When Discounts Hurt Sales: The Case of Daily-Deal Markets

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Abstract

We investigate whether the discounts offered by online daily deals help attract consumer purchases. By tracking the sales of 19,978 deals on Groupon.com and conducting a battery of identification and falsification tests, we find that deep discounts *reduce* sales. A one-percent increase in a deal's discount decreases sales by 0.035%–0.256%. If a merchant offers 10% more discount from the sample mean of 55.6%, the sales could decrease by 0.63%–4.60%, or 0.80–5.24 units and $42–$275 in revenue. This negative effect of discount is more prominent among credence goods and deals with low sales, and when the deals are offered in cities with higher income and better education. Our findings suggest that consumers are concerned about product quality and excessive discounts may reduce sales immediately. A follow-up lab experiment provides further support to this quality-concern explanation. Furthermore, it suggests the existence of a "threshold" effect: The negative effect on sales is present only when the discount is sufficiently high. Additional empirical analysis shows that deals displaying favorable third-party support, such as Facebook fans and online reviews, are more susceptible to this adverse discount effect. We draw related managerial implications.

Keywords: daily-deal; Groupon; price promotion; quality concern; uncertainty; online markets

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1. Introduction

Online daily-deal platforms, such as Groupon and LivingSocial, have become a prominent price promotion venue (Dholakia 2011). Consumer surveys have shown that 60% of online visitors to the top 40 websites enroll in at least one daily-deal email program (Foresee 2012). One-sixth of Americans aged 12 or above register for at least one daily-deal service (Edison Research 2012). As two-sided markets, daily-deal platforms allow merchants to attract new consumers via discounts (Subramanian and Rao 2016). They also provide consumers with a venue to explore a wide variety of products and services in their regions (Dholakia and Kimes 2011; Wang et al. 2013).

daily-deal platforms charge merchants by performance-based commission, which is appealing to small- and medium-sized local merchants with limited marketing budgets. Instead of paying hefty fees for advertising campaigns, merchants share a fraction of their revenues with the daily-deal platforms carrying their promotions. Daily deals are particularly effective in attracting new customers (Constant Contact 2013). Almost 80% of daily-deal vouchers are sold to first-time customers during or even beyond their seventh promotion (Dholakia 2012).

Most daily deals offer substantial discounts. In general, discounts should appeal to consumers because it helps save costs (Blattberg et al. 1995). However, its effect is not trivial for online daily deals because of the intrinsic uncertainty and risks involved in the setting. The spatial and temporal separation between daily-deal buyers and sellers encompasses significant information asymmetry. Buyers cannot inspect the products before and usually do not consume the products immediately after purchasing the deals (Pavlou et al. 2007; Ghose 2009; Dimoka et al. 2012). Hence, consumers face a high degree of uncertainty and might worry that daily-deal sellers could engage in precontractual quality misrepresentation (adverse selection) or postcontractual quality reduction (moral hazard). This is especially the case for merchants selling vouchers for experience or credence goods, the quality of which is difficult to assess before consumption.

The quality uncertainty is aggravated when most merchants on online daily-deal platforms are small- and medium-sized local merchants who are often less well known and less visible to consumers. When consumers cannot assess product quality because of information asymmetry and when the merchants are not well known, offering discounts may not help promote and sell the products. In fact, discounts, or discounted prices, are often considered a signal of *low* quality (Rao and Monroe 1989; Kirmani and Rao 2000; Erdem et al. 2008).

Perhaps recognizing the concern about product quality, many online daily-deal platforms provide third-party support information as a supplementary quality signal. Such support signals may, however, contradict the price signal if consumers associate discounts with low quality. Prior research suggests that, in the presence of multiple and inconsistent quality signals, a "negativity bias" could anchor consumers to the negative signal (Boulding and Kirmani 1993; Smith and Vogt 1995; Miyazaki et al. 2005). This implies that third-party support may not help the seller if the discount is considered as a negative signal. In fact, it may even arouse suspicion as consumers may wonder why a discount is necessary for such favorably appraised products.

To test the empirical effect of discounts in a setting where information asymmetry is inevitable, we compiled a panel data set from a leading daily-deal platform, Groupon.com, from January 8th to March 31st, 2014. Our data set comprises 19,978 deals covering products and services in a wide range of categories from 172 cities in the United States and Canada. We captured the characteristics of each deal, including the discount offered, and recorded its hourly sales in terms of the number of vouchers sold. Consumers can use the purchased vouchers to redeem the promoted products or services at a later time. Our data set has a total of 1,835,794 observations. We conducted a series of statistical tests to examine whether offering more discounts would help the online daily-deal merchants sell more vouchers.

By estimating a panel-data model with rich fixed effects to account for product characteristics and time trends, and robust standard errors clustered by product subcategories to allow for cross-item and intertemporal demand correlations over time, we find a significant *negative* effect of discount on the number of vouchers sold. A one-percent increase in discount decreases sales by 0.0352% [0.0105%, 0.0600%] per hour.[1] To our knowledge, prior research has not documented such an *immediate* negative effect of discount on sales in a large-scale field setting.

A potential concern in our setting is that the discounts could be endogenous. For example, there could be reverse causality: Merchants with higher sales enjoy better economies of scale and hence could afford to offer bigger discounts to consumers. To strengthen our identification, we conducted two instrumental-variable (IV) estimations using exogenous IVs from multiple sources.

[1] We report the 95% confidence intervals in parentheses throughout the paper.

Furthermore, we conducted a cluster analysis and tested the discount effect on merchants with differing degrees of popularity. We also applied quantile regression and a sample selection model that accommodates a continuous treatment variable (the discount in our case; Garen 1984). We find that the negative effect of discount is robust in all of these estimations, implying merchant self-selection to offering discounts is not a potent explanation of our finding.

Overall, our various estimates using the whole sample suggest that if the merchants on Groupon offer an additional 10% of discount from the sample mean of 55.6%, the sales of the deals could drop by 0.63%–4.60%, or 0.80–5.24 vouchers and \$42–\$275 in revenue. This effect is economically significant as the deals are mostly offered by small businesses. More importantly, the merchants may hope to increase their exposure through these discounted deals by, for example, attracting consumers to their stores to make other purchases in the future. It defeats the merchants' advertising or promotional purposes if the discounts drive consumers away.

We conducted additional tests to explore the nature of this negative discount effect. Specifically, we isolated deals that are not subject to local congestion. We find that the negative discount effect persists among these deals, meaning concerns on consumption congestion cannot explain the finding. We then used three strategies to test whether product-quality concerns are a potent explanation. The first strategy exploits differential quality uncertainty on credence vis-à-vis experience goods (Darby and Karni 1973; Emons 1997; Dulleck and Kerschbamer 2006). The second strategy exploits the recent finding that well-sold deals tend to provide a better quality signal due to observational learning (Li and Wu 2013; Luo et al. 2014; Subramanian and Rao 2016). The third strategy exploits the fact that consumers with higher socioeconomic status (SES) tend to be less price sensitive and more quality sensitive (Tirole 1988; Schaninger 1993; Magnusson et al. 2001). All three tests support the presence of quality concern. The negative effect of discount on online daily-deal sales is more prominent among credence goods, deals with lower sales, and regions with higher SES.

Finally, we investigated whether displaying third-party support—viz. the number of Facebook fans and review quotes, count, and ratings from Yelp, Yahoo! and Google—can help moderate the adverse effect of discount on the sales of deal vouchers. We find that deals with more Facebook fans, positive consumer comments, and higher review counts and ratings are *more vulnerable* to the adverse discount effect. This finding is consistent with the "negativity bias" theory (Boulding and Kirmani 1993; Smith and Vogt 1995; Miyazaki et al. 2005). When consumers face two inconsistent quality cues—viz. the discount and favorable online third-party support—they tend to rely on the negative cue in evaluating quality. Hence, the negative discount effect prevails.

To corroborate the empirical analysis, we conducted a lab experiment to directly test whether quality concern underlies the negative discount effect. We systematically manipulated the discounts in a set of realistic deals and measured the subjects' uncertainty on the quality of the promoted items. We find strong support for the quality-concern explanation. More importantly, the experimental results reveal an interesting threshold effect. The negative discount effect surfaces only when the discount exceeds a certain threshold.

Our paper offers four important contributions. First, we present empirical evidence that discounts can hurt sales and drive consumers away in an online setting where consumers are not familiar with the merchants and cannot appraise the quality of the products before purchasing. Second, we pin down quality concern as one driving force of this negative effect by presenting triangulated evidence from both empirical analysis of large-scale field data and a tightly controlled lab experiment. We are thus among the first to rigorously demonstrate that the quality-signaling effect of discount can dominate its cost-saving benefit to consumers in an online setting featuring insurmountable information asymmetry. Third, we show that displaying favorable third-party support can backfire when the discount is steep. Fourth, we uncover a novel threshold effect; the discount negatively affects sales only when it exceeds a certain threshold. We provide concrete guidance to merchants on how to design better deals to attract more purchases through discounts and to platform owners on how they can improve the daily-deal business model.

The remainder of this paper is organized as follows. Section 2 surveys the related literature. Section 3 describes the research setting. Section 4 presents the empirical model and estimation results. Section 5 presents the lab experiment and the related analysis. Section 6 discusses the implications of this research and concludes the paper.

