical setting and our identification strategy.

4.1 Empirical Setting and Data

We estimate our model and discuss the analysis of the user growth strategy using data from the daily deal market. Daily deal platforms such as Groupon emerged around 2008 as two-sided markets connecting merchants and consumers with discounted deals. Figure 3 shows the growth of Groupon's consumer base, profit, revenue, and market value over the past ten years. Groupon experienced rapid convex growth in its first several years, before reaching 2013 revenues of $2.6 billion, but then it almost stopped growing. As a forecast of future growth, its market value experienced a sharp decline in 2012. Analysts observed that the consumer base and revenues had a highly correlated trend. For years, a central question for Groupon senior management was: *Should Groupon further promote the growth of its user base?* This question makes Groupon a valuable setting for our research.

The daily deal market is ideal to answer our research questions for several rea-

sons. The market was largely dominated by two leading platforms: Groupon and LivingSocial, making it easier to control for the competition effects. Around our data collection period, Groupon and LivingSocial made up roughly 59% and 17% of the total revenue in the U.S. daily deal market, respectively.[6] In our estimation, we use Groupon as the focal platform to estimate the parameters of interest and use LivingSocial to control for competition. Perhaps more importantly, it is critical for us to examine how SS_{-1} and CS_0 vary by product categories (especially between experience goods and search goods) after the overall quality and brand name of the platform are controlled for. Comparing different platforms would face tremendous identification challenges, because the nature of products offered by different platforms would be indistinguishable from the intrinsic quality of the platforms. Fortunately, Groupon offers products from both experience and search categories. By leveraging the panel data structure across categories and markets, we can estimate the effects of users after eliminating the effects attributable to platform quality or brand name.

Our sample includes Groupon's largest 108 markets from January 2012 to December 2012. Table 4 provides summary statistics by market and week. Note that the platform's consumer base is not directly observed in this study. In the estimation, it is represented using the transaction volume. Using transaction volume has an advantage of capturing the number of active users rather than dormant users who did not make a purchase. Compared with the number of registered accounts, transaction volume is better aligned with the decision-making process underlying Equations 2 and 5, because consumers and merchants can observe the transaction

[6]Statistica 2013, http://www.statista.com/statistics/322293/groupon-market-share-us/.

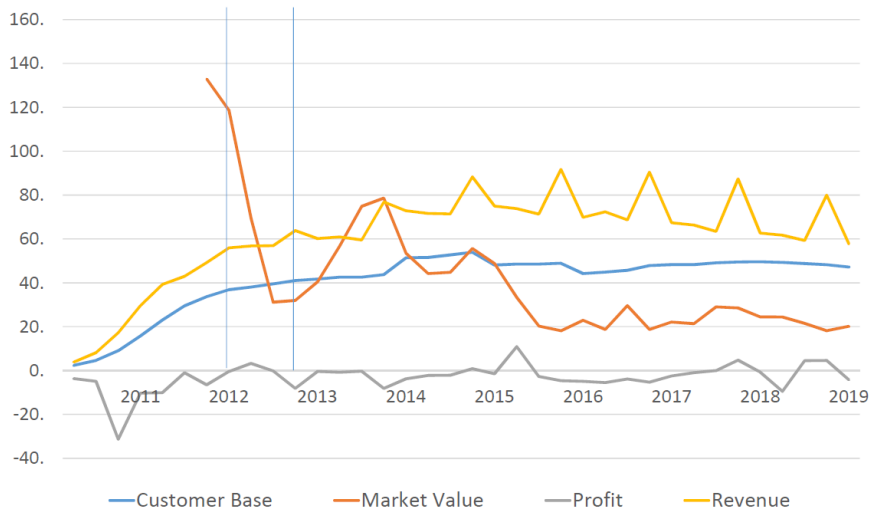


Figure 3: Groupon Growth from 2010-2019. Bars Show Observation Period

volume but not the number of inactive consumers.

Table 4: Descriptive Statistics by Market and Week

Variable	*Obs*	*Mean*	*SD*	*Min*	*Max*
Consumer base	5,707	4,685.12	6,085.98	4	111,820
Merchant base	5,707	22.4	17.19	1	130
Average deal price ($)	5,707	78.06	53.94	11	770
Rival's consumer base	5,707	2,828.47	8,935.2	0	425,030
Rival's merchant base	5,707	10.9	9.16	0	57
Returning merchant indicator	5,707	0.59	0.2	0	1
Deal duration (days)	5,707	4.15	0.97	0	13.54

4.2 Estimation and Identification

In this section, we present the estimation and identification strategy for the inter-temporal and within-period network effects.

4.2.1 Identification for the Inter-temporal Network Effect

We begin by discussing the estimation for the SS_{-1}. As shown in Equations 2 and 5, the SS_{-1} is captured by the lag(s) of the consumer base and merchant base. As the dependent variable, i.e., the logarithm of relative market share, is also a function of the user base, our specification is a variant of the dynamic panel linear model. This specification has the advantage of controlling for heterogeneity and allowing the distinction between the short-run and long-run dynamics, but calls for special attention on estimation.

It is well known that the ordinary least square (OLS) estimator for the lagged user base (i.e., β_1 and β_2) is biased in dynamic panel linear models. By construction, $\ln n_{j,t-1}$ in Equation 2 and $\ln m_{j,t-1}$ in Equation 5 are correlated with the market fixed effects. To eliminate the unobserved market effects, we apply the first-difference approach proposed by Anderson and Hsiao (1981) and Arellano and Bond (1991). Take Equation 2 as an example. After the first-difference transformation, it becomes

$$\Delta \ln Y_{j,t}^n = \beta_1 \Delta \ln n_{j,t-1} + \gamma_1 \Delta \ln m_{jt} + \rho_1 \Delta \ln p_{jt} + \theta_1 \Delta \ln R_{jt} + \eta_1 \Delta X_{jt} + \phi_1 \Delta T_t^n + \Delta \xi_{jt}^n,$$

where $Y_{j,t}^n = s_{jt}^n / s_{0jt}^n$, $\Delta \ln Y_{j,t}^n = \ln Y_{j,t}^n - \ln Y_{j,t-1}^n$, $\Delta \ln n_{j,t-1} = \ln n_{j,t-1} - \ln n_{j,t-2}$ and so on. The error terms are assumed to have zero serial correlations for the same cross-sectional unit, i.e., $E(\xi_{jt}^n \xi_{jt'}^n) = 0$ for all $t \neq t'$ [7].

Furthermore, the levels of the dependent variable lagged two periods or more are valid instruments in the equation of first-differences (Arellano and Bond, 1991).

[7] The test results for the auto-correlation assumption is presented in the results section.

The identification restriction is specified as

$$E(\ln n_{j,t-p}\Delta\xi^n_{jt}) = 0, where\ p \in \{2, 3, .., t-1\}; t \in \{3, 4, ..., T\}.$$

The instruments are used to form the objective function for the generalized method of moments (GMM) (Hansen, 1982; Wooldridge, 2010), forming the Difference GMM (DGMM) estimator (Arellano and Bover, 1995).

4.2.2 Identification for the Within-period Network Effect

The identification challenge underlying the parameters for the classic network effect is that the consumer base and merchant base are simultaneously determined in Equations 2 and 5, causing an endogeneity concern. We address this problem by providing instrumental variables for $\ln n_{jt}$ and $\ln m_{jt}$, respectively.

