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Abstract

This paper highlights how the provision of information about user participation can serve as a strategic marketing tool for firms seeking to grow two-sided exchange networks. A two-sided exchange network is a business model (such as Ebay or Craiglist) where revenue is generated from persuading people to buy and sell items through that particular exchange. It is not immediately clear whether broadcasting information about the number of sellers will grow further seller participation. On the one hand, a strong rival presence may dissipate payoff (a "congestion effect"). On the other hand, a large number of rivals may signal high buyer demand (a "cross-platform effect"). We use field experiment data from a B2B web site that brings together buyers and sellers of used equipment and real estate. Before each seller made a posting request, the web site randomized whether to disclose the number of buyers and/or sellers, and the exact number to disclose. We find that when presented together with the number of buyers, a larger number of sellers makes sellers less likely to list their products, indicating a negative congestion effect. However, when the number of sellers is presented in isolation, its negative impact on entry is significantly reduced, indicating a positive cross-platform effect. Higher buyer search intensity amplifies the moderating role of demand uncertainty. The results suggest that information on the number of users can be an effective tool to grow two-sided networks but should be used strategically. A network can attract more users by advertising dense competition when demand is not transparent, especially in search-intensive markets.

Keywords: Competition, Entry, Inference, Congestion, Decision-making Under Uncertainty, Two-Sided Markets

JEL Classifications: C93, D83, L11, M31

1 Introduction

Two-sided exchange networks as a contemporary business model have been a magnet to entrepreneurs. Some are able to expand at a furious pace. EBay's number of listings exploded from none in 1995 to 340,00 auctions closing per day by 1999 (Lucking-Reiley 2000). Match.com started from scratch in 1994 and now has listings from over 12 million men and 8 million women. However, there are also numerous well-funded two-sided networks that have never gained traction. Chemdex.com, despite pioneering the B2B portal model and raising $112.5 million through its IPO, never accumulated enough clients to make a profit. Similarly, Amazon Auctions, while feted as an "EBay Killer," was quietly dropped two years after its launch after attracting less than two percent of auction listings.[1] Knowing how to grow network participation would help firms avoid costly flops in this high stakes game. This paper suggests ways to grow participation using a deceptively simple tool—information on the number of network users itself.

Publicizing the number of users is a popular practice on the internet, but it is unclear whether this practice stunts or accelerates the growth of two-sided networks. Consider the following scenario: a B2B website is trying to attract business's that sell used medical equipment to make listings. The web site advertises that it has already signed up 200 sellers of used medical equipment. How does information affect the a potential client's decision to list? On the one hand, a potential seller may balk at the idea of ferocious competition. On the other hand, it may be more likely to sign up, reasoning that the 200 other firms may have joined the web site because of a large buyer base, or that the number of sellers on the web site might have attracted a large number of buyers.

We identify "demand uncertainty" as a key moderator of how peer presence affects network entry decisions. In the medical equipment example, the potential seller's demand uncertainty is its uncertainty about the number of buyers that will browse its listing on the web site. We

[1] "Auctions getting lost in Amazon's jungle," CNET News, July 31, 2002.

distinguish between two effects of peer presence that are governed by the availability of demand information: A "congestion effect" where potential entrants avoid payoff-dissipating competition, and an "cross-platform effect" where potential entrants infer high demand from heavy peer presence, either because high demand has attracted substantial entry or because substantial entry has created high demand.

Empirically, it is difficult to establish causality when a seller enters a two-sided network packed with other sellers, given the abundance of alternative explanations as to why entry decisions are correlated. Equally challenging are the sparse observations of potential sellers who choose not to participate and of the factors that lead to this nonparticipation decision (see Bradlow and Park (2007) for a discussion of latent auction participants and a model of imputing the competitor set). Previous empirical studies using historical data on entry decisions have not been able to isolate the effects of demand uncertainty, due to the lack of data on the degree of uncertainty or on the variation of uncertainty across time or market. Recent progress on estimating equilibrium models of entry has required researchers to focus on contexts where there is full information about demand (e.g., Seim (2006), Orhun (2007), Zhu, Singh, and Dukes (2005)). A few studies take the opposite approach and estimate the equilibrium assuming that firms lack information about market conditions (e.g., Toivanen and Waterson (2005) and Vitorino (2007)). Both approaches rely on assumptions about demand information availability and then use them to interpret entry correlations. However, the importance of these assumptions is hard to quantify. First, it is unusual for researchers to observe the exact information structure of potential entrants. Therefore, the validity of the informational assumptions key to this stream of research is hard to test. Second, even if researchers have precise information on a firm's knowledge about market conditions, information acquisition itself may be an endogenous variable (e.g., Hitsch (2006)). This endogeneity problem may further confound the results because firms' decision to acquire information is affected by their (often unobserved to the researcher) knowledge about the products' chance of success, which in turn affects their subsequent entry decisions. We adopt a field experimental approach to address both questions by exogenously controlling the level of market uncertainty and tracing the causal effect of information.

We circumvent these empirical challenges by using data from a field experiment where potential network entrants were randomly informed about demand. The field experiment was conducted by a web site that brings together sellers and buyers of various categories of used goods and real estate properties in one metropolitan area. Before each potential seller decided whether to list their good, the web site randomized whether to display the number of buyers and/or sellers and, if so, how many buyers and sellers to claim.

We find that when information on both the number of buyers and the number of sellers is presented, a larger number of sellers reduces a potential seller's posting propensity. However, when information about the number of sellers is presented in isolation, it has a less negative effect on the seller's posting decision. Therefore, the effect of peer presence on entry can be negative or positive, depending on how much potential entrants use peer presence to resolve demand uncertainty.

Furthermore, we investigate how demand uncertainty interacts with a firm's expectations of the behavior of buyers on the other side of the network. We examine how buyers' likelihood of browsing multiple listings affects seller entry behavior. When the web site discloses the number of users on both sides of the market, a large number of sellers discourages entry in search-intensive categories. However, when the web site supplies information on only the number of sellers, a large number of sellers boosts posting propensities in more search-intensive categories. This second result initially seems counter-intuitive. Firms would presumably be more concerned about competition where customers like comparison shopping. However, in a two-sided network setting with cross-group network externalities, the high density of sellers can be an attraction to buyers who have the need for intensive search. This is analogous to a retailer choosing to locate in a mall with many other rivals if customers enjoy browsing shops and as a consequence prefer malls with more options (e.g., Dudey (1990), Gould, Pashigian, and Prendergast (2005)).

