WHEN DISCOUNTS HURT SALES: THE CASE OF DAILY-DEAL MARKETS

ONLINE APPENDIX

The materials presented here follow the order of appearance in the main text.

Figure A.1. Sample Deal Page

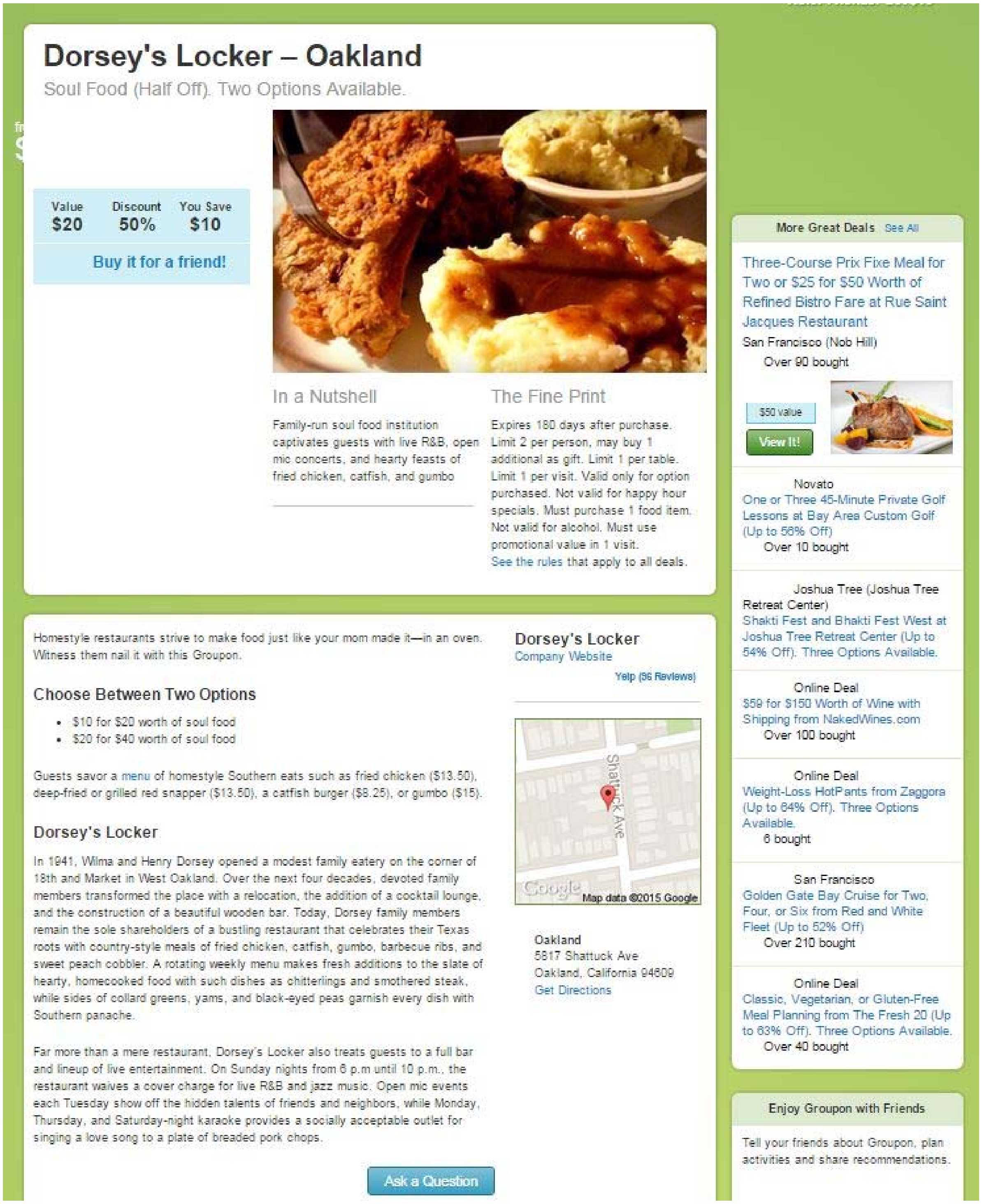


Table A.1. List of the subcategories

Automotive Services:	Auto Glass Services, Auto Parts & Accessories, *Auto Repair*,* Car Dealers, Car Wash & Detailing, Motorcycle Dealers, Oil Change, Parking, Stereo Installation, Tires & Wheels (Total: 10)
Beauty and Spas:	Beauty Products, Body Wrap, Body Contouring, Body Massage, Eyelash Services, Facial Care, Foot Massage, Hair Salon, *Laser Hair Removal**, Makeup Artists, Men's Salon, Nail Salon, Oxygen Bar, Reiki, Salt Therapy, Sauna, Skin-Tag Removal, Tanning Salon, Tattoo Removal, Teeth Whitening, Vein Treatment, Waxing (Total: 22)
Education:	Acting Classes, Art Classes, Bartending Schools, Camera Techniques, Computer Training, Cooking Classes, Cosmetology Schools, Dance Lessons, Driving Lessons, Educational Services, Flight Instruction, Language Schools, Makeup Class, Music Lessons, Paddleboard Lesson, Preschools, Private Tutors, Specialty Schools, Speed Reading, Swimming Lessons, Training & Vocational Schools, Wine Classes (Total: 22)
Entertainment:	Alcohol Event, Amusement Park, Aquariums, Archery, Arts/Crafts/Hobbies, Balloon Ride, Biking, Boat Tour, Boating, Botanical Garden, Bowling, Brewery Tour, Casino, Circus, Comedy, Country Clubs, Creamery Tour, Dance, Dinner Theater, Diving, Farm Tours, Film Festival, Fishing, Flight, Food Tour, Gaming, Ghost Tour, Go-Kart, Golf, Historical Tour, Home/Garden Show, Horse/Carriage Ride, Individual Speakers, Karaoke, Kid's Activities, Laser Tag, Magic Show, Miniature Golf, Miscellaneous Events, Miscellaneous Exhibition, Movie Tickets, Museum, Music Concert, Mystery Date, Other Outdoor Adventure, Other Specialty Tour, Paintball, Palace of Wax, Pool Party, Running Event, Segway Tour, Shooting, Sightseeing Tour, Skating, Skiing, Skydiving, Speedway, Sporting Activity, Sporting Event, Spring Jumping, Supercar Driving, Surfing, Symphony & Orchestra, Talent Show, Theater & Plays, Train Tour, Water Park, Winery Tour, Workshops and Seminars, Zipline Tour, Zoos (Total: 71)
Food & Drinks:	Alcohol Store, Bagel Shops, Breweries, Butchers & Meat Shops, Candy Stores, Cheese Shops, Chocolate Shops, Coffee & Tea Shops, Cupcakes/Dessert/Bakery, Food Delivery Services, Grocery Stores, *Health Stores**, Ice Cream & Frozen Yogurt, Juice Bars & Smoothies, *Organic Food*,* Seafood Markets (Total: 16)
Health & Fitness:	Badminton, Baseball, Bootcamp, Crossfit, Fitness Classes, Gyms & Fitness Centers, Karate, Kickboxing, Martial Arts, Personal Training, Pilates, Rock Climbing, Taekwondo, Tennis, Yoga (Total: 15)
Home Services:	Carpet Cleaning, Chimney Sweep, Gardeners, Gutter Cleaning, *Handyman Services**, *Heating & Ventilation & Air Conditioning**, Home Cleaning, *Home Repair**, *Interior Designers & Decorators**, Junk

