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Threshold Effects in Online Group Buying

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This paper studies two types of threshold-induced effects: a *surge* of new sign-ups around the time when the thresholds of group-buying deals are reached, and a *stronger* positive relation between the number of new sign-ups and the cumulative number of sign-ups *before* the thresholds are reached than afterward. This empirical study uses a data set that records the intertemporal cumulative number of sign-ups for group-buying deals in 86 city markets covered by Groupon, during a period of 71 days when Groupon predominantly used "a deal a day" format for each local market and posted the number of sign-ups in real time. We find that the first type of threshold effect is significant in all product categories and in all markets. The second type of threshold effect varies across product categories and markets. Our results underscore the importance of considering product and market characteristics in threshold design decisions for online group buying.

Data, as supplemental material, are available at http://dx.doi.org/10.1287/mnsc.2014.2015.

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1. Introduction

The online group-buying industry has witnessed phenomenal growth since the debut of Groupon in 2008 (Pepitone 2011). Most group-buying websites were created to facilitate coordination among a group of interested buyers to achieve their common purchase goals, often in the form of price discounts. The discounts are not available until the total number of committed purchases exceeds a prespecified deal threshold. Determinants of such purchase thresholds may vary across the deals. For instance, although the threshold for a wine deal can be based on the supplier's inventory and acquisition costs, the threshold for a restaurant deal is likely to depend on the restaurant's cost structure, capacity, and business model.

In this paper, taking the presence of deal thresholds as given, we empirically investigate the effect of thresholds on consumers' sign-up behavior. Our investigation utilizes a data set collected from Groupon.com during a time period when the company predominantly used "a deal a day" format for each local market. For each Groupon deal, deal characteristics, threshold levels, and *real-time* updated numbers of sign-ups were posted on the website. These data provide us with an opportunity to infer the effects of thresholds from the sign-up patterns over time. Our study finds two types of threshold-induced behavior. The first type of threshold effect refers to a *substantial increase* in the number of sign-ups around the time when the threshold is reached. Our results show that this effect is significant in all product categories and in all markets. The second threshold effect refers to a *stronger* positive relation between the number of new sign-ups and cumulative number of sign-ups *before* the thresholds are met than afterward. When comparing across many product categories, we find the latter effect to be stronger for the category consisting of non-American food restaurants. When comparing across cities, we find the latter effect to be stronger among the largest cities and those cities located in the *Northeast* region of the United States.

Our paper is related to the growing analytical literature on group buying as a selling mechanism. In the presence of demand uncertainty, the group-buying mechanism is shown to outperform posted pricing under demand heterogeneity, economies of scale (Anand and Aron 2003), and risk-seeking sellers (Chen et al. 2007). Group buying can also be used as a mechanism for price discrimination and advertising (Edelman et al. 2015). Jing and Xie (2011) examine the use of the group-buying mechanism in facilitating social interactions. Their analysis shows that group buying dominates referral programs when interpersonal communication is very efficient or when the less-informed consumers have high product valuation. Hu et al. (2013) investigate the benefit of revealing the cumulative number of sign-ups in increasing deal success rates. Revealing the sign-up information can reduce consumers' reluctance to sign up for deals for fear that the deals fail in reaching the thresholds.

A few researchers have also empirically studied the group-buying industry. Dholakia (2010) investigates the profitability of Groupon promotions via a survey of 150 businesses that had run Groupon promotions and finds that promotion was profitable for approximately two-thirds of the respondents. Byers et al. (2012) collect data from Groupon and LivingSocial to investigate the relation between total sales and deal characteristics. They also couple the daily deal data set with an additional data set from Facebook and provide evidence that significant word-of-mouth referral took place during the lifetime of daily deals. Similarly, Li and Wu (2012) explore the impacts of observational learning and word-of-mouth referrals on facilitating sales of daily deals on Groupon. Finally, our paper is closely related to the work of Zhang and Liu (2012), who investigate the observational learning behavior in the microloan market. Lenders in the microloan market needed to cooperate with each other to reach the full amount requested by the borrower. Unlike the above papers, our research focuses on the thresholds as a mechanism and examines the effects of thresholds on stimulating the interest in signing up for group-buying deals.

2. Background and Data

2.1. Industry Background

Group-buying firms are third-party intermediaries that facilitate coordination among a large group of consumers. Such coordination permits consumers to collectively enjoy the quantity discounts offered by sellers. Online group-buying firms first emerged in the late 1990s to reach geographically dispersed consumers through the Internet. They offered attractive deals, often in the form of deep discounts for durable goods such as cameras; these deals would be on if and only if a predetermined number of consumers would sign up within a predetermined time period. Most leading players, including Mercata and Mobshop, ceased their operations after a few years (Kauffman and Wang 2002). However, starting in 2008, led by Groupon, the online group-buying industry was resurrected. The new generation of group-buying firms offered "a deal a day" at each city market to local consumers. When a deal was on, the group-buying firm typically kept half of the revenue during the time period when our data were collected.

The online group-buying industry has experienced remarkable growth in the last few years. Groupon, since its debut in 2008, increased its total number of subscribers to over 200 million as of March 2013. Groupon extended its coverage to more than 500 markets in 48 countries, up from just 28 U.S. markets in 2009. Meanwhile, the company's phenomenal success had quickly attracted a large number of competitors entering the market. Currently, there are approximately 500 websites offering similar group-buying services, but only LivingSocial had emerged as a genuine competitor. By November 2012, Groupon commanded approximately 50%–55% of the industry's market share, whereas the market share of No. 2 site LivingSocial was approximately 20%–25%. To meet the needs of vendors and fend off competition from other group-buying websites, Groupon started offering multiple deals a day, some with longer sign-up periods (Fowler 2010). Our data were collected before this move. During the data collection period, Groupon predominantly operated under "a deal a day" format.

2.2. Data

We hired a research assistant at a major university to build a data crawler on the Google App Engine platform. The data crawler extracted deal information, such as deal description, deal price, discount level, and threshold, whenever a new deal was posted. The program updated the cumulative number of sign-ups with the interval of every five minutes. We use this real-time data set to keep track of consumers' responses to various group-buying deals during the lifetime of each deal and to uncover the patterns of sign-up accumulation.

We focus on the market leader Groupon. Our data include a total of 4,208 deals from 86 cities or regions covered by Groupon between September 28, 2010, and December 7, 2010. The duration of the observation period was 71 days in total. For each deal, we recorded a set of deal attributes and monitored the intertemporal sign-up process. Table 1 presents the summary statistics for all 4,208 deals. The average deal price in the sample was $30.68, with an average discount level of 56% off. Each of these deals contained a threshold of sign-up numbers for the deal to succeed. A group-buying deal would be off if the total number of committed consumers did not reach the threshold. The average threshold value specified by Groupon was approximately 55. The average number of coupons purchased for each deal was approximately 785. In our sample, all deals reached the thresholds before expiration.

Table 1 Summary Statistics of All Deals

	Mean	Std. dev.	Minimum	Maximum
Deal attributes				
Deal price ($)	30.68	30.53	2	250
Discount level (%)	56.35	9.96	19	96
Threshold	55.40	68.50	3	800
Market population (thousands)	854.30	1,332.94	56	8,364
Outcome				
Total amount purchased	784.80	1,331.57	5	29,380

Notes. *Deal price* denotes the net price a consumer needed to pay if the deal tipped. *Discount level* denotes the markdown of deal price relative to the regular price. *Threshold* denotes the minimum number of committed purchases for the deal to succeed. *Market population* is the population of the local market where the deal was posted. *Total amount purchased* denotes the number of consumers who purchased the product or service by the end of the sign-up process.

Table 2 **Description of Deal Categories**

Category	Description
Arts and entertainment	Symphony, concert, ballet, etc.
Sports and recreation	Sports games (golf, basketball, bowling, football) and outdoor activities
Beauty and spas	Spa, manicure, facial treatment, hair service, skin care
Fitness and nutrition	Gym or fitness center membership, yoga, etc.
Photography and photo services	Photography class, photo session, photo or video digitalization, photo books
Travel and hospitality	Travelling-related services, such as transportation and hotel
Kids and pets	Services and products for kids or pets
Automotive	Auto detailing, oil and filter replacement, vehicle inspection, etc.
Classes and workshops	Dance, wine, painting, flight classes
Dental	Teeth whitening, dental cleaning, etc.
Health and medical	Medical exam, x-ray, chiropractic, etc.
Clothing and accessories	Clothing, accessories, shoes, etc.
Home products and services	House cleaning, floor installation, furniture
Fast food	Pizza, burger, sandwich, pastry, popcorn, etc.
American food	Pub, bar, steakhouse, etc.
Other food	Italian, French, Chinese, Japanese food or home-delivered food
Other physical products	Wine, books, personalized paper products, fine art prints, etc.

We divide all the deals into 17 different product and service categories based on deal descriptions by consulting popular online deal aggregators such as dealradar.com. The definition of each category is given in Table 2. Most of them were service categories, except for *clothing and accessories* and *other physical products*, which consisted of physical goods exclusively. We manually linked all the deals to the categories. The distribution of deals across categories is summarized in Table 3. The most popular category was *beauty and spas*, accounting for over 15% of deals in the sample. Table 3 also shows the summary statistics of deal thresholds and total amounts purchased for each category. There were considerable variations in threshold size and purchase amount both within and across categories. On average, the food categories, including *fast food*, *American food*, and *other food*, had very high thresholds and large numbers of purchases. Finally, the *clothing and accessories* category had 1,639 sign-ups per deal, the highest for a single category.

We supplemented the deal data with geographic information, namely market population and the geographic region where the market is located. We summarize the location statistics in Tables 4 and 5. City population statistics were collected from the U.S. Census Bureau. In all the markets where Groupon operated, the average market size was approximately 0.85 million. We also divided these markets into five regions according to their geographic locations, namely, West, Midwest, South, Northeast, and Canada. The definition of four regions within the United States follows the same approach adopted by the U.S. Census Bureau.