Our results suggest that high popularity among peer users is more likely to help a network recruit new customers when demand from the other side of the market is less transparent, but can hurt a network when potential customers are well-informed about demand. This implies that the decision whether to release popularity information about either side of the market should depend on the dynamics on the other side. Demand uncertainty plays a critical role in such decisions, especially in categories where buyers tend to search intensively.

There is a growing body of research that models participation decisions in two-sided networks (Rochet and Tirole (2006) and Armstrong (2006)). This research underlines that the drivers of two-sidedness for exchange networks are the transaction costs buyers and or sellers incur when seeking out multiple matching options. Fath and Sarvary (2003) explicitly model these insights and investigate the adoption dynamics in buyer-side exchange platforms. They find it optimal for platforms to encourage participation by subsidizing buyers rather than sellers. Chen and Xie (2007) show that in markets with cross-market network effects, customer loyalty can have ambiguous effects in driving demand. Tucker (2008) investigates how the success of federal government intervention to subsidize the customer base of electronic payment systems led to more adoption by banks. Our study contributes to this literature by studying the efficacy and optimal use a new growth tool for two-sided networks: the information about the number of customers.

This paper also sheds light on some documented ambiguities on the effect of competition on entry. Research in both marketing and industrial organization has emphasized the entry deterrence role of competition, both theoretically and empirically (e.g., Salop (1979), Bresnahan and Reiss (1991), Berry (1992)). However, this received wisdom has been questioned by robust findings of "competition neglect" (e.g., Camerer and Lovallo (1999), Simonsohn (2006)), and "competition contagion" (e.g., Narasimhan and Zhang (2000), Debruyne and Reibstein (2005)), where firms are indifferent or even more likely to enter heavily congested markets. This paper helps reconcile the controversy by identifying demand uncertainty as a moderator of how entrants respond to existing competition.

Meanwhile, while many studies rely on bounded rationality, such as limited iterative thinking capacity (Camerer, Ho, and Chong (2004)), to explain excess entry and high incidence of post-entry failure, our conceptualization of competition provides an angle to interpret non-negative correlations in entry within a rational framework. It can even explain inefficiencies in entry. If potential entrants indeed infer demand from prior firms' entry decisions, early entrants could initiate a socially irrational bandwagon of repeated entry, even if inference is a rational engagement for each individual firm.[2]

Our approach to inferences echoes that of Wernerfelt (1995), who reinterprets the compromise effect as a rational process where consumers infer product utilities from existing product offerings on the market, assuming that firms make optimal product-design decisions given consumers' taste information. Our paper, correspondingly, reinterprets competition neglect as a rational outcome where entrants infer market potential from existing sellers, who are assumed to be informed about market conditions.

The rest of the paper is organized as follows. §2 describes the field experiment and §3 presents the data. §4 first discusses the main results where sellers react differently to the level of competition, depending on whether they are given demand information. We then discuss the augmented analysis where buyer search intensity amplifies the impact of demand uncertainty. §6 summarizes the paper and discusses potential directions for future research. In addition, the Appendix collects an analytical decomposition of the congestion effect and the cross-platform effect, data to verify experimental randomization, and robustness checks of empirical results.

[2]Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992) model how individually rational observational learning triggers irrational aggregate decisions due to information externalities.

2 Business Context and Field Experiment

We obtained field experiment data from a B2B web site that in appearance resembles craigslist.org.[3] The web site provides a common platform for sellers and buyers of used equipment and real estate to advertise these items and to read the advertisements. The target customers are largely one-person businesses and small-time entrepreneurs. Figure 1 presents the span and size of product categories. More than 40 major metropolitan areas are served. The click-stream data suggests that there is little cross-geographical market browsing. This means that each metropolitan area roughly corresponds to an isolated market. The web site draws revenues mainly from banner advertisements on their main page, and does not charge sellers for using its posting service or buyers for browsing postings. The web site receives a total of 240,000 clicks per day.

Although a fee is not charged, a seller must register and log in to an individual user account at the web site, and subsequently fill in a "posting form" to be able to list an item for sale. A seller will post their item and "enter" if their expected return from posting exceeds the opportunity cost of time spent filling out the forms, any future time costs of monitoring transactions on this web site, and any switching costs.[4] After a posting is submitted, it is listed chronologically on the web site. Buyers can view postings without signing up for the web site.

Many internet portals publicize information on peer presence. For example, YouTube highlights the number of new videos posted that day and also how many times viewers have viewed a video. In response to this trend, the web site conducted a field experiment to answer how disclosing the number of users on either side of the platform affects how likely potential sellers were to list their product. The web site randomly varied whether to display the number of sellers

[3]The web site's name and location is protected due to confidentiality agreements.

[4]We can look at seller attrition rate as a way to empirically test if seller entry costs are significant: If sellers' entry costs are zero, all sellers should enter the market. However, a significant 11.5% of sellers decide not to enter the market *after* receiving the experiment treatment, suggesting nontrivial entry costs. Also, we can empirically test if sellers perceive buyer entry costs to be zero: if sellers believe that all buyers will enter the market at zero costs, there is no need to infer the number of buyers from the number of sellers.

and/or buyers to potential sellers, and if so, how many sellers/buyers to claim.[5]

The web site employed a between-subject design. Right after a potential seller has chosen the product category they intend to post in, and before they continue to the next webpage to fill out the posting form, they were exposed to an "information page". The text content displayed on the information page was randomly drawn from the following four treatment conditions.

1. "Presently, there are S postings and B users viewing these postings in the [category name] category of [city name]."
2. "Presently, there are S postings in the [category name] category of [city name]."
3. "Presently, there are B users viewing these postings in the [category name] category of [city name]."
4. (blank)

The number of postings S and the number of viewers B, if shown, were randomly drawn for each potential seller regardless of the product category. Individual-level randomization ensures that the correlation between entry and S or B does not pick up market-specific unobservable factors. Based on the actual long-run site traffic, both S and B were drawn from a uniform distribution between 5 and 200. By using the opaque word "presently" to describe the time frame, management avoided deceiving customers by the randomization procedure. We ran a series of regressions to ensure random assignment. These results are reported in full in the appendix.[6]

Before the experiment ran, there was no information displayed about the number of buyers. Meanwhile, the formatting of the web site obscured number of sellers. The categories we study are almost uniformly for sellers with a single unit of a good for sale. A seller could potentially

[5] Management of the website targeted their experiment towards sellers as opposed to buyers, as they hoped eventually to generate revenue from growing this side of the market.