We first present the instrumental variables for the merchant base $\ln m_{jt}$ in Equation 2. A valid instrument should be correlated with the number of merchants but orthogonal to the demand shock ξ^n_{jt}. We used two sets of instruments here. First, following the pre-determined variable in Arellano and Bond (1991), we use the lag of merchant size (after logarithm transformation) as the instrument. The argument is that the demand shock to consumer base in period t should not be correlated with the merchant size in period $t-2$, after controlling for all the other variables in the model. Second, we also leverage political advertising as an exogenous variation for identification. Our data collection year, 2012, happened to be a presidential election year in the U.S.. During an election year, political candidates and interest groups (including party committees and outside political action groups known as PACs and

superPACs) invest heavily in television advertising, leading to an increase in ad prices (Moshary et al., 2021). The increased cost of advertising leads merchants to look for alternative marketing avenues such as participating in daily deals (Dholakia, 2011; Edelman et al., 2016). Thus, the number of merchants on deal platforms should be correlated with the amount of political election advertising in the market.[8]

We collect data on political advertisements across four types of elections that year (presidential, gubernatorial, House, and Senate elections) (Fowler and Ridout, 2015), and compute the total amount of air time and ad spending across all candidates and parties in each market j during week t.[9] In this empirical setting, it often takes some time for the merchants to negotiate with the platform to determine the terms (Li et al., 2017). Thus, we use the political advertising in period $t-1$ as the instrument because such a specification captures the time lag associated with the merchant base in t. The lagged advertising variable also helps the exogenous assumption in that past political advertising should not directly affect the current deal demand ξ_{jt}^{n}.

We follow a similar identification strategy for the consumer base $\ln n_{jt}$ in Equation 5. We use two sets of instruments: (1) the lag of consumer base with a degree

[8]In our data, we find positive correlations between merchant base and political advertising (the Pearson correlation coefficient was 0.19 ($p<0.001$) with ad spending and 0.05 ($p<0.001$) with air time, indicating that there was a positive association between the number of merchants on Groupon and the amount of TV election ads in the market. We provide the detailed first-stage analysis in the results section.

[9]The data on political advertising are at the designated market area (DMA) level. We map the advertising data onto the Groupon divisions (i.e., markets). The markets that fall into the same DMA have the same value for the advertising variables. Including ads from gubernatorial, House, and Senate elections helped address the unequal allocation of campaign resources between battleground and non-battleground states for presidential elections. In our data, only 5 (4.7%) DMAs received zero political advertising in 2012 and the remaining 95.3% all had some levels of election advertising on TV.

of 2, and (2) the precipitation and temperature in each market. The identification argument for precipitation and temperature is based on the finding that consumers' online shopping behaviors are shown to be influenced by weather conditions. Using data from large-scale field experiments, Li et al. (2017) provided robust evidence that consumer online shopping behaviors deviate significantly on rainy days from sunny days, because of the impacts of weather on the mood and psychological states of consumers. Based on these, we argue that the local weekly temperature and precipitation should correlate with consumers' intention to shop Groupon deals, providing the first-stage variation for identification. However, precipitation and temperature at time t should not be correlated with the supply-side error $\xi^m_{j,t}$, because the merchant base has been determined prior to t due to the processing and negotiation time gap required for merchants to show up on the platform. Thus, the exogenous requirement for using precipitation and temperature as the instrumental variable is met.

4.2.3 Other Variables

Market size. Our specification requires the "size" for each market. On the consumer side, the market size is defined as the total number of users who could participate in the daily deal market. Because anyone with Internet access could use a deal site, we use the number of Internet users as the measure of market size. The data are retrieved from the "October 2012 School Enrollment and Internet Use Survey," a supplement to the Current Population Survey (CPS) by the U.S. Census Bureau.

On the merchant size, we measure the market size using the number of businesses in each local market in 2012, which is extracted from the County Business Patterns

(CBP) database from the the U.S. Census Bureau [10]. This data source tracks the number of businesses in each market along with the NAICS industry code and a short description. We matched the NAICS with the merchant types in Groupon and LivingSocial and selected the business categories that have participated in the daily deal industry.

Experience versus Search Goods. We code product categories on Groupon into experience goods and search goods based on the nature of the product and services. Following Li and Wu (2018), we administered an online survey to classify whether a good or service possesses more experience attributes or search attributes. A total of 818 respondents were asked to imagine that "user reviews are not available" on a platform and then asked to assess for each category, "to what extent it is easy (hard) to evaluate the quality without seeing or trying it."[11] The score closer to "easy" (coded as 1) corresponds to more of a search good, and vice versa for experience goods if the score is closer to "hard" (coded as 7) (Nelson, 1974). To ensure that respondents can finish the survey within 5 minutes, each respondent answered a random selection of 15 categories (on average, each category was rated by 136.3 respondents).

Table 5 presents the summary statistics from the survey. Across the total of 78 categories, the mean score is 4.72 (Standard Deviation = 1.02) and the median is 4.97. We used the median split and code each category into two groups: experience

[10] https://www.census.gov/programs-surveys/cbp/data/datasets.html. Accessed Feb 2021.

[11] A total of 1,112 respondents were recruited on Amazon MTurk to participate the survey. 294 (26%) respondents failed the attention filler questions and hence were removed from the analysis. The detailed survey design and summary statistics are included in the Appendix.

goods if the average score of that category is greater than the median and vice versa for search goods. Among our categories, the highest i.e. experience goods scores were "hair salons," "facials," and "makeup services," while those with the lowest, i.e. search goods, scores were "holiday decor," "gifts: candles, phone cases, stationary," and "office supplies." Note that the mean split yielded very similar results since only two categories in the middle would switch groups. In subsequent analysis, we used the MTurk responses to classify the categories.

Table 5: Summary Description of Amazon MTurk Online Survey

	N	Mean	SD	Median	Min	Max
All categories	78	4.72	1.02	4.97	1.98	6.39
Experience Goods	39	5.59	0.36	5.51	5.01	6.39
Search Goods	39	3.85	0.65	3.97	1.98	4.94

To cross-check our experience-versus-search goods classification, we conducted an offline survey using a different design. Twenty-eight business-school graduate students at a major U.S. university participated in the survey. Each student was asked to code the product/service categories on Groupon using a binary response: the "search" type (denoted as $E_i = 0$) or the "experience" type (denoted as $E_i = 1$). Across all respondents, the Fleiss' Kappa is 0.603, indicating a moderate level of average inter-coder reliability (Fleiss, 1971). For each category, we used the majority voting: a category was classified as the experience type if more than half of the respondents coded $E_i = 1$. Out of the categories, 8 (10.3%) were coded as search goods by MTurk respondents but switched to experience type in the validation survey; 5 (6.4%) switched from experience to search type; and the rest 65 (83.3%) were consis-

tent between the two surveys. We estimated the main models based on the validation survey and obtained qualitatively similar results. The detailed model estimates are presented in the appendix.

Price. Lastly, deal price in Equations 2 and 5 could also be endogenous. A rational platform would strategically adjust the deal price in response to an expected shock in demand and supply. For example, if the demand is expected to be low, a platform would be incentivized to reduce the price. In the same vein, if the supply is expected to be strong, the platform would also be incentivized to adjust prices to increase profits. To address this issue, we use the lagged deal prices as the instrument for p_{jt}, as proposed and tested in Villas-Boas and Winer (1999). The identification assumption is that, the prices from the previous periods should be correlated with the current price due to the common cost factors. But after controlling for the market fixed effects and other variables, they should be exogenous to the demand and supply shock in the current period. We consider this assumption reasonable in the Groupon setting, because many merchants on the platform provide services to local customers and thus the cost of service within the market should be correlated over time. However, Groupon typically feature different merchants in consecutive weeks and thus the lagged prices should be uncorrelated with the current demand or supply shock.

5 Empirical Findings

5.1 Parameter Estimates

In this section, we present the parameter estimates. As aforementioned, we leverage the fact that Groupon offers products and services of different categories in different markets, which allows us to estimate different types of network effects in a quasi multi-platform context. We estimate the consumer-side model (Equation 2) for search and experience goods, respectively, and present the results in Table 6. Similarly, the estimates for the merchant-side model (Equation 5) for search and experience goods are presented in Table 7. For each table, we present the fixed effect estimator and the results based on the DGMM estimator after applying first-differencing and the instruments. In the subsequent section, we interpret the coefficients based on the DGMM results.