Table 3 **Distribution of Deals Across Categories**

	Observations		Threshold		Total amount purchased	
	Count	%	Mean	Std. dev.	Mean	Std. dev.
Arts and entertainment	340	8.08	49.66	52.98	882	1,722
Sports and recreation	468	11.12	53.40	56.54	849	1,252
Beauty and spas	660	15.68	54.17	65.30	637	972
Fitness and nutrition	192	4.56	41.69	52.32	426	505
Photography and photo services	239	5.68	38.10	46.01	564	662
Travel and hospitality	41	0.97	43.41	40.95	372	374
Kids and pets	52	1.24	57.21	93.24	708	943
Automotive	76	1.81	64.93	92.67	1,119	1,508
Classes and workshops	166	3.94	42.08	50.21	580	1,334
Dental	76	1.81	40.20	44.90	345	456
Health and medical	85	2.02	42.41	42.58	490	491
Clothing and accessories	178	4.23	53.96	68.22	1,639	3,742
Home products and services	115	2.73	40.57	39.76	471	467
Fast food	382	9.08	63.77	83.61	1,041	1,388
American food	314	7.46	92.04	97.41	1,071	902
Other food	403	9.58	79.02	91.84	988	1,008
Other physical products	421	10.00	37.24	35.24	450	576

Table 4 Distribution of Deals by Market Populations

	Observations		Threshold		Total amount purchased	
	Count	%	Mean	Std. dev.	Mean	Std. dev.
< 0.25 mil	988	23.50	30.92	29.21	467.9	724.4
0.25–0.5 mil	972	23.10	38.42	35.48	553.9	685.9
0.5–1.0 mil	1,562	37.12	59.64	62.92	944.0	1,496.0
> 1.0 mil	686	16.30	105.05	114.00	1,206.0	1,977.5

Table 5 Distribution of Deals Across Geographic Regions

	Observations		Threshold		Total amount purchased	
	Count	%	Mean	Std. dev.	Mean	Std. dev.
West	953	22.65	60.03	56.58	949.8	1,742
Midwest	962	22.86	56.68	83.64	744.0	1,115
South	1,401	33.29	54.81	66.33	755.7	1,306
Northeast	634	15.07	54.48	74.56	667.3	1,131
Canada	258	6.13	38.93	27.72	773.9	734

The majority of the markets, approximately 94.2%, were within the United States, and the rest, approximately 5.8%, were spread over Canada. Within the United States, Groupon was most active in the South region, operating in 29 markets. Groupon operated in the least number of markets in the Northeast region, with only 12 markets. The number of markets within the other two regions were similar, with 19 markets in the West region and 21 markets in the Midwest region. At the deal level, the distribution of deals across different regions is consistent with the distribution of cities across regions, because deals were typically offered daily in each market.

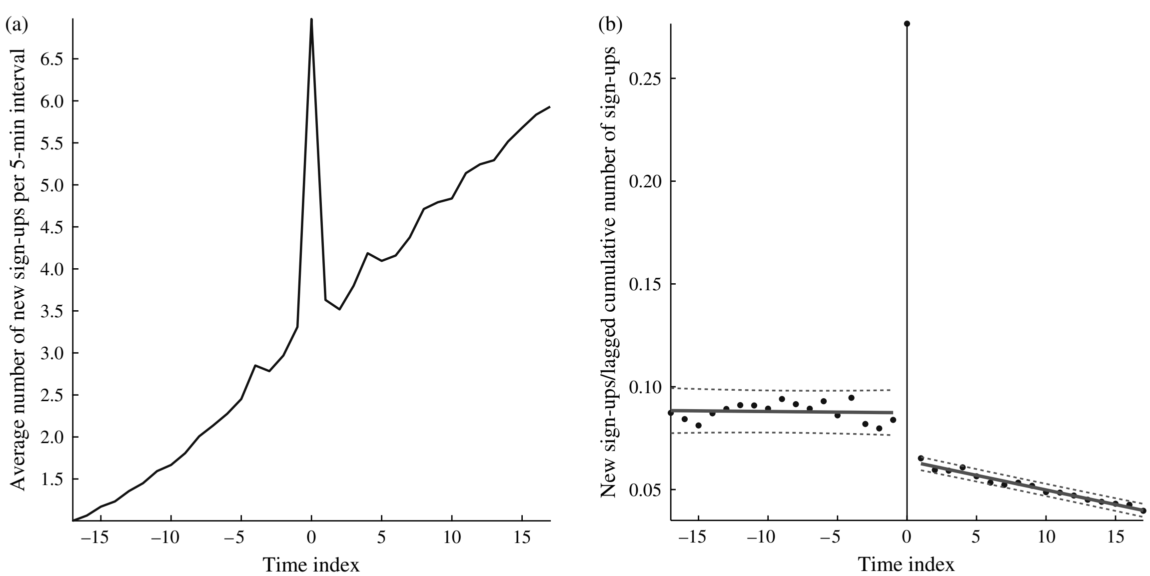
During our data-collection period, deals were posted daily for a duration of 24 hours from Monday to Thursday. However, the duration of deals posted on Fridays and weekends could vary from 24 hours to 72 hours. In some relatively small markets, Groupon would post 72-hour deals on Friday. We also saw a transition from 72-hour deals to 48-hour deals during our data-collection period.

3. Threshold Effects on Sign-Up Behavior

3.1. Preliminary Evidence

The main objective of this paper is to investigate the effects of thresholds on the rate of signing up for the deals. To derive some intuition on potential threshold effects, we first examine the raw data and seek any consistent sign-up pattern around the times when thresholds were reached. Since the deals were tipped at different time points of the day, for each deal we realign the time periods in data by the time period when the threshold was reached. With the realigned data, time 0 is the period when all deals reached their thresholds. We plot the average sign-up pattern across all deals during the one-and-a-half-hour (90 minutes) time window before and after the threshold was reached (see Figure 1). In particular, the curve in Figure 1(a) shows the average number

Figure 1 Sign-Up Pattern During the One-and-a-Half-Hour Time Window Before and After the Threshold Was Reached



Notes. The *x* axis indicates the time index. The *y* axis in panel (a) denotes the average number of new sign-ups during each five-minute time interval. The *y* axis in panel (b) denotes the ratio between the number of new sign-ups during a time interval and the cumulative number of sign-ups up to the end of the previous time interval. Solid lines are fitted values from first-order polynomial regressions on either side of the time interval when the threshold was reached, and dotted lines are 95% confidence intervals.

of sign-ups every five minutes. We also compute the ratio between the number of new sign-ups during the current time interval and the cumulative number of sign-ups at the end of the previous time interval and plot the ratio over time in Figure 1(b).

The figures suggest two interesting patterns around the time when the thresholds were reached. First, Figure 1(a) shows a spike during the time interval when the thresholds were reached. In other words, the number of sign-ups during the periods when thresholds were reached is substantially higher than that during the time periods right before or right after. Second, Figure 1(b) shows a significant level shift in the ratio before and after the thresholds were reached: the ratio stays stable before the thresholds were reached, but shifts downward right after the thresholds were reached and maintains a downward trend afterward.[1]

3.2. Empirical Model

The preliminary evidence from the data indicates that the thresholds may indeed affect consumers' sign-up behavior. However, many confounding factors, such as varying online traffic to the websites at different times of the day and unobserved deal heterogeneity, may contribute to the sign-up pattern observed in Figure 1. In this section, we seek to more rigorously establish the threshold effects through formal statistical analyses.

3.2.1. The Base Model. We start our analysis with a flexible model specification to distill the sign-up pattern around the thresholds. We include a series of time dummy variables, with each variable capturing the sign-up pattern during a five-minute time interval around the time period when the threshold was reached. The dependent variable in our model, denoted by $y_{i,t}$, is the number of new sign-ups during the tth time interval for deal i. To control the unobserved deal heterogeneity, we apply a deal fixed effect model with the following specification:

$$y_{i,t} = \sum_{j=-T}^{T} \alpha_j I_{\{s_{i,t}=j\}} + \psi_t + \mu_i + \epsilon_{i,t}, \tag{1}$$

where t represents the time index before realigning the deals and $s_{i,t}$ indicates the time index after realigning the deals at the time period when the threshold was reached. Recall that, with the realigned data, time 0 is the period when a deal reaches its threshold. Consequently, $s_{i,t}$ is equal to 0 if deal i reaches its threshold at time period t. Similarly, $s_{i,t} = j$ for all $j > 0$ (resp., $j < 0$) represents that time period t is the jth period after (resp., before) deal i reaches its threshold, and $I_{\{s_{i,t}=j\}}$ for all j is a dummy variable which is equal to 1 if $s_{i,t} = j$ and 0 otherwise. The set of time dummy variables, $I_{\{s_{i,t}=j\}}$, $j = -T, \ldots, T$, is used to capture the sign-up pattern around the time when the thresholds are reached, where T reflects the width of the time window. In addition, ψ_t measures the time-of-the-day fixed effect using the five-minute time dummy, and μ_i measures the deal fixed effects. The term $\epsilon_{i,t}$ is the error component.

To estimate the base model, we can apply standard approaches for estimating fixed-effects panel models. The fixed effects can be eliminated by either taking differences between adjacent observations from the same deal or subtracting the average over time from every variable, i.e., time-demeaning. Then, we can apply the generalized least squared (GLS) estimator to the transformed data.

3.2.2. The Extended Model with Lagged Variables. Although the base model allows us to capture the sign-up pattern around thresholds in a flexible way, it does not reflect the dependency of the new sign-ups on the cumulative number of sign-ups as suggested by Figure 1(b). Consequently, we extend the base model by introducing the lagged cumulative sign-ups, $Y_{i,t-1}$, into the model. The extended model can be formulated as follows:

$$y_{i,t} = \sum_{j=-T}^{T} \alpha_j I_{\{s_{i,t}=j\}} + \sum_{j=-T}^{T} \beta_j I_{\{s_{i,t}=j\}} Y_{i,t-1} + \psi_t + \mu_i + \epsilon_{i,t}. \tag{2}$$

Similar to the base model, we include the interactions between time dummies after realignment, $I_{\{s_{i,t}=j\}}$, and the lagged cumulative number of sign-ups, $Y_{i,t-1}$, to capture the relation between the new sign-ups and the cumulative number of sign-ups in a flexible way.

However, unlike the base model, which can be estimated consistently using the GLS estimator, the estimation of a fixed-effects model with lagged variables is more technically involved. The lagged regressor is likely to be correlated with the fixed effects, which gives rise to dynamic panel bias (Nickell 1981). To solve this problem, we apply the generalized method of moments (GMM) approach proposed by Arellano and Bond (1991). First, we take difference of Equation (2) to eliminate the deal fixed effects:

$$\begin{aligned} y_{i,t} - y_{i,t-1} = &\sum_{j=-T}^{T} \alpha_j (I_{\{s_{i,t}=j\}} - I_{\{s_{i,t-1}=j\}}) \\ &+ \sum_{j=-T}^{T} \beta_j (I_{\{s_{i,t}=j\}} Y_{i,t-1} - I_{\{s_{i,t-1}=j\}} Y_{i,t-2}) \\ &+ (\psi_t - \psi_{t-1}) + (\epsilon_{i,t} - \epsilon_{i,t-1}). \end{aligned} \tag{3}$$

[1] The decreasing trend of ratio in Figure 1(b) can occur during a natural diffusion process. However, a level shift is not expected to occur. Figures A.1 and A.2 in the appendix plot the sign-up patterns for longer time horizons, with time realigned with thresholds in Figure A.1 but not realigned in Figure A.2. In these figures, the level shift is only observed around the time when thresholds were reached.