[6] The only marginally significant correlation we found was that sellers in the "tickets" and "general" categories were more likely to see a higher number of sellers. Conversations with the firms about these categories lead us to believe that this is merely a statistical accident. For robustness, however, we repeated our empirical analyses with and without the "tickets" and "general" categories and obtained qualitatively similar results. We also report all results with errors clustered at the category level, to adjust for any within-category correlation.

visit the category multiple times and see contradictory information pages. We retained data on the first visit in our empirical analysis, but removed subsequent visits on the same day.

After being presented with the information page, a potential seller could either quit posting or proceed to the next page, fill in the posting form and complete the posting process. Once the seller had submitted the posting form, their item appeared on the web site immediately. We were not allowed access to the posting content data (such as prices) because such information would have been identifiable. It is plausible that listing decisions already take into account post-entry profit maximization. In this paper focus on the effects of pre-listing perception of supply and demand.

3 Data

The field experiment ran from November 29, 2006 to January 15, 2007 in the largest city market, which accounts for 16% of the total site traffic. During the period of the experiment, the other city markets showed no traffic change on either the seller or the buyer side, reassuring us that there were no nationwide market shocks which could have contaminated the experimental results. During the experiment, the web site received 9,722 new posting requests in the test city markets. Figure 1 shows the distribution of seller postings across product categories during the experiment. Rentals, Commercial Property, and Office were the most active categories.

Two separate datasets were collected: a click-stream dataset and a treatment dataset. First, using its Apache web server, the web site captures the precise sequence of webpages requested by each user, identified by an IP address. Each entry in this click-stream data consists of a time stamp, the user's IP address, a record of all webpage requests, an error code, and the web browser used. This click-stream allows us to track whether a potential seller did actually make a posting, and the browsing sequence of a buyer. Second, during the experiment the web site also compiled a treatment dataset that recorded the "information page" each potential seller was exposed to. Each entry in the treatment data contains an IP address, a time-stamp, the product

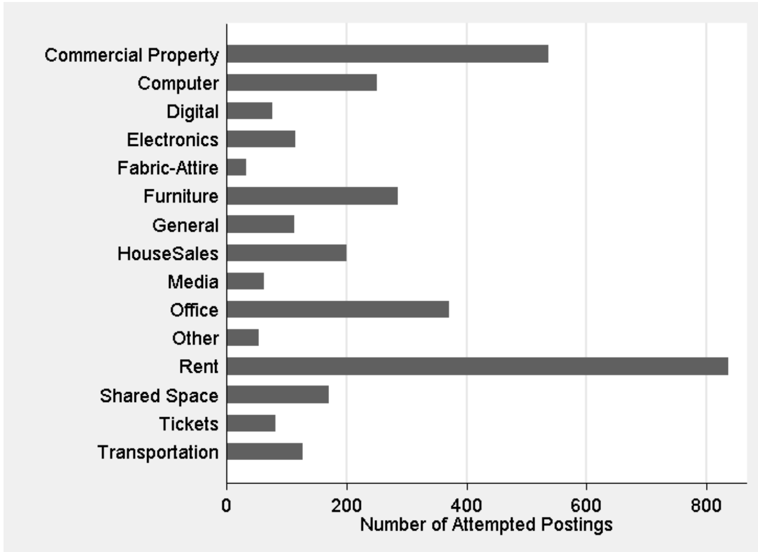

Figure 1: Distribution of Seller Postings across Categories

category the potential seller intended to post in, whether information on the number of buyers and/or sellers was displayed, and the actual number of buyers and/or sellers drawn if applicable. These treatment data spanned all potential sellers, including those who decided not to continue posting after receiving the treatment information.[7]

A major challenge in interpreting the data is from the large number of repeat postings. The majority of repeat postings came from spammers, who employed automated posting tools that produce a large number of repeated posts. For example, one user (or bot) made 735 postings during the experiment, most of which were in the used computer equipment category. Since spammers enter the market regardless of the information page content, we exclude spammers from the analyses. We defined a spammer as a seller who had submitted over 10 postings within the same category during the experiment, and removed 1,509 postings as a result. Other repeat postings were made by sellers who either accidentally posted twice in one day (for example, by refreshing the posting page or double-clicking the submit button), or deliberately posted their items in different categories. 83% of these repeat postings were made in the same category or

[7]We match the treatment data with the browsing data using the IP address and the time stamp. We are unable to match 128 observations that contain errors, generally caused by time-outs or web-browser incompatibility. We exclude these 128 observations from our empirical analyses. There was no statistically significant relationship between our ability to match the data and the treatment condition.

in closely related categories (such as computers and electronics). Accidental repeat posts would inflate the statistical weight of the corresponding data points; while deliberate re-posters might have been exposed to contradictory information pages due to the full randomization protocol. Therefore, we retained data on the first posting, but removed subsequent postings from the same IP address on the same day.[8]

Among the remaining 3,315 potential sellers, 808 were given a blank information page, 872 only saw information about the number of buyers, 823 only saw information about the number of sellers, and 812 saw information about both buyers and sellers. The average entry probabilities are 85 percent in each of the conditions where information is displayed, and 84 percent in the condition where no information is displayed. This suggests that there is no automatic boost from any one of the information conditions, but that instead that any impact of these different information disclosure strategies lies in how potential sellers respond to different number of sellers and buyers claimed across the four conditions. To investigate this we turn to more detailed econometric analysis.