	Removal, Lawn Care Services, Movers, Painters, Pest & Animal Control, Pool Cleaners, Tree Services, Window Washing (Total: 17)
Medical Treatments:	*Acupuncture*, Arthritis*, Chiropractic*, Craniosacral Therapy*, Dentists*, Dermatology*, Detoxification*, Food Allergy*, Hearing aid*, Hormone Therapy*, Hydrotherapy*, Hypnotherapy*, Laser Eye Surgery/Lasik*, Medical Exam & Consultation*, Nail-Fungus Treatment*, Optometrists*, Orthodontics*, Reflexology*, Stress Management** (Total: 19)
Nightlife and Bars:	Cigar Bars, Dance Clubs, Gay Bars, Irish Pubs, Jazz & Blues Clubs, Lounges, Music Venues, Night Clubs, Piano Bars, Pool Halls, Pubs/Sports Bars, Social Clubs, Wine Bars (Total: 13)
Pet Services:	Horse Services & Equipment, *Pet Boarding/Pet Sitting**, Pet Groomers, Pet Washing, *Veterinarians** (Total: 5)
Restaurants:	African, American, Asian, Breakfast & Brunch, Cafe & Tearoom, Caribbean, Deli & Fast Food, European, French, Fusion Dishes, Hawaiian, Indian, Italian, Latin, Mediterranean, Middle Eastern, Pub Food, Seafood, Spanish, Specialty Meal, Vegan & Health Food (Total: 21)
Other Professional Services:	Accountants, Car Rental, Catering & Bartending Services, Digital Conversion, Dry Cleaning & Laundry, *Electronics Repair**, Event Planner, Magazine Subscription, Photography, Printing & Copying Equipment & Services, Resume Services, Self-Storage, *Shoe Repair**, *Watch Repair** (Total: 14)

Notes. Subcategories classified as credence goods are in italics and labeled with an asterisk.

Table A.2. List of the local geographic markets

American Cities:	Abilene, Akron-Canton, Albany Capital Region, Albany (GA), Albuquerque, Allentown-Reading, Amarillo, Anchorage, Ann Arbor, Appleton, Asheville, Athens (GA), Atlanta, Augusta, Austin, Bakersfield, Baltimore, Baton Rouge, Billings, Birmingham, Boise, Boston, Buffalo, Cedar Rapids-Iowa City, Central Jersey, Charleston, Charlotte, Chattanooga, Chicago, Cincinnati, Cleveland, Colorado Springs, Columbia, Columbia (MO), Columbus, Columbus (GA), Corpus Christi, Dallas, Dayton, Daytona Beach, Denver, Des Moines, Detroit, El Paso, Erie, Eugene, Evansville, Fairfield County, Fort Lauderdale, Fort Myers--Cape Coral, Fort Wayne, Fort Worth, Fresno, Gainesville, Grand Rapids, Green Bay, Greenville, Hampton Roads, Harrisburg, Hartford, Honolulu, Houston, Huntsville, Indianapolis, Inland Empire, Jackson, Jacksonville, Kalamazoo, Kansas City, Knoxville, Lakeland, Lansing, Las Vegas, Lexington, Lincoln, Little Rock, Long Island, Los Angeles, Louisville, Lubbock, Macon, Madison, Memphis, Miami, Midland--Odessa, Milwaukee, Minneapolis--St. Paul, Mobile Baldwin County, Modesto, Montgomery, Napa--Sonoma, Naples, Nashville, New Orleans, New York, North Jersey, Ocala, Ogden, Oklahoma City, Omaha, Orange County, Orlando, Palm

	Beach, Pensacola, Philadelphia, Phoenix, Piedmont Triad, Pittsburgh, Portland, Portland (ME), Providence, Raleigh--Durham, Reno, Richmond, Rio Grande Valley, Roanoke, Rochester, Rockford, Sacramento, Salem (OR), Salt Lake City, San Angelo, San Antonio, San Diego, San Francisco, San Jose, Santa Barbara, Santa Cruz, Savannah--Hilton Head, Seattle, Shreveport--Bossier, Sioux Falls, South Bend, Spokane Coeur D'Alene, Springfield (MA), Springfield (MO), St. Louis, Stockton, Syracuse, Tallahassee, Tampa Bay Area, Toledo, Topeka--Lawrence, Tucson, Tulsa, Ventura County, Washington DC, Westchester County, Wichita, Wilmington--Newark, Worcester, Youngstown (Total: 159)
Canadian Cities:	Abbotsford, Barrie, Calgary, Edmonton, Greater Toronto Area, Halifax, Kelowna, Kingston, Kitchener--Waterloo, London, Ottawa, Regina, Saskatoon, St. John's, St. Catharines--Niagara, Sudbury, Vancouver, Victoria, Windsor, Winnipeg (Total: 20)

SURVEY ON CONSUMER FAMILIARITY WITH GROUPON MERCHANTS (SECTION 3)

We compare consumers' familiarity with the local merchants featured in daily-deal websites to their familiarity with some large or national brands that often appear in online retailing websites. Within the Automotive and Food & Drink categories, we randomly chose five Groupon deals offered by local merchants in a big U.S. city in our sample. Then, we randomly selected five brands offering similar products on Amazon.com. We provided the screenshots of these 10 merchants in the survey and asked respondents to rate, on a 7-point Likert scale, their familiarity with each merchant (1 = *less familiar*, 7 = *more familiar*). The following table lists the merchants used in the survey. The survey is available at: https://www.surveymonkey.com/r/KF3R9SR.

Groupon merchants	**Amazon merchants**
DFW Camper Corral	Mobil 1
Precision Auto Care	Stoner
MasterTech Auto	Kensun
Rodriguez Bakery & Restaurant	Hostess
Sweet Genius Treats	Oreo

We conducted the survey on SurveyMonkey (https://www.surveymonkey.com/). We acquired 50 responses from residents in the city where the five local merchants used in the survey are located. The mean familiarity score for the five Groupon merchants is 2.0, whereas the mean familiarity score for the five Amazon merchants is 4.5. The difference is statistically significant (t = 13.6, p < 0.01). This result implies that relative to the brands in Amazon.com, people are less aware or familiar with the local merchants featured on Groupon.

IV ESTIMATOR INSTRUMENTING FOR BOTH PRICE AND DISCOUNT (SECTION 4.2)

Table A.3 reports the IV estimator instrumenting for both transaction price and discount. The results in the Entertainment and Restaurant categories are largely consistent with those reported in Table 5, columns (1) and (2). Importantly, the coefficients of *discount* in Table A.3, columns (1) and (2), remain negative and statistically significant.

The results with AHW and HPI as instruments are similar to those reported in Table 5, column (3), with the exception that both *price* and *discount* have a negative sign that is not statistically significant. This is unsurprising because, as discussed in Section 4.2, HPI is not a good instrument. In fact, neither AHW nor HPI is a good instrument for transaction price.