Because $Y_{i,t-1}$ is correlated with the error term, specifically $\epsilon_{i,t-1}$, GLS yields inconsistent estimates after the first-difference transformation. However, if there is no serial correlation in the error term $\epsilon_{i,t}$, then the longer lags of the regressors—i.e., $Y_{i,k}$, $k = t-2, \ldots, 1$, which are correlated with $y_{i,t-1}$ (see Equation (2)) and thus $Y_{i,t-1}$, but not with the error term $\epsilon_{i,t-1}$—can serve as instruments for the model after the first-difference transformation. In the case of our model, $Y_{i,t-2}$ and $I_{\{s_{i,t-1}=j\}} Y_{i,t-2}$, together with their longer lags, can serve as GMM instruments for Equation (3). The differences of the strictly exogenous variables, i.e., $I_{\{s_{i,t-1}=j\}}$ and ψ_t, can serve as standard instruments.

We capture the unobserved heterogeneity across deals with deal fixed effects. The observed deal variations as described by product/service categories, deal prices and discounts, and city characteristics are unlikely to capture all sources of deal heterogeneities. For example, restaurants within a city can have different locations, offer different cuisines, and enjoy different reputations. For Equation (2) to identify threshold effects on group-buying deals, we implicitly assume that unobserved deal attributes are accounted for by a time-invariant component, i.e., μ_i. This fixed component controls for unobserved deal attributes, which may positively correlate with both lagged cumulative number of sign-ups, $Y_{i,t-1}$, and the number of new sign-ups, $y_{i,t}$, and thus solves an "errors in variables" type of endogeneity problem (Villas-Boas and Winer 1999). Given the panel data structure, we are able to use deal-specific fixed effects to control the variations across deals.

3.3. Results

We next present the empirical results for the base model and the extended model. Our analysis uses a one-and-a-half-hour time window before and after the threshold was reached for regression analysis, i.e., $T = 17$. The usage of a relatively small time window around the time when thresholds were reached eliminates other unrelated factors and allows us to focus on the effects of thresholds on consumers' sign-up behavior.

Since the earliest observation serves as the reference level, we have a total of 34 five-minute time dummy variables, i.e., $I_{\{s_{i,t}=j\}}$, $j = -16, \ldots, 17$, to capture the sign-up pattern around thresholds. To focus on the main findings, we do not interact every single time dummy variable with the lagged cumulative number of sign-ups. Instead, we divide the three-hour time window into four nonoverlapping time periods of equal length; create four new time dummies, with each representing a 45-minute time interval; and interact the newly created time dummies with the lagged cumulative number of sign-ups. The interaction terms between these four time dummies and the lagged cumulative number of sign-ups are sufficient to capture the level shift in the ratio between new sign-ups and the cumulative number of sign-ups when the thresholds were passed, as well as the trend of the ratio both before and after reaching the thresholds.

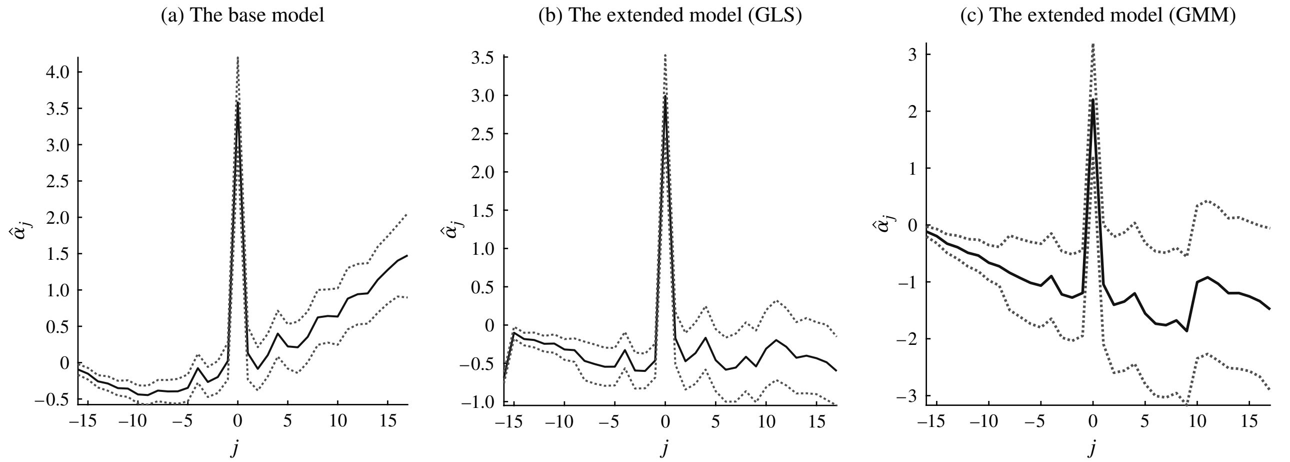
Table 6 shows the regression result of our base model. The coefficient of the time dummy when the thresholds were reached ($\hat{\alpha}_0 = 3.582$, $p < 0.01$) is significantly greater than the coefficients of other time dummies. We also visualize the estimated coefficients by plotting the estimates and their corresponding 95% confidence intervals in Figure 2(a). Even if we control for heterogeneous time traffic and unobserved deal heterogeneity, we observe a clear spike in the number of sign-ups during the time interval when the thresholds were reached,

Table 6 Regression Results of the Base Model Using Three-Hour Data

	Estimates		Estimates		Estimates		Estimates		Estimates		Estimates
α_{-16}	−0.094**	α_{-10}	−0.437***	α_{-4}	−0.076	α_1	0.131	α_7	0.355**	α_{13}	0.953***
	(0.037)		(0.063)		(0.101)		(0.185)		(0.178)		(0.212)
α_{-15}	−0.152***	α_{-9}	−0.447***	α_{-3}	−0.266**	α_2	−0.085	α_8	0.623***	α_{14}	1.140***
	(0.041)		(0.067)		(0.106)		(0.152)		(0.193)		(0.232)
α_{-14}	−0.257***	α_{-8}	−0.385***	α_{-2}	−0.198*	α_3	0.104	α_9	0.642***	α_{15}	1.277***
	(0.043)		(0.074)		(0.112)		(0.150)		(0.187)		(0.237)
α_{-13}	−0.288***	α_{-7}	−0.396***	α_{-1}	0.023	α_4	0.400**	α_{10}	0.634***	α_{16}	1.403***
	(0.051)		(0.080)		(0.130)		(0.161)		(0.198)		(0.252)
α_{-12}	−0.351***	α_{-6}	−0.394***	α_0	3.582***	α_5	0.223	α_{11}	0.881***	α_{17}	1.477***
	(0.052)		(0.087)		(0.315)		(0.156)		(0.216)		(0.296)
α_{-11}	−0.357***	α_{-5}	−0.347***			α_6	0.211	α_{12}	0.942***		
	(0.058)		(0.094)				(0.181)		(0.212)		
Time-of-the-day fixed effects								Yes			
Deal fixed effects								Yes			
Number of observations								147,112			
Number of deals								4,208			
Adjusted R-squared								0.026			

Notes. The dependent variable is the number of new sign-ups per five-minute time interval. Standard errors are clustered by deal and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Figure 2 **Estimated Sign-Up Pattern During the One-and-a-Half-Hour Time Window Before and After the Threshold Was Reached**



Notes. The solid lines in panels (a), (b), and (c) denote the estimated coefficients of time dummies, i.e., $\hat{\alpha}_j$, $j = -16, \ldots, 17$, from the base model, the extended model using the GLS estimator, and the extended model using the GMM estimator with two lags, respectively. The dotted lines are 95% confidence intervals.

similar to that shown in Figure 1(a) created from the raw data. This verifies the first type of threshold effect: a *surge* in the number of new sign-ups around the time when the threshold was reached.

Table 7 shows the regression results of our extended model. The result from the GLS estimator is presented as a benchmark. We show the results from the GMM estimator using two, three, and four lags of the GMM instrumental variables. Specifically, GMM instruments include the lagged cumulative number of sign-ups, and the lagged interaction terms between the 45-minute time dummies and the cumulative number of sign-ups. In theory, we can use all valid lagged regressors, i.e., those with lags of two and more. However, the number of instruments would be quadratic in the time dimension of the panel, and the GMM estimator may perform poorly with a large number of instruments (Roodman 2009). Too many instruments may overfit endogenous variables and bias coefficient estimates, and thus the results from the finite sample may be far from the asymptotic ideal. In our analysis, we apply the GMM estimator using two, three, and four lags of the instrumental variables. As shown in the second, third, and fourth columns in Table 7, the results are robust with respect to the number of lags used.

The estimated coefficients of time dummies, i.e., $\hat{\alpha}_j$, $j = -16, \ldots, 17$, using the GLS estimator and GMM estimator (with two lags), are plotted in Figure 2(b) and Figure 2(c), respectively. After controlling for the lagged cumulative number of sign-ups, we find that the surge in the number of sign-ups during the interval when the threshold was reached still remains. We further verify this finding by conducting Wald tests on the differences between the estimated coefficients of the time dummy when the threshold was reached and other time dummies within the half-an-hour time window either before or after the threshold was reached. As shown in Table 8, the differences between the coefficients are all statistically significant. To facilitate the comparison of this effect across different cities and product categories, we define a *spike index* as the measure for the additional number of sign-ups due to thresholds. Specifically, the *spike index* is equal to $\sum_{j=-5}^{5}(\hat{\alpha}_0 - \hat{\alpha}_j)/10$. Using the results from the GMM estimator with two lags, the spike index across all deals is 3.424. That is, on average, approximately 3.424 more consumers would sign up to the deal during the five-minute time interval when the threshold was reached (statistically significant, $p < 0.01$). To assess the magnitude of this effect, note that during the half-an-hour time window before and after the threshold was reached, on average there were approximately 3.6 consumers signing up every five minutes. Thus, the existence of thresholds produces a substantial boost in sales.