On the consumer side, the SS_{-1} is estimated to heterogeneous between experience and search goods. While the SS_{-1} is positive and significant for experience goods (0.096, $p < 0.05$), it is insignificant for search goods (-0.034, $p>0.10$). As hypothesized, because of the higher uncertainty prior to consumption, more existing consumers can shed light on the quality of goods on the platform and attract more future consumers, yielding a positive SS_{-1}. However, the quality uncertainty for search goods can be reduced through information search (for example, doing online searches or reading consumer reports), the size of existing consumer base is no longer found important for attracting future consumers.

The pattern is different for the CS_0. The effect of merchants on consumers is

Table 6: Parameter Estimates for Consumer-Side Model

Experience Goods	*FE*		*DGMM*	
	Est	(SE)	Est	(SE)
Lagged consumer base (β_1)	0.030**	(0.013)	0.096**	(0.039)
Merchant base (γ_1)	1.297***	(0.029)	1.439***	(0.072)
Deal price (ρ_1)	-0.286***	(0.016)	-0.656***	(0.098)
Rival consumer base (θ_{1n})	0.073***	(0.012)	0.075**	(0.019)
Rival merchant base (θ_{1m})	-0.013	(0.035)	-0.057	(0.050)
Returning merchants	-0.418***	(0.074)	-0.278**	(0.114)
Deal duration	0.102***	(0.010)	0.142***	(0.028)
Week	-0.007***	(0.001)	-0.008***	(0.001)
Week-square	2.9E-6	(4.4E-5)	2.6E-5	(5.0E-5)
Sample size	5,324		5,212	
R-square	0.723			
Number of instruments			110	
Hansen test of overidentification			$\chi^2(101) = 101.88$, p = 0.457	
Difference-in-Hansen test for consumer base			$\chi^2(50) = 19.81$, $p = 1.000$	
Difference-in-Hansen test for merchant base			$\chi^2(9) = 2.89$, $p = 0.968$	
Difference-in-Hansen test for price			$\chi^2(51) = 14.58$, $p = 1.000$	

Search Goods	*FE*		*DGMM*	
	Est	(SE)	Est	(SE)
Lagged consumer base (β_1)	-0.018	(0.012)	-0.034	(0.036)
Merchant base (γ_1)	2.012***	(0.040)	1.970***	(0.128)
Deal price (ρ_1)	-0.383***	(0.019)	-0.448***	(0.100)
Rival consumer base (θ_{1n})	-0.005	(0.023)	-0.032	(0.047)
Rival merchant base (θ_{1m})	-0.118*	(0.067)	-0.180	(0.137)
Returning merchants	-0.533***	(0.074)	-0.325***	(0.113)
Duration	-0.036***	(0.013)	0.043	(0.029)
Week	-0.013***	(0.001)	-0.014**	(0.005)
Week-square	-6.6E-5	(8.3E-5)	-1.8E-5	(2.1E-4)
Sample size	4175		3,801	
R-square	0.554			
Number of instruments			110	
Hansen test of overidentification			$\chi^2(101) = 94.20$, $p = 0.671$	
Difference-in-Hansen test for consumer base			$\chi^2(50) = 27.66$, $p = 0.996$	
Difference-in-Hansen test for merchant base			$\chi^2(9) = 5.50$, $p = 0.789$	
Difference-in-Hansen test for price			$\chi^2(51) = 28.51$, p = 0.995	

FE is the fixed-effect estimator and DGMM is the first-difference GMM estimator.
*** p<0.01, ** p<0.05

Table 7: Parameter Estimates for Merchant-Side Model

Experience Goods	*FE*		*DGMM*	
	Est	SE	Est	SE
Lagged merchant base (β_2)	0.190***	(0.016)	0.417***	(0.053)
Consumer base (γ_2)	0.276***	(0.005)	0.423***	(0.018)
Deal price (ρ_2)	0.107***	(0.008)	0.411***	(0.050)
Rival consumer base (θ_{2n})	0.013**	(0.006)	-0.023**	(0.011)
Rival merchant base (θ_{2m})	0.151***	(0.017)	0.131***	(0.028)
Returning merchants	0.155**	(0.035)	0.173**	(0.067)
Week	0.003***	(0.000)	0.002**	(0.001)
Week-square	-6.0E-5***	(2.1E-5)	6.6E-5**	(2.7E-5)
Sample size	5,324		5,242	
R-square	0.8773			
Number of instruments			111	
Hansen test of overidentification			$\chi^2(103) = 106.05$, $p = 0.399$	
Difference-in-Hansen test for consumer base			$\chi^2(10) = 5.64$, $p = 0.844$	
Difference-in-Hansen test for merchant base			$\chi^2(50) = 17.32$, $p = 1.000$	
Difference-in-Hansen test for price			$\chi^2(51) = 12.35$, $p = 1.000$	

Search Goods	*FE*		*DGMM*	
	Est	SE	Est	SE
Lagged merchant base (β_2)	0.024	(0.017)	0.242***	(0.057)
Consumer base (γ_2)	0.276***	(0.005)	0.380***	(0.023)
Deal price (ρ_2)	0.153***	(0.008)	0.196***	(0.052)
Rival consumer base (θ_{2n})	0.024**	(0.010)	-0.002	(0.018)
Rival merchant base (θ_{2m})	0.103***	(0.028)	0.117**	(0.050)
Returning merchants	0.194**	(0.031)	0.170***	(0.051)
Week	0.012***	(0.001)	0.009***	(0.002)
Week-square	1.9E-4***	(348E-5)	-5.1E-5	(8.7E-5)
Sample size	4,175		3,801	
R-square	0.834			
Number of instruments			111	
Hansen test			$\chi^2(103) = 97.56$, $p = 0.633$	
Difference-in-Hansen test for consumer base			$\chi^2(10) = 0.31$, $p = 1.000$	
Difference-in-Hansen test for merchant base			$\chi^2(50) = 31.75$, $p = 0.979$	
Difference-in-Hansen test for price			$\chi^2(51) = 25.00$, $p = 0.999$	

FE is the fixed-effect estimator and DGMM is the first-difference GMM estimator.
*** p<0.01, ** p<0.05, * p<0.1

found to be positive and significant for both categories. The CS_0 for experience goods is estimated to be 1.439 (p<0.01), and the CS_0 for search goods is estimated to be even 37% higher than the former (1.970, p<0.01).

On the merchant side, the SS_{-1} is estimated to be positive and significant for experience goods (0.417, p<0.01) and search goods (0.242, p<0.01). The CS_0 of consumers on merchants is also estimated to exist for both product markets. The CS_0 for experience goods is estimated to be 0.423 (p<0.01), and the CS_0 for search goods is estimated to be 0.380 (p<0.01).

In sum, on the merchant side, the SS_{-1} for experience goods is found to be approximately 1.7 as large as that for search goods, while the CS_0 is qualitatively similar between these two categories. This is again consistent with our hypothesized effects. In the experience-goods category, merchants benefit from the UGC that existing consumers have contributed, because it can help reduce quality uncertainty and create demand. Thus, the SS_{-1} of the merchants is found to be larger for merchants of experience goods. In contrast, merchants offering search goods do not benefit as much from existing UGC, and the SS_{-1} in the search-goods category is significant but weaker.

Next, we present the results for control variables. Not surprisingly, price is estimated to have a negative effect on consumer base and a positive effect on the merchant base. For experience goods, the consumer price elasticity is estimated to be -0.656 (p<0.01), and the merchant price elasticity is estimated to be 0.411 (p<0.01). For search goods, the consumer price elasticity is estimated to be -0.448 (p<0.01), the merchant price elasticity is estimated to be 0.196 (p<0.01).