2. Related Literature

This research is closely related to the literature on quality uncertainty and signaling in online commerce. Consumers are often concerned about product quality in online transactions because of the intrinsic prevalence of information asymmetry between sellers and buyers. There could be adverse selection, where low-quality sellers tend to join the market, and moral hazard, where sellers could reduce product quality after consumers have purchased their items (Dewan and Hsu 2004; Jin and Kato 2006; Pavlou et al. 2007; Ghose 2009; Dimoka et al. 2012). Because of product-quality concerns, consumers may use electronic channels only when uncertainty is low (Overby and Jap 2009) or when buying low-value items (Kim and Krishnan 2015).

Prior research has proposed several solutions to address the quality concerns in online transactions. One solution is to offer promotions to acquire early customers, who may provide informative quality signals to help attract other consumers. Theoretical analysis suggests that the group buying strategy with discounted pricing can achieve such quality signaling because of social interaction and observational learning (Jing and Xie 2011; Hu et al. 2013; Subramanian and Rao 2016). This strategy is particularly attractive to patient and relatively unknown firms (Shivendu and Zhang 2013; Edelman et al. 2014). Empirical research has found supportive evidence to this strategy. Group buying or daily-deal websites can facilitate product sales by displaying information on deal popularity or social influence (Li and Wu 2013; Luo et al. 2014; Wu et al. 2015).

Another common solution to addressing quality concern in online markets is to display third-party reviews. In particular, positive online word of mouth (WOM) or user reviews can help increase sales (Liu 2006; Dellarocas et al. 2007; Chintagunta et al. 2010), but negative reviews may decrease sales (Chevalier and Mayzlin 2006; Chen et al. 2011). The effect of third-party reviews on sales is moderated by contextual cues, such as reviewers' identity, buyers' Internet experience, or sellers' brands (Forman et al. 2008; Zhu and Zhang 2010; Ho-Dac et al. 2013). More importantly, online third-party reviews need not be credible because of reviewer self-selection, that early buyers tend to like the product more than other people, or strategic manipulation by sellers (Dellarocas 2006; Jin and Kato 2006; Mayzlin 2006; Li and Hitt 2008; Mayzlin et al. 2014).

Neither of these streams of research considers the direct impact of discounted pricing, which is commonly used by online daily-deal merchants to attract consumers. Ample experimental evidence has shown that price is positively related to perceived quality (Rao and Monroe 1989). Consumers may not have enough cognitive resources to evaluate all product attributes. Hence, they may simply adopt a price–quality heuristic in appraising and choosing products (Rao 2005). The information-economics literature also suggests that it is rational for consumers to associate price with quality because only high quality firms could afford to use high prices as quality signals (Kirmani and Rao 2000; Rao 2005).

Prior research suggests that such quality signaling effect of price is robust in different market structures (see, e.g., Wolinsky 1983; Bagwell and Riordan 1991; Daughety and Reinganum 2008). If consumers indeed use price as a quality signal, then the steep discounts offered by online daily deals do not necessarily help merchants draw early customers, who may be instrumental in helping merchants build positive quality signals to attract future consumers. Furthermore, the negative signal carried by discounted pricing may contradict the positive signal embodied in favorable third-party reviews. The extant literature does not consider the nuanced signaling effect of discounted pricing when analyzing other quality-signaling mechanisms in online markets.

A related stream of work has considered how seller attributes, such as brand or website quality, affect consumers' product perceptions (Rao et al. 1999; Keller and Lehmann 2006; Wells et al. 2011; Ho-Dac et al. 2013). In general, with asymmetric information, consumers use a wide variety of marketing-mix variables to infer product quality (Kirmani and Rao 2000). This study focuses on the online daily-deal setting where the brand effect is less salient because most merchants are relatively unknown to consumers. Moreover, all merchants in this study offer their promotions on a common online daily-deal platform, making their websites less relevant. Practically, unlike many online shops that promote search products, most online daily deals feature experience or credence goods, the quality of which cannot be easily inferred by marketing-mix variables.

More broadly, this research is related to the vast price-promotion literature (Blattberg et al. 1995). Frequent price promotions may negatively affect brand sales in the long run as consumers adjust their reference prices (Lattin and Bucklin 1989), become more sensitive to price and promotions (Mela et al. 1997), stockpile products (Mela et al. 1998), or form a poorer perception of the brand over time (Jedidi et al. 1999; Erdem et al. 2008). Our setting departs from these studies in that most buyers of online daily deals are first-time customers (Dholakia 2012). Hence, we study the *immediate* effect of price promotion before these long-run mechanisms kick in.

To conclude, recent research has analyzed the merits of novel quality-signaling mechanisms such as group buying and third-party reviews in online markets. However, the prior literature is relatively silent on how these mechanisms interact with discounted pricing, which itself may serve as a salient quality signal about the promoted items. This research tests the net impact of discount on sales with triangulated evidence in the online daily-deal setting.

3. The Setting

Since the daily-deal business model was introduced in 2004, more than 100 daily-deal websites have emerged worldwide. Among them, Groupon has the highest exposure and commands considerable pricing power against its merchants (Dholakia and Kimes 2011; Zhang and Chung 2016). It offers an affordable means for small- and medium-sized local merchants to offer price promotions to a large customer base. These promotions are carried in the form of vouchers sold at discounted prices. The vouchers can then be redeemed for specific products or services later.

Groupon hosts many deals in multiple categories. It uses a dedicated page to describe each deal and the deal's merchant. The deals typically last for several days (the median lifespan of a deal is 96 hours, 4 days, in our data set). Figure A.1 in the Online Appendix shows an example of a deal on Groupon.com. We collected the data on 19,992 completed deals from Groupon.com from 8 January to 31 March 2014. Specifically, we scraped the attributes for each deal including its original and transaction prices (*price*), discount percentage (*discount*), number of days until the voucher expires after purchase (*days before expiration*), maximum quantity allowed for purchase per session (*maximum purchases allowed*), number of purchase options (*options*), terms of use as specified by the merchants under the "fine prints" section and, if available, number of Facebook fans (*facebook fans*), quotes of reviews from third-party websites including Yelp, Yahoo!, and Google (*has review quotes*), and the volume and valence (measured by average rating) of these reviews (*review count* and *average rating*). Note that the third-party support—i.e., Facebook fans, online reviews, etc.—is provided by the merchant *before* releasing its deals and *remains fixed* during the deal's lifespan. As is evident from its Terms of Sale, Groupon does not verify this merchant-supplied information. Hence, the merchants always select positive reviews and comments to display on their pages.

For every deal in our data set, we recorded the number of vouchers sold ("sales") in an hourly interval using the Groupon Application Programming Interface (API). We obtained two additional pieces of data through this API: (i) whether the deal's webpage was created by Groupon or the merchant itself using Groupon's deal-building tool (*merchant-created deal*)[2] and (ii) whether a deal was sold out before the end of its preset duration (*sold out finally*). This variable indicates whether

[2] Details about the Groupon API and Build-Your-Own-Deal tool are available at `http://www.groupon.com/pages/api` and `http://investor.groupon.com/releasedetail.cfm?releaseid=824464` (accessed 7 March 2017).

the merchant has set a limit on the supply of the product.

Note that the Groupon API truncates the displayed sales. When the number of vouchers sold lies between 10 and 1,000, it rounds the number down to the nearest multiples of 10. For example, 89 is reported as 80 and 101 is reported as 100. Moreover, when the number of vouchers sold exceeds 1,000, it will not update the sales again until the sales reaches 5,000. The first type of truncation should have little impact on our estimation because it applies to the whole data set and so the noises should cancel each other out. To address the second type of truncation, we exclude 14 deals with sales exceeding 1,000. Hence, the final data set contains 19,978 deals.

Groupon organized the deals into 12 categories: Automotive services, beauty and spas, education, entertainment, food and drinks, health and fitness, medical treatments, home services, nightlife and bars, pet services, restaurants, and other professional services. Each category further contains multiple subcategories. Table 1 presents the number and percentage of deals in each category. The top three categories are entertainment, beauty and spas, and restaurants. Our data set covers 152 U.S. and 20 Canadian markets defined at the *city* or equivalent level. For the deals in Canada, we converted the prices from Canadian dollar to U.S. dollar using the exchange rate on 6 May 2014. We present the complete list of subcategories and the 172 U.S. and Canadian markets in the Online Appendix.

** Table 1. Deal Distribution **

We conducted a survey to check consumers' familiarity with Groupon merchants. We randomly selected five Groupon deals offered by local merchants in a big U.S. city within the Automotive and Food and Drinks categories from our sample. We randomly selected another five brands offering similar products in Amazon.com. We asked 50 subjects to rate their familiarity with each of these 10 merchants on a 7-point Likert scale (1 = *less familiar*, 7 = *more familiar*). The results show that consumers are less familiar with the Groupon merchants. The mean familiarity for the Groupon and Amazon merchants are 2.0 and 4.5. The difference is statistically significant ($t = 13.6$, $p < 0.01$). Indeed, Groupon tends to attract lesser-known local merchants (Shivendu and Zhang 2013; Edelman et al. 2014). We report the details of this survey in the Online Appendix.