The level shift in the ratio between the new sign-ups and the cumulative number of sign-ups as suggested in Figure 1(b) also remains after we control for time-of-the-day effects and deal fixed effects. Specifically, our test results show that the ratio in the 45-minute time window before the thresholds is higher than that in the 45-minute time window after the thresholds by approximately 0.01, which is consistent among the results from the GLS estimator and GMM estimator with various lags (see test results of $\beta_1 - \beta_2$ in Table 8). The difference in the ratio before and after the thresholds is significant from the GLS estimator and GMM estimator when using either two lags or four lags. However, the difference is insignificant from the GMM estimator when using three lags. The underlying reason might be the weak instruments for three and four lags, to be discussed below. The estimated coefficients from the GMM estimator also indicate that the ratio between new sign-ups and the cumulative number of sign-ups

Table 7 Regression Results of the Extended Model Using Three-Hour Data

	GLS	GMM (2 lags)	GMM (3 lags)	GMM (4 lags)		GLS	GMM (2 lags)	GMM (3 lags)	GMM (4 lags)
α_{-16}	−0.069*	−0.115***	−0.123***	−0.126***	α_{1}	−0.172	−1.044*	−1.029*	−0.920
	(0.037)	(0.044)	(0.044)	(0.044)		(0.174)	(0.536)	(0.550)	(0.609)
α_{-15}	−0.101**	−0.196***	−0.213***	−0.220***	α_{2}	−0.473**	−1.403**	−1.377**	−1.265*
	(0.040)	(0.063)	(0.063)	(0.064)		(0.188)	(0.610)	(0.624)	(0.681)
α_{-14}	−0.183***	−0.329***	−0.354***	−0.365***	α_{3}	−0.366*	−1.346**	−1.309**	−1.193*
	(0.042)	(0.083)	(0.083)	(0.084)		(0.204)	(0.619)	(0.633)	(0.698)
α_{-13}	−0.195***	−0.391***	−0.424***	−0.438***	α_{4}	−0.166	−1.202*	−1.153*	−1.034
	(0.049)	(0.104)	(0.103)	(0.105)		(0.212)	(0.632)	(0.647)	(0.710)
α_{-12}	−0.245***	−0.489***	−0.528***	−0.546***	α_{5}	−0.459**	−1.555**	−1.494**	−1.371*
	(0.053)	(0.123)	(0.121)	(0.123)		(0.207)	(0.633)	(0.645)	(0.710)
α_{-11}	−0.242***	−0.537***	−0.581***	−0.603***	α_{6}	−0.583***	−1.735***	−1.659**	−1.533**
	(0.061)	(0.142)	(0.139)	(0.141)		(0.213)	(0.649)	(0.651)	(0.711)
α_{-10}	−0.319***	−0.664***	−0.713***	−0.739***	α_{7}	−0.555**	−1.761***	−1.669**	−1.539**
	(0.069)	(0.158)	(0.155)	(0.158)		(0.226)	(0.649)	(0.651)	(0.717)
α_{-9}	−0.328***	−0.725***	−0.778***	−0.808***	α_{8}	−0.414*	−1.677**	−1.570**	−1.437**
	(0.078)	(0.173)	(0.169)	(0.172)		(0.229)	(0.652)	(0.649)	(0.710)
α_{-8}	−0.468***	−0.840**	−0.832**	−0.802**	α_{9}	−0.540**	−1.864***	−1.739***	−1.602**
	(0.128)	(0.335)	(0.347)	(0.368)		(0.239)	(0.665)	(0.660)	(0.721)
α_{-7}	−0.510***	−0.931***	−0.919**	−0.890**	α_{10}	−0.309	−1.004	−0.941	−0.669
	(0.131)	(0.349)	(0.361)	(0.383)		(0.257)	(0.685)	(0.747)	(0.852)
α_{-6}	−0.544***	−1.017***	−1.003***	−0.974**	α_{11}	−0.196	−0.920	−0.843	−0.561
	(0.127)	(0.367)	(0.376)	(0.399)		(0.266)	(0.687)	(0.750)	(0.860)
α_{-5}	−0.544***	−1.066***	−1.046***	−1.018**	α_{12}	−0.284	−1.032	−0.938	−0.647
	(0.125)	(0.375)	(0.385)	(0.407)		(0.257)	(0.689)	(0.740)	(0.852)
α_{-4}	−0.327***	−0.898**	−0.872**	−0.845**	α_{13}	−0.427*	−1.198*	−1.085	−0.785
	(0.121)	(0.382)	(0.390)	(0.415)		(0.238)	(0.672)	(0.725)	(0.835)
α_{-3}	−0.594***	−1.220***	−1.184***	−1.158***	α_{14}	−0.400	−1.198*	−1.066	−0.757
	(0.120)	(0.387)	(0.392)	(0.417)		(0.251)	(0.679)	(0.726)	(0.840)
α_{-2}	−0.600***	−1.276***	−1.231***	−1.206***	α_{15}	−0.433*	−1.255*	−1.103	−0.786
	(0.116)	(0.388)	(0.390)	(0.415)		(0.240)	(0.671)	(0.707)	(0.819)
α_{-1}	−0.463***	−1.195***	−1.139***	−1.116***	α_{16}	−0.486*	−1.339**	−1.168*	−0.841
	(0.113)	(0.384)	(0.383)	(0.405)		(0.250)	(0.677)	(0.708)	(0.818)
α_{0}	2.992***	2.204***	2.273***	2.294***	α_{17}	−0.601***	−1.484**	−1.294*	−0.958
	(0.272)	(0.506)	(0.478)	(0.466)		(0.229)	(0.728)	(0.745)	(0.833)
Lag cumulative sign-ups						0.049***	0.069***	0.067***	0.071***
						(0.014)	(0.024)	(0.026)	(0.026)
Lag cumulative sign-ups × *Within 45 minutes before threshold dummy* (β_1)						0.006	0.004	0.002	0.000
						(0.006)	(0.007)	(0.007)	(0.008)
Lag cumulative sign-ups × *Within 45 minutes after threshold dummy* (β_2)						−0.004	−0.007	−0.008	−0.011
						(0.008)	(0.012)	(0.013)	(0.014)
Lag cumulative sign-ups × *From 45 minutes to 90 minutes after threshold dummy* (β_3)						−0.008	−0.018	−0.018	−0.023
						(0.010)	(0.014)	(0.016)	(0.017)
Time-of-the-day fixed effects						Yes	Yes	Yes	Yes
Deal fixed effects						Yes	Yes	Yes	Yes
Number of observations						147,112	142,904	142,904	142,904
Number of deals						4,208	4,208	4,208	4,208
Adjusted R-squared						0.389			

Notes. The dependent variable is the number of new sign-ups per five-minute time interval. Standard errors are clustered by deal and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

continues to decrease after reaching the thresholds (see test results of $\beta_2 - \beta_3$ in Table 8). After the thresholds, the ratio in the second 45-minute time period is significantly lower than that in the first 45-minute time window.

It is worth noting that the validity of the GMM estimator will be violated if the error component $\epsilon_{i,t}$ is serially correlated over time. To address this concern, we apply postestimation tools of the GMM estimator and examine the serial correlation structure of the new error component $\epsilon_{i,t} - \epsilon_{i,t-1}$. The second-order serial correlation is -0.662 ($p = 0.508$), suggesting that the error components in Equation (2), i.e., $\epsilon_{i,t}$, are indeed uncorrelated over time.

Another potential concern with the GMM estimator is weak instruments. When the correlation between instrumental variables and the endogenous variable is low, the asymptotic distribution of the coefficients breaks down, and GMM estimates may not be consistent (Bound et al. 1995). In this case, the standard errors on GMM estimates are likely to be larger than those on GLS estimates. For our model, the concern of weak instruments may become important if the lagged

Table 8 Statistical Tests Using Estimates in Table 7

	GLS	GMM (2 lags)	GMM (3 lags)	GMM (4 lags)		GLS	GMM (2 lags)	GMM (3 lags)	GMM (4 lags)
$\alpha_0 - \alpha_{-5}$	3.535***	3.270***	3.319***	3.312***	$\alpha_0 - \alpha_1$	3.164***	3.248***	3.302***	3.215***
	(0.330)	(0.335)	(0.335)	(0.327)		(0.303)	(0.348)	(0.369)	(0.388)
$\alpha_0 - \alpha_{-4}$	3.319***	3.102***	3.145***	3.139***	$\alpha_0 - \alpha_2$	3.465***	3.607***	3.651***	3.559***
	(0.323)	(0.325)	(0.326)	(0.320)		(0.330)	(0.392)	(0.417)	(0.444)
$\alpha_0 - \alpha_{-3}$	3.586***	3.423***	3.457***	3.452***	$\alpha_0 - \alpha_3$	3.358***	3.550***	3.582***	3.487***
	(0.312)	(0.312)	(0.314)	(0.309)		(0.348)	(0.418)	(0.437)	(0.466)
$\alpha_0 - \alpha_{-2}$	3.591***	3.480***	3.504***	3.500***	$\alpha_0 - \alpha_4$	3.158***	3.406***	3.427***	3.328***
	(0.304)	(0.303)	(0.305)	(0.301)		(0.337)	(0.416)	(0.437)	(0.463)
$\alpha_0 - \alpha_{-1}$	3.455***	3.399***	3.412***	3.410***	$\alpha_0 - \alpha_5$	3.451***	3.759***	3.767***	3.665***
	(0.296)	(0.295)	(0.296)	(0.295)		(0.328)	(0.412)	(0.431)	(0.461)
$\beta_1 - \beta_2$	0.010***	0.011*	0.009	0.010*	$\beta_2 - \beta_3$	0.004	0.011***	0.010***	0.011***
	(0.003)	(0.006)	(0.006)	(0.007)		(0.003)	(0.003)	(0.003)	(0.003)

Notes. Standard errors are clustered by deal and reported in parentheses. Significance levels are related to the null hypothesis H_0: combination of coefficients equals 0.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 9 *F*-Statistics for the Instrumental Variable Regressions

	2 lags	3 lags	4 lags
F-statistic of $Y_{i,t-1}$	18.03	16.32	12.56
F-statistic of $Y_{i,t-2}$	11.37	0.40	0.36
F-statistic of $Y_{i,t-3}$		13.21	0.24
F-statistic of $Y_{i,t-4}$			7.23

cumulative number of sign-ups is not informative in predicting the new sign-ups. To test the existence of weak instruments, we regress the endogenous variable after the first-difference transformation, i.e., $y_{i,t}$, on various lags of cumulative number of sign-ups. The regression analysis is conducted by using two lags to four lags, and the F-statistics are summarized in Table 9. We refer to the rule of thumb suggested by Staiger and Stock (1997) that the finite-sample bias of instrumental variables is not a serious problem when the F-statistic is greater than 10. When we use only two lags, the F-statistics on both lags are greater than the cutoff value of 10. However, the results with more than two lags show that the correlation between the number of new sign-ups and some lagged cumulative number of sign-ups is low. Since the incremental number of sign-ups within a short period of time is likely to be highly correlated, utilizing more lagged cumulative number of sign-ups may not increase the power in predicting the number of new sign-ups, rendering some lagged variables as weak instruments. Based on the above test results, in the subsequent analysis we will report only the results from the GMM estimator with two lags. We will continue to report results from the GLS estimator as the benchmark.