4 Model and Results

4.1 How does Information on the Number of Sellers and Buyers Affect Participation?

We want to assess how information on the number of buyers and sellers affects potential sellers' entry probabilities. Let N^{S*} denote the existing number of sellers in the market, N^{B*} the existing number of buyers, and $U^S(N^{S*}, N^{B*})$ a potential seller's utility from entering this market, which depends on the number of participants on both sides. As we show in detail in the Appendix, if this potential seller observes N^{S*} but not N^{B*}, her utility from entry is affected by the number

[8]Since IP addresses do not uniquely identify users, we may have deleted observations where different users shared the same public computer. However, the empirical results including all potential sellers are similar to the results excluding repeat postings.

of sellers in the following way:[9]

$$\frac{dU^S(N^{S*}, N^{B*}(N^{S*}))}{dN^{S*}} = \frac{\partial U^S}{\partial N^{S*}} + \frac{\partial U^S}{\partial N^{B*}} \cdot \frac{\partial N^{B*}}{\partial N^{S*}} \tag{1}$$

We label the first component in the above equation, $\frac{\partial U^S}{\partial N^{S*}}$, the "congestion effect" of competition. We label the second component, $\frac{\partial U^S}{\partial N^{B*}} \cdot \frac{\partial N^{B*}}{\partial N^{S*}}$, the "cross-platform effect" of competition, where a potential seller infers the number of buyers from the number of sellers. The cross-platform effect is always nonnegative under the plausible assumption that traders prefer more people on the other side of the market but fewer people on their own side,

The equation yields two empirical predictions. First, when the number of buyers is disclosed together with the number of sellers, removing the necessity for inference, a larger number of sellers hinders entry through a pure congestion effect. Second, when only the number of sellers is disclosed, its total effect on entry depends on how the congestion effect and cross-platform effect play out, but should be more positive than the effect when numbers on both sides are disclosed.

To explore these predictions, we estimate a probit model where the dependent variable is whether a potential seller makes a posting after being exposed to the experimental manipulation.[10] We pool data from all conditions together, and identify conditions using a set of dummy variables: "SellerInfoOnly" equals 1 when only the number of sellers is displayed; "BuyerInfoOnly" equals 1 when only the number of buyers is displayed; and "BuyerSellerInfo" equals 1 when both the number of buyers and the number of sellers are displayed. The independent variables include these three condition dummies, their interaction with the number of sellers and/or sellers if displayed, which yields four interactive terms labeled as β_1 to β_4 in Table 1, and a series of category dummies, week dummies and day-of-week dummies. Table 1 reports the resulting estimates and marginal effects.[11]

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[9]We do not examine the potential for forward-looking behavior or dynamics. See Dube, Hitsch, and Chintagunta (2008) for an example of research that explicitly incorporates dynamics into a two-sided network model.

[10]Though our theory is set up in a linear manner, the monotonicity of the pooled probit ensures that our theoretical predictions hold in a non-linear model.

[11]For all the Tables presented, standard errors are clustered at the category (i.e., market) level to allow for

Table 1: Market Information and Entry Probabilities

	Estimate	**S.E.**	**Marginal Effect**	**S.E.**
SellerInfoOnly * #Sellers (β_1)	-0.0002	(0.001)	-0.0000	(0.000)
BuyerInfoOnly * #Buyers (β_2)	0.0001	(0.000)	0.0000	(0.000)
BuyerSellerInfo * #Sellers (β_3)	-0.0012***	(0.000)	-0.0003***	(0.000)
BuyerSellerInfo * #Buyers (β_4)	0.0018**	(0.001)	0.0004**	(0.000)
Category Dummies	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
# Observations	3297			
Log-Likelihood	-1266.34			
Pseudo-R^2	0.11			

Sample: sellers contemplating posting; Dependent variable: Dummy of whether a seller posts
*p<0.10, **p<0.05, ***p<0.01; Standard errors clustered by category

When both the number of sellers and the number of buyers are displayed, entry declines with the number of sellers shown (β_3). That is, when there is no demand uncertainty, rival presence poses a traditional congestion effect. Second, seller presence has no significant impact on entry when only the number of sellers is displayed (β_1). The hypothesis that $\beta_1 = \beta_3$ is rejected ($\chi^2 = 4.00$, $p = 0.04$). The results suggest a positive cross-platform effect that offsets congestion concerns. The marginal effects displayed in column 2 of table 1 suggest that if 200 seller are displayed to a potential seller in the full information condition then this will decrease the probability of entry by 6 percent. In the same condition, a claim of 200 buyers would increase the probability of entry by 8 percent. In the conditions where information on only one side of the market is presented the effect would be statistically insignificant.

The number of buyers, when shown in conjunction with the number of sellers, has a positive effect on entry (β_4). However, when only the number of buyers is displayed, its effect on entry seems neutral (β_2). The hypothesis that $\beta_2 = \beta_4$ is rejected ($\chi^2 = 25.34$, $p = 0.00$). The reason is that potential sellers may infer competition from demand, similarly to the way they infer demand

unobservable category-specific common shocks. We have also estimated the model using either robust standard errors, or standard errors clustered by other potential sources of inter-group correlation (such as day of week). These different specifications of the error term lead to similar estimation results, as expected in a randomized field experiment.

from competition. In fact, we can derive a dual formula of equation 1 as $\frac{dU^S(N^{B*})}{dN^{B*}} = \frac{\partial U^S}{\partial N^{B*}} + \frac{\partial U^S}{\partial N^{S*}} \cdot \frac{\partial N^{S*}}{\partial N^{B*}}$, where the first component on the right-hand side represents a positive "surplus-extraction effect" of higher demand, whereas the second component represents a negative "competition inference effect". The intuition is familiar. A new textbook promoter, for instance, should be cautious in entering a large college market, as the readily observed high demand for textbooks might have attracted a number of veteran sellers.

5 Further Explorations and Managerial Implications

These results demonstrate that the information and uncertainty govern participation in two-sided markets. At a practical level these results emphasize two things. First, the decision to release information about participation in two-sided markets should be a strategic decision, and not just based on technological ability, since the decision to release information has significant effects on future participation. Second, any decision to release information on one side of the market should not be taken in isolation with the decision to release information on the other side of the market. In our setting, for example, if a category had a large number of sellers, it would be advantageous on average to not release information about the number of buyers unless the number of buyers was sufficiently high to counterbalance the loss of the cross-platform effect. This insight goes against current industry practice. For example, we interviewed a company whose regional job-market portals displayed participation information about number of resumes and job postings when they each reached a certain threshold. By contrast, our research suggests that the decision to display information about one side of the market should not be taken independently from the decision to display information about the other side of the market.

One crucial question of immediate practical relevance is whether there are category features or particular customer segments on the other side of the market that guide optimal information disclosure. We answer this question while exploring the behavioral mechanisms underlying the cross-platform effect.

5.1 The mechanism for the Cross-Platform effect

Table 1 implies that demand uncertainty reduces the negative effect of competition. This could happen either because sellers infer high existing demand from the number of sellers, or because they expect that the high number of sellers will attract a large number of buyers to the market.1

We empirically distinguish between these two mechanisms in our setting by introducing two new sets of moderating variables. The first moderating variable is variation in seller past experience with the website. The logic is that experience reduces the need to infer existing demand from the current degree of competition.