To help identify the impact of discounts on sales, we compiled median household income (*income*) and the percentage of population aged 25 or above with at least a bachelor degree (*education*) from the 2010 U.S. Census. For IV estimation, we obtained national monthly industry-specific occupational hourly wage estimates for Q1 2014 from Bureau of Labor Statistics' *Current Employment Statistics* (CES). We matched each Groupon subcategory to one industry code in CES.[3] The average hourly wage (AHW) serves as a proxy for the merchants' labor costs. We also obtained the U.S. monthly housing price index (HPI) in nine census divisions (Pacific, Mountain, West North Central, West South Central, East North Central, East South Central, New England, Middle Atlantic, and South Atlantic) in Q1 2014 from the Federal Housing Finance Agency. We matched the deals to HPI based on their starting dates and the merchants' locations. HPI serves as a proxy for the merchants' rental costs.

Tables 2 and 3 present the summary statistics and correlations of the variables. Figure 1 plots the distribution of discounts. The mode discount is 50% in our data set. Most merchants offered at least 30% discount. The fifth percentile is 38.86%.

** Table 2. Summary Statistics **

** Table 3. Correlations **

** Figure 1. Distribution of Discount Percentage **

Figure 2 plots the average hourly sales of deals with different discounts. Panel (a) plots the sales in the 30th, 40th, 50th, and 60th percentiles of time in each deal's lifespan. Panel (b) plots the total sales after the deals have ended. The fitted trends have clear downward slopes, meaning the sales of the vouchers decreased with discount percentage. Figure 2 provides a model-free overview of how sales change with the discounts.[4]

** Figure 2. Deal Sales and Discount Percentage **

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[3] The CES uses the North American Industry Classification System (NAICS). One industry code in CES can match with multiple Groupon subcategories. For more details on the use of NAICS in CES, see `http://www.bls.gov/bls/naics.htm` (accessed 7 March 2017).

[4] In both panels, we exclude deals with discounts below the fifth percentile due to the limited number of observations. In Panel (b), we also exclude short and long deals—deals with lifespans below the 20th percentile or above the 80th percentile—to avoid potential confounds due to extremity in deal exposure.

4. Empirical Model and Results

Our analysis proceeds as follows. First, we establish the causal impact of discount on sales of the Groupon vouchers by exploiting the wide variation of discounts offered by the deals in our sample. We strengthen our identification using multiple IV estimators. We further conduct a cluster analysis and several validation tests to rule out alternative explanations concerning merchant self-selection to offer discounts. Second, we use multiple empirical strategies to rule out consumers' concern on local congestion in using the vouchers as one candidate explanation of the discount impact. Instead, we pin down quality concern as one plausible explanation of our finding. Third, we test whether the presence of third-party support—the number of Facebook fans and other online reviews—moderates the discount impact. We then present the evidence from a lab experiment corroborating the findings from the empirical analysis of the Groupon data.

Our first analysis uses the following panel fixed-effects model that accounts for other factors such as price, deal characteristics, and time trends.

$$\ln(S_{ijt}) = \beta_1 \ln(discount_{ij}) + \beta_2 \ln(price_{ij}) + \beta_3 \ln(CS_{ij,t-1}) + \alpha X_{ij} + \gamma_j + \tau_t + \epsilon_{ijt}, \qquad (1)$$

where S_{ijt} denotes the sales of deal i in city j in hour t; $discount_{ij}$ denotes the discount percentage offered by deal i, which does not vary over time; $price_{ij}$ denotes deal i's final transaction (discounted) price; $CS_{ij,t-1}$ denotes deal i's cumulative sales up to hour $t-1$, X_{ij} is a set of characteristic variables of deal i; γ_j captures city-specific effects; τ_t captures hour-specific effects; ϵ_{ijt} captures idiosyncratic random errors. We specify all nonindex continuous variables in logarithms. As appropriate, we add one to the variables to avoid logarithm of zero.

X_{ij} includes all the deal characteristics scraped from Groupon as discussed in Section 3. In addition, we include each deal's duration (*duration*). As a proxy variable for the restrictions imposed on the deals (*use-restriction proxy*), we count the number of characters in the fine print. To account for usage costs, we construct a dummy variable (*online deal*) to flag deals with titles containing either "online deal" or "redeem at home", which do not require customers to visit the merchants' physical stores for consumption.

Furthermore, merchants that promote in multiple markets probably enjoy better brand awareness. We include a dummy variable that indicates whether a deal's merchant operates in multiple geographical markets (*multiregion deal*). Frequency of promotion may also affect consumers' reference prices (Lattin and Bucklin 1989) or price sensitivity (Mela et al. 1997). Therefore, we include a merchant's frequency of promoting on Groupon in our data window (*deal frequency*).

Finally, to account for competition within the same geographical market, we include the number of simultaneously active deals in the same subcategory in the same city (*competing deals*). We also include subcategory fixed effects in X_{ij} to account for categorical differences in sales between different product types. As specified in equation (1), our analysis focuses on explaining the differences in sales of the deal vouchers within a local market and product subcategory, and from hourly averages. We cluster the standard errors by product subcategories to allow for demand correlations across deals in the same subcategories over time.

4.1. Results

Table 2 shows that only a subset of deals have third-party reviews. We first fit equation (1) to all deals by excluding review count and average rating from X_{ij}. As reported in Table 4, column (1), the estimates are consistent with our expectation. Price is negatively correlated with sales. The cumulative sales up to the hour before, which captures unobserved noises such as deal quality, social influence or diffusion, is positively correlated with sales (Jing and Xie 2011; Hu et al. 2013; Luo et al. 2014; Subramanian and Rao 2016). More Facebook fans and displaying positive review quotes increase sales (Li and Wu 2013). By contrast, the number of competing deals negatively affects the focal deal's sales. These estimates provide face validity that our empirical model captures the key considerations in online daily-deal sales.

** Table 4. Estimation Results **

Importantly, the coefficient of *discount*, -0.0195, is negative and precisely estimated ($p < 0.01$). With the double-log specification, the elasticity is -0.0352.[5] Accordingly, a 1% increase in a deal's discount decreases its hourly sales of deal vouchers by 0.0352%. In our data set, the mean discount offered is 55.6%. Hence, our estimate implies that increasing the discount by 10% from 55.6% could have reduced hourly sales by $10 \div 55.6 \times 0.0352 \times 100\% = 0.63\%$ $[0.19, 1.08]$. This is equivalent to a decrease in overall sales of 0.80 voucher and \$42 in revenue.

[5] We correct for the "1" added to the dependent variable in all calculations of elasticities.

Next, we consider deals with third-party reviews by including the review count, average rating, and their interaction.[6] As shown in Table 4, column (2), the sample size decreases by about two-thirds. Review count increases the deals' sales, but average rating does not have a significant impact on sales. The coefficient of discount, -0.0295, remains negative and statistically significant. This estimate implies that increasing the discount by 10% from 55.6% could have reduced hourly sales by 0.96% $[0.26, 1.66]$, or 1.22 vouchers and $64 in revenue in total.

We repeat the estimation in each of the three major product categories: entertainment, beauty and spas, and restaurants. As shown in Table 4, columns (3)–(5), the effect of discount is always negative, and it is statistically significant in two of the three categories. In view of the robust findings in the subsample estimates in Table 4, columns (2)–(5), we prefer the estimate obtained using the whole sample of all 12 categories in Table 4, column (1). The reason is that discount is a well-understood measure of price promotion that delivers a clear message: the merchants' willingness to offer price saving, regardless of the original price or product type. We do not have any a priori reason to isolate or omit any particular product categories. Statistically, our model includes many deal characteristics and subcategory fixed effects, which helps control for the heterogeneity in the deals and product categories. Pooling all deals in the estimation should enhance statistical power without confounding the effect of the discounts.

4.2. Identification

An obvious concern with the estimation above is that the discounts could be endogenous. The online daily-deal merchants might devise discount strategies based on projected consumer demand. A higher volume of sales may reduce the merchants' cost margins due to economies of scale, leading them to offer more discounts in the long run. Unobserved merchant or deal characteristics may also correlate with discount percentage and lead to biased estimates.

We use two IV estimators to strengthen the identification. The first uses the characteristics of competing products in a differentiated product market as instruments (Berry 1994; Berry et al. 1995; Nevo 2000; Berry and Haile 2014). For each focal deal, the competitors comprise other active deals in the same category offered by merchants located in the same city. The intuition follows standard oligopoly pricing models: A product will likely have a low markup above the cost and

[6] We mean-center the continuous variables when estimating the interaction effects.

hence low price (high discount) if it faces good substitutes (Berry 1994; Berry et al. 1995). As this IV estimator requires consumers to see competing deals as substitutes, we apply it separately to the restaurant and entertainment deals. Consumers seeking restaurant deals are likely looking for dining options, meaning other restaurant deals in the same cities are potential substitutes. A similar consideration applies for consumers seeking entertainment deals.