3.4. Heterogeneous Threshold Effects Across Categories and Cities

3.4.1. Category Level Regression Results. To further understand threshold effects, we investigate how such effects may vary across product categories. We select seven categories with the largest number of observations and estimate the extended model using the GMM estimator for each of these seven product categories. The estimates and related test results are listed in Table A.1 (of the appendix) and Table 10, respectively. The test results show that the spike index is statistically significant in all product categories. The values of the index range from 2.165 to 6.955, suggesting a significant increase in the number of sign-ups around the time the thresholds were reached.

The test results on the relationship between the number of new sign-ups and the cumulative number of sign-ups show significant variations across product categories. Specifically, results from the GLS estimator show that the ratio during the 45-minute time period is significantly higher before reaching the thresholds than afterward in four categories, namely, *sports and recreation*, *American food*, *other food*, and *other physical products*. The differences are only significant in *other food* from the GMM estimator. Moreover, under both estimators, two of the seven selected categories show a clear downward trend after the thresholds were reached.

3.4.2. City Level Regression Results. Next we examine whether the threshold effects vary across different cities. We divide the cities into four groups according to city population and estimate the extended model for each city group separately. The estimates for each city group are summarized in Table A.2 of the appendix, and the relevant statistical test results are listed in Table 11.

The results show that spike indexes are statistically significant in all city groups. Interestingly, the test results on the ratio before and after the thresholds show stark contrast between cities of different sizes. Specifically, the differences in the ratio before and after the thresholds exhibit a nonlinear relationship with the size of cities: the differences are significant in the largest cities with populations of over 1 million as well as in the relatively small cities with populations of less

Table 10 **Statistical Tests Using Category Level Regression Results**

	Spike index		$\beta_1 - \beta_2$		$\beta_2 - \beta_3$	
	GLS	GMM (2 lags)	GLS	GMM (2 lags)	GLS	GMM (2 lags)
Arts	5.110***	5.002***	−0.002	0.003	−0.007	−0.006
	(1.356)	(1.254)	(0.007)	(0.007)	(0.005)	(0.005)
Sports	3.499***	3.833***	0.018***	0.006	0.006***	0.007*
	(0.302)	(0.337)	(0.006)	(0.008)	(0.002)	(0.004)
Beauty	4.072***	4.361***	0.001	−0.013	0.005**	−0.000
	(1.002)	(1.202)	(0.011)	(0.024)	(0.002)	(0.011)
Fast food	6.207***	6.955***	0.007	−0.017	−0.002	−0.004
	(2.296)	(2.553)	(0.009)	(0.024)	(0.012)	(0.011)
American food	2.900***	3.069***	0.007*	0.004	0.011***	0.011***
	(0.318)	(0.409)	(0.004)	(0.006)	(0.003)	(0.004)
Other food	1.971***	2.165***	0.021***	0.016***	0.009***	0.005
	(0.247)	(0.253)	(0.002)	(0.004)	(0.002)	(0.004)
Other products	2.331***	2.433***	0.009**	0.002	0.012***	0.000
	(0.208)	(0.242)	(0.004)	(0.008)	(0.004)	(0.008)

Notes. Standard errors are clustered by deal and reported in parentheses. Significance levels are related to the null hypothesis H_0: combination of coefficients equals 0.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 11 **Statistical Tests Using Population-Categorized Regression Results**

	Spike index		$\beta_1 - \beta_2$		$\beta_2 - \beta_3$	
	GLS	GMM (2 lags)	GLS	GMM (2 lags)	GLS	GMM (2 lags)
< 0.25 mil	3.375***	3.209***	0.001	0.019	−0.002	0.012***
	(0.566)	(0.539)	(0.009)	(0.014)	(0.006)	(0.003)
0.25–0.5 mil	3.054***	3.169***	0.014**	0.007**	0.010***	0.007
	(0.221)	(0.208)	(0.005)	(0.004)	(0.003)	(0.006)
0.5–1.0 mil	3.458***	3.846***	0.001	−0.013	0.007*	0.006
	(0.505)	(0.705)	(0.007)	(0.017)	(0.004)	(0.009)
>1.0 mil	4.498***	4.569***	0.013***	0.012***	0.001	0.006**
	(1.387)	(1.254)	(0.004)	(0.003)	(0.006)	(0.003)

Notes. Standard errors are clustered by deal and reported in parentheses. Significance levels are related to the null hypothesis H_0: combination of coefficients equals 0.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

than 500,000 but over 250,000; however, there is no evidence of significant differences in the midsize cities.

We also categorize the cities by their geographic locations. According to the results in Table A.3 of the appendix and Table 12, the spike indexes are statistically significant in all regions. In cities within the *Northeast* region, the ratio is significantly different before and after the thresholds were reached. In this region, the ratio is also significantly reduced after the thresholds were reached. However, the changes in ratio

Table 12 **Statistical Tests Using Regional Level Regression Results**

	Spike index		$\beta_1 - \beta_2$		$\beta_2 - \beta_3$	
	GLS	GMM (2 lags)	GLS	GMM (2 lags)	GLS	GMM (2 lags)
West	2.829***	2.983***	0.006	0.002	0.002	0.008***
	(0.234)	(0.222)	(0.005)	(0.005)	(0.003)	(0.003)
Midwest	3.892***	3.929***	0.011	0.007	0.008***	0.007
	(0.705)	(0.680)	(0.007)	(0.010)	(0.002)	(0.006)
South	4.020***	4.096***	0.007	0.007	−0.001	0.009
	(0.740)	(0.743)	(0.005)	(0.016)	(0.007)	(0.005)
Northeast	2.672***	2.736***	0.015***	0.013***	0.009***	0.008**
	(0.251)	(0.247)	(0.003)	(0.003)	(0.003)	(0.003)
Canada	2.924***	3.405***	−0.001	−0.027*	0.004	−0.010
	(0.412)	(0.440)	(0.007)	(0.014)	(0.005)	(0.006)

Notes. Standard errors are clustered by deal and reported in parentheses. Significance levels are related to the null hypothesis H_0: combination of coefficients equals 0.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

in other regions are either marginally significant or insignificant.

4. Potential Mechanisms Behind Threshold Effects

Our analysis in previous sections has documented and substantiated two types of threshold effect in online group buying. However, the aggregate nature of the data prevents us from identifying the exact mechanisms contributing to these effects. In this section, we discuss several mechanisms compatible with the findings that may serve as potential hypotheses for future research.[2]

For the first type of threshold effect, i.e., the sudden surge of sign-ups around the time when thresholds were reached, we consider three possible mechanisms: value enhancement, postponed decision making, and higher consumer awareness. First, a consumer may derive positive psychological value from beating a target. When the cumulative number of sign-ups approaches a threshold, consumers may experience an urge to beat the target and sign up in a "frenzy" fashion. Such a "frenzy", which is similar to the "bidding frenzy" phenomenon widely observed toward the ends of auctions, may reflect a mental state "characterized by a high level of excitement, a strong sense of competition, and an intense desire to win" (Häubl and Popkowski Leszczyc 2004, p. 91; for other examples, see Ku et al. 2005 and Heyman et al. 2004). Second, some consumers may postpone sign-up decisions until the deals are about to be on. When the number of sign-ups is small, consumers face uncertainty about deal success and the risk of not receiving the discount at the end. Thus, some consumers may choose to postpone their sign-up decisions if the cost to track the sign-up numbers is sufficiently low. Such postponement of action could lead to a surge in the number of sign-ups around the time when the thresholds were reached. Third, the number of sign-ups may surge around the thresholds because of increased consumer awareness of the deals generated by the firm's communication strategy. When a deal comes close to its threshold, a group-buying firm may feature the deal on its front page, highlight the deal in its email to the subscribers, or coordinate with third-party deal aggregators to enhance the placement of the deal on their websites.

For the second type of threshold effect, i.e., the level shift of the ratio between the number of new sign-ups and the cumulative number of sign-ups before and after the thresholds were reached, we discuss four alternative mechanisms: word-of-mouth referral, observational learning, consumer heterogeneity, and demand satiation. First, people who have already signed up for deals play an active role in disseminating deal information. In our model, the positive relation between the number of new sign-ups and the cumulative number of sign-ups may capture the intensity of such referrals (e.g., Bass et al. 1994). Following this logic, our regression results would suggest a stronger intensity of referrals before the thresholds were reached. This result is consistent with the view of group-buying business as a marketing tool to exploit social interactions between consumers. For instance, Jing and Xie (2011) show that some informed consumers can be motivated to persuade their social contacts to join the group-buying deals to ensure deal success.

Second, herding behavior or observational learning may explain the positive relation between the number of new sign-ups and the cumulative number of sign-ups, as demonstrated in Zhang and Liu (2012). In the context of group buying, some consumers can be uncertain about the true quality of the suppliers and hence the value of the deals. These consumers may infer the quality of suppliers from the number of consumers who have already signed up for the deal. Following this rationale, the level shift of β_j indicates that, when making their own purchase decisions, individual consumers would be more likely to resort to the decisions of others before the thresholds were reached and when the deals were uncertain.

Third, different types of consumers may arrive at the deal site before and after thresholds are reached. For instance, tech-savvy consumers may learn about the deals and sign up earlier. These consumers can be more capable of engaging in referrals through online social networks. The early arrivals may also perceive the referrals to be more valuable because their contacts are unlikely to be aware of the deal. As a result, word-of-mouth referrals should be stronger before the thresholds were reached. Finally, there might exist satiation in both the market demand and the reach of word-of-mouth referrals. If the satiation levels happen to be reached around the same time that thresholds were reached, then we would observe more sign-ups per five-minute interval before the thresholds than afterward.

The mechanisms discussed above have different implications on the economic impact of threshold effects. Based on the GMM estimator with two lags, on average there were 3.4 additional sign-ups during the periods when thresholds were reached. Moreover, the relation between the number of new sign-ups and the cumulative number of sign-ups experienced a drop right after reaching the thresholds and continued the decreasing trend afterward. To accurately quantify the economic implications of threshold effects, it is necessary to account for specific underlying mechanisms. For example, for the first type of threshold effect, one needs to know the extent of intertemporal substitutions, i.e.,

[2] We thank the associate editor and anonymous reviewers for suggesting many alternative mechanisms.

whether some consumers might sign up sooner or later if thresholds did not exist. Similarly, for the second type of threshold effect, one needs to confirm if word-of-mouth referral was the driving force. Because data limitation prevents us from identifying such specific mechanisms, we leave to future research to investigate the economic implications of threshold effects. For both types of threshold effect, the magnitude of effect is likely to be greater when the success rate is lower or the stake is higher. The Groupon daily deals studied in this paper were generally expected to be on. The success rate can be much lower in other group-buying markets. For instance, the success rate was 43% at Kickstarter (blog.kickstarter.com) and 12.3% at Prosper.com (Zhang and Liu 2012). Economic implications of threshold effects are thus expected to be higher in these markets.