Table A.3. IV Estimator Instrumenting for both Price and Discount

	(1) BLP instruments; entertainment	(2) BLP instruments; restaurants	(3) AHW and HPI as instruments
price	0.0577	-0.1013*	-0.4958
	(0.0867)	(0.0542)	(0.3863)
discount	-0.0872***	-0.5086***	-0.0445
	(0.0266)	(0.1008)	(0.0703)
lag cumulative sales	0.1378***	0.1361***	0.0420
	(0.0102)	(0.0034)	(0.0526)
days before expiration	0.0137*	0.0563***	0.0882*
	(0.0074)	(0.0061)	(0.0462)
merchant-created deal	0.0627***	0.2229***	0.1253**
	(0.0152)	(0.0856)	(0.0532)
facebook fans	0.0046***	0.0066***	0.0087***
	(0.0009)	(0.0006)	(0.0029)
has review quotes	0.0119	0.1060***	0.1111**
	(0.0241)	(0.0161)	(0.0531)
sold out finally	0.1780***	0.2554***	0.3186***
	(0.0211)	(0.0229)	(0.0688)
duration	-0.3123***	-0.3478***	-0.1822***
	(0.0237)	(0.0076)	(0.0501)
options	0.0083	-0.0193***	-0.1064
	(0.0191)	(0.0056)	(0.0728)
competing deals	-0.0360***	0.0004	-0.0325***
	(0.0093)	(0.0059)	(0.0109)
maximum purchases allowed	0.0104	0.0088***	-0.0328
	(0.0092)	(0.0034)	(0.0268)
Use-restriction proxy	-0.0148	0.0008	0.0411

	(0.0112)	(0.0068)	(0.0317)
online deal	-0.0839	--	0.2454
	(0.1011)		(0.2280)
multiregional deal	0.0064	-0.0677***	0.0125
	(0.0141)	(0.0139)	(0.0086)
deal frequency	-0.0410**	-0.0058	0.0053
	(0.0163)	(0.0122)	(0.0184)
division fixed effects	Yes	Yes	Yes
subcategory fixed effects	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes
Observations	615,036	287,913	1,704,202
R-squared	0.174	0.133	0.024

Notes. The dependent variable is log hourly sales. Robust standard errors clustered by product subcategory in parentheses. **** p<0.01, ** p<0.05, * p<0.1.*

FIRST-STAGE REGRESSION RESULTS FOR THE IV ESTIMATORS (SECTION 4.2)

Table A.4 reports the first-stage regression results for the IV estimators reported in Table 5.

Table A.4. First-Stage Regression Results

	(1) BLP instruments; entertainment	(2) BLP instruments; restaurants	(3) AHW and HPI as instruments
price	-0.1136***	-0.0972***	-0.0725***
	(0.0116)	(0.0029)	(0.0058)
lag cumulative sales	-0.0029	0.0062***	0.0047*
	(0.0045)	(0.0008)	(0.0026)
days before expiration	-0.0581***	-0.0445***	-0.0408***
	(0.0123)	(0.0013)	(0.0054)
merchant-created deal	0.0045	-0.0145**	-0.0095
	(0.0303)	(0.0066)	(0.0300)
facebook fans	0.0030	-0.0013***	0.0026**
	(0.0019)	(0.0002)	(0.0012)
has review quotes	0.0125	0.0049	0.0005
	(0.0436)	(0.0039)	(0.0224)
sold out finally	0.0536***	-0.0522***	0.0476**
	(0.0208)	(0.0029)	(0.0189)
duration	0.0094	-0.0421***	-0.0054
	(0.0261)	(0.0025)	(0.0147)
options	0.0415**	-0.0085***	0.0295***
	(0.0172)	(0.0026)	(0.0077)
maximum purchases allowed	-0.0385***	-0.0024	-0.0054

	(0.0129)	(0.0020)		(0.0063)
use-restriction proxy	-0.0257**	-0.0113***		-0.0180***
	(0.0111)	(0.0014)		(0.0038)
online deal	0.5151***	--		0.2548***
	(0.0996)			(0.0566)
multiregional deal	-0.0206	-0.1172***		-0.0143
	(0.0161)	(0.0039)		(0.0102)
deal frequency	-0.0224	0.0307***		-0.0042
	(0.0344)	(0.0049)		(0.0155)
competing deals	-0.0016	0.0214***		-0.0009
	(0.0222)	(0.0019)		(0.0085)
days before expiration (others)	-0.0002	-0.0014***	*AHW*	-0.3940***
	(0.0012)	(0.0002)		(0.0502)
merchant-created deal (others)	0.0087***	-0.0032	*HPI*	0.0019
	(0.0022)	(0.0027)		(0.0026)
facebook fans (others)	0.0005	-0.0001***		--
	(0.0011)	(0.0000)		
has review quotes (others)	0.0066***	-0.0083***		--
	(0.0011)	(0.0005)		
sold out finally (others)	-0.0001	0.0031***		--
	(0.0001)	(0.0012)		
duration (others)	0.0167***	0.0001***		--
	(0.0051)	(0.0000)		
options (others)	0.0130***	-0.0020***		--
	(0.0015)	(0.0003)		
maximum purchases allowed	0.0022**	0.0041***		--
(others)	(0.0009)	(0.0002)		
use-restriction proxy (others)	-0.0249	0.0005***		--
	(0.0188)	(0.0002)		
online deal (others)	-0.0020	--		--
	(0.0013)			
multiregional deal (others)	-0.0065***	0.0022***		--
	(0.0013)	(0.0003)		
deal frequency (others)	-0.0078**	0.0014***		--
	(0.0039)	(0.0002)		
division fixed effects	Yes	Yes		Yes
subcategory fixed effects	Yes	Yes		Yes
time fixed effects	Yes	Yes		Yes
Observations	615,036	287,913		1,704,202
R-squared	0.412	0.141		0.401

Notes. The dependent variable is log discount. Robust standard errors clustered by product subcategory in parentheses. **** p<0.01, ** p<0.05, * p<0.1.*

CLUSTER ANALYSIS (SECTION 4.3)

We conduct a cluster analysis to separate the 19,978 deals based on their characteristics. We use the following deal characteristics in the clustering: *transaction price*, *discount percentage*, *days before expiration*, *merchant-created deal*, *Facebook fans*, *has review quotes*, *sold out finally*, *duration*, *number of options*, *number of competing deals*, *holiday percentage*, *maximum purchases allowed*, *use-restriction proxy*, *online deal*, *multiregional deal*, *deal frequency*, *city*, and *subcategory*. We exclude the online review data as they are not available on all deals. In performing the clustering, we use the original (unlogged) version of these variables.

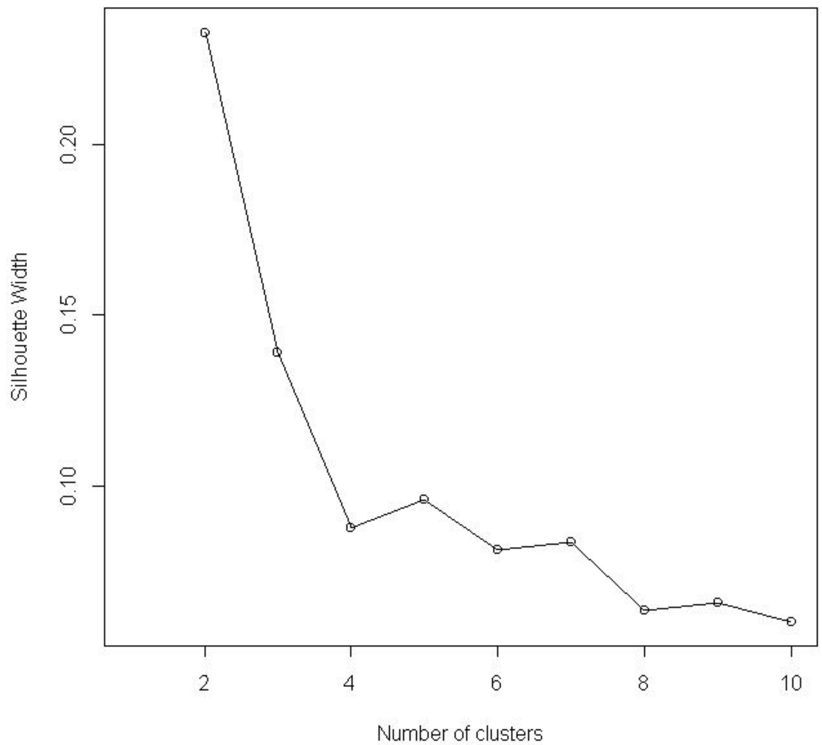
Because the deal characteristics do not vary over time, we use the cross-sectional deal data to perform the clustering. We compute the number of competing deals as the total number of deals that have ever overlapped with the focal deals during their entire lifespans. Furthermore, to account for "seasonality" of the online daily deals, we construct another variable, *holiday percentage*, that represents the percentage of weekends and public holidays in each deal's duration.