Furthermore, after controlling for SS_{-1} and CS_0, the number of returning merchant is found to be negatively related with consumer base for experience goods (-0.278, $p < 0.05$) and search goods (-0.325, $p < 0.01$), indicating that consumers overall respond more positively to new merchants. This finding is consistent with the "switching risk reduction" hypothesis in (Li et al., 2011): because user reviews are more helpful for informing consumers for experience goods, consumers find it less risky to try new products rather than sticking with known products, resulting in a negative association between returning merchants and the consumer base. In other words, consumers respond more positively to new merchants than to existing merchants.

5.2 Robustness Analyses

To verify the validity of our results, it is critical to assess the extent to which the assumptions are met for the DGMM estimator. The first important assumption is that the instrumental variables used for identification should be exogenous to the errors. We present the results from the Hansen test of overidentification restrictions. On the consumer side, the Hansen test statistics are $\chi^2(101) = 101.88$ ($p = 0.457$) and $\chi^2(101) = 94.20$ ($p = 0.671$) for experience and search goods, respectively. On the merchant side, the test statistics are $\chi^2(103) = 106.05$ ($p = 0.399$) for experience goods and $\chi^2(103) = 97.56$ ($p = 0.633$) for search goods. These results indicate that the null hypothesis of that all IVs are exogenous should not be rejected at 0.05 level. Furthermore, Tables 6 and 7 include the Difference-in-Hansen test for each endogenous variable in our models. The results indicate that the exogenous IV

assumption is not rejected for all endogenous variables.

Table 8: Results of First-stage Regression

Consumer Side	Endogeneous Variable	R2	Partial R2	F Statistic	p
Experience Goods	Consumer Base	0.808	0.016	4.723	p<0.001
	Merchant Base	0.889	0.012	24.801	p<0.001
Search Goods	Consumer Base	0.413	0.026	6.074	p<0.001
	Merchant Base	0.539	0.010	15.189	p<0.001
Merchant Side		R2	Partial R2	F Statistic	p
Experience Goods	Consumer Base	0.810	0.014	17.277	p<0.001
	Merchant Base	0.456	0.002	2.190	p<0.001
Search Goods	Consumer Base	0.911	0.013	3.983	p=0.053
	Merchant Base	0.527	0.026	6.590	p<0.001

Next, we present the first-stage diagnostic statistics for the instrumental variables (see Table 8). To examine the strength of the instruments, the first-stage model was fit regressing the endogenous consumer base and merchant base on its respective instruments, controlling for all the exogenous variables including the market fixed effects. We begin by the consumer side model. For experience goods, the first-stage R-square was higher than 0.80 for both endogenous variables, which was perhaps due to the market fixed effects and week effect. After removing the effect due to the exogenous variables, market and time effects, the first-stage F statistic was 4.723 ($p < 0.001$) for the consumer base and the F statistic was 24.801 ($p < 0.001$) for the merchant base. For search goods, the overall R-square was lower, but the first-stage test statistics were still significant ($F = 6.074$, $p < 0.001$ for consumer base and $F = 15.189$, $p < 0.001$ for merchant base). Although the first-stage F statistics were modest for the endogenous consumer base, we would like to emphasize that the IV estimates were substantially different across the two types of products: the SS_{-1} was

positive and significant (0.096, $p < 0.05$) for the experience goods and insignificant for search goods (-0.034, $p > 0.010$). Thus, the heterogeneous SS_{-1} between experience and search products is not driven by the difference in the explanatory power of the IVs. The first-stage statistics are qualitatively similar for the merchant size model. The F statistics are modest for both endogenous variables but the p-values were all smaller than 0.1, even after controlling for all the exogenous variables, the time effect, and the extensive set of market fixed effects.

We conduct another robustness analysis to validate our estimates of the network effects. Specifically, we replace the focal market's SS_{-1} and CS_0 effects with the non-local counterparts. For the new SS_{-1}, we add up the customer size and merchant size (for Equations 2 and 5 respectively) in the previous period across all the markets on Groupon other than the focal market. The CS_0 variables are constructed similarly. Because these variables reflect the (lagged) customer size and merchant size of the platform in other markets, they capture the network effects due to non-local influences (if any). The parameters are presented in Tables 18 and 19. From the results, we see that the non-local network effects are all estimated to be close to zero and weaker than the local network effects, indicating that consumers and merchants on Groupon are attracted bySS_{-1} and CS_0 within the same local market.

This analysis also provides additional validation for the IV estimates of our main models. The non-local variables should be uncorrelated with the local market political advertising and weather conditions, and thus our instruments would not provide the needed variation for identification. As expected, the corresponding coefficient estimates are much reduced, providing validation evidence for using the instrumental

variables to identify the local network effects.

5.3 The Analysis of A User Growth Strategy

In this section, we calculate $CLV2$ and $MLV2$ based on the parameter estimates from the foregoing models and examine the effectiveness of the user growth strategy.

5.3.1 The Customer Lifetime Value in Two-sided Markets

To calculate $CLV2$ and $MLV2$, we first transform the unit free elasticity coefficients from Table 6 and 7 to the unit denominated marginal coefficients needed for marginal analysis in Table 9. We then use the calculation of $CLV2$ as an example for demon-

Table 9: Marginal Effects Of Independent Variables

Marginal Effects	$\tilde{\beta}_1$	$\tilde{\beta}_2$	$\tilde{\gamma}_1$	$\tilde{\gamma}_2$	$\tilde{\rho}_1$	$\tilde{\rho}_2$
Experience Goods	0.096	0.416	320.7	0.002	-32.7	0.092
Search Goods	0	0.242	365.4	0.002	-3.455	0.008

stration. Since the marginal cost of serving an additional consumer is almost zero for digital platforms, π^n of Groupon equals to its gross profit generated by a consumer in each period. Note that Groupon's gross profit is not directly observed in the data. Thus, we use its revenue multiplied by the gross margin to approximate it. First, we use half of the gross billing as a proxy for revenue according to Dholakia (2011) [12]. Gross billing is the total sales on Groupon, which is calculated from the transaction volume and deal price. Note that the transaction volume is used as a proxy for the

[12]It is also consistent with the ratio of revenue to gross billing in Groupon's 2012 annual report. Groupon's gross billings and revenue in North America in 2012 is \$2,373.153 million and \$1,165.7 million, respectively, yielding a ratio of gross billing to revenue of 49.12%.

consumer base. Thus, we use the increased consumer base multiplied by the deal price to calculate the gross billing. Second, in Groupon's 2012 annual report, the gross profit accounted for less than 70% of Groupon's revenue. In later years, this percentage decreased to around 50%. We use 70% of Groupon's revenue to represent the gross profit, which sets an upper bound of $CLV2$.

According to Equation 7, we calculate $CLV2$ in experience-goods and search-goods markets, respectively. The same logic applies to the $MLV2$. Table 10 reports the $CLV2$ and $MLV2$ in experience-goods and search-goods markets. According to our calculation, a consumer is worth \$62 and a merchant is worth \$31,654 in the experience-goods market. In the search-goods market, a consumer is worth \$54 and a merchant is worth \$26,338. Although the CS_0 of experience goods and search goods are all positive and significant, the $CLV2$ and $MLV2$ in the experience goods market are larger than those in the search goods market, as a result of the differences in SS_{-1}. In the experience-goods market, the SS_{-1} of consumers amplifies the $CLV2$ by 1.15 times, and the SS_{-1} of merchants amplifies the $MLV2$ by 1.66 times. In the search-goods market, due to the absence of a significant SS_{-1} of consumers and a relative weaker SS_{-1} of merchants, the value created on both sides of the market has less opportunity to be amplified over time. The positive shocks that a market may receive in one period quickly dissipate and do not result in persistent value creation.