5. Conclusion

Our paper empirically studies two types of threshold-induced effect on sign-up behavior in online group buying. The first type of threshold effect refers to a substantial increase in the number of sign-ups around the time when the threshold was reached, and the second type of threshold effect refers to a stronger positive relation between the number of new sign-ups and the cumulative number of sign-ups before reaching the thresholds than afterward. Using the GMM estimator, we find that the first type of threshold effect exists consistently across all product categories and in all geographic locations. The second type of threshold effect, although significant overall, is strong in the category of *other food* but weak in other categories. The second type of threshold effect is most significant in the markets of the *Northeast* region of the United States. These results imply that threshold effects could vary significantly across products and markets. Thus, managers may need to consider the product and local market characteristics when making decisions on the use of thresholds for group-buying deals.

Although our research offers useful insights about the threshold-induced behavior in the online group-buying context, future research is required to enrich our understanding of the issue. First, although our research shows evidence for threshold-induced effects, we do not directly observe individual level behavior. Although we propose several potential mechanisms that are compatible with our empirical findings, further research is needed to identify the specific driving forces behind these effects. Second, the group-buying deals offered by Groupon had a single threshold for each deal. A more general group-buying mechanism could have multiple thresholds. For example, the fundraising site Kickstarter.com and many early group-buying sites like Mercata have used multiple levels of threshold. Typically, a greater reward is offered for achieving a higher threshold. Future research can investigate if the threshold effects may diminish or increase when higher thresholds come close.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2014.2015.

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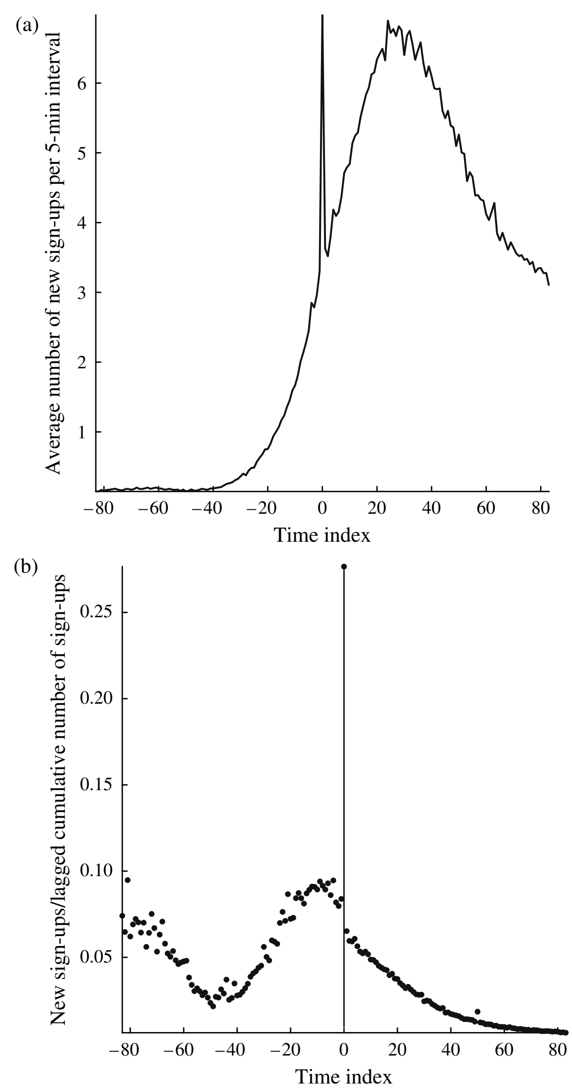
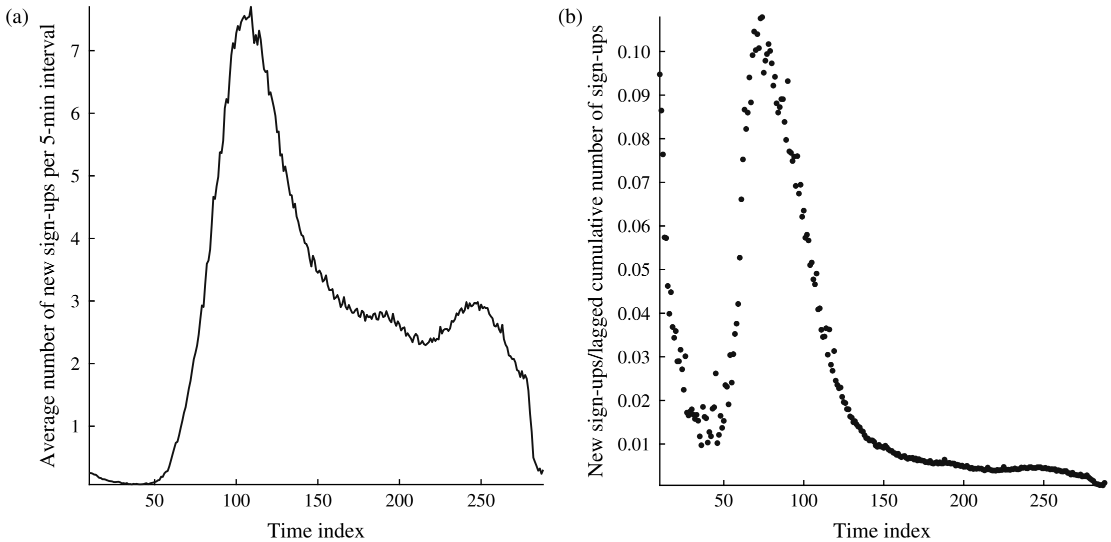
Appendix

Figure A.1 Sign-Up Pattern During the Seven-Hour Time Window Before and After the Threshold Was Reached



Notes. The x axis indicates the time index, *after* being realigned to the time when thresholds were reached. The y axis in panel (a) denotes the average number of new sign-ups during each five-minute time interval. The y axis in panel (b) denotes the ratio between the number of new sign-ups during a time interval and the cumulative number of sign-ups up to the end of the previous time interval.

Figure A.2 **Sign-Up Pattern in a Day**



Notes. The x axis indicates the time index, *before* being realigned to the time when thresholds were reached. The y axis in panel (a) denotes the average number of new sign-ups during each five-minute time interval. The y axis in panel (b) denotes the ratio between the number of new sign-ups during a time interval and the cumulative number of sign-ups up to the end of the previous time interval.

Table A.1 **Category Level Regression Results from Three-Hour Data Using GMM Estimator with Two Lags**

	Arts	Sports	Beauty	Fast food	American food	Other food	Other products		Arts	Sports	Beauty	Fast food	American food	Other food	Other products
α_{-16}	−0.177	−0.021	−0.223	−0.103	−0.421***	0.065	0.009	α_{1}	−1.617***	−0.907**	−3.236*	−0.345	−1.554***	−0.259	−0.693**
	(0.148)	(0.136)	(0.147)	(0.161)	(0.158)	(0.167)	(0.083)		(0.607)	(0.451)	(1.914)	(1.582)	(0.508)	(0.391)	(0.333)
α_{-15}	−0.119	−0.210	−0.464*	−0.277	0.077	−0.157	−0.084	α_{2}	−2.099***	−1.048**	−4.471*	0.074	−1.958***	0.090	−0.964**
	(0.158)	(0.135)	(0.252)	(0.182)	(0.192)	(0.138)	(0.075)		(0.745)	(0.470)	(2.555)	(1.682)	(0.622)	(0.404)	(0.378)
α_{-14}	−0.393**	−0.235*	−0.632	−0.122	−0.241	−0.341**	0.016	α_{3}	−1.616**	−1.194**	−4.333	−0.390	−1.490**	−0.375	−0.595*
	(0.177)	(0.131)	(0.387)	(0.274)	(0.191)	(0.145)	(0.094)		(0.727)	(0.532)	(2.642)	(1.679)	(0.616)	(0.449)	(0.351)
α_{-13}	−0.439**	−0.284*	−0.693	−0.218	−0.075	−0.322*	−0.091	α_{4}	−1.950***	−1.281**	−4.174	0.436	−0.770	0.138	−0.589
	(0.179)	(0.159)	(0.478)	(0.339)	(0.325)	(0.185)	(0.091)		(0.724)	(0.585)	(2.629)	(1.864)	(0.743)	(0.490)	(0.381)
α_{-12}	−0.539**	−0.343*	−0.949*	−0.287	−0.090	−0.494***	−0.061	α_{5}	−1.906***	−1.434***	−4.631*	−0.006	−1.667**	0.243	−0.916**
	(0.217)	(0.179)	(0.573)	(0.407)	(0.259)	(0.191)	(0.114)		(0.709)	(0.555)	(2.615)	(1.856)	(0.675)	(0.452)	(0.363)
α_{-11}	−0.545**	−0.287	−1.116*	−0.172	−0.013	−0.653***	−0.167	α_{6}	−2.190***	−1.702***	−4.938*	0.584	−1.459*	−0.400	−0.976**
	(0.229)	(0.195)	(0.676)	(0.487)	(0.275)	(0.190)	(0.119)		(0.644)	(0.631)	(2.595)	(2.130)	(0.774)	(0.447)	(0.439)
α_{-10}	−0.870***	−0.676***	−1.192	−0.047	−0.290	−0.416*	−0.084	α_{7}	−2.012***	−1.448**	−4.846*	0.406	−2.139***	−0.663	−0.655
	(0.265)	(0.198)	(0.725)	(0.561)	(0.307)	(0.231)	(0.158)		(0.768)	(0.616)	(2.581)	(2.065)	(0.734)	(0.447)	(0.401)
α_{-9}	−0.848***	−0.737***	−1.285*	0.220	−0.019	−0.617***	−0.297**	α_{8}	−2.159***	−1.780***	−4.008*	0.218	−2.121***	−0.049	−0.813*
	(0.284)	(0.200)	(0.766)	(0.650)	(0.342)	(0.222)	(0.138)		(0.806)	(0.689)	(2.358)	(2.241)	(0.741)	(0.505)	(0.415)
α_{-8}	−1.140***	−0.718**	−2.315	−0.442	−1.211***	−0.444	−0.399*	α_{9}	−2.225***	−1.490**	−4.764**	0.060	−2.076**	−0.094	−1.011**
	(0.414)	(0.304)	(1.481)	(0.546)	(0.311)	(0.350)	(0.204)		(0.755)	(0.669)	(2.405)	(2.251)	(0.818)	(0.520)	(0.425)
α_{-7}	−1.084**	−0.802**	−2.544	−0.281	−1.452***	−0.487*	−0.542**	α_{10}	−2.786***	−1.158**	−4.958	0.330	−0.081	−0.165	−0.876*
	(0.445)	(0.340)	(1.563)	(0.602)	(0.364)	(0.268)	(0.218)		(0.960)	(0.548)	(3.266)	(1.655)	(0.852)	(0.706)	(0.461)
α_{-6}	−1.312***	−0.932**	−2.544	−0.255	−1.459***	−0.713*	−0.629**	α_{11}	−2.623**	−0.743	−4.580	0.072	−0.534	0.710	−0.741
	(0.508)	(0.375)	(1.630)	(0.668)	(0.383)	(0.365)	(0.253)		(1.062)	(0.505)	(3.196)	(1.815)	(0.843)	(0.651)	(0.522)
α_{-5}	−1.316**	−0.768**	−2.830*	0.071	−1.667***	−0.493	−0.736***	α_{12}	−2.926***	−1.482**	−4.384	0.162	−0.606	0.110	−0.773
	(0.552)	(0.366)	(1.664)	(0.786)	(0.368)	(0.365)	(0.251)		(1.134)	(0.631)	(3.183)	(1.813)	(0.930)	(0.794)	(0.569)
α_{-4}	−1.206**	−0.796**	−2.531	0.365	−1.063***	−0.587*	−0.565**	α_{13}	−2.955***	−1.420**	−4.951	0.381	−0.910	−0.039	−1.189**
	(0.578)	(0.377)	(1.702)	(0.854)	(0.396)	(0.351)	(0.236)		(1.033)	(0.613)	(3.025)	(1.788)	(0.924)	(0.658)	(0.547)
α_{-3}	−1.370**	−0.767*	−2.909*	−0.152	−1.439***	−0.742**	−0.624**	α_{14}	−3.441***	−1.643**	−4.797	1.096	−0.252	0.195	−0.901*
	(0.569)	(0.430)	(1.698)	(0.927)	(0.421)	(0.328)	(0.275)		(1.219)	(0.669)	(3.019)	(1.998)	(1.010)	(0.787)	(0.509)
α_{-2}	−1.422***	−1.014**	−2.918*	0.341	−1.646***	−0.796**	−0.687**	α_{15}	−3.221**	−1.501**	−4.227	0.206	−0.892	−0.172	−1.121**
	(0.502)	(0.421)	(1.698)	(1.048)	(0.443)	(0.360)	(0.288)		(1.266)	(0.654)	(2.865)	(1.933)	(0.989)	(0.721)	(0.569)