Because the deal characteristics comprise both qualitative and quantitative variables, we use Gower's distance (Gower 1971) to calculate the deals' (dis)similarity matrix. Gower's distance uses a different distance metric for each variable type. For quantitative variables, it uses range-normalized Manhattan distance. For nominal variables with k categories, it first converts the data into k binary columns and then computes the Dice similarity coefficient (Dice 1945). Also, because of the mixed variable type, we use the K-medoid clustering algorithm, which is similar to the widely used K-means algorithm. We use the common partitioning around medoids (PAM) method. The detailed steps are as follows.

1. Choose K random observations (deals) as medoids (centers or exemplars).
2. Assign all remaining observations to their closest medoids according to distance.
3. For each cluster, identify the observation that yields the lowest average distance if it were to be assigned as the medoid. Make this observation the new medoid.
4. Return to Step 2 and repeat the steps if at least one medoid has changed.

To determine the number of clusters, we use the *average silhouette* value (Rousseeuw 1987). It measures the similarity of an object to its own cluster when compared with other clusters. The silhouette value ranges from -1 to 1. A higher silhouette value indicates that the object is well matched to its own cluster and poorly matched to neighboring clusters. Hence, the average silhouette value measures how well the data have been clustered. Having too many or too few clusters will cause the average silhouette value to drop. Referring to Figure A.2, the highest average silhouette value (0.2328) is attained when K = 2.

Figure A.2. Average silhouette value



With K = 2, one cluster has 13,203 deals and the other cluster has 6,775 deals. Table A.5 compares the two clusters in terms of deal characteristics. Table A.6 presents the distribution of deals in the 12 categories in the two clusters. In general, the deals in Cluster 2 have more Facebook fans than the deals in Cluster 1 (t = 14.79, p < 0.01). They are more likely sold out, too (t = 19.77, p < 0.01). Furthermore, the deals in Cluster 2 are more likely offered by merchants that operate in multiple cities (t = 170.00, p < 0.01) and have more online reviews (t = 24.10, p < 0.01). In view of these post hoc comparisons, we believe the cluster analysis has successfully separated the deals into an “unpopular” segment (Cluster 1) and “popular” segment (Cluster 2).

Table A.5. Comparison of Deal Characteristics

	Cluster 1					Cluster 2					*p*-value of *t*-tests
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	
transaction price	13,203	53.11	154.82	2	6,440	6,775	50.07	150.47	2	2981	0.181
discount percentage	13,203	56.12	12.43	1	98	6,775	54.95	17.63	1	99	0.000
days before expiration	13,203	163.25	101.81	30	358	6,775	302.00	98.96	30	358	0.000
merchant-created deal	13,203	0.00	0.05	0	1	6,775	0.06	0.24	0	1	0.000
facebook fans	13,203	4,708.98	251,258.50	0	2.67E+07	6,775	573,527.10	3,161,434.00	0	5.11E+07	0.000
has review quotes	13,203	0.02	0.13	0	1	6,775	0.01	0.11	0	1	0.002
sold out finally	13,203	0.01	0.10	0	1	6,775	0.08	0.27	0	1	0.000
duration	13,203	90.79	28.31	12	926	6,775	95.74	32.18	24	765	0.000
nr. of options	13,203	2.14	1.06	1	32	6,775	1.74	1.84	1	42	0.000
nr. of competing deals	13,203	4.32	5.29	1	41	6,775	3.34	4.50	1	38	0.000
holiday percentage	13,203	0.32	0.21	0	1	6,775	0.34	0.22	0	1	0.000
max. purchases allowed	13,203	4.11	23.51	1	540	6,775	7.86	14.74	1	540	0.000
use-restriction proxy	13,203	383.47	106.16	0	734	6,775	495.90	144.87	0	734	0.000
online deal	13,203	0.01	0.11	0	1	6,775	0.01	0.12	0	1	0.327
multiregional deal	13,203	0.05	0.21	0	1	6,775	0.85	0.35	0	1	0.000
deal frequency	13,203	1.09	0.33	1	4	6,775	1.11	0.41	1	6	0.000
review count	4,422	57.38	114.57	1	2,951	2,270	1,229.23	2,315.37	1	8,778	0.000
average rating	4,422	3.64	0.72	1	5	2,270	3.83	0.55	1	5	0.000

Table A.6. Deal Distributions

	Cluster 1		Cluster 2	
Category	**Freq.**	**Percent**	**Freq.**	**Percent**
Automotive	172	1.3	99	1.46
Beauty & Spas	4,801	36.36	429	6.33
Education	175	1.33	516	7.62
Entertainment	2,502	18.95	4,022	59.37
Food & Drink	381	2.89	241	3.56
Health & Fitness	1,467	11.11	337	4.97
Home Services	143	1.08	83	1.23
Medical	461	3.49	94	1.39
Nightlife	54	0.41	6	0.09
Pets	29	0.22	61	0.9
Professional Services	115	0.87	619	9.14
Restaurants	2,903	21.99	268	3.96
Total	13,203	100	6,775	100

QUANTILE REGRESSION AND ACCOUNTING FOR CONTINUOUS ENDOGENOUS TREATMENT EFFECT (SECTION 4.3)

We conduct a quantile regression to estimate the impacts of discount at the lower quartile, median, and upper quartile of sales. Because the concern lies in merchants self-selecting into offering different levels of discount, we focus exclusively on between-merchant differences. In particular, we regress the final sales of the deals on the discounts offered using a cross-section of the 19,978 deals without the time-varying covariates such as lagged cumulative sales. Because of the change in specification, some of the independent variables in the panel model do not apply. Please refer to footnote 16 in the main text for the details.

We perform simultaneous-quantile regression, which allows us to test the equality of the coefficients at the different quartiles. Table A.7, columns (1)–(3), reports the lower quartile, median, and upper quartile regressions. The discount effect is negative and statistically significant among merchants in the median and upper quartile of sales ($p < 0.01$), but it is statistically insignificant among the lower-quartile merchants. This negative discount effect is not statistically different among the median and upper-quartile merchants ($F = 0.17$, $p = 0.68$). Because the discount effect is weakest in the lower quartile and not different between the median and upper quartile, the quantile regression result does not support the competing explanation that merchants self-select to offer discounts by their expected sales levels.

To ensure that our result is robust in the panel data, we repeat the quantile regression using the whole panel specification in equation (1). The results are reported in Table A.7, columns (4)–(6). Once again, the result does not support the merchant self-selection explanation. Despite the consistent evidence, we caution that this regression does not strictly separate the merchants into the different quartiles because there are many observations for each merchant (due to the inclusion of multiple time periods).

Furthermore, we follow the approach proposed by Garen (1984) to examine the potential selectivity bias in our treatment variable, *discount*. We follow the procedures in Wooldridge (2015), using bootstrapping to obtain valid standard errors. We set the number of repetitions to 1,000. In principle, this analysis is akin to an extended two-stage least squares regression. In the first-stage, we use average hourly wage (AHW) and housing price index (HPI) as the excluded instruments. In addition to the endogenous variable, *discount*, the residuals from the first-stage regression and its interaction with *discount* are added to the second-stage regression. In this framework, a positive coefficient of the interaction effect in the second stage is consistent with the presence of selectivity bias (Wooldridge 2015).

As reported in Table A.7, column (7), the coefficient of the focal interaction, *discount x discount_resid,* is statistically insignificant, which does not support the presence of selectivity bias according to discount. The coefficient of *discount* remains negative and statistically significant. Interestingly, the coefficient of the residuals from the first-stage regression is positive and statistically significant. This implies that deals offering unexpectedly large discounts (after accounting for potentially endogenous discount strategy) did tend to enjoy better sales, possibly because they help consumers save costs.