Table 10: Estimated Customer Lifetime Value

Customer Lifetime Value	$CLV2$	$MLV2$
Experience Goods(\$)	62	31,654
Search Goods (\$)	54	26,338

5.3.2 The User Acquisition Cost

To boost growth, platforms can consider marketing to increase their consumer base, hoping that the incremental consumer base could lead to future increases in the consumer base and merchant base. In this section, we consider two commonly used marketing strategies: (1) advertising to buy consumers, and (2) implementing price discounts. We then compare the $CLV2$ computed in the previous section to the consumer acquisition cost. Note that this analysis can be applied to both consumer side and merchant side. However, platforms' cost to acquire merchants is typically unavailable to researchers, which is the case for Groupon. In its annual report, Groupon reported neither the expense of acquiring merchants nor the growth of its merchant base. As a result, our cost-and-benefit analysis focuses on the consumer side.

Intervention – Acquisition Through Marketing. We first look at the scenario when the platform uses advertising marketing as the user-growth strategy. The consumer acquisition cost (CAC) in this case is calculated as the total marketing expense divided by the total number of acquired consumers (Gupta et al., 2004; McCarthy and Fader, 2018). In its 2012 annual report, Groupon reported a total marketing expense of \$336.85 million with 7.3 million consumers acquired worldwide, yielding an acquisition cost of \$46 per new consumer globally. In North America, the marketing expense was \$105.9 million, but the report did not include the total number of consumers acquired in North America. Based on the proportion of gross billing in North America (\$2.37 billion) relative to worldwide sales (\$5.38 billion), we esti-

mated the number of new consumers in North America as 3.22 million, which yields an estimated cost of \$33 to acquire a new consumer. Table 11 reports Groupon's net $CLV2$ in North America, which is equal to $CLV2$ minus CAC. It represents a net $CLV2$ of \$29 in the experience-goods market but a net $CLV2$ of \$21 in the search-goods market, which implies that the consumer acquisition through marketing is less effective in the search-goods market than the experience goods market due to different $CLV2$ in these markets. Note that fixed costs and operating costs associated with serving consumers are not included in this calculation. If we amortize these costs to each consumer, the net $CLV2$ will become negative.

Table 11: Cost-and-Benefit Analysis of Marketing Acquisition

	Experience Goods	Search Goods
Consumer Lifetime Value (\$)	62	54
Consumer Acquisition Cost (\$)	33	33
Net Consumer Lifetime Value (\$)	29	21

Intervention – Price Cut. In a two-sided market, a price cut can stimulate greater participation on the discounted side and the other side of the market through various network effects. We analyze the cost and benefit of a price cut on each side of the market. We use the formula of the marginal effect of the deal price in Section 5.2.1 to calculate the increase in the consumer base and merchant base for the promotion on each side, which is then multiplied by the $CLV2$ and $MLV2$ to obtain the total increased value.

Table 12 illustrates these results. For experience goods, a \$1 cut in the deal price brings 33.2 additional consumers and 0.063 additional merchants, yielding a

total increased value of $4,035. Based on the average transaction volume of each market, the promotion cost is calculated to be $3,959. Thus, the net gain from deal promotion is $ 76. For search goods, a $1 cut in the deal price brings 4.03 additional consumers and 0.008 additional merchants, yielding a total increased value of $435. Based on the average transaction volume of each market, the promotion cost is calculated to be $704. Thus, the net gain from deal promotion is $ -269. Due to the difference between the $CLV2$ and $MLV2$ in the experience-goods and search-goods markets, the deal promotion for experience goods is cost-effective but the deal promotion for search goods is not cost-effective.

Table 12: Cost-and-Benefit Analysis of Price Promotion

$1 price cut	Experience Goods	Search Goods
Increase in consumer base	33.2	4.03
Increase in merchant base	0.063	0.008
Total increase in value ($)	4,035	435
Promotion cost ($)	3,959	704
Net gain ($)	76	-269

6 Managerial Implications: Platform Designs to Enhance User Stickiness

For platforms with a strong CS_0 but a weak SS_{-1}, platform design choices that enhance user stickiness may offer greater leverage than common marketing strategies that bring users to a platform. In this research, we define user stickiness as the ability of the platform to continually attract users in each period. We first calculate

the $CLV2$ and $MLV2$ in simulations when the user stickiness is enhanced, and then discuss two methods of enhancing user stickiness. One method considers platform design choices such as improved reputation systems that are derived from user network effects. The second method considers the design choices that are not derived from user network effects but from the improved platform quality. For example, the development of a merchant information management system reduces the risk of disintermediation and reroutes transactions through the platform rather than conducting them off-platform. The direct implications of this design intervention is that users become stickier on the platform, leading to increases in $CLV2$ and $MLV2$. Lastly, we discuss the feasibility of these platform design choices as compared to a similar platform.

6.1 Simulating Enhanced User Stickiness

We use the $CLV2$ and $MLV2$ in the experience-goods market as an example to simulate the impact of changing the strength of SS_{-1} of consumers (i.e., modifying β_1). We simulate three scenarios of β_1: 0.1, 0.5, and 0.9, and compute the corresponding updated $CLV2$ and $MLV2$. Similarly, we simulate the impact of changing the strength of SS_{-1} of merchants by modifying β_2. Table 13 presents the results.

When the SS_{-1} of consumers or merchants changes, it has a substantial impact on $CLV2$ and $MLV2$. Boosting β_1 from 0.096 to 0.5 would improve the $CLV2$ by 1.8 times and the $MLV2$ by 1.4 times. Boosting β_1 from 0.096 to 0.9 would improve the $CLV2$ by 9 times and the $MLV2$ by 5.2 times. Boosting β_2 from 0.417 to 0.5 would improve the $CLV2$ by 1.1 times and the $MLV2$ by 1.2 times. Boosting β_1

Table 13: $CLV2$ and $MLV2$ in Response to Changing the Strength of SS_{-1}

SS_{-1} of Consumers (β_1)	0.1	0.096(observed)	0.5	0.9
Consumer value ($)	62	62	111	557
Merchant value ($)	31,728	31,654	45,086	165,317

SS_{-1} of Merchants (β_2)	0.1	0.417(observed)	0.5	0.9
Consumer value ($)	51	62	67	211
Merchant value ($)	20,505	31,654	36,908	184,541

from 0.417 to 0.9 would improve the $CLV2$ by 3.4 times and the $MLV2$ by 5.8 times. Note that changing CC_{-1} has a greater impact on $CLV2$ than on $MLV2$. Similarly, changing the MM_{-1} has a greater impact on $MLV2$ than on $CLV2$. It is worth noting that participant acquisition marketing becomes more cost-effective as any inter-temporal same side network effect SS_{-1} increases.

6.2 Discussion of Platform Design Choices

The scale of these effects raises the question of whether enhancing user stickiness is feasible. Could managerial decisions concerning platform design have large strategic growth implications? Evidence from another daily deal platform suggests that these outcomes are indeed possible. Meituan launched in 2010, two years after Groupon, as a daily deal platform that used an identical business model which leveraged group buying power to offer coupons and volume discounts to price-sensitive consumers. In contrast to Groupon's strategy that ran several years of losses in an effort to buy user growth, Meituan adopted platform designs that focused on enhancing user

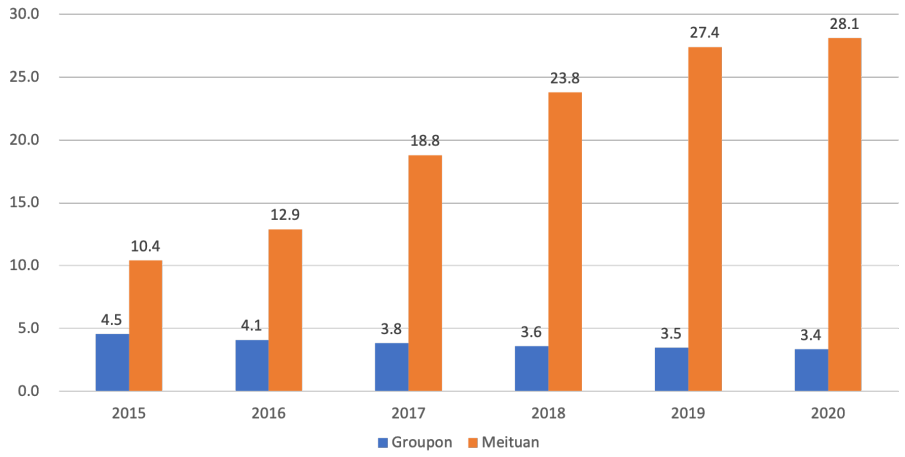


Figure 4: Average Units per Consumer: Groupon vs Meituan

stickiness and sustaining network effects. We first summarize two types of platform designs that enhance user stickiness, then compare the performance of Groupon and Metiuan.