Table A.1 (Continued)

	Arts	*Sports*	*Beauty*	*Fast food*	*American food*	*Other food*	*Other products*		*Arts*	*Sports*	*Beauty*	*Fast food*	*American food*	*Other food*	*Other products*
α_{-1}	−1.514**	−0.912*	−3.203*	0.542	−0.705	−0.661*	−0.563**	α_{16}	−3.279***	−1.690***	−4.585*	1.210	−0.242	−0.145	−0.988*
	(0.589)	(0.466)	(1.687)	(1.132)	(0.669)	(0.369)	(0.269)		(1.230)	(0.647)	(2.777)	(2.142)	(1.081)	(0.783)	(0.583)
α_0	3.401***	2.821***	0.838	7.049**	1.673***	1.821***	1.740***	α_{17}	−3.374***	−1.734**	−5.011*	2.069	−0.499	−0.180	−1.247**
	(1.298)	(0.481)	(0.985)	(3.262)	(0.503)	(0.377)	(0.314)		(1.038)	(0.693)	(2.674)	(2.862)	(1.091)	(0.854)	(0.571)
Lag cumulative sign-ups									0.034*	0.053***	−0.041	−0.012	0.024	0.074***	0.015
									(0.021)	(0.015)	(0.097)	(0.061)	(0.018)	(0.021)	(0.025)
Lag cumulative sign-ups × *Within 45 minutes before threshold dummy* (β_1)									0.012	0.004	0.035	0.015	0.021**	−0.007	0.020**
									(0.011)	(0.007)	(0.026)	(0.018)	(0.009)	(0.009)	(0.010)
Lag cumulative sign-ups × *Within 45 minutes after threshold dummy* (β_2)									0.009	−0.002	0.048	0.032	0.018	−0.023**	0.018
									(0.016)	(0.008)	(0.049)	(0.041)	(0.013)	(0.011)	(0.015)
Lag cumulative sign-ups × *From 45 minutes to 90 minutes after threshold dummy* (β_3)									0.015	−0.010	0.048	0.036	0.007	−0.028*	0.018
									(0.020)	(0.008)	(0.059)	(0.043)	(0.012)	(0.015)	(0.019)
Time-of-the-day fixed effects									Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal fixed effects									Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations									11,514	15,894	22,399	12,956	10,670	13,702	14,309
Number of deals									340	468	660	382	314	403	421

Notes. The dependent variable is the number of new sign-ups per five-minute time interval. Standard errors are clustered by deal and reported in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.2 Population-Categorized Regression Results from Three-Hour Data Using GMM Estimator with Two Lags

	< 0.25 mil	0.25–0.50 mil	0.5–1 mil	> 1 mil		< 0.25 mil	0.25–0.5 mil	0.5–1 mil	> 1 mil
α_{-16}	−0.118*	−0.156**	−0.040	−0.185	α_1	0.506	−0.476**	−2.783***	−1.372
	(0.060)	(0.063)	(0.068)	(0.146)		(0.451)	(0.216)	(0.989)	(0.878)
α_{-15}	−0.127*	−0.231***	−0.260***	−0.016	α_2	0.225	−0.757***	−3.389***	−1.243
	(0.065)	(0.067)	(0.093)	(0.177)		(0.462)	(0.223)	(1.092)	(1.076)
α_{-14}	−0.195***	−0.207***	−0.409***	−0.372*	α_3	0.174	−0.625**	−3.124***	−1.503
	(0.070)	(0.075)	(0.123)	(0.203)		(0.456)	(0.245)	(1.145)	(0.982)
α_{-13}	−0.100	−0.280***	−0.536***	−0.456**	α_4	0.252	−0.399	−3.067***	−1.106
	(0.083)	(0.079)	(0.159)	(0.228)		(0.507)	(0.280)	(1.144)	(1.001)
α_{-12}	−0.086	−0.149	−0.777***	−0.658**	α_5	0.145	−0.714***	−3.491***	−1.568
	(0.094)	(0.097)	(0.173)	(0.279)		(0.468)	(0.275)	(1.125)	(1.018)
α_{-11}	−0.106	−0.327***	−0.856***	−0.378	α_6	0.076	−0.747***	−3.780***	−1.715
	(0.103)	(0.112)	(0.196)	(0.323)		(0.474)	(0.280)	(1.074)	(1.221)
α_{-10}	−0.108	−0.371***	−0.954***	−0.799**	α_7	−0.185	−0.646**	−3.602***	−1.879*
	(0.113)	(0.115)	(0.213)	(0.356)		(0.463)	(0.325)	(1.122)	(1.081)
α_{-9}	−0.130	−0.313**	−1.052***	−0.937**	α_8	0.166	−0.751**	−3.493***	−1.808
	(0.117)	(0.128)	(0.228)	(0.380)		(0.490)	(0.322)	(1.121)	(1.117)
α_{-8}	0.081	−0.362**	−1.757***	−0.938*	α_9	−0.130	−0.686**	−3.608***	−2.180*
	(0.193)	(0.162)	(0.627)	(0.548)		(0.455)	(0.334)	(1.137)	(1.150)
α_{-7}	0.122	−0.538***	−1.908***	−0.889	α_{10}	0.609	−0.457	−3.298***	−1.373
	(0.191)	(0.184)	(0.637)	(0.586)		(0.494)	(0.354)	(1.264)	(1.111)
α_{-6}	0.076	−0.489**	−2.031***	−0.988	α_{11}	0.332	−0.446	−3.112**	−0.851
	(0.210)	(0.196)	(0.644)	(0.648)		(0.516)	(0.352)	(1.244)	(1.159)
α_{-5}	0.108	−0.508**	−1.898***	−1.506**	α_{12}	0.371	−0.459	−3.148**	−1.384
	(0.227)	(0.199)	(0.633)	(0.665)		(0.480)	(0.395)	(1.226)	(1.192)
α_{-4}	0.141	−0.371*	−1.825***	−0.690	α_{13}	0.301	−0.543	−3.353***	−1.609
	(0.211)	(0.193)	(0.610)	(0.702)		(0.462)	(0.385)	(1.138)	(1.182)
α_{-3}	0.114	−0.594***	−2.140***	−1.337*	α_{14}	0.320	−0.633*	−3.181***	−1.765
	(0.209)	(0.222)	(0.573)	(0.749)		(0.502)	(0.370)	(1.105)	(1.248)
α_{-2}	0.122	−0.664***	−2.176***	−1.320*	α_{15}	0.001	−0.627	−3.139***	−1.606
	(0.219)	(0.216)	(0.541)	(0.752)		(0.438)	(0.402)	(1.087)	(1.287)

Table A.2 (Continued)

	< 0.25 mil	0.25–0.50 mil	0.5–1 mil	> 1 mil		< 0.25 mil	0.25–0.5 mil	0.5–1 mil	> 1 mil
α_{-1}	0.039	−0.559**	−1.903***	−1.260	α_{16}	−0.035	−0.592	−3.258***	−1.677
	(0.206)	(0.223)	(0.485)	(0.820)		(0.466)	(0.463)	(1.049)	(1.275)
α_0	3.392***	2.603***	1.266***	3.279*	α_{17}	−0.022	−1.059***	−3.365***	−1.518
	(0.509)	(0.259)	(0.383)	(1.888)		(0.448)	(0.390)	(0.963)	(1.807)
Lag cumulative sign-ups						0.116***	0.056***	0.001	0.066***
						(0.035)	(0.017)	(0.060)	(0.012)
Lag cumulative sign-ups × *Within 45 minutes before threshold dummy* (β_1)						−0.010	0.003	0.021	0.002
						(0.009)	(0.009)	(0.015)	(0.005)
Lag cumulative sign-ups × *Within 45 minutes after threshold dummy* (β_2)						−0.029	−0.005	0.034	−0.010
						(0.020)	(0.009)	(0.030)	(0.007)
Lag cumulative sign-ups × *From 45 minutes to 90 minutes after threshold dummy* (β_3)						−0.040*	−0.012	0.028	−0.016**
						(0.021)	(0.013)	(0.037)	(0.008)
Time-of-the-day fixed effects						Yes	Yes	Yes	Yes
Deal fixed effects						Yes	Yes	Yes	Yes
Number of observations						33,545	33,003	53,057	23,299
Number of deals						988	972	1,562	686