Table A.7. Results from Quantile Regression and as per Garen (1984)

	(1) Final sales: lower quartile	(2) Final sales: median	(3) Final sales: upper quartile	(4) Panel: lower quartile	(5) Panel: median	(6) Panel: upper quartile	(7) Garen (1984)
price	-0.6960***	-0.6883***	-0.6953***	-0.0017***	-0.0013**	-0.0043***	-0.0915***
	(0.0128)	(0.0131)	(0.0182)	(0.0005)	(0.0005)	(0.0006)	(0.0013)
discount	-0.0505	-0.2451***	-0.2350***	-0.0043***	-0.0000	-0.0091***	-1.1415***
	(0.0485)	(0.0318)	(0.0166)	(0.0008)	(0.0011)	(0.0016)	(0.0144)
discount_resid	--	--	--	--	--	--	1.1401***
							(0.0143)
discount_resid x discount	--	--	--	--	--	--	-0.0008
							(0.0009)
lag cumulative sales	--	--	--	0.0138***	0.0187***	0.0359***	0.1120***
				(0.0002)	(0.0002)	(0.0003)	(0.0005)
days before expiration	0.2036***	0.2374***	0.3050***	0.0078***	0.0082***	0.0147***	-0.0124***
	(0.0271)	(0.0251)	(0.0288)	(0.0006)	(0.0006)	(0.0008)	(0.0013)
merchant-created deal	0.1398*	0.1560**	0.3447***	0.0129***	0.0190***	0.0358***	0.0582***
	(0.0821)	(0.0756)	(0.0896)	(0.0019)	(0.0015)	(0.0035)	(0.0047)
facebook fans	0.0475***	0.0504***	0.0445***	0.0013***	0.0015***	0.0024***	0.0078***
	(0.0043)	(0.0027)	(0.0027)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
has review quotes	0.3412***	0.4782***	0.4218***	0.0111***	0.0135***	0.0283***	0.0534***
	(0.0852)	(0.1073)	(0.0635)	(0.0021)	(0.0020)	(0.0039)	(0.0056)
sold out finally	1.7125***	1.3789***	1.1193***	0.0500***	0.1069***	1.0085***	0.2843***
	(0.0759)	(0.0745)	(0.0501)	(0.0016)	(0.0041)	(0.0112)	(0.0058)
duration	0.8152***	0.7148***	0.5857***	-0.0500***	-0.0630***	-0.1009***	-0.2499***
	(0.0446)	(0.0353)	(0.0376)	(0.0011)	(0.0011)	(0.0017)	(0.0025)
options	-0.3728***	-0.3976***	-0.2799***	-0.0030***	-0.0021***	-0.0078***	0.0148***
	(0.0265)	(0.0284)	(0.0218)	(0.0007)	(0.0004)	(0.0008)	(0.0014)
competing deals	-0.0477***	-0.0563***	-0.0687***	-0.0022**	-0.0040***	-0.0107***	-0.0175***
	(0.0158)	(0.0155)	(0.0159)	(0.0010)	(0.0008)	(0.0012)	(0.0019)
maximum purchases allowed	0.0546**	0.0159	0.0064	-0.0014***	-0.0011***	-0.0003	-0.0054***
	(0.0213)	(0.0152)	(0.0162)	(0.0004)	(0.0004)	(0.0004)	(0.0008)
use-restriction proxy	0.0484	0.0365**	0.0306*	0.0016**	-0.0005	-0.0011***	-0.0187***
	(0.0335)	(0.0159)	(0.0157)	(0.0006)	(0.0003)	(0.0004)	(0.0010)
online deal	-0.2434	-0.3490	-0.3235	-0.0221***	-0.0492***	-0.0385***	0.2630***
	(0.2842)	(0.3771)	(0.1980)	(0.0076)	(0.0119)	(0.0073)	(0.0132)
multi-region deal	0.0438	0.0806**	0.1226***	0.0059***	0.0011	-0.0021***	-0.0048***
	(0.0273)	(0.0329)	(0.0415)	(0.0006)	(0.0007)	(0.0008)	(0.0016)
deal frequency	-0.1041**	-0.1225**	-0.1078	-0.0064***	-0.0034***	-0.0009	-0.0167***
	(0.0417)	(0.0507)	(0.0674)	(0.0013)	(0.0011)	(0.0018)	(0.0023)
Holiday percentage	0.0939	0.0625	0.0684	--	--	--	--
	(0.0643)	(0.0488)	(0.0515)				
division fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
subcategory fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
time fixed effects	No	No	No	Yes	Yes	Yes	Yes
Observations	19,978	19,978	19,978	1,835,794	1,835,794	1,835,794	1,704,202
R-squared	n.a.	n.a.	n.a.	--	--	--	0.066

Notes. Standard errors in parentheses. **** p<0.01, ** p<0.05, * p<0.1.*

CLASSIFICATION OF CREDENCE GOODS (SECTION 4.4)

Table A.1 in this Appendix presents the list of credence and experience goods. We verified our classification of credence goods in two ways. First, we recruited five PhD students and provided them with the following definition of credence goods:

> *A credence good is defined as a good whose utility is difficult or impossible for consumers to ascertain even after consumption. Common examples of credence goods include expert services such as medical or legal consultations, as well as repair services provided by auto mechanics and appliance service persons. In these services, the service providers often serve as "experts" who determine how much treatment or repair the clients need, and they have incentives to "overtreat" the clients. For example, brake shoes changed prematurely work just as if the shoes replaced had really been faulty; so does the patient with his appendix removed unnecessarily (Emons 1997, page 107). Organic food is also an example of credence good because consumers cannot ascertain whether the food is really produced organically (Dulleck et al. 2011, page 527).*
>
> *Credence good is often contrasted against experience good whose utility can be ascertained after consumption (Nelson 1970). For example, people can immediately know the quality or value of a dish/movie after consuming or experiencing it.*
>
> References:
> Dulleck, Uwe, Rudolf Kerschbamer, and Matthias Sutter. 2011. The Economics of Credence Goods: An Experiment on the Role of Liability, Verifiability, Reputation, and Competition. *The American Economic Review*, 101(2), pp. 526-555.
>
> Emons, Winand. 1997. Credence Goods and Fraudulent Experts. *The RAND Journal of Economics*, 28(1), pp. 107-119.
>
> Nelson, Philip. 1970. Information and Consumer Behavior. *Journal of Political Economy*, 78(2), pp. 311-329.

We then asked each of the five PhD students to rate, on a scale of 1 to 7 (1 = *least likely* and 7 = *most likely*), the extent to which each of the 245 deal subcategories (see Table A.1) is a credence good. The following example shows the format of the questions:

Category	**Sub-category**	**Scale (Please Circle Your Answer)** Least Likely → Most Likely						
Automotive Services:	Auto Glass Services	1	2	3	4	5	6	7
	Auto Parts & Accessories	1	2	3	4	5	6	7
	Auto Repair	1	2	3	4	5	6	7
	Car & Motorcycle Dealers	1	2	3	4	5	6	7

The average score of the subcategories classified as credence goods is 4.3, whereas the average score of those that we do not classify as credence goods is 2.4. This difference in score, 1.9, is large in view of the fact that the overall average for all 245 subcategories is only 2.6 and the variance is 1.1.