We treat all deal attributes except sales, price, and discount as exogenous characteristics. Following Berry et al. (1995), Bresnahan et al. (1997), and Hui (2004), the instruments for deal i's discount include (i) all exogenous attributes of deal i and (ii) the sum of exogenous attributes of deal i's competitors (active deals in the same category in the same city). We do not instrument for transaction price because, technically, it is determined by the level of discount offered.[7]

The IV estimators for the restaurant and entertainment deals are reported in Table 5, columns (1) and (2). The first-stage R^2 are 0.41 and 0.14, and F statistics are 14.01 ($p < 0.01$) and 145.10 ($p < 0.01$). The coefficients of *price* and *discount* are consistently negative and larger in magnitude than the OLS estimators reported in Table 4, columns (3) and (5).[8] This is consistent with previous empirical findings that the price coefficient tends to be more negative in IV estimation (e.g., Berry et al. 1995; Bresnahan et al. 1997; Hui 2004). The two IV estimators in Table 5, columns (1) and (2), imply that increasing the discount by 10% from the sample mean could have reduced sales by 3.32% $[1.90, 4.74]$ or 15.79% $[10.06, 21.51]$.

** Table 5. Identification **

The IV estimators above do not apply to all product categories because it is not easy to define the competitors for deals in categories such as education or health & fitness. Also, categories such as nightlife and bars and pet services contain too few deals for separate estimation. Hence, our second IV estimator uses generic instruments that apply to all product categories. The first such instrument is AHW, which varies across time and product subcategories. The average wage reflects merchants' labor costs. The second instrument is HPI, which varies across time and the nine Census

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7 In the Online Appendix, we report the estimation when we instrument for both transaction price and discount. The result is qualitatively similar.

8 The sample sizes differ across Tables 4 and 5 because, for a small number of deals, we cannot construct the instruments due to lack of competitors in the same categories and cities.

Divisions in the United States. HPI reflects merchants' rental costs. Because we obtained the AHW and HPI data only for the United States, we exclude all Canada deals from this estimation.

The first-stage R^2 and F statistic for this IV estimator are 0.40 and 17.97 ($p < 0.01$). Table 5, column (3), reports the second-stage regression result. The coefficient of discount is negative but not statistically significant ($p = 0.11$). However, the Hansen J statistic, $\chi^2 = 5.11$ ($p = 0.02$), shows that at least one of the two instruments is invalid. The first-stage regression coefficients of AHW and HPI are -0.3940 ($p < 0.01$) and 0.0019 ($p = 0.46$), suggesting that HPI is the problematic instrument. Hence, in Table 5, column (4), we report another IV estimator using AHW as the only instrument. The estimate is very close to the one reported in Table 5, column (3). The coefficient of *discount* is statistically significant at the 10% level ($p = 0.09$).[9] This estimator implies that increasing the discount by 10% from the sample mean of 55.6% could have reduced hourly sales by 2.11% $[-0.32, 4.54]$, or 2.69 vouchers and \$141 in revenue in total.

4.3. Competing Explanation

One explanation for the negative discount effect on sales is that there could be self-selection: Merchants may choose discount levels based on their expected sales. Merchants who are confident in sales, perhaps due to higher quality or popularity, may offer lower discounts. This would empirically give rise to a negative correlation between discount and sales, but the change in sales would not be caused by the variation in discounts. Self-selection is not likely the explanation in our setting because merchants on online daily-deal websites are often less well known to consumers (Dholakia and Kimes 2011; Wang et al. 2013; Luo et al. 2014). It would be challenging for the merchants to gauge their sales potential among unfamiliar consumers. As described in Section 3, we have conducted a survey to assess consumers' familiarity with Groupon merchants and, indeed, consumers are less familiar with the merchants on Groupon than those on Amazon.com. In addition, the IV estimators in Table 5 should also address selection bias.

Nevertheless, to critically assess the self-selection explanation, we conduct a cluster analysis that divides the 19,978 deals into separate groups based on the deals' characteristics. Because the deals have both qualitative and quantitative attributes, we use Gower's distance measure (Gower

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[9] The power of the IV estimators in Table 5, columns (3) and (4), is low because AHW and HPI vary only by city and product subcategory but not by deal. There may not be enough variation to precisely identify the discount impact. We report the first-stage regression results in the Online Appendix.

1971) and the K-medoids algorithm (Friedman et al. 2001) to cluster the deals.[10] We select the number of clusters, K, by comparing the average silhouette value (Rousseeuw 1987) for each $K \in \{2, 3, \ldots, 10\}$.[11] The highest average silhouette value is obtained when $K = 2$: The deals are best grouped into two clusters, one including 13,203 deals and the other including 6,775 deals. The deals in the second cluster have more Facebook fans and longer time to expire, allow for larger purchase quantities, and are more often offered in multiple cities when compared with the deals in the first cluster. They are also more likely to sell out. Please refer to the details of the two clusters of deals in the Online Appendix. These characteristic differences suggest that the deals in the second cluster are more popular and enjoy more exposure than the deals in the first cluster.

Based on the cluster-analysis results, we create a new dummy variable, *popular deals*, that indicates whether a deal falls in the "popular" cluster. We add *popular deals* and *popular deals* × *discount* to the regression. If merchant self-selection drives the negative discount effect, then we expect the discount effect to be weaker among popular deals, meaning *popular deals* × *discount* should positively correlate with sales. As reported in Table 5, column (5), this is not the case. The coefficient of *popular deals* × *discount* is *negative* and statistically insignificant. The coefficient of *discount*, -0.0185 ($p < 0.05$), continues to be negative and statistically significant, meaning the negative discount effect applies to all merchants with different popularity. In fact, combining the main and interaction effects, discount has an even more negative effect, -0.0203 ($p < 0.05$), on sales among the popular deals.

We use two additional strategies to test the merchant self-selection explanation.[12] First, if the merchants offered discounts based on expected sales, then the discount effect should diminish as the level of sales increases — presumably, deals with higher sales should be less affected if the discount effect found above is spurious. On this basis, we compare the effects of discount at the lower quartile, median, and upper quartile of merchants (defined by final deal sales) using a quantile regression.

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[10] The K-medoids algorithm is similar to the widely used K-means algorithm, except that it can also be applied to categorical data. We provide more discussion about Gower's distance, the K-medoids algorithm, and our cluster analysis in the Online Appendix.

[11] The silhouette value measures the similarity of an object with its own cluster as compared with other clusters. It 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.

[12] We thank an anonymous reviewer for suggesting these two tests.

We find that the discount effect is negative and statistically significant among the median and upper-quartile merchants, but it is statistically insignificant among the lower-quartile merchants. The effect is not statistically different among the median and upper-quartile merchants. These findings go against the explanation of merchant self-selection to offer discounts by sales. Please refer to the Online Appendix for the details of this quantile regression.

Second, we carry out another estimation that considers discount as a continuous and endogenous treatment variable to account for potential selectivity bias (Garen 1984). As reported in the Online Appendix, the result does not indicate the presence of selectivity bias. The discount effect continues to be negative and statistically significant after incorporating the bias-correction terms. Once again, this implies that merchant self-selection to offer discounts is not a potent explanation to the negative discount impact on the daily-deal sales.

4.4. Consumption Congestion

Groupon carries many deals for local services such as dining, spa, and education that often have capacity constraints and hence are prone to consumption congestion. One possible explanation of the negative discount effect is that consumers may fear the heavily discounted deals could attract too many purchases that lead to congestion later when they try to redeem the purchased vouchers. We test this explanation with three empirical strategies in this section.

First, we include an interaction term, *days before expiration* $\times$ *discount*, and reestimate equation (1). Having fewer days before the vouchers expire should arouse a stronger concern on consumption congestion because consumers will have less time to redeem the voucher. If congestion concern is the explanation, then we expect *days before expiration* to attenuate the negative discount effect. That is, *days before expiration* $\times$ *discount* should positively correlate with sales. As reported in Table 6, column (1), this is not the case. The coefficient of *days before expiration* $\times$ *discount* is negative instead of positive, and statistically significant.

** Table 6. Tests of Candidate Explanations **

Second, we identify subcategories of deals that are not likely affected by congestion at the time of consumption. These include deals involving take-away products or self-services—Food & Drinks, Auto Parts & Accessories (Automotive Services), Beauty Products (Beauty & Spas), Magazine Subscription (Professional Services), and Self-Storage (Professional Services)—and deals that will not likely encounter congestion because of large service capacity—Amusement Park (Entertainment), Aquariums (Entertainment), Botanical Garden (Entertainment), Museum (Entertainment), Water Park (Entertainment), and Zoos (Entertainment). We repeat the estimation using this subsample of "noncongestive" deals. If the concern on local congestion causes our finding, then the negative effect of discount should be smaller in this subsample. As reported in Table 6, column (2), this is not the case. The coefficient of *discount* is negative, -0.0382 ($p < 0.05$), and *more negative* than our baseline estimate in Table 4, column (1).

Third, we examine how the discount effect varies over each deal's life cycle. We construct a new variable, *progress*, that equals the amount of time that a deal has elapsed over the deal's total lifespan. We include *progress* and $progress \times discount$ in the regression. If consumers are concerned about consumption congestion, then the negative discount effect should be more pronounced as a deal progresses and the sales gradually build up. Table 6, column (3), reports the estimation result. The coefficient of $progress \times discount$ is positive and statistically significant, implying the negative effect of discount is *attenuated* as a deal progresses to the later stage in its life cycle. This finding contradicts the consumption-congestion explanation.