We use the number of web pages each seller has browsed in one month prior to the experiment ($\#PriorPages$) as a proxy of seller experience, and add both $\#PriorPages$ and its interactive terms with the number of buyers (sellers) to the right-hand size of the Probit specification. If uncertainty about existing demand is a significant driver of the cross-platform effect, we should expect the interactive effect between $\#PriorPages$ and the number of sellers when displayed in isolation to be negative.

The second moderating variable we use is cross-category variation in buyer search intensity. On the one hand, intensive buyer search may aggravate congestion concerns, as a firm may be deterred from posting if they know that customers are more likely to browse others' listings. On the other hand, customers who need to browse a lot will be attracted to markets with more sellers. This would affect seller expectations of That is, if the demand creation effect is significant, we would expect the interactive term of $SearchIntensity$ and the number of sellers when displayed in isolation to be positive.

Possible factors that affect buyer search intensity are the nature of the goods (e.g., search product vs. experience product), product similarity in the category, and product substitutability. Therefore, we treat search intensity as inherent to the category, and measure it as the number of seller listings browsed by buyers divided by the number of all listings in that category. It is plausible that a seller would have a sense of relative search intensity in a category (for example, attire vendors would be aware that attire customers liked to browse broadly) without knowing the precise number of participants in this category. Figure 2 shows the cross-category variation in buyer search intensity. "Fabric-Attire" and "Other Categories" received the most intensive browsing per user.[12] Users browsed fewer computer postings, however, before ending their search.

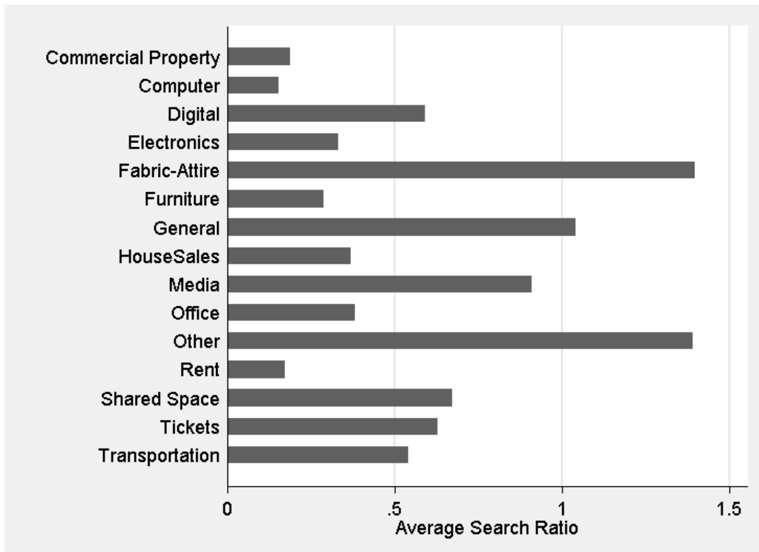

Figure 2: Distribution of Search Intensity across Categories

We augment the previous specification by adding the interactive terms of the number of buyers (sellers) and $SearchIntensity$ to the right-hand side. We use pre-experiment data to calibrate search intensity.[13] Since we measure search intensity as a category-specific attribute, its main effect on entry is captured by the category dummies.

Table 2 reports the results. $\#PriorPages$ has a significantly positive main effect. This can result from positive state dependence or seller heterogeneity. The interactive terms of $\#PriorPages$ and the number of buyers (sellers) are all insignificant, which suggests that demand inference is not a driver of the specific cross-platform effect that we document. On the other hand, a larger number of sellers discourages entry in search-intensive categories when both

[12] "Other Categories" contain disparate products such as medical equipment and beauty salon supplies.

[13] The correlation in buyer search intensity between the pre-experiment period and the during-experiment period is 0.99.

demand and supply information is displayed, but increases entry in search-intensive categories when only the number of sellers is displayed. Meanwhile, a larger number of buyers encourages entry in search-intensity categories, but the effect is smaller when only the number of buyers is displayed than when the numbers on both sides are displayed. This supports a demand-creation interpretation of the cross-platform effect.

Table 2: Exploring The Mechanism

	Estimate	**S.E.**	**Marginal Effect**	**S.E.**
SellerInfoOnly * #Sellers	-0.0010	(0.001)	-0.0002	(0.000)
BuyerInfoOnly * #Buyers	-0.0005	(0.000)	-0.0001	(0.000)
BuyerSellerInfo * #Sellers	0.0001	(0.000)	0.0000	(0.000)
BuyerSellerInfo * #Buyers	-0.0007	(0.001)	-0.0001	(0.000)
#PriorPages	0.3262***	(0.092)	0.0567***	(0.013)
SellerInfoOnly * #Sellers * #PriorPages	0.0001	(0.002)	0.0000	(0.000)
BuyerInfoOnly * #Buyers * #PriorPages	-0.0002	(0.000)	-0.0000	(0.000)
BuyerSellerInfo * #Sellers * #PriorPages	-0.0031	(0.003)	-0.0006	(0.001)
BuyerSellerInfo * #Buyers * #PriorPages	0.0016	(0.003)	0.0003	(0.001)
SellerInfoOnly * #Sellers * SearchIntensity	0.0023***	(0.001)	0.0005***	(0.000)
BuyerInfoOnly * #Buyers * SearchIntensity	0.0017***	(0.000)	0.0004***	(0.000)
BuyerSellerInfo * #Sellers * SearchIntensity	-0.0034***	(0.000)	-0.0007***	(0.000)
BuyerSellerInfo * #Buyers * SearchIntensity	0.0074***	(0.001)	0.0015***	(0.000)
Category Dummies	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
# Observations	3297			
Log-Likelihood	-1257.10			
Pseudo-R^2	0.11			

Sample: sellers contemplating posting; Dependent variable: Dummy of whether a seller posts
*p<0.10, **p<0.05, ***p<0.01; Standard errors clustered by category

Substantively, the results help identify search-intensive categories as the most susceptible to market size information. Methodologically, the results further confirm the central role of demand uncertainty in moderating the impact of competition on entry. In particular, besides demand uncertainty, the different amount of information across conditions could induce different levels of affect (e.g., a more informative page might make the web site appear more professional), and different information evaluability (e.g., the information on the number of sellers is harder to evaluate when presented in isolation, and is therefore discounted (Hsee (2000)). While affect difference is ruled out by the lack of variation in baseline entry across conditions, evaluability could be a competing explanation of demand uncertainty. However, the results in Table 2 rule out evaluability since it cannot explain the interactive effects of the number of sellers/buyers and search intensity.