Second, we conducted a similar survey on SurveyMonkey. Due to length concerns, SurveyMonkey does not allow us to launch a survey with 245 questions for all subcategories. Hence, we reorganized the 245 subcategories into 37 groups. Each group contains subcategories that involve similar degrees of quality uncertainty. Furthermore, to avoid confusing subjects with terms such as experience or credence goods, we used a more intuitive introduction in this survey and asked subjects to rate, on a scale of 1 to 7 (1 = *extremely easy* and 7 = *extremely difficult*), the difficulty in assessing the products' quality after consumption. The survey is available at: https://www.surveymonkey.com/r/KHRDZXP.

We collected 50 responses from a random sample of U.S. residents. Among them, seven are invalid because the subjects chose the same answer for all or the majority (> 90%) of the questions. Hence, we discarded these seven responses. The average score of the subcategories that we classify as credence goods is 3.5, whereas the average score of those that we do not classify as credence goods is 2.9. The difference is statistically significant ($t = 6.2$, $p < 0.01$). Once again, the survey result suggests that our classification of credence goods is valid.

We repeated the test in Table 6, column (4), by replacing the *credence* indicator with the average scores obtained from the 43 survey responses. The following table presents the key coefficients of interest:

Variables	DV: hourly sales
price	-0.0103**
	(0.0040)
discount	-0.0240***
	(0.0066)
avgScore × discount	-0.0223
	(0.0199)
lag cumulative sales	0.1070***
	(0.00615)
Observations	1,835,794
R-squared	0.159

The main effect of *avgScore* is collinear with the subcategory fixed effects and hence cannot be separately estimated. Consistent with our empirical strategy, the coefficient of the interaction effect, *avgScore* × *discount*, is negative, but it is not statistically significant ($p = 0.26$). This could be due to the coarse grouping of subcategories in the survey.

ADDITIONAL IDENTIFICATION AND ROBUSTNESS TESTS (SECTIONS 4.5 & 4.6)

Columns (1) and (2) of Table A.8 present the estimation results when the threshold is set to 200 and 400. The results are consistent with those reported in Table 6, column (5), which uses 300 as the threshold. Column (3) reports a robustness test that excludes extreme transaction prices. Column (4) includes linear and quadratic time trends. Column (5) includes day-specific city fixed effects, and column (6) includes day-specific subcategory fixed effects. Column (7) clusters the standard errors by deal instead of product subcategory. All of these tests produce the same conclusion, that discount has a negative impact on online daily-deal sales.

Moreover, we apply the GMM framework to test for the presence of autocorrelation in our data (Arellano and Bond 1991; Zhang and Liu 2012). We estimate a first-difference model with hourly sales as the dependent variable and include one lag of the DV as a regressor. The first difference removes all time-invariant attributes, which is also why we cannot use the GMM model to identify the discount effect. We then test the null hypothesis of no serially correlated errors by checking whether there are second-order serial correlations in the residuals of the first-difference equation. Note that first-order serial correlations in the first-difference equation are expected by design (Arellano and Bond 1991; Zhang and Liu 2012). From this dynamic GMM estimation, we find no statistically significant second-order serial correlations of the residuals (z = -0.297, p = 0.766).

Table A.8. Additional Identification and Robustness Tests

	(1) Deal popularity; threshold= 200	(2) Deal popularity; threshold= 400	(3) Excluding transaction price outliers	(4) Add linear and quadratic time trend	(5) Add day--division fixed effects	(6) Add day--subcategory fixed effects	(7) Standard errors clustered by deal
price	-0.0186***	-0.0137***	-0.0374***	0.0161***	-0.0110***	-0.0080*	-0.0103***
	(0.0030)	(0.0034)	(0.0076)	(0.0046)	(0.0034)	(0.0043)	(0.0025)
discount	-0.0191**	-0.0227***	-0.0305***	-0.0154***	-0.0210***	-0.0172**	-0.0195***
	(0.0095)	(0.0085)	(0.0116)	(0.0039)	(0.0080)	(0.0084)	(0.0048)
salesAboveThreshold	0.3540***	0.3408***	--	--	--	--	--
	(0.0239)	(0.0320)					
salesAboveThreshold	0.0234**	0.0602***	--	--	--	--	--
× discount	(0.0102)	(0.0180)					
lag cumulative sales	0.0685***	0.0883***	0.1055***	0.1472***	0.1078***	0.1070***	0.1071***
	(0.0042)	(0.0051)	(0.0072)	(0.0093)	(0.0057)	(0.0074)	(0.0014)
days before	0.0281***	0.0297***	0.0356***	0.0234***	0.0340***	0.0354***	0.0330***
expiration	(0.0045)	(0.0048)	(0.0060)	(0.0052)	(0.0051)	(0.0060)	(0.0030)
merchant-created	0.0600***	0.0599***	0.0906***	0.0632***	0.0670***	0.0771***	0.0702***
deal	(0.0191)	(0.0202)	(0.0258)	(0.0180)	(0.0197)	(0.0185)	(0.0134)
facebook fans	0.0043***	0.0046***	0.0048***	0.0034***	0.0054***	0.0045***	0.0049***

	(0.0007)	(0.0008)	(0.0012)	(0.0008)	(0.0008)	(0.0008)	(0.0005)
has review quotes	0.0282*	0.0387**	0.0463*	0.0333**	0.0450***	0.0511***	0.0448***
	(0.0153)	(0.0155)	(0.0241)	(0.0153)	(0.0170)	(0.0191)	(0.0143)
sold out finally	0.1779***	0.1948***	0.2246***	0.1782***	0.2259***	0.2102***	0.2247***
	(0.0246)	(0.0277)	(0.0417)	(0.0303)	(0.0228)	(0.0318)	(0.0149)
duration	-0.2422***	-0.2337***	-0.2329***	-0.0687***	-0.2404***	-0.2258***	-0.2382***
	(0.0277)	(0.0272)	(0.0383)	(0.0235)	(0.0254)	(0.0279)	(0.0134)
options	-0.0176***	-0.0186***	-0.0184***	-0.0055	-0.0192***	-0.0174***	-0.0169***
	(0.0047)	(0.0049)	(0.0064)	(0.0053)	(0.0055)	(0.0061)	(0.0037)
competing deals	-0.0208***	-0.0208***	-0.0272***	-0.0135**	-0.0227***	-0.0224***	-0.0214***
	(0.0050)	(0.0049)	(0.0080)	(0.0053)	(0.0058)	(0.0064)	(0.0043)
maximum purchases	0.0016	0.0009	-0.0037	0.0015	0.0009	0.0007	0.0005
allowed	(0.0033)	(0.0037)	(0.0051)	(0.0035)	(0.0040)	(0.0035)	(0.0021)
use-restriction proxy	0.0027	0.0028	0.0053	-0.0002	0.0020	-0.0010	0.0017
	(0.0026)	(0.0028)	(0.0033)	(0.0032)	(0.0030)	(0.0031)	(0.0026)
online deal	-0.0428	-0.0417	-0.0795*	-0.0205	-0.0435	-0.0412	-0.0404
	(0.0473)	(0.0494)	(0.0466)	(0.0571)	(0.0545)	(0.0528)	(0.0413)
multiregional deal	0.0093	0.0081	0.0121	0.0076	0.0120	0.0144*	0.0105**
	(0.0069)	(0.0073)	(0.0111)	(0.0069)	(0.0084)	(0.0085)	(0.0045)
deal frequency	-0.0016	-0.0024	-0.0072	-0.0032	-0.0074	-0.0014	-0.0084
	(0.0077)	(0.0082)	(0.0105)	(0.0076)	(0.0091)	(0.0086)	(0.0068)
division fixed effects	Yes	Yes	Yes	Yes	No	Yes	Yes
subcategory fixed effects	Yes	Yes	Yes	Yes	Yes	No	Yes
hour fixed effects	Yes	Yes	Yes	Yes	No	No	Yes
day-division fixed effects	No	No	No	No	Yes	No	No
day-subcategory fixed effects	No	No	No	No	No	Yes	No
linear time trend	No	No	No	Yes	No	No	No
quadratic time trend	No	No	No	Yes	No	No	No
Observations	1,835,794	1,835,794	1,169,609	1,835,794	1,835,794	1,835,794	1,835,794
R-squared	0.172	0.166	0.1582	0.1827	0.1322	0.1373	0.1586