Figure 3 plots the deals' sales against discount percentage at the lower quartile, median, and upper quartile of deal completion time. As indicated by the fitted trends, the negative discount effect is robust across merchants during different stages of the deals' sales, but it seems slightly smaller (i.e., the slopes of the fitted trends become less steep) when the sales is closer to completion. Overall, the evidence in Table 6, columns (1)–(3) and Figure 3 does not support the consumption-congestion explanation.

** Figure 3. Discount Effects over Deal Life Cycle **

4.5. The Quality-Concern Explanation

Why would discount reduce sales of online daily deals? Prior research on online commerce suggests that information asymmetry could cause consumers to use price as a quality signal (Overby and Jap 2009; Kim and Krishnan 2015). When the discount is large, consumers may perceive that the product quality is low (Rao 2005). Ample experimental evidence has shown that such price–quality association exists in the presence of quality uncertainty (Rao and Monroe 1989).

In the online daily-deal setting, because consumers usually do not consume the purchased items immediately, there is an added concern that the merchants could cheat on quality (e.g., use poor ingredients in restaurants or low-quality aromatherapy oils in massage). There is indeed qualitative evidence that consumers of daily-deal websites are uncertain about deal quality and so do not blindly pursue deeply discounted items (Dholakia and Kimes 2011; Wang et al. 2013).

We apply three empirical strategies to test whether the quality-concern explanation is tenable. These strategies are founded on a priori reasoning that predicts the discount impact to vary in a specific direction if quality concern is the underlying causal mechanism.

The first strategy considers whether the deals involve credence goods. Typical examples of credence goods include medical treatment, automotive repair, and expert services (Darby and Karni 1973; Emons 1997; Dulleck and Kerschbamer 2006). Following Dulleck et al. (2011), we also consider health and organic food as credence goods. Unlike search and experience goods, the quality of credence goods is difficult to ascertain even after consumption without the relevant knowledge. Hence, consumers often have to rely on the merchants' claims to appraise the products. If quality concern underlies the negative discount effect, then we expect the effect to be larger among credence-good deals, which allow merchants to cheat on quality more easily.

We classify the Groupon deals into experience goods and credence goods based on the difficulty in assessing their quality after consumption.[13] We cross-checked our classification with independent judgments made by five trained PhD students and survey responses from 43 randomly selected U.S. residents. The results show that our classification is valid in the sense that it successfully separates deals that differ in terms of the difficulty of assessing the products' quality after consumption. We report the classification and verification results in the Online Appendix.

We use a dummy variable, *credence*, to flag the subcategories of credence-good deals. We add *credence* and its interaction with *discount* to the regression. Note that we cannot separately estimate the effect of *credence* because it is collinear with the subcategory fixed effects.

Table 6, column (4), reports the results. The coefficient of *discount* remains negative and precisely estimated. Importantly for our identification strategy, the coefficient of $credence \times discount$ is -0.0696 and statistically significant ($p < 0.05$), implying discount reduces sales particularly for credence goods. This is consistent with the quality-concern expectation. This estimate implies that

[13] Table A.1 in the Online Appendix lists the subcategories that we consider as credence goods.

increasing the discount by 10% from the sample mean could have reduced sales by an additional 2.26% $[0.08, 4.44]$ if the deal involves a credence good (cf. experience goods). This is equivalent to 2.88 vouchers and $151 in revenue in total.

Our second strategy uses an insight from prior analysis of online daily deals, which suggests that displaying the number of previous purchases reduces consumers' quality concern because of observational learning (Hu et al. 2013; Li and Wu 2013; Luo et al. 2014; Subramanian and Rao 2016). Groupon displays the number of purchases for all deals that it carries on a real-time basis. Accordingly, we construct a new dummy variable, $SalesAboveThreshold$, that indicates whether a deal's sales exceeds a selected threshold in each time period. We then add this new variable and its interaction with *discount* to the regression.

Referring to Table 2, the average lagged cumulative sales in our data set is 76. Hence, we choose 300, which is considerably greater than 76, as the threshold. Deals that have achieved this threshold are more likely to benefit from observational learning. As reported in the Online Appendix, the estimation result is robust if we change this threshold to 200 or 400.

Table 6, column (5), reports the estimation results. Consistent with the presence of observational learning, the coefficient of $SalesAboveThreshold$ is positive and precisely estimated. Importantly for our identification strategy, the coefficient of $SalesAboveThreshold \times discount$ is positive, 0.0479, and statistically significant ($p < 0.01$). This means the negative discount effect is *weaker* for well-sold deals, supporting our interpretation that the discount is used as a negative quality signal when uncertainty is high (i.e., for deals that do not meet the threshold).[14]

Our third empirical strategy exploits the preferences of people of varying socioeconomic status. In particular, income and education may moderate a consumer's quality preference and attitude toward uncertainty. Wealthier consumers tend to have lower marginal utility of income or, equivalently, a taste for higher quality (Schaninger 1993; Tirole 1988, pp. 96-97). This implies that

[14] Unlike the test in Table 6, column (5), which uses a sales threshold to separate the deals, the test reported in Table 5, column (5), separates the deals by popularity as defined by a cluster analysis of the deal characteristics. The "popular" deals there need not have more sales. In fact, among the 6,775 "popular" deals as classified in Section 4.3, only 1,107 (16.34%) meet the threshold of selling at least 300 vouchers. The result in Table 6, column (5), is consistent with that in Table 6, column (3), which shows that the discount effect attenuates as sales progress. Note, also, that the tests reported in Table 6, columns (3) and (5), focus on the sales progress *within a deal*, whereas the cluster analysis and quantile regression reported in Section 4.3 (to test the competing explanation of merchant self-selection to offer discount by popularity or sales) focus on between-merchant differences.

high-income consumers are less sensitive to price, less tolerant of poor quality, and more averse to uncertainty. Similarly, better-educated consumers may have a stronger preference for quality as is the case in the consumption of organic food (e.g., Jolly 1991; Magnusson et al. 2001). They are also more experienced with Internet purchases (Li et al. 1999) and hence should be more aware of the threats posed by asymmetric information and fraudulent seller behavior.

Accordingly, if the discount arouses a quality concern, then its effect should be stronger among high-income and better-educated consumers. On this basis, we enter the interaction between income and discount and the interaction between education and discount in the next two regressions. We measure income by median household income and education by the percentage of population aged 25 or above with at least a bachelor degree from U.S. Census 2010. The results are reported in Table 6, columns (6) and (7). Note that we cannot obtain the main effects of income and education because they are collinear with the city fixed effects. We use only the U.S. deals in this test because we only have the U.S. demographic data.

As expected, the coefficients of *income* $\times$ *discount* and *education* $\times$ *discount* are negative, -0.0593 and -0.0410, and statistically significant at $p < 0.01$. The negative effect of discount is particularly pronounced among consumers with high income and better education. Once again, this is consistent with the interpretation that quality concerns drive the negative impact of discount on sales of the daily-deal vouchers.

4.6. Falsification and Robustness Checks

We conduct a falsification exercise to show that the negative discount effect ceases to exist when quality concern should be absent. Specifically, we collected a fresh sample of *Groupon Goods*, which is a relatively new category of deals launched in 2011. For these deals, Groupon acts as the retailer and promotes mostly search goods such as electronics, toys, apparel, etc. Because Groupon goods are sold directly by Groupon instead of other third parties and can be freely returned within 14 days of delivery, consumers should have less concern on their quality.[15] Hence, we expect the negative effect of discount to be less salient for Groupon Goods.

We collected 382 deals of Groupon Goods from 8 January to 31 March 2014. We follow the

[15] For more details on Groupon's return policy, please visit `https://www.groupon.com/faq#faqs:content-104` (accessed 15 March 2017).

same procedures as described in Section 3 to compile the data and reestimate equation (1). We omit several variables, such as *merchant-created deal* or *online deal*, because they do not apply to this sample (Groupon offered all of these deals through its home-delivery service). Table 7 reports the descriptive statistics of the Groupon Goods sample.

** Table 7. Descriptive Statistics: Groupon Goods **

The estimation results are reported in Table 8, column (1). In sharp contrast to Table 4, column (1), the coefficient of discount becomes *positive*, 0.3714, and is precisely estimated ($p < 0.01$). When quality uncertainty is eased, discount can actually *increase* daily-deal sales. This falsification test provides powerful support to our interpretation that the negative impact of discount identified in this study is caused by consumers' quality concerns.

** Table 8. Falsification and Robustness Tests **

We next conduct several robustness tests. First, we use the final sales after the deals were concluded instead of hourly sales as the dependent variable. The sample then comprises a cross-section of 19,978 deals without the time-varying covariates such as lagged cumulative sales.[16] Table 8, column (2), reports the estimation result. Consistent with the panel estimates, the coefficient of discount is negative, -0.1415, and statistically significant ($p < 0.01$). This estimate implies that offering an additional 10% discount from the sample mean of 55.6% could have reduced total sales by 4.60% [2.85, 6.35], or 5.24 vouchers and $275 in revenue.