Enhancing User Stickiness Through Network Effects. First, Meituan merged with Dianping (a Chinese Yelp) to offer more UGC on the platform. As new transactions generated more user-review data, UGC improved recommendations, created positive feedback, and increased user stickiness. Second, Meituan rewarded consumers for generating ideas and for repeat purchases. It then used this data to help merchants identify new products and situate new stores, which, again, increased their dependence on Meituan. By design, it helped users create more value for other users.

Enhancing User Stickiness Through Factors Other Than Network Effects. Meituan invested heavily in delivery and reservation systems. It expanded its services to handle logistics and deliver not only food to consumers but also supplies to restau-

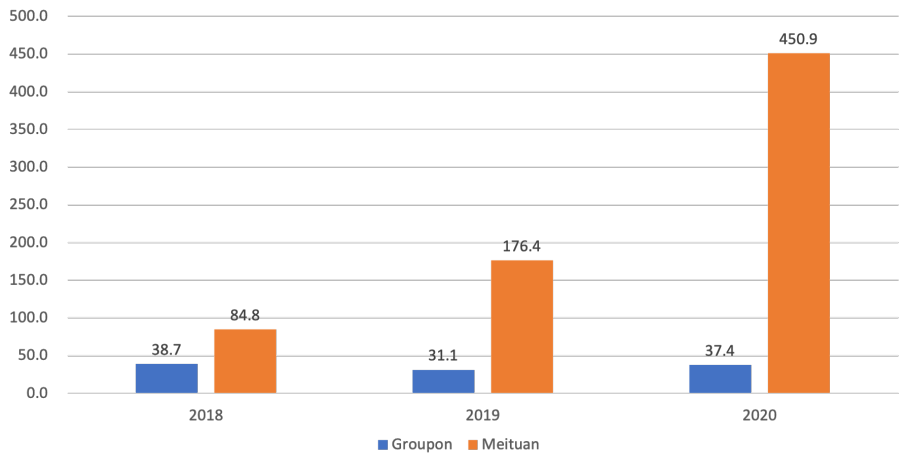


Figure 5: $CLV2$: Groupon vs Meituan ($)

rants. Using technology to reduce friction encouraged restaurants and consumers to rely on Meituan, effectively enhancing user stickiness.

Comparison of Meituan and Groupon's Performance. Figure 4 and Figure 5 show the average units per consumer[13] and $CLV2$ of Groupon and Meituan,[14] respectively. We consider the average units per consumer as a direct indicator of user stickiness. Groupon's average units per consumer gradually decreases while Meituan's average units per consumer continues to increase. A number of factors may have contributed to the divergent $CLV2$ of Meituan and Groupon yet it is worth noting that the average units per consumer of Meituan is 8.3 times that of Groupon in 2020, and $CLV2$ of Meituan is 12 times that of Groupon.

[13]In Groupon's and Meituan's financial reports, the average units per consumer are the number of purchases per consumer during the reporting period.

[14]Meituan appeared in stock market listings in 2018, so we can only collect data and compare $CLV2s$ of Meituan and Groupon from 2018-2020.

7 Limitations & Research Opportunities

There are several directions for future research. First, platforms have multiple ways to improve their long-term value. Should a platform invest in user growth, the design of network effects, key assets, brand, or other factors? It is worth gathering real data on the comparative costs and benefits of these strategies before the platform makes investment decisions. Second, in our empirical setting, we include the competition effect from the primary competing platform. Although this should capture the competition in many markets, we acknowledge that, in some markets, there could be other major platforms as a key player. Future analysis can improve the competition analysis. Third, our $CLV2$ model is not based on accounting profit in each future period. Following Zhang et al. (2012) and Li et al. (2020), we identify users' impact on future profits. Since we want to estimate the value created by users, our model is suitable for this research. However, our model cannot capture the impact of increased platform quality on future profits, it may underestimate the $CLV2$ when platform quality increases during the observation period. It would be valuable to develop a $CLV2$ model that can capture the impact of network effects as well as platform quality on future profits. Lastly, the strengths of the inter-temporal effects and within-period effects can differ strongly across different markets. We have shown that they vary by product categories on one platform, and in future research, we aim to identify and compare the inter-temporal effects across multiple platforms.

8 Conclusions

We study how users drive nework value in two-sided markets. Introducing time, we develop a discrete-choice model to estimate both within and across period network effects, which have been under-studied in empirical research (Jullien et al., 2021). Our model underscores, in particular, the importance of same-side intertemporal attraction. For certain platforms, weak same-side effects SS_{-1} yield poor user stickiness and the impacts of strong cross-side effects CS_0 may not persist. Based on our estimates, we develop a model to calculate consumer ($CLV2$) and merchant ($MLV2$) lifetime value in two-sided markets. By comparing $CLV2$ and user acquisition costs, a platform can examine the effectiveness of different user growth strategies. We theorize that the mechanism behind heterogeneous SS_{-1} is the "product learning" effect: products with higher uncertainty garner a higher value from user contributions (Hagiu and Wright, 2020; Li et al., 2017). Our theoretical simulations and empirical estimates confirm different levels of SS_{-1} between search and experience goods. We then discuss platform strategic responses when cross-side effects CS_0 are strong but same-side effects SS_{-1} are weak. Results show that stickiness enhancing platform designs can increase $CLV2$ and $MLV2$. After users become stickier, user acquisition marketing becomes more cost-effective. Data on customer lifetime value at Meituan demontrates that enhancing user stickiness is feasible and can be designed. Overall, our findings remind managers not to overemphasize user growth when the user stickiness is poor and instead focus on platform designs that increase user to user stickiness.

We believe these results offer the following three contributions. First, theoretical

models of network effects have largely been static. Empirical models of network effects have largely been absent or have struggled to address the reflection problem. Extending these works, our model addresses dynamic network effects, including both within and across period attraction, for two-sided markets. We address the reflection problem by using prior period instruments for both sides as well as current period instruments affecting only one side. Main results are economically and statistically significant. In cases where our instruments are not strong, we contrast within market estimates to demonstrate key results hold.

Second, the customer lifetime value literature has omitted network spillovers in CLV calculations (Gupta and Mela, 2008). Our research provides a straightforward set of tools for making these estimates, accounting for how CLV2 and MLV2 affect each other. This can also account for the lifetime value of "free" customers, who attract other sides of the market but do not themselves pay. Of necessity, these calculations are interdependent when network effects are present. Our results show spillovers are, in fact, present confirming the need for such a model.

Third, we identify factors that can strengthen or weaken each of the four sets of network effects in our study. As illustration, selling experience goods raises the importance of same-side customer adoption whereas selling search goods does not. By contrast, both matter for merchants' network attraction. Other salient factors include a competitor's customer and merchant bases, own and rival prices, and local versus non-local interaction. Equipped with the ability to estimate attraction, retention, and now cross-market spillovers, managers and investors can design marketing and information systems interventions that offer greater lifetime value leverage. Be-

yond the suggestive examples of Amazon, SAP, Airbnb and others, case analyses of Meituan and Groupon provide helpful guidance.

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Appendices

A Survey Design

We conducted an Amazon MTurk online survey and asked the respondents to code all the categories on Groupon (a total of 78 categories). The respondents were first asked to review the definition and examples of "search" and "experience" goods as follows:

In this study, imagine you are browsing a deal website, for example, Groupon.