In particular, the finding that information has larger impacts in categories where sellers browse more intensively suggests the following rough calculations of the consequences of various managerial strategy. Suppose there is a category that has 200 sellers. Then the recommendation of whether to advertise information on the number of sellers would depend on buyer browsing behavior in that category. If the ratio of browsing to daily postings were pretty much equivalent, then displaying the information on number of sellers in isolation would lead to a 10% boost in posting probabilities. By contrast, if the browsers only looked at 10% of the daily posts then this would suggest that there would only be a 1% increase in posting probability from displaying seller information by itself. In the situation where there was no demand uncertainty and the website also chose to display seller information and buyer information, the effect of displaying information that there were 200 sellers in the high search category would lead to a 14% decrease in posting probability verses a 1.4% decrease in the low search category.

5.2 Seller Expectations of Market Size

The cross-platform effects shows the importance of expected buyer behavior on potential sellers listing behavior. However, their expectations over the nature of the category may also have affected their behavior. By drawing from the same distribution of number of buyers or sellers, the firm unintentionally introduced a second cross-category source of experimental variation: the extent to which the number of buyers or sellers claimed matched reality for that category. The rich variation in actual category sizes, as shown in Figure 1, implies that potential sellers may have wide-ranging expectations about the size of different categories. This means that they may respond differently to the same information about participation across categories. If these expectations matter, the same number randomly drawn from the experiment will have different impact on categories of different sizes. For example, if potential sellers expect 50 sellers in the "Fabric-Attire" category and 200 in "Computer," announcing 100 sellers is greater than expected for Fabric-Attire but lower than expected for Computer.

To capture the effect of expectations, we add a set of new variables that compute the ratio of the displayed number of buyers (sellers) over the actual number of buyers (sellers) in that category. Since actual traffic is measured at the category level, its main effect on entry is controlled by the category dummies. The displayed numbers of buyers (sellers) continue to capture the main experimental effect.

Table 3 presents the results. The number of sellers shows similar main effects as in Table 1. Prior expectations about the number of sellers have insignificant impact on entry. On the other hand, prior expectations about the number of buyers do matter: a high displayed number of buyers is more likely to encourage entry when it is larger than expected. From a manager's perspective, this suggests that as expected an unusually large number of buyers for a category is an effective marketing tool for attracting sellers. Crucially however, it also implies, that a high number of sellers relative to expectations however, that this does not have a correspondingly negative effect on entry. In other words, exceeding expectations about number of buyers is more important than exceeding expectations about a lack of competition. Using the marginal estimates in table 3 suggests that if the firm claimed 100 buyers, but the historical average is 50, this would give a boost of 12 percent relative to a situation where the historical average was 100 buyers. However, if a firm claims 100 sellers, but the historical average was 50, this would be statistically similar to the situation where the historical average was 100.

6 Conclusion

This paper examines how information on the number of users affects user participation in two-sided networks. We identify demand uncertainty as a key moderator of how competitiveness

Table 3: Seller Expectation of Market Size

	Estimate	**S.E.**	**Marginal Effect**	**S.E.**
SellerInfoOnly * #Sellers / Actual #Sellers	0.0742	(0.059)	0.0154	(0.012)
BuyerInfoOnly * #Buyers / Actual #Buyers	0.2972***	(0.046)	0.0616***	(0.009)
BuyerSellerInfo * #Sellers / Actual #Sellers	-0.0011	(0.043)	-0.0002	(0.009)
BuyerSellerInfo * #Buyers / Actual #Buyers	0.2805***	(0.049)	0.0581***	(0.011)
SellerInfoOnly * #Sellers (β_1)	-0.0005	(0.001)	-0.0001	(0.000)
BuyerInfoOnly * #Buyers (β_2)	-0.0012**	(0.001)	-0.0002**	(0.000)
BuyerSellerInfo * #Sellers (β_3)	-0.0012***	(0.000)	-0.0003***	(0.000)
BuyerSellerInfo * #Buyers (β_4)	0.0005	(0.001)	0.0001	(0.000)
Category Dummies	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
# Observations	3297			
Log-Likelihood	-1262.35			
Pseudo-R^2	0.11			

Sample: sellers contemplating posting; Dependent variable: Dummy of whether a seller posts
*p<0.10, **p<0.05, ***p<0.01; Standard errors clustered by category

of a market impacts entry decisions. Specifically, we decompose the effect of competition into two components: a negative congestion effect that comes from post-entry competition, and a positive cross-platform effect where a potential entrant deduces high market potential from heavy competitor presence. Using field experiment data from a web site that brings together buyers and sellers of used equipment and real estate, we are able to tease apart these two effects empirically. In particular, when the number of buyers is displayed together with the number of sellers, which renders inference unnecessary, a higher number of sellers reduces seller posting propensity. However, when the number of sellers is displayed in isolation, it has a significantly less negative effect on posting decisions, indicating a positive cross-platform effect. In a similar vein, potential sellers react more positively to high demand when competition density information is also provided than when high demand information is presented in isolation. Furthermore, we find that buyer search intensity amplifies the effect of demand uncertainty: a larger number of sellers discourages entry in search intensive categories when information on both sides of the market is displayed, but encourages entry in search intensive categories when only the number of sellers is displayed.

Our results suggest ways for two-sided networks to attract more traffic. The number of existing users can be a simple yet powerful network growth tool, but should be applied wisely. For example, networks should target information about of high (low) seller concentration to potential sellers who know less (more) about demand. Similarly, if it is easily found out that sellers are scarce, to attract more sellers the network should make demand information transparent too. Whether potentially sellers know about demand is especially important when buyers tend to engage in intensive search. Our framework may also help reconcile the opposing findings in the literature on how competition affects entry. The results suggest that the direction and magnitude of the total effect of competition crucially depends on what market information is available to potential entrants. We contribute to the entry literature by experimentally identifying market information availability as a driver of entry decisions.