Despite the consistent estimates, we prefer using the panel structure of our data set because it allows us to model the dynamics in deal sales. For example, with an hourly panel, we can include lagged cumulative sales as a control variable to account for unobserved deal quality, social influence, and diffusion effects. Furthermore, we can calibrate the number of competing deals by hour with a panel. These features should help increase the power of our identification.

For our second robustness check, to more specifically control for deal heterogeneity, we use a random effects (RE) model which allows us to estimate the coefficients of the time-invariant vari-

[16] We calculate the number of competing deals as the total number of deals that overlapped with the focal deal during its lifespan. Because we cannot include time fixed effects in this specification, we add a new variable, *holiday percentage*, to measure the percentage of weekends and public holidays in a deal's lifespan to control for heterogeneous propensity of online daily-deal purchases.

ables, including *discount* and the other deal characteristics. As reported in Table 8, column (3), the result is qualitatively similar. The effect of discount on sales is negative, -0.0270, and statistically significant ($p < 0.05$). Note, however, that the RE model imposes a strong assumption, that the random deal effects are not correlated with the observed deal characteristics. This assumption is unlikely to hold in the online daily-deal setting. Indeed, the Hausman test rejects this assumption ($\chi^2 = 1811.92$, $p < 0.01$). Hence, we prefer the estimation in Table 4, column (1), to the RE model.

Third, we estimate a linear version of equation (1). As reported in Table 8, column (4), the discount effect is -0.0045 and statistically significant ($p < 0.05$). This estimate implies that offering an additional discount of 10% from the sample mean could have reduced hourly sales by 3.63% [0.31, 6.95]. This estimate is greater than the one reported in Table 4, column (1). However, the linear specification does not fit the data as well as the double-log specification.

Fourth, to allow for flexible social influence and diffusion effects, we estimate another specification that includes the square of lagged cumulative sales as an additional covariate. The result is reported in Table 8, column (5). The relationship between lagged cumulative sales and current-period sales is convex, suggesting that sales could be self-reinforcing when the volume is large. The coefficient of *discount* remains negative and statistically significant.

We check the robustness to exclusion of outliers in the last two tests. One excludes deals with original price below the 20th or above the 80th percentile, which prunes the price variation from \$5–\$12,582 to \$30–\$165. To the extent that unobserved deal characteristics correlate with price, this procedure helps ensure that our results are not caused by omitted characteristics of some extreme deals. Similarly, in the second test, we exclude outliers in terms of duration by discarding deals with durations below the 20th or above the 80th percentile, which reduces the range from 12–926 to 93–97 hours. As reported in Table 8, columns (6) and (7), the negative effect of discount is robust to exclusion of outliers in terms of price and duration.[17]

[17] We have conducted additional robustness tests. In the first test, we exclude deals with extreme transaction prices. In the second test, we include linear and quadratic time trends in the regression. In the third and fourth tests, we include day-specific city fixed effects and day-specific subcategory fixed effects. In the fifth test, we cluster the standard errors by deal instead of product subcategory. We find that the discount effect is consistently negative and statistically significant in all of these tests. Please refer to Table A.8 in the Online Appendix for the detailed estimation results. Moreover, we apply the dynamic generalized method of moment (GMM) estimator (Arellano and Bond 1991) and find no evidence of autocorrelation in our data. Note that we cannot use the GMM estimator for our main estimation as the discounts do not change within the deals' lifespans.

4.7. Third-Party Support from Online Social Networks

Groupon provides merchants with an option to selectively display third-party support from other social networks, viz. the number of Facebook fans and review quotes, and counts and ratings from Yelp, Yahoo! and Google. The results in Table 4 show that the number of Facebook fans and customers' reviews help increase online daily-deal sales. This raises an interesting question: *Can such third-party support thwart the negative quality signal delivered by the discount?*

We answer this question with several tests. We add the interactions between discount and the number of Facebook fans and a dummy variable indicating whether a deal page displays customers' review quotes in the regression. As reported in Table 9, column (1), both of these two interaction effects are *negative* and statistically significant, implying the negative effect of discount on sales is *exacerbated* in the presence of third-party support.

** Table 9. Impact of Third-Party Support **

Another indication of third-party support is the quality of online reviews. In the next test, we use the subsample of deals with online reviews and include the interactions between discount, review count, and review rating in the regression. As reported in Table 9, column (2), both interaction effects are negative but not statistically significant. However, prior research has suggested that consumers may not take online reviews seriously when the number of reviews is small (Li and Wu 2013). In Table 9, column (3), we repeat the same regression by confining the sample to 3,501 deals that have at least 30 online third-party reviews. Both review count and review rating significantly exacerbate the negative effect of discount on sales.

One concern with these estimates is that the display of third-party support could be endogenous. Low-quality merchants tend to offer more discounts and at the same time manipulate the support, which may induce less trust and hence lower sales. We use propensity score matching (PSM) to identify a sample of "control" deals (without third-party reviews) that match with the "treated" deals (with third-party reviews) in characteristics. We use one-to-one nearest neighbor matching without replacement and an appropriate caliper to balance all covariates between the treated and control groups. We have successfully identified 4,184 pairs of matched deals, the details of which are reported in the Online Appendix. Table 9, column (4) reports the estimation using this matched sample. The result is qualitatively similar to that reported in Table 4, column

(1). We then add the interactions between discount and the number of Facebook fans and the review quote dummy variable in the next regression. As reported in Table 9, column (5), both interaction effects are negative and the one with review quotes is statistically significant ($p < 0.01$).

Overall, the estimates in Tables 4 and 9 point to a converging conclusion: Third-party support from other online social networks can improve sales but exacerbate the negative effect of discount. The net effect of third-party support is contingent on the level of discount offered.[18]

In general, favorable third-party support should "reinforce" the prices charged by merchants, making consumers more likely to accept high prices. Hence, it is not surprising that it helps increase sales. Referring to Table 9, the main effects of the third-party support are mostly positive, meaning it increases sales when the discount is low. However, why would it decrease sales when the discount is large (i.e., when the price is low)? If third-party support helps convince consumers that a deal is good, why would consumers dislike a high discount that saves them money?

Previous experimental evidence provides a useful hint. When consumers see inconsistent quality signals, negativity bias may cause them to anchor on the negative signal (Boulding and Kirmani 1993; Smith and Vogt 1995; Miyazaki et al. 2005). In our setting, the merchants display third-party support as a positive quality cue, but a big discount may send a (dominating) negative signal, which could cause consumers to refrain from purchasing the deals.

Another related explanation is consumers' distrust in the merchants' selection of third-party support. They may fear that merchants could manipulate the third-party support to create biased impressions (Dellarocas 2006; Jin and Kato 2006; Mayzlin 2006; Li and Hitt 2008; Filan 2012; Mayzlin et al. 2014). This is especially likely when consumers are not familiar with the daily-deal merchants. In the presence of negativity bias due to discount and in the absence of familiarity and trust in merchants, consumers may suspect that the merchants need third-party support and offer

[18] Note that, referring to the cluster analysis in Section 4.3 and the Online Appendix, deals in the "popular" cluster also have more Facebook fans. However, that cluster analysis uses all available deal characteristics to segment the deals. Hence, it identifies the latent "popularity" of the deals instead of third-party support per se. This explains why the interaction effect between popular deals and discount in Table 5, column (5), is insignificant whereas the interaction effects between third-party support and discount are mostly negative and statistically significant in Table 9. To check the robustness of the results in Table 9, we conduct another cluster analysis using only two variables, *Facebook fans* and *has review quotes*. The result shows that the clustering of the deals is completely different from the cluster analysis reported in Section 4.3, with the deals now optimally separated into two clusters by the *has review quotes* variable alone. This indicates that the cluster analysis reported in Section 4.3 does not focus on third-party support. Please refer to the Online Appendix for the details of this cluster analysis.

large discounts at the same time because their product quality is low. This may explain why the discount effect is more negative when third-party support is high.

Indeed, Groupon cautions consumers:

> *Descriptions of the merchant offerings and products advertised on the site are provided by the merchant or other referenced third parties. Groupon does not investigate or vet merchants.*[19]

To explore whether consumer trust (or lack of trust) of the reviews underscores our findings, we conducted another survey of 50 randomly selected U.S. residents. We found suggestive evidence that people place less trust in the reviews displayed on Groupon's deal pages than the reviews from Yelp. We report the details of this survey in the Online Appendix.

5. Lab Experiment

We conducted a lab experiment to corroborate the empirical analysis of the field data from Groupon. The purpose of this experiment is two-fold. First, we directly test the quality-concern explanation by systematically manipulating the discount levels and measuring consumers' perceptions of product quality. Second, because the distribution of discount in the Groupon data is skewed (see Figure 1), we test the robustness of its effect on sales along a broader range of discounts.

We created 19 different deals featuring products and services chosen from various product subcategories that best capture the distribution of deals in our field data set obtained from Groupon. For each of these 19 deals, we manipulated the discount levels in increments of 5%. Hence, we created 19 treatment groups for each deal offering discounts of $5\%, 10\%, 15\%, \ldots, 95\%$. The 19 versions of each deal are identical in appearance and all displayed attributes except the discounts offered. We provide a sample deal page in the Online Appendix.