Notes. The dependent variable is the number of new sign-ups per five-minute time interval. Standard errors are clustered by deal and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.3 Regional Level Regression Results from Three-Hour Data Using GMM Estimator with Two Lags

	West	Midwest	South	Northeast	Canada		West	Midwest	South	Northeast	Canada
α_{-16}	−0.190**	−0.173	−0.048	−0.143	0.051	α_1	−1.160***	−0.567	−1.066	−1.843***	−1.084**
	(0.076)	(0.109)	(0.081)	(0.099)	(0.117)		(0.446)	(1.076)	(1.429)	(0.640)	(0.534)
α_{-15}	−0.188**	−0.305*	−0.153	−0.245**	0.136	α_2	−1.457***	−1.407	−1.160	−2.096***	−1.099**
	(0.088)	(0.161)	(0.122)	(0.119)	(0.127)		(0.464)	(1.364)	(1.480)	(0.628)	(0.498)
α_{-14}	−0.294***	−0.526**	−0.163	−0.478***	−0.053	α_3	−1.279***	−1.346	−1.111	−2.014***	−1.135**
	(0.103)	(0.210)	(0.166)	(0.130)	(0.138)		(0.474)	(1.392)	(1.529)	(0.679)	(0.553)
α_{-13}	−0.269**	−0.629**	−0.264	−0.556***	0.085	α_4	−1.167**	−0.901	−0.923	−2.143***	−1.045*
	(0.128)	(0.253)	(0.211)	(0.157)	(0.141)		(0.485)	(1.409)	(1.585)	(0.714)	(0.582)
α_{-12}	−0.410***	−0.681**	−0.327	−0.682***	0.018	α_5	−1.441***	−1.248	−1.413	−2.275***	−1.099*
	(0.138)	(0.299)	(0.255)	(0.192)	(0.159)		(0.512)	(1.359)	(1.629)	(0.748)	(0.572)
α_{-11}	−0.300*	−0.757**	−0.371	−0.879***	0.002	α_6	−1.799***	−1.293	−1.431	−2.562***	−1.184**
	(0.168)	(0.343)	(0.293)	(0.226)	(0.202)		(0.522)	(1.348)	(1.709)	(0.685)	(0.519)
α_{-10}	−0.601***	−0.838**	−0.379	−0.962***	−0.129	α_7	−1.615***	−1.181	−1.440	−3.045***	−1.024*
	(0.165)	(0.353)	(0.346)	(0.258)	(0.209)		(0.543)	(1.333)	(1.724)	(0.830)	(0.564)
α_{-9}	−0.541***	−0.813**	−0.490	−1.235***	0.186	α_8	−1.585***	−0.931	−1.518	−2.557***	−0.955*
	(0.201)	(0.375)	(0.375)	(0.294)	(0.252)		(0.569)	(1.243)	(1.792)	(0.848)	(0.565)
α_{-8}	−0.765***	−1.134	−0.569	−1.216***	−0.733***	α_9	−1.657***	−1.051	−1.740	−2.789***	−0.901
	(0.248)	(0.874)	(0.517)	(0.401)	(0.282)		(0.559)	(1.235)	(1.832)	(0.831)	(0.617)
α_{-7}	−0.642**	−1.381	−0.714	−1.178***	−0.784**	α_{10}	−1.225**	−0.456	−0.909	−2.194***	−1.867***
	(0.257)	(0.899)	(0.552)	(0.419)	(0.309)		(0.577)	(1.626)	(1.487)	(0.793)	(0.612)
α_{-6}	−0.605**	−1.346	−0.803	−1.592***	−0.739**	α_{11}	−0.935	−0.318	−0.844	−2.543***	−1.330*
	(0.270)	(0.954)	(0.600)	(0.455)	(0.330)		(0.585)	(1.622)	(1.556)	(0.866)	(0.713)
α_{-5}	−0.608**	−1.477	−0.830	−1.646***	−0.384	α_{12}	−1.141*	−0.133	−1.062	−2.618***	−1.320*
	(0.285)	(0.993)	(0.618)	(0.483)	(0.299)		(0.619)	(1.571)	(1.569)	(0.889)	(0.780)
α_{-4}	−0.457	−1.241	−0.636	−1.511***	−0.228	α_{13}	−1.663***	−0.092	−1.079	−2.603***	−1.699**
	(0.294)	(0.999)	(0.643)	(0.523)	(0.369)		(0.612)	(1.499)	(1.560)	(0.899)	(0.679)
α_{-3}	−0.623**	−1.610	−0.972	−1.636***	−0.760**	α_{14}	−1.717***	0.298	−1.131	−2.852***	−1.717**
	(0.315)	(1.015)	(0.670)	(0.526)	(0.360)		(0.636)	(1.547)	(1.600)	(0.907)	(0.791)
α_{-2}	−0.709**	−1.502	−0.991	−1.993***	−0.497	α_{15}	−1.470**	0.018	−1.152	−3.023***	−1.450*
	(0.320)	(1.023)	(0.687)	(0.545)	(0.393)		(0.682)	(1.435)	(1.614)	(0.966)	(0.753)
α_{-1}	−0.498	−1.432	−0.950	−1.863***	−0.180	α_{16}	−1.479**	−0.117	−1.250	−3.227***	−0.739
	(0.365)	(1.018)	(0.683)	(0.525)	(0.444)		(0.727)	(1.458)	(1.631)	(0.982)	(0.696)

Table A.3 (Continued)

	West	Midwest	South	Northeast	Canada
α_0	2.043***	2.656***	3.091**	0.835	2.654***
	(0.377)	(0.757)	(1.259)	(0.610)	(0.533)
α_{17}	−2.194***	−0.038	−1.064	−2.892***	−2.176***
	(0.664)	(1.442)	(1.840)	(0.944)	(0.780)
Lag cumulative sign-ups	0.070***	0.027	0.064**	0.069***	−0.055
	(0.020)	(0.054)	(0.031)	(0.020)	(0.042)
Lag cumulative sign-ups × *Within 45 minutes before threshold dummy* (β_1)	−0.001	0.014	0.007	0.003	0.038**
	(0.007)	(0.017)	(0.006)	(0.008)	(0.016)
Lag cumulative sign-ups × *Within 45 minutes after threshold dummy* (β_2)	−0.003	0.007	−0.001	−0.009	0.065**
	(0.011)	(0.026)	(0.021)	(0.010)	(0.029)
Lag cumulative sign-ups × *From 45 minutes to 90 minutes after threshold dummy* (β_3)	−0.011	0.000	−0.010	−0.018	0.075**
	(0.013)	(0.031)	(0.019)	(0.012)	(0.033)
Time-of-the-day fixed effects	Yes	Yes	Yes	Yes	Yes
Deal fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	32,351	32,673	47,594	21,525	8,761
Number of deals	953	962	1,401	634	258

Notes. The dependent variable is the number of new sign-ups per five-minute time interval. Standard errors are clustered by deal and reported in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

References

Anand KS, Aron R (2003) Group buying on the Web: A comparison mechanism of price-discovery. *Management Sci.* 49(11):1546–1562.

Arellano M, Bond S (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev. Econom. Stud.* 58(2):277–297.

Bass FM, Krishnan TV, Jain DC (1994) Why the Bass model fits without decision variables. *Marketing Sci.* 13(3):203–223.

Bound J, Jaeger DA, Baker RM (1995) Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *J. Amer. Statist. Assoc.* 90(430):443–450.

Byers JW, Mitzenmacher M, Zervas G (2012) Daily deals: Prediction, social diffusion, and reputational ramifications. *Proc. Fifth ACM Internat. Conf. Web Search Data Mining, Seattle, WA*.

Chen J, Chen X, Song X (2007) Comparison of the group-buying auction and the fixed pricing mechanism. *Decision Support Systems* 43(2):445–459.

Dholakia UM (2010) How effective are Groupon promotions for businesses? Working paper, Rice University, Houston.

Edelman B, Jaffe S, Kominers SD (2015) To Groupon or not to Groupon: The profitability of deep discounts. *Marketing Lett*. Forthcoming.

Fowler GA (2010) Groupon grows beyond one deal per day. *Wall Street Journal* (November 30), http://blogs.wsj.com/digits/2010/11/30/groupon-grows-beyond-one-deal-per-day/.

Häubl G, Popkowski Leszczyc PTL (2004) Bidding frenzy: Intensity of competitive interaction among bidders and product valuation in auctions. *Adv. Consumer Res.* 31:90–93.

Heyman JE, Orhun Y, Ariely D (2004) Auction fever: The effect of opponents and quasi-endowment on product valuations. *J. Interactive Marketing* 18(4):7–21.

Hu M, Shi M, Wu J (2013) Simultaneous vs. sequential group-buying mechanisms. *Management Sci.* 59(12):2805–2822.

Jing X, Xie J (2011) Group buying: A new mechanism for selling through social interactions. *Management Sci.* 57(8):1354–1372.

Kauffman RJ, Wang B (2002) Bid together, buy together: On the efficacy of group-buying business models in internet-based selling. *The E-Business Handbook* (CRC Press, Boca Raton, FL).

Ku G, Malhotra D, Murnighan JK (2005) Towards a competitive Arousal model of decision-making: A study of auction fever in live and internet auctions. *Organ. Behav. Human Decision Processes* 96(2):89–103.

Li X, Wu L (2012) Measuring effects of observational learning and social-network word-of-mouth on the sales of daily-deal vouchers. *Workshop Inform. Systems Econom., Orlando, FL*.

Nickell S (1981) Biases in dynamic models with fixed effects. *Econometrica* 49(6):1417–1426.

Pepitone J (2011) Groupon anxiety: The online-coupon firm will have to move fast to retain its impressive lead. *Economist* (March 17), 70–71.

Roodman D (2009) A note on the theme of too many instruments. *Oxford Bull. Econom. Statist.* 71(1):135–158.

Staiger D, Stock JH (1997) Instrumental variables regressions with weak instruments. *Econometrica* 65(3):557–586.

Villas-Boas JM, Winer RS (1999) Endogeneity in brand choice models. *Management Sci.* 45(10):1324–1338.

Zhang J, Liu P (2012) Rational herding in Microloan markets. *Management Sci.* 58(5):892–912.