One direction of future research is to explicitly integrate the impact of information on both sides of a two-sided network. This current research examines how competitor information affects seller behavior in a two-sided network, and Tucker and Zhang (2008) examine how popularity information affects buyer choices, but there has been no work that investigates the effect of information on both sides of the market simultaneously. This direction of research is important in understanding the positive feedback mechanism between the two sides that drives network growth. Future research could also investigate other strategic variables like post-entry price (as discussed in Chen, Iyer, and Padmanabhan (2002)), which were not available to us in this study. Another possibility is to incorporate the intricacies of the meanings conferred by numbers. For example, it has been found that having more options may lead to fewer choices (e.g., Iyengar and Lepper (2000), Kuksov and Villas-Boas (2005)). It would be interesting to explore how buyers' mixed reaction towards the number of sellers modifies the cross-platform effect of competition.

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1 Appendix

1.1 Modeling the cross-platform effect of competition

In this section, we build an analytical model to show how potential entrants can infer demand from competition. To stay general, we abstract where possible from parameterizing the firm objective function and focus on directional conclusions. However, once we specify a functional form for a given market, our model yields point predictions of the magnitude of the cross-platform effects.

Let there be two groups of traders on the market: buyers and sellers. For example, on web sites such as craigslist.com, the buyers are the viewers of the posts, and the sellers are the posters. Let N^i denote the number of traders on side i, where $i \in \{B, S\}$ stands for buyers or sellers. The utility for a trader on side i to enter the market is:

$$U^i = U^i(N^i, N^j) - c^i \tag{2}$$

where $j \in \{B, S\}, j \neq i$ denotes the other side of the market. The functional form of $U^i(\ )$ is common knowledge. Without loss of generality, we assume that

$$\frac{\partial\ U^i}{\partial\ N^j} \geq 0, \quad \frac{\partial\ U^i}{\partial\ N^i} \leq 0 \tag{3}$$

The above utility specification captures the dynamics of most markets, where a trader (weakly) benefits from an increased number of traders on the other side of the market, and is (weakly) hurt by a larger number of traders on its own side. For example, compared to a monopolistic market, a market with more firms dissipates firm profits and increases consumer surplus.[14] The literature on two-sided platforms has focused on positive feedback mechanisms in markets such

[14]Note that the model applies to both homogenous-goods and differentiated-goods markets, in the sense that a seller's expected profit may decrease with the number of competing sellers, as long as the products are partially substitutable.

as video-games, and has therefore assumed away congestion effects (e.g., Rochet and Tirole 2006, Armstrong 2006). Our model nests the classic specification of two-sided network utilities that does not consider congestion effects (i.e., $\frac{\partial U^i}{\partial N^i} = 0$), where a trader's gain from participation is written as $U^i = a^i \cdot N^j - c^i$, where $a^i > 0$.

Suppose a trader incurs a fixed cost in order to enter the market. Let c^i denote such a cost for a trader on side i. We allow traders to be heterogeneous with respect to their entry costs. Let c^i be randomly distributed across side-i traders following a cumulative distribution function $F^i(\cdot)$, which is common knowledge. In other words, although a trader does not directly observe the entry cost of a particular competitor, she knows the distribution of entry costs across all traders. Last, let M^i denote the total number of *potential* traders on side i. The value of M^i is exogenous to the model. Among these M^i potential traders, those with $U^i(N^i, N^j) \geq c^i$ will choose to enter the market. While the potential market size M^i is exogenous, in equilibrium the actual number of entrants on both sides of the market N^i is endogenously determined in the following way:

$$N^{B*} = M^B \cdot F^B(U^B(N^{B*}, N^{S*}))$$
$$N^{S*} = M^S \cdot F^S(U^S(N^{S*}, N^{B*})) \tag{4}$$

From this simultaneous equation system, we can derive the equilibrium number of traders on both sides of the market, once we know the functional form of the utilities and of the entry cost distribution. For example, if the trade utility is $U^i = \frac{N^j}{N^i} - c^i$ for a two-sided network that allows congestion within the same side, and if entry costs on side i are uniformly distributed over $[0, \bar{c}^i]$, it can be shown that in equilibrium $N^{i*} = \sqrt[3]{\frac{M^{i2} M^j}{\bar{c}^{i2} \bar{c}^j}}$. Note that the number of traders on one side of the market increases in the market potential (M^j) and decreases in the entry costs on the other side.

Now suppose that the market has evolved to an equilibrium, and that another agent (a seller without loss of generality) has newly arrived at the market and is contemplating entry. Her entry decision is straightforward if she observes both the equilibrium number of buyers and the equilibrium number of sellers, which is equivalent to knowing M^B and M^S. In a more interesting case, assume that this seller knows the equilibrium number of sellers N^{S*} but does not know N^{B*}, and has no information on M^B or M^S. This potential seller then bases her actions on the knowledge that in equilibrium the number of buyers is related to the number of sellers through the function $N^{B*}(N^{S*})$. Below we derive how N^{B*} is related to N^{S*} in equilibrium.

We want to use the Implicit Function Theorem to derive the equilibrium relation between N^{B*} and N^{S*}. To do so, we first define a function ϕ of N^B and N^S that equals 0 when N^B and N^S equal their equilibrium values N^{B*} and N^{S*} respectively. Then the Implicit Function Theorem will allow us to recover $\frac{\partial N^{B*}}{\partial N^{S*}}$ from the partial derivatives $\frac{\partial \phi}{\partial N^{S}*}$ and $\frac{\partial \phi}{\partial N^{B}*}$.

Let $\phi = N^{B*} - M^B \cdot F^B(U^B(N^{B*}, N^{S*})) = 0$, which holds by Equation 4. We know $\frac{\partial \phi}{\partial N^{S*}} = -M^B \cdot f^B(U^B(N^{B*}, N^{S*})) \cdot \frac{\partial U^B}{\partial N^{S*}}$, where $f(\cdot) \geq 0$ is the density function of entry cost c^B. Since $\frac{\partial U^B}{\partial N^{S*}} \geq 0$, $\frac{\partial \phi}{\partial N^{S*}} \leq 0$. Similarly, $\frac{\partial \phi}{\partial N^{B*}} = 1 - M^B \cdot f^B(U^B(N^{B*}, N^{S*})) \cdot \frac{\partial U^B}{\partial N^{B*}} \geq 0$. By the Implicit Function Theorem, $\frac{\partial N^{B*}}{\partial N^{S*}} = -\frac{\partial \phi}{\partial N^{S*}} / \frac{\partial \phi}{\partial N^{B*}} \geq 0$. That is, given the rather mild assumption stated in Equation 3, a potential entrant can infer a (weakly) larger number of buyers from a larger number of sellers.