We presented each subject with 19 deal pages. We counterbalanced the presentation of deals so that each subject will see all 19 products and all 19 discount percentages. This is to ensure that the subjects cannot infer the purpose of the experiment by seeing repetitive deals or discounts. We randomized the presentation sequence of the deals and discounts to avoid any ordering effect. Before presenting each deal, we asked the subjects to imagine a scenario in which they are considering the

[19] See Groupon's Terms of Sale: `https://www.groupon.com/pages/terms-of-sale` (accessed 15 March 2015).

products or services carried by the deal. After seeing each of the 19 deals, we asked the subjects to respond to three statements on 7-point Likert scales: (1) "I am uncertain about the overall quality of the ... shown in the deal." (1 = *strongly disagree*, 7 = *strongly agree*). (2) "The overall quality of the ... shown in the deal is high." (1 = *strongly disagree*, 7 = *strongly agree*). (3) "How likely will you purchase this deal?" (1 = *extremely unlikely*, 7 = *extremely likely*).

We recruited 217 undergraduate and postgraduate students in a large European university to participate in the experiment. Because each subject evaluated 19 deals, we have a total of $217 \times 19 = 4,123$ observations. Figure 4 plots the average perceived quality uncertainty, perceived quality, and willingness-to-buy (WTB) against discount percentage. Evidently, there exist some thresholds. The perceived quality uncertainty increases rapidly after the discount exceeds 60%. Similar trends exist for perceived quality and WTB. The perceived quality starts to decrease and WTB ceases to increase after the discount exceeds around 60%.

** Figure 4. Perceived Quality Uncertainty, Perceived Quality, and WTB **

We conduct piecewise regressions on the experimental data to examine the nonlinear effect of discount. Specifically, we incorporate a "breakpoint" and allow the discount effect to change before and after the breakpoint. Guided by the patterns in Figure 4, we choose 60% as the breakpoint. We show that the results are robust if we use 50% or 55% as the breakpoint in the Online Appendix. We include deal, subject, and order fixed effects in these regressions. We cluster the standard errors by subject to allow for correlations in rating by the same subject.

Table 10 presents the regression results using the experimental data. For perceived quality uncertainty, the coefficient of discount is not statistically significant when the discount is below 60%, but it is positive and statistically significant when the discount is 60% or above. Similarly, the effect of discount on perceived quality is negative and statistically significant only when the discount is 60% or above. Discount has a significant positive effect on WTB only when it is below 60%. The WTB does not change after the discount has reached 60%.

** Table 10. Threshold Effect of Discount **

These results triangulate our findings from the empirical analysis of the Groupon data. Because we systematically manipulated the discount levels and measured the subjects' quality perceptions, the experimental results provide a high level of confidence that the effect of discount on quality concern is *causal*. We also find that quality concern arises only when the discount exceeds some threshold. This implies that a moderate level of discount can help attract consumers (Alba et al. 1999). Indeed, we find that discount increases the subjects' WTB when it is not too high (say, 60% or below). To our knowledge, this threshold effect of discount is novel.

We conclude this section by highlighting several limitations of the experiment. All subjects are university students who may have different price–response functions compared with working adults. We captured the subjects' responses by a questionnaire, which may lead to bias because stated preferences are often different from revealed preferences (see, e.g., Bishop and Heberlein 1979; Diamond et al. 1993; Diamond and Hausman 1994). The subjects could have inflated their WTB because they do not need to pay real money in the experiment, which may explain why their WTB stays high even for deals offering discounts above 60%. This is somewhat different from our empirical findings where large discounts tend to decrease sales (see Figure 2).

Nevertheless, despite these limitations due to the experimental setting, our results point to a consistent picture—high discount arouses quality concern and could affect people's appraisal and purchase of online daily deals.

6. Implications and Conclusion

By conducting a series of statistical analysis, we show that discount has an immediate negative effect on the sales of online daily deals. Our various estimates suggest that offering an additional 10% discount from the average of 55.6% could reduce sales by 0.63%–4.60%, or 0.80–5.24 vouchers and \$42–\$275 in revenue. This effect is economically significant because many online daily deals are offered by local businesses (Shivendu and Zhang 2013; Edelman et al. 2014). Our finding echoes recent statistics showing an adverse effect of deep discounts on sales (Dror 2014).

More importantly, this finding questions the tactic of using discount to attract new customers in the online daily-deal business model. As shown in Figure 1, many merchants on Groupon offer big discounts, some even exceeding 80%. The merchants may hope to use such big discounts to catch consumer attention and increase exposure to consumers by, for example, attracting consumers to visit their stores and make other purchases in the future. It defeats the merchants' promotional purposes if the discounts drive consumers away instead of attracting them to the merchants' stores.

The discounts could also undermine the merchants' advertising objective if it is viewed as a signal of poor quality, which may dampen the merchants' quality image. Apparently, consumers use daily deals to discover novel items with "good value for money" around their local regions instead of pursuing price saving per se (Dholakia and Kimes 2011; Wang et al. 2013).

We find robust and triangulated evidence that the negative discount effect on sales is caused by consumers' quality concern. So, how can a merchant ease such quality concerns? One obvious way is to confine the discounts offered. However, this does not seem to be a good solution because it is not targeted. As shown in Sections 4.6 and 5, discounts can help attract consumers for Groupon goods and when they do not exceed some threshold. Hence, a good solution should address the root of the problem: concerns on product quality.

The analysis of Groupon Goods in Section 4.6 and Table 8, column (1), provides useful insights. The discounts increase sales when the deals are carried by Groupon with a guaranteed return policy. Hence, a two-prong approach may help. First, the platform provider can establish a league of "trustworthy" merchants, much like the T-Mall feature provided by Taobao.com, one of the biggest platforms for business-to-consumer electronic commerce. Conceptually, this practice is akin to notarizing online daily-deal merchants. Prior research suggests that notarization of online retailers through a third-party quality assurance seal helps increase consumer purchases (Ozpolat et al. 2013). Second, online daily-deal merchants can make better use of return policies, which directly reduce consumers' risks of getting low-quality products. Properly configured return policies can serve as a quality signal too (Bonifield et al. 2010; Zhang et al. 2017).

As shown in Table 6, column (5), another setting for discount to help is when the daily-deal has reached a high level of sales. This finding is strikingly consistent with previous theoretical analysis (Jing and Xie 2011; Hu et al. 2013; Subramanian and Rao 2016). Interestingly, in the early days, Groupon required a "tipping point", i.e., minimum number of purchases, for some deals before they can be established. With such a requirement, informed consumers would have more incentive to promote the deals for merchants offering high-quality products to uninformed consumers. This unique social interaction distinguishes the early group-buying model from general online retailing. However, as Groupon migrated to the online daily-deal model, it dropped this minimum purchase requirement. Perhaps it is advisable for Groupon, or other online marketplaces featuring less known sellers, to reinstate the minimum purchase requirement.

Previous research suggests that third-party reviews can help ease consumers' quality concern in online commerce (Dellarocas et al. 2007). The analysis in Section 4.7 and Table 9, however, shows that such third-party support is a double-edged sword. It can help increase sales by itself, but it may decrease sales when coupled with high discounts. This is a novel and important finding that corroborates prior work on the quality signaling effect of online reviews (Forman et al. 2008; Zhu and Zhang 2010; Ho-Dac et al. 2013). We do not have concrete evidence to explain why third-party support is bad in the presence of deep discounts, but we speculate that it could have raised consumers' suspicion on product quality when the discount serves as a negative quality signal. This may be especially the case when most online daily-deal merchants are not well known to consumers, and when they can selectively curate such third-party support.

Incidentally, since restructuring its website in 2015, Groupon has ceased displaying any third-party support on the deals' pages. Instead, it now shows recommendations and comments from Groupon users who have prior experience with the specific merchants. Our findings support this restructuring. More broadly, this study advances an intricate nuance in displaying peripheral information. In the presence of a negative quality signal such as discount, an ostensibly positive signal such as favorable third-party support may become a curse, whereas some other quality signals such as sales volume may help. Future research should scrutinize the mechanisms underlying these intriguing interactions between different quality signals in an online market.

One practical implication of this research is that the offering of discounts should be tied to consumers' confidence in product quality, meaning a one-size-fits-all strategy will not be optimal. Indeed, as shown in Table 6, column (5), and Table 8, column (1), offering high discounts work well for Groupon goods and well-sold deals. Hence, the key is to assess the deals' quality and credibility. Obviously, the platform provider would not know the deals better than the offering merchants. Lacking guidance on how to assess deal quality, perhaps the platform provider can offer a "price menu" to encourage responsible pricing and discount strategy by merchants. For example, it can peg the revenue-sharing percentage with the discount proposed by merchants, such as 10% revenue sharing for deals offering 20% discount, 30% for deals offering 40% discount, 50% for deals offering discounts above 60%, and so on. This structure encourages merchants to avoid offering suspiciously deep discounts unless they can be sure that their deals are going to sell well.