Notes. The dependent variable is log hourly sales. Robust standard errors clustered by product subcategory or deals in parentheses. **** p<0.01, ** p<0.05, * p<0.1.*

PROPENSITY SCORE MATCHING (PSM) RESULTS (SECTION 4.6)

We apply PSM to identify a sample of control deals without third-party reviews that match with the "treated" deals with third-party reviews. The first step is to use a Probit model to estimate the propensity of disclosing third-party reviews for all 19,978 deals in the sample. We use all available deal characteristics, including *transaction price*, *discount percentage*, *days before expiration*, *merchant-created deal*, *Facebook fans*, *has review quotes*, *sold out finally*, *duration*, *number of options*, *number of competing deals*, *holiday percentage*, *maximum purchases allowed*, *use-restriction proxy*, *online deal*, *multiregional deal*, *deal frequency*, *city*, and *subcategory* in the Probit model.

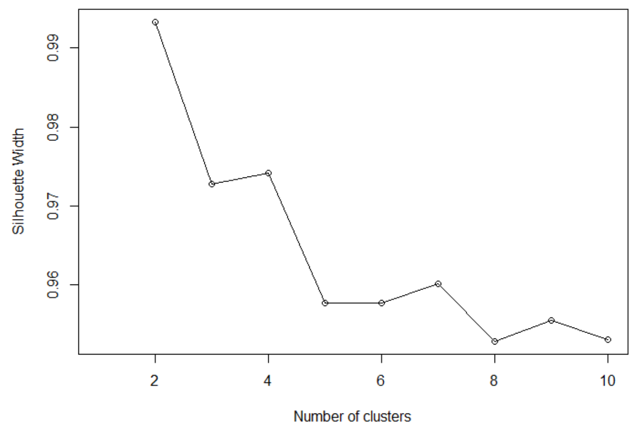
We use the one-to-one nearest neighbor without replacement matching method. In our setting, if no caliper (i.e., the maximum permitted difference between matched subjects) is set, the matched sample is quite unbalanced in the covariate distributions. Therefore, based on trial and error, we use 0.01 as the caliper, which is the largest value that achieves full balance in all covariate distributions. All together, we identify 4,184 pairs of matched deals. All the covariate distributions are balanced between the treated and control groups. Table A.9 shows the *t*-tests of the mean differences between the treated and control groups in all characteristics (except *city* and *subcategory*). After PSM, the two groups are not significantly different.

Table A.9. T-test results for matched and unmatched samples

	Matched Sample				Unmatched Sample			
	Mean		*t*-test (Control – Treated)		Mean		*t*-test (Control – Treated)	
	Control	Treated	*t*	Pr(|*T*| > |*t*|)	Control	Treated	*t*	Pr(|*T*| > |*t*|)
ln*(price)*	3.306	3.318	-0.694	0.488	3.492	3.241	20.792	0.000
ln*(discount)*	3.930	3.940	-1.221	0.222	3.989	3.905	14.000	0.000
ln*(days before expiration)*	5.167	5.156	0.859	0.391	5.130	5.227	-10.281	0.000
merchant-created deal	0.031	0.030	0.318	0.751	0.017	0.031	-5.847	0.000
ln*(Facebook fans)*	3.353	3.277	0.809	0.419	2.444	4.931	-33.986	0.000
has review quotes	0.008	0.010	-0.934	0.350	0.003	0.041	-15.523	0.000
sold out finally	0.027	0.021	1.785	0.074	0.014	0.073	-17.819	0.000
ln*(duration)*	4.487	4.482	0.794	0.427	4.478	4.486	-1.573	0.116
ln*(options)*	0.541	0.552	-1.012	0.312	0.594	0.491	13.727	0.000
ln*(maximum purchases)*	1.113	1.092	1.147	0.252	1.133	1.162	-2.324	0.020
ln*(use restriction)*	5.981	5.976	0.478	0.633	5.934	6.010	-9.417	0.000
online deal	0.008	0.008	-0.125	0.901	0.016	0.007	6.343	0.000
multiregional deal	0.259	0.251	0.828	0.408	0.327	0.309	2.500	0.012
ln*(deal frequency)*	0.067	0.068	-0.225	0.822	0.061	0.066	-1.781	0.075
ln*(competing deals)*	0.987	0.975	0.602	0.547	0.818	1.034	-15.426	0.000
holiday percentage	0.327	0.325	0.510	0.610	0.328	0.332	-1.311	0.190

CLUSTER ANALYSIS BASED ON THIRD-PARTY SUPPORT (SECTION 4.7)

We conduct another cluster analysis using just two variables related to the third-party support: *Facebook fans* and *has review quotes*. Again, we select the number of clusters by comparing the average silhouette value for each $K \in \{2,3,\dots,10\}$. Here again, the highest average silhouette value is obtained when $K = 2$, as shown in the following figure.



This cluster analysis separates the 19,978 deals into two clusters, one including 19,672 deals and the other including only 306 deals. As a matter of fact, the deals are now clustered purely by the *has review quotes* variable. The 306 deals in the second cluster all have review quotes, whereas the 19,672 deals in the first cluster have no review quotes. However, the deals in the first cluster have more Facebook fans (mean = 25.81) than those in the second cluster (mean = 12.64). The difference is statistically significant (t = 3.11, p < 0.01). This implies the cluster analysis reported in Section 4.3 captures other deal differences instead of third-party support per se.

SURVEY ON CONSUMER TRUST OF GROUPON REVIEWS (SECTION 4.6)

In this survey, we explore consumers' trust of the third-party reviews displayed on Groupon's deal pages. Within the Restaurant category, we randomly chose five Groupon deals. Then, we extracted five restaurants with comparable review volumes and ratings from Yelp. We provided the screenshots of these 10 restaurants in the survey and asked respondents to rate, on a 7-point Likert scale, their trust in the review displayed for each restaurant (1 = *lower trust*, 7 = *higher trust*). The following table lists the restaurants used in the survey. The survey is available at: https://www.surveymonkey.com/r/KF3R9SR.

Groupon merchants	**Yelp merchants**
Cavanaugh's Bar and Restaurant (Chicago)	Hogwash (San Francisco)
Benjamin Restaurant and Bar (San Francisco)	The Spice Jar (San Francisco)
Paper Moon (Washington, DC)	Parson's Chicken & Fish (Chicago)
The Park Grill at Le Meridien (San Francisco)	Print (New York)
Aperto (San Francisco)	Taqueria Habanero (Washington, DC)

We administrated this survey along with the familiarity survey reported on page A4, i.e., we also obtained 50 responses from the residents in a large U.S. city via SurveyMonkey. The mean trust score for the reviews displayed on Groupon is 4.7, whereas the mean trust score for the reviews displayed on Yelp is 4.8. The difference is not statistically significant (t = 0.7, p = 0.24). Nevertheless, the direction of the difference is consistent with our expectation.