For some goods, you must see, try or experience them at least once to judge their quality. For example, you might need to taste the cuisine at a specific restaurant or

try a particular haircut to know if you like the result. These goods are referred to as "experience goods."

For other goods, you can easily judge their value without having to try them. For example, one brand of table salt is like any other brand of table salt. And a gallon of regular gas at one gas station is indistinguishable from a gallon of regular gas at a different gas station. These goods are referred to as "search goods." You can often evaluate the quality of search goods simply by reading its product description.

Next, you will be provided with 15 goods and asked to evaluate each of them according to the extent they are "experience" versus "search" goods.

Please assume that there are no product reviews available.

The respondents were then asked to assess for each of the 15 categories, "to what extent it is easy (hard) to evaluate the quality without seeing or trying it." The 15 questions included "haircut" and "gas," both of which are NOT the original Groupon categories. These two products are used as the filler questions to check whether respondents paid attention in replying.

A total of 818 respondents passed the two attention filler questions and their responses were aggregated to calculate the score for each category. The score closer to "easy" ("hard") corresponds to search (experience) goods. Based on the scores, we used the median split and code the categories into two groups: experience goods and search goods. We also used the mean split and yielded qualitative similar results. The detailed survey responses are presented in Tables 14 and 15.

Table 14: MTurk Online Survey: Experience Goods

Groupon Category	N	Mean	SD	Min	Max
Haircut (Attention Checking Question)	818	6.46	7	0.71	5
Hair Salons	175	6.39	7	0.93	2
Facials	159	6.21	7	1.08	1
Makeup Services	195	6.13	6	1.20	1
Spa Treatment	164	6.12	7	1.18	2
Health & Beauty Services	153	6.11	6	1.16	2
Restaurants	133	6.11	6	1.18	1
Dance Classes	122	6.01	7	1.46	1
Massage	145	5.99	7	1.46	1
Wine Tasting	135	5.88	6	1.47	1
Comedy Clubs	127	5.87	6	1.27	2
Personal Trainer	109	5.85	6	1.41	1
Concerts	136	5.77	6	1.70	1
Shows	134	5.74	6	1.45	1
Martial Arts Classes	128	5.73	6	1.48	1
Skin Care	159	5.67	6	1.25	1
Nail Care	140	5.66	6	1.47	1
Chiropractor Classes	132	5.60	6	1.60	1
Photography Service	105	5.54	6	1.62	1
Waxing	157	5.52	6	1.60	1
Teeth Whitening	168	5.51	6	1.50	1
Life Skills Classes	158	5.50	6	1.53	1
Boot Camp	105	5.50	6	1.66	1
Dental Clinic and Dental Care	129	5.48	6	1.53	1
Outdoor Adventures	138	5.47	6	1.88	1
City Tours	148	5.47	6	1.63	1
Fitness Classes	119	5.45	6	1.71	1
Bridal Services	123	5.44	6	1.75	1
Kids Activities: Summer camp, play party	120	5.43	6	1.84	1
Museums	144	5.40	6	1.61	1
Bars & Lounges	149	5.33	6	1.71	1
Tanning	166	5.29	6	1.93	1
Dessert	115	5.28	6	1.84	1
Food: seafood orders, healthy snacks	123	5.18	6	1.79	1
Skiing	144	5.13	6	1.76	1
Yoga	125	5.10	6	1.75	1
Home Services	138	5.09	5	1.65	1
Pilates	119	5.07	6	1.93	1
Skydiving	127	5.02	6	2.16	1
Wine	151	5.01	6	1.91	1

Table 15: MTurk Online Survey: Search Goods

Groupon Category	N	Mean	SD	Min	Max
Vision and Eye Care	142	4.94	5	1.81	1
Women's Clothing	136	4.85	5	1.62	1
Travel Packages	125	4.65	5	2.02	1
Gym Membership	114	4.58	5	1.84	1
Men's Fashion	150	4.53	5	1.83	1
Automotive Services	135	4.50	5	1.89	1
Sweets	133	4.48	5	1.95	1
Home Improvement	123	4.46	5	1.82	1
Women's Fashion	119	4.40	5	1.99	1
Photo Services	139	4.38	4	1.81	1
Entertainment Goods: movies, magazine subscription	153	4.35	4	2.05	1
Coffee & Tea	99	4.32	5	1.91	1
Golf	119	4.28	5	2.05	1
Men's Clothing	138	4.22	4	1.74	1
Women's (Clearance Sale)	124	4.14	4	1.96	1
College Test Prep Courses	143	4.11	4	1.85	1
Decor	142	4.08	4	2.14	1
Organic Produce and Food	153	4.07	4	1.98	1
Pet Products and Services	117	4.01	4	1.63	1
Home Theater	138	3.97	4	1.89	1
Personal Electronics	111	3.81	3	1.95	1
Furniture	147	3.79	4	1.91	1
Gadgets: Headphone, speaker dock, electronic clock	128	3.78	4	1.96	1
Bowling	133	3.75	4	2.00	1
Men's (Clearance Sale)	148	3.72	4	1.92	1
Women's Accessories	144	3.65	4	2.01	1
Cameras	115	3.64	4	1.98	1
Men's Accessories	140	3.43	3	1.66	1
Baby Products: Clothing, Diapers, Monitors	133	3.38	3	1.91	1
Home Goods	138	3.36	3	1.79	1
T-Shirts	144	3.34	3	1.63	1
GPS & Navigation	120	3.21	3	1.78	1
Computers & Hardware	144	3.21	3	1.86	1
Cooking Gadgets	141	3.21	3	1.68	1
Groceries	150	3.07	3	1.69	1
Sports Tickets	141	3.01	2	2.09	1
Holiday Decor	124	2.98	2	1.87	1
Gifts: candles, phone cases, stationary	142	2.60	2	1.68	1
Office Supplies	132	1.98	2	1.34	1
Gas (Attention Checking Question)	818	1.24	1	0.50	1

B Validation Survey

We do a parallel offline survey at a major U.S. university to check the robustness of our results. Twenty-eight business-school undergraduate students participated in the survey. Each student was asked to assess the product/service categories on Groupon. The category is coded as the experience type if more than half of the respondents coded so.

Based on the survey, we re-estimate the consumer-side model for search and experience goods, respectively, and present the results in Table 16. Similarly, the estimates for the merchant-side model for search and experience goods are presented in Table 17. Our main conclusions hold using category coding from this validation survey.

C Robust Analysis: Non-local Network Effects

In this analysis, we replace the focal market's SS_{-1} and CS_0 effects with the non-local counterparts. The parameter estimates of our main model are presented as follows.

Table 16: Validation Survey: Parameter Estimates for Consumer-Side Model

Experience Goods	*FE*		*DGMM*	
	Est	(SE)	Est	(SE)
Lagged consumer base (β_1)	0.030**	(0.013)	0.128***	(0.038)
Merchant base (γ_1)	1.238***	(0.029)	1.449***	(0.061)
Deal price (ρ_1)	-0.241***	(0.015)	-0.365***	(0.093)
Rival consumer base (θ_{1n})	0.071***	(0.012)	0.068**	(0.018)
Rival merchant base (θ_{1m})	-0.012	(0.034)	-0.053	(0.050)
Returning merchants	-0.453***	(0.073)	-0.570***	(0.181)
Deal duration	0.109***	(0.010)	0.118***	(0.022)
Week	-0.007***	(0.001)	-0.007***	(0.001)
Week-square	1.9E-5	(4.2E-5)	6.5E-5	(5.6E-5)
Sample size	5,354		5,242	
R-square	0.737			
Number of instruments			110	
Hansen test of overidentification			$\chi^2(101) = 101.71$, p = 0.461	
Difference-in-Hansen test for customer base			$\chi^2(50) = 14.02$, $p > 0.999$	
Difference-in-Hansen test for merchant base			$\chi^2(9) = 1.11$, $p = 0.999$	
Difference-in-Hansen test for price			$\chi^2(51) = 12.17$, $p > 0.999$	