It is worth noting that Equation 1 only describes the equilibrium state of the market, but but allows the market to reach this equilibrium through different paths and at different paces. Therefore, Equation 1 is equally applicable if the number of buyers and sellers accumulate to the equilibrium level through sequential entry.

1.2 Robustness Checks

Table 4 reports the estimation results of a set of alternative specifications.

Table 4: Robustness Checks

	Model 1	**Model 2**	**Model 3**	**Model 4**
SellerInfoOnly*#Sellers (β_1)	-0.0001	-0.0001	-0.0001	-0.0006***
	(0.001)	(0.001)	(0.001)	(0.000)
BuyerInfoOnly*#Buyers (β_2)	0.0001	0.0001	0.0003	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
BuyerSellerInfo*#Sellers (β_3)	-0.0012***	-0.0013***	-0.0011***	-0.0010***
	(0.000)	(0.000)	(0.000)	(0.000)
BuyerSellerInfo*#Buyers (β_4)	0.0018**	0.0019**	0.0015*	0.0020***
	(0.001)	(0.001)	(0.001)	(0.001)
SellerInfoOnly				0.0742
				(0.137)
BuyerInfoOnly				0.0111
				(0.050)
BuyerSellerInfo				-0.0358
				(0.106)
Category Dummies	Yes	Yes	No	Yes
Time Dummies	Yes	No	Yes	Yes
Condition Dummies	No	No	No	Yes
# Observations	3297	3297	3314	3297
Log-Likelihood	-1266.18	-1273.85	-1414.36	-1265.96
Pseudo-R^2	0.11	0.10	0.01	0.11
$\beta_1 = \beta_3$: χ^2	21.42	1.02	41.63	3.98
$p-$Value	0.00	0.31	0.00	0.05
$\beta_2 = \beta_4$: χ^2	196.18	173.73	76.63	27.80
$p-$Value	0.00	0.00	0.00	0.00

Sample: sellers contemplating posting; Dependent variable: Dummy of whether a seller posts
*p<0.10, **p<0.05, ***p<0.01; Standard errors clustered by category

1.3 Check Randomization of Experimental Manipulation

We ran a series of regressions to ensure that the web site had correctly implemented randomization. Table 5 reports the regression results. The first three columns investigate whether the assignment into the four treatment conditions was correlated with category, time of posting, or day of the week. We also regressed the numbers of sellers and buyers displayed on category, time of posting, and day of the week. These results are reported in the last two columns of table 5. The only marginally significant correlation we found was that sellers in the "tickets" and "general" categories were more likely to see a higher number of sellers. Conversations with the firms about these categories lead us to believe that this is merely a statistical accident. None, the less we have clustered standard errors at the category level and also include category specific dummies in our specifications as a precaution.

Table 5: Empirical Check of Randomization

	Multinomial Logit Regression			Linear Regression	
Dependent Variable:	Sellers & Buyers Displayed	Only Buyers Displayed	Only Sellers Displayed	#Sellers Displayed	#Buyers Displayed
Day of Week	-0.0443	0.0392	-0.0987	7.0978***	-1.6292
	(0.0946)	(0.0946)	(0.0925)	(2.6564)	(2.6947)
Day of Week Sq	0.0129	-0.0074	0.0228	-1.1088***	0.1024
	(0.0151)	(0.0153)	(0.0148)	(0.4258)	(0.4265)
Time	0.6734	2.0303*	0.8570	28.5447	-14.4693
	(1.0515)	(1.1149)	(1.0410)	(31.2777)	(30.2691)
Time Sq	-0.6146	-1.6084*	-0.5837	-23.2414	21.5615
	(0.8802)	(0.9212)	(0.8657)	(25.9803)	(25.2270)
Computer	0.1850	0.1602	0.3580	-4.0974	1.8440
	(0.2337)	(0.2227)	(0.2183)	(6.2501)	(6.1470)
Digital	-0.1924	-0.0793	-0.0456	3.7913	-10.5662
	(0.3649)	(0.3352)	(0.3357)	(10.1564)	(10.2675)
Electronics	-0.0188	-0.1091	-0.0636	5.4123	-3.2366
	(0.2990)	(0.2873)	(0.2878)	(8.3947)	(8.5046)
Fabric-Attire	0.2120	0.2889	-0.2731	6.9713	1.2659
	(0.5336)	(0.4987)	(0.5702)	(13.5575)	(15.8440)
Furniture	0.1126	-0.3324	0.0996	-0.4064	-1.0208
	(0.2113)	(0.2149)	(0.2022)	(6.1287)	(5.8282)
General	0.1297	-0.1000	-0.4369	-10.0497	14.1735
	(0.2868)	(0.2838)	(0.3101)	(8.0605)	(8.7652)
HouseSales	0.3401	-0.2158	-0.0819	-2.9314	-3.9186
	(0.2340)	(0.2424)	(0.2402)	(6.5974)	(6.6142)
Media	-0.2423	-0.5263	-0.0728	14.1885	1.5678
	(0.3864)	(0.3924)	(0.3517)	(11.9638)	(10.8358)
Office	-0.0769	-0.2863	-0.1516	0.3984	1.8786
	(0.1965)	(0.1908)	(0.1897)	(5.6045)	(5.6232)
Other	0.1645	-0.5130	0.1730	1.6370	4.9431
	(0.4061)	(0.4505)	(0.3886)	(12.4067)	(10.9627)
Rent	0.1312	0.0578	00.0678	2.7513	3.2216
	(0.1627)	(0.1564)	(0.1582)	(4.4921)	(4.5924)
Shared Space	0.2433	-0.3006	-0.0535	-15.9461**	-3.4092
	(0.2463)	(0.2574)	(0.2480)	(7.1188)	(6.9704)
Tickets	-0.0924	-0.6141*	0.0136	10.9550	18.3150**
	(0.3359)	(0.3604)	(0.3118)	(10.5577)	(9.3267)
Transportation	0.334	-0.112	-0.0274	4.8382	-10.4943
	(0.2794)	(0.2874)	(0.2861)	(7.8064)	(7.8730)
Constant	-0.2783	-0.4543	-0.1736	89.8177***	105.9281***
	(0.3427)	(0.3597)	(0.3387)	(10.0699)	(9.9069)
Observations	3314	3314	3314	1634	1686
Log-Likelihood	-4566	-4566	-4566	-8917	-9218

Sample: Customers included in the field experiment
* p<0.10, ** p<0.05, ***p<0.01