DETAILS OF THE LAB EXPERIMENT (SECTION 5)

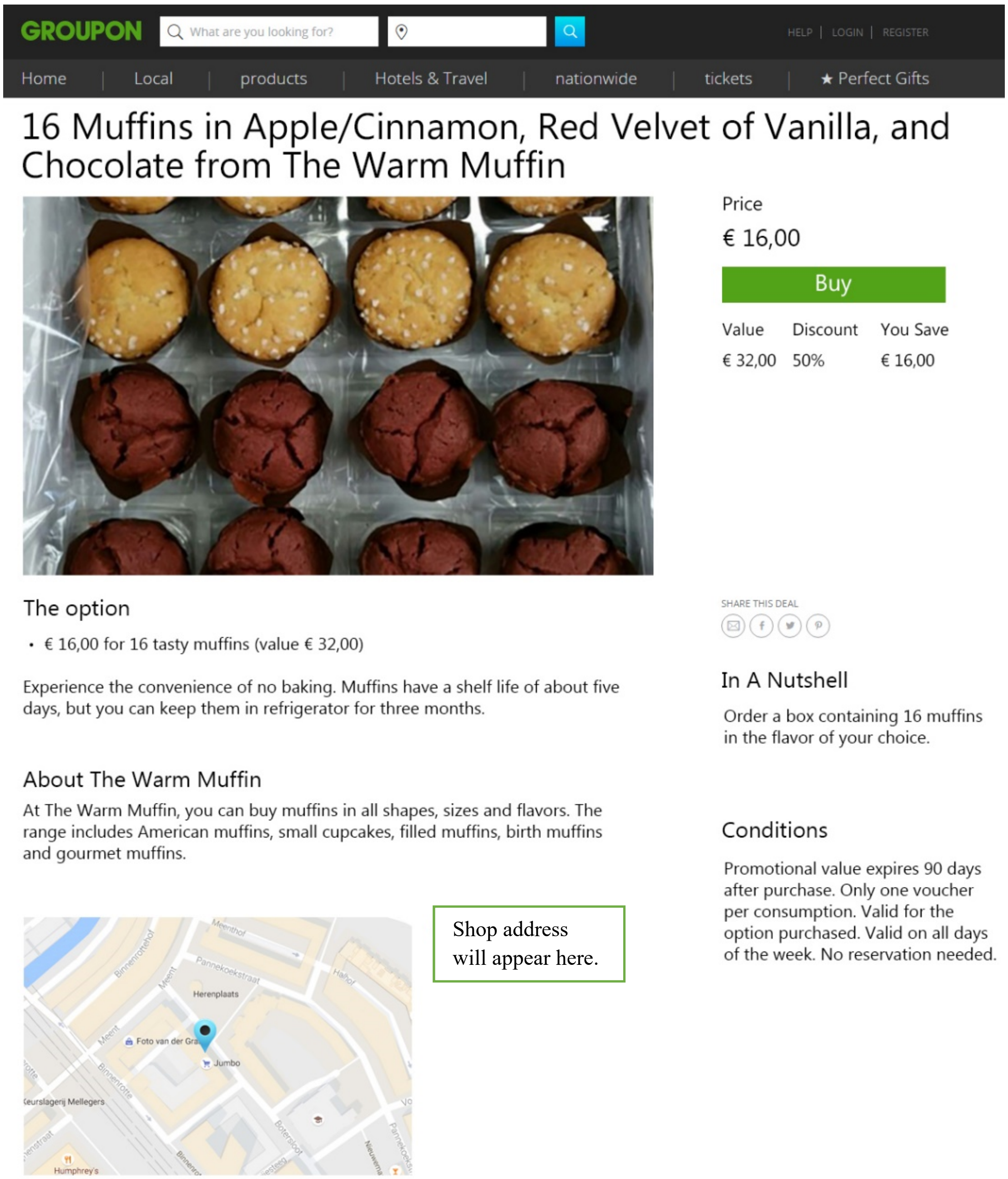
We create the experimental deals based on the distribution of deals in the Groupon data shown in Table 1. We create multiple deals for several categories because they are more often offered on Groupon. For these categories with multiple deals, we create one experimental deal for each of their top subcategories. The following table summarizes the distribution of the 19 deals used in the experiment.

Category	Proportion in Groupon	No. of Deals in experiment	Top subcategories
Automotive	1.36%	1	Car Wash & Detailing
Beauty & Spas	26.18%	3	Massage; Hair Salon; Teeth Whitening
Education	3.46%	1	Art Classes
Entertainment	32.66%	4	Concert; Theater & Plays; Sporting Event; Running Event
Food & Drink	3.1%	1	Cupcakes/Dessert/Bakery
Health & Fitness	9.03%	1	Fitness Classes
Home Services	1.13%	1	Carpet Cleaning
Medical Treatment	2.79%	1	Chiropractic
Nightlife	0.3%	1	Pubs
Pet Services	0.45%	1	Pet Boarding & Sitting
Other Professional Services	3.67%	1	Photography
Restaurants	15.87%	3	American; Italian; Asian
Total	100%	19	

The following picture shows a sample deal page. To enhance realism, we create the deals using information on some (real) existing deals in the corresponding product subcategory. We used some fictitious names for the merchants to avoid any memory effect or bias due to the merchants' names. We also chose the merchant address carefully so that they appear real to the subjects. For example, the merchant in the sample deal page below has an address in a popular shopping mall with many bakery shops. The hypothetical scenario presented to the subjects in this example is:

> *"Suppose you want to buy a box of muffins for snacks, and you find the following deal on Groupon."*

We asked the subjects to answer three questions measuring their perceived quality uncertainty, perceived quality, and willingness to buy (WTB) the deal after evaluating each deal. Following Pavlou et al. (2007) and Dimoka et al. (2012), we using the following single-item scale to measure the subjects' perceived quality uncertainty.



Please choose the extent to which you agree with the following statement: I am uncertain about the overall quality of X shown in the deal. [X is the name of the product featured in the deal. 1 = *strongly disagree*, 7 = *strongly agree*]

Following Peterson and Jolibert (1976) and Kirmani and Wright (1989), we using the following single-item scale to measure the subjects' perceived product quality:

> *Please choose the extent to which you agree with the following statement: The overall quality of X shown in the deal is high.* [X is the name of the product featured in the deal. 1 = *strongly disagree*, 7 = *strongly agree*]

We use the following item to measure the subjects' WTB:

> *How likely will you purchase this deal?* [1 = *extremely unlikely*, 7 = *extremely likely*]

We recruited a total of 217 undergraduate and master's students as subjects from a large European University. We provided either a monetary reward of five Euros or course credit as incentives for participating in the experiment. The following table presents the demographics of the subjects.

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Female (dummy)	217	0.677	0.468	0	1
Age	217	20.853	2.199	18	30
Average monthly shopping frequency online	217	2.343	2.478	0	20
Average monthly shopping frequency on Groupon	217	0.153	0.398	0	2

Figure 3 plots the subjects' responses. Table 10 presents the piecewise regression results. We tested the robustness of the regression results by choosing 50% and 55% as the breakpoint in the regression. Table A.10 reports the results, which are qualitatively the same as those reported in Table 10 in the main text.

Table A.10. Threshold Effect of Discount for Different Breakpoints

	(1) 55%: quality uncertainty	(2) 55%: quality perception	(3) 55%: WTB	(4) 50%: quality uncertainty	(5) 50%: quality perception	(6) 50%: WTB
discount (<60%)	-0.0017	0.0034**	0.0295***	-0.0020	0.0042**	0.0316***
	(0.0018)	(0.0016)	(0.0022)	(0.0020)	(0.0018)	(0.0024)
discount (≥60%)	0.0160***	-0.0122***	0.0020	0.0136***	-0.0106***	0.0041
	(0.0027)	(0.0022)	(0.0031)	(0.0024)	(0.0019)	(0.0028)
deal-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
subject-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
order-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,123	4,123	4,123	4,123	4,123	4,123
R-squared	0.265	0.263	0.311	0.264	0.263	0.311

Notes. All variables are specified in their original values (without taking logs). Robust standard errors clustered by subject in parentheses. *** *p<0.01, ** p<0.05, * p<0.1*.

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