Search Goods	*FE*		*DGMM*	
	Est	(SE)	Est	(SE)
Lagged consumer base (β_1)	-0.019	(0.013)	-0.018	(0.029)
Merchant base (γ_1)	2.099***	(0.044)	2.077***	(0.136)
Deal price (ρ_1)	-0.706***	(0.025)	-0.694***	(0.153)
Rival consumer base (θ_{1n})	-0.018	(0.027)	-0.004	(0.057)
Rival merchant base (θ_{1m})	-0.041	(0.076)	-0.084	(0.156)
Returning merchants	-0.163**	(0.08)	0.063	(0.397)
Duration	-0.032**	(0.015)	-0.030	(0.031)
Week	-0.012***	(0.002)	-0.015**	(0.007)
Week-square	-2.8E-4***	(9.5E-5)	-1.8E-4	(2.7E-4)
Sample size	3,662		3,213	
R-square	0.551			
Number of instruments			110	
Hansen test of overidentification			$\chi^2(101) = 91.85$, $p = 0.731$	
Difference-in-Hansen test for consumer base			$\chi^2(50) = 23.3$, $p > 0.999$	
Difference-in-Hansen test for merchant base			$\chi^2(9) = 6.15$, $p = 0.725$	
Difference-in-Hansen test for price			$\chi^2(51) = 32.25$, p = 0.981	

FE is the fixed-effect estimator and DGMM is the first-difference GMM estimator.
*** p<0.01, ** p<0.05

Table 17: Validation Survey: Parameter Estimates for Merchant-Side Model

Experience Goods	*FE*		*DGMM*	
	Est	SE	Est	SE
Lagged merchant base (β_2)	0.182***	(0.016)	0.398***	(0.056)
Consumer base (γ_2)	0.278***	(0.006)	0.420***	(0.019)
Deal price (ρ_2)	0.099***	(0.007)	0.360***	(0.048)
Rival consumer base (θ_{2n})	0.013**	(0.006)	-0.028***	(0.010)
Rival merchant base (θ_{2m})	0.158***	(0.016)	0.149***	(0.027)
Returning merchants	0.149**	(0.036)	0.236***	(0.064)
Week	0.004***	(0.0004)	0.001***	(0.001)
Week-square	-8.3E-5***	(2.0E-5)	-8.3E-5	(2.0E-5)
Sample size	5,354		5,242	
R-square	0.882			
Number of instruments			111	
Hansen test of overidentification			$\chi^2(103) = 106.05$, $p = 0.399$	
Difference-in-Hansen test for consumer base			$\chi^2(10) = 2.34$, $p = 0.993$	
Difference-in-Hansen test for merchant base			$\chi^2(50) = 14.77$, $p > 0.999$	
Difference-in-Hansen test for price			$\chi^2(51) = 9.65$, $p > 0.999$	

Search Goods	*FE*		*DGMM*	
	Est	SE	Est	SE
Lagged merchant base (β_2)	0.025	(0.017)	0.192***	(0.061)
Consumer base (γ_2)	0.275***	(0.006)	0.369***	(0.019)
Deal price (ρ_2)	0.263***	(0.01)	0.362***	(0.058)
Rival consumer base (θ_{2n})	0.037***	(0.01)	0.031*	(0.015)
Rival merchant base (θ_{2m})	0.065**	(0.029)	0.024	(0.045)
Returning merchants	0.081**	(0.036)	0.078	(0.057)
Week	0.010***	(0.001)	0.006*	(0.003)
Week-square	3.8E-4***	(3.8E-5)	7.0E-5	(1.3E-4)
Sample size	3,662		3,213	
R-square	0.833			
Number of instruments			111	
Hansen test			$\chi^2(103) = 92.88$, $p = 0.753$	
Difference-in-Hansen test for consumer base			$\chi^2(10) = 2.34$, $p = 0.993$	
Difference-in-Hansen test for merchant base			$\chi^2(50) = 14.77$, $p > 0.999$	
Difference-in-Hansen test for price			$\chi^2(51) = 25.33$, $p = 0.999$	

FE is the fixed-effect estimator and DGMM is the first-difference GMM estimator.
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Parameter Estimates: Customer-Side Model for Non-local Effects

Experience Goods	*FE*		*DGMM*	
	Est	(SE)	Est	(SE)
Lagged customer base (β_1)	0.0006*	(0.0004)	0.0010**	(0.0004)
Merchant base (γ_1)	0.0140***	(0.0010)	0.0130***	(0.0010)
Deal price (ρ_1)	-0.265***	(0.017)	-0.473***	(0.098)
Rival customer base (θ_{1n})	0.050***	(0.013)	0.052**	(0.022)
Rival merchant base (θ_{1m})	-0.032	(0.039)	0.015	(0.061)
Returning merchants	-0.417***	(0.08)	-0.164	(0.114)
Deal duration	0.061***	(0.012)	0.092***	(0.023)
Week	-0.014***	(0.001)	-0.016***	(0.001)
Week-square	1.86E-05	(4.71E-05)	3.40E-05	(5.85E-05)
Sample size	5,324		5,212	

Search Goods	*FE*		*DGMM*	
	Est	(SE)	Est	(SE)
Lagged customer base (β_1)	-0.0008**	(0.0004)	-0.0008*	(0.0004)
Merchant base (γ_1)	0.0132***	(0.0009)	0.0128***	(0.0016)
Deal price (ρ_1)	-0.271***	(0.023)	-0.099	(0.176)
Rival customer base (θ_{1n})	0.031	(0.029)	0.070	(0.049)
Rival merchant base (θ_{1m})	-0.101	(0.085)	-0.200	(0.128)
Returning merchants	-0.582***	(0.092)	-0.442***	(0.151)
Deal duration	0.031*	(0.016)	-0.027	(0.048)
Week	-0.007***	(0.002)	0.001	(0.007)
Week-square	5.32E-05	(1.07E-04)	-3.48E-04	(2.71E-04)
Sample size	4,175		3,801	

FE is the fixed-effect estimator and DGMM is the first-difference GMM estimator.
*** p<0.01, ** p<0.05

Table 19: Parameter Estimates: Merchant-Side Model for Non-local Effects

Experience Goods	*FE*		*DGMM*	
	Est	SE	Est	SE
Lagged merchant base (β_2)	-0.0003	(0.0004)	-0.0004	(0.0004)
Customer base (γ_2)	0.0036***	(0.0001)	0.0035***	(0.0002)
Deal price (ρ_2)	0.036***	(0.008)	0.186***	(0.044)
Rival customer base (θ_{2n})	0.001	(0.006)	-0.012	(0.007)
Rival merchant base (θ_{2m})	0.059***	(0.018)	0.112***	(0.022)
Returning merchants	0.083**	(0.038)	0.207**	(0.087)
Week	-0.0002487	(0.001)	-0.001	(0.001)
Week-square	-6.3E-05***	(2.21E-05)	-2.07E-05	(3.07E-05)
Sample size	5,324		5,212	

Search Goods	*FE*		*DGMM*	
	Est	SE	Est	SE
Lagged merchant base (β_2)	0.0010**	(0.0005)	-0.0005	(0.0008)
Customer base (γ_2)	0.0029***	(0.0001)	0.0035***	(0.0002)
Deal price (ρ_2)	0.078***	(0.009)	-0.098**	(0.043)
Rival customer base (θ_{2n})	0.021*	(0.012)	0.019	(0.017)
Rival merchant base (θ_{2m})	0.035	(0.035)	0.035	(0.049)
Returning merchants	-0.017	(0.038)	0.027	(0.062)
Week	0.008***	(0.001)	0.01***	(0.003)
Week-square	9.54E-05**	(4.26E-05)	1.56E-05	(1.17E-04)
Sample size	4,175		3,801	

FE is the fixed-effect estimator and DGMM is the first-difference GMM estimator.
*** p<0.01, ** p<0.05, * p<0.1