On the other hand, merchants could proactively preempt consumers' concern about discounted products. Our analysis suggests several specific strategies. First, sellers of credence goods, such as expert services or health and organic foods, should avoid offering deep discounts because such discounts arouse consumers' suspicion. Second, discounts may be helpful when the deal has acquired more buyers. This implies that merchants may want to work with the platform provider to facilitate flexible discount structures, such as volume-based discounting. For example, a merchant can offer a discount of 10% when the sales is less than 50, 20% when the sales exceeds 50, 30% when the sales exceeds 100, and so on. Third, merchants should consider the location or market. Discounts may not attract high-income or better-educated consumers. Hence, the extent of discounts in daily deals should be defined with the population demographics in mind. Fourth, merchants should carefully assess the quality signals carried by their marketing tactics. Adding a noncredible positive signal, such as curated online third-party support, may fail to boost consumer confidence. Worse still, it may aggravate the negative impression due to other signals, such as discounts.

In terms of research, our findings offer an alternative perspective to price promotion. Previous research has generally agreed that "*temporary retail price promotions cause a significant short-term sales spike ... this result is fundamental to virtually all research done in the area of promotions*" (Blattberg et al. 1995, p. G123). Although some researchers have advocated the negative long-term effects of price promotion (Lattin and Bucklin 1989; Mela et al. 1997, 1998; Jedidi et al. 1999; Erdem et al. 2008), we show that the negative effect can come immediately, deterring even some consumers' first purchases. This is an important caution to marketing managers.

Furthermore, we demonstrate that displaying more Facebook fans and review quotes, and better review counts and ratings from third-party websites could hurt a merchant. We need to expand the theoretical research in online third-party support to provide a holistic understanding of its effects. This is imminent when social network or social media marketing is gaining momentum and harvesting Facebook "likes" or Twitter "follows" have become important marketing tactics.

Last but not least, although we derive our findings from the online daily-deal setting, we believe our insights extend to general markets involving small and less-known sellers (e.g., consumer-to-consumer trading platforms, online search advertising). The key considerations are quality uncertainty, seller credibility, and the interplay between different product signals, which are predominant in almost all online marketplaces featuring heterogeneous products.

We conclude the paper by identifying several research opportunities. First, as shown in the lab experiment, the effect of discount is nonlinear. Low discounts may work well without provoking consumer suspicion. A good topic for future research is to explore the optimal discount strategy. Although our experiment suggests that the discount threshold is around 60%, we hesitate to generalize this result because it is derived from a lab experiment. After all, our field data show that discount starts to decrease sales at 40%, and another large-scale field study has suggested the best discount to lie between 5% and 15% (Dror 2014). Evidently, we need a more general framework to guide the discount strategy in different online markets.

Second, our data set confines us to studying the immediate effect of discount on daily-deal sales. The effect of daily-deal promotion could linger even after the promotional campaign has finished. Future research should go beyond deal sales and scrutinize the long-term impact of online daily-deal promotions. This would require comprehensive data covering online daily-deal purchases as well as the merchants' subsequent engagement with the customers. On this front, individual-level longitudinal data, such as that collected via mobile phone app usage in Luo et al. (2014), would be highly valuable.

Finally, it would be interesting to extend our analysis to other platforms that involve "pricing", such as microfinance, peer-to-peer lending (for which excessive returns may raise suspicion from investors), or crowd-funding projects (for which low pledge amounts may cause consumers to worry that the project may not succeed). Guided by the insights from our analysis, we suspect heavy "discounting" may also arouse consumers' concerns in these settings.

References

Alba, J. W., C. F. Mela, T. A. Shimp, J. E. Urbany. 1999. The effect of discount frequency and depth on consumer price judgments. *Journal of Consumer Research* **26**(2) 99–114.

Arellano, M., S. Bond. 1991. Some tests of specification for panel data: Monte Carlo evidence and an application toemployment equations. *Review of Economic Studies* **58**(2) 277–297.

Bagwell, K., M. H. Riordan. 1991. High and declining prices signal product quality. *American Economic Review* **81**(1) 224–239.

Berry, S. T. 1994. Estimating discrete-choice models of product differentiation. *RAND Journal of Economics* **25**(2) 242–262.

Berry, S. T., P. A. Haile. 2014. Identification in differentiated products markets using market level data. *Econometrica* **82**(5) 1749–1797.

Berry, S. T., J. Levinsohn, A. Pakes. 1995. Automobile prices in market equilibrium. *Econometrica* **63**(4) 841–890.

Bishop, R. C., T. A. Heberlein. 1979. Measuring values of extramarket goods: Are indirect measures biased? *American Journal of Agricultural Economics* **61**(5) 926–930.

Blattberg, R. C., R. Briesch, E. J. Fox. 1995. How promotions work. *Marketing Science* **14**(3) G122–G132.

Bonifield, C., C. Cole, R. L. Schultz. 2010. Product returns on the internet: A case of mixed signals? *Journal of Business Research* **63**(9–10) 1058–1065.

Boulding, W., A. Kirmani. 1993. A consumer-side experimental examination of signaling theory: do consumers perceive warranties as signals of quality? *Journal of Consumer Research* **20**(1) 111–123.

Bresnahan, T. F., S. Stern, M. Trajtenberg. 1997. Market segmentation and the sources of rents from innovation: Personal computers in the late 1980's. *RAND Journal of Economics* **28**(0) S17–S44.

Chen, Y., Q. Wang, J. Xie. 2011. Online social interactions: A natural experiment on word of mouth versus observational learning. *Journal of Marketing Research* **48**(2) 238–254.

Chevalier, J. A., D. Mayzlin. 2006. The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research* **43**(3) 345–354.

Chintagunta, P. K., S. Gopinath, S. Venkataraman. 2010. The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets. *Marketing Science* **29**(5) 944–957.

Constant Contact. 2013. Research survey Accessed November 23, 2015, http://news.constantcontact.com/press–release/customer–engagement–major–focus–small–business–technology–according–constant–contact–t.

Darby, M. R., E. Karni. 1973. Free competition and the optimal amount of fraud. *Journal of Law and Economics* **16**(1) 67–88.

Daughety, A. F., J. F. Reinganum. 2008. Imperfect competition and quality signalling. *RAND Journal of Economics* **39**(1) 163–183.

Dellarocas, C. 2006. Strategic manipulation of internet opinion forums: Implications for consumers and firms. *Management Science* **52**(10) 1577–1593.

Dellarocas, C., X. Zhang, N .F. Awad. 2007. Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing* **21**(4) 23–45.

Dewan, S., V. Hsu. 2004. Adverse selection in electronic markets: Evidence from online stamp auctions. *Journal of Industrial Economics* **52**(4) 497–516.

Dholakia, U. M. 2011. How businesses fare with daily deals as they gain experience: A multi-site analysis of Groupon, LivingSoical, OpenTable, Travelzoo, and BuyWithMe promotions Available at SSRN: http://ssrn.com/abstract=1863466.

Dholakia, U. M. 2012. How businesses fare with daily deals as they gain experience: A multi-time period study of daily deal performance Available at SSRN: http://ssrn.com/abstract=1863466.

Dholakia, U. M., S. E. Kimes. 2011. Daily deal fatigue or unabated enthusiasm? A study of consumer perceptions of daily deal promotions Working Paper, Rice University.

Diamond, P. A., J. A. Hausman. 1994. Contingent valuation: Is some number better than no number? *Journal of Economic Perspective* **8**(4) 45–64.

Diamond, P. A., J. A. Hausman, G. K. Leonard. 1993. Does contingent valuation measure preferences? *Contingent valuation: A critical assessment.* Emerald Group Publishing Limited. 41–89.

Dimoka, A., Y. Hong, P. A. Pavlou. 2012. On product uncertainty in online markets: Theory and evidence. *MIS Quarterly* **36**(2) 395–426.

Dror, Y. 2014. Your discounts may be killing off your sales Accessed 26 November, 2015, http://www.geektime.com/2014/06/01/your–discounts–may–be–killing–off–your–sales/.

Dulleck, U., R. Kerschbamer. 2006. On doctors, mechanics, and computer specialists: The economics of credence goods. *Journal of Economic Literature* **44**(1) 5–42.

Dulleck, U., R. Kerschbamer, M. Sutter. 2011. The economics of credence goods: An experiment on the role of liability, verifiability, reputation, and competition. *American Economic Review* **101**(2) 526–555.

Edelman, B., S. Jaffe, S. D. Kominers. 2014. To Groupon or not to Groupon: The profitability of deep discounts Working Paper, Harvard Business School.

Edison Research. 2012. Report on daily deals. Accessed November 23, 2015, http://www.edisonresearch.com/wp–content/uploads/2012/04/Edison–Research–Daily–Deals–Report–2012.pdf.

Emons, W. 1997. Credence goods and fraudulent experts. *RAND Journal of Economics* **28**(1) 107–119.

Erdem, T., M. P. Keane, B. Sun. 2008. A dynamic model of brand choice when price and advertising signal product quality. *Marketing Science* **27**(6) 1111–1125.

Filan, J. 2012. Facebook ads: What are you really paying for? Accessed 26 November, 2015, https://www.searchenginejournal.com/facebook–ads–what–are–you–really–paying–for/46194/.

Foresee. 2012. Daily deal websites and emails bring in new and existing customers for retailers. *Foresee Daily Deal Commentary* .

Forman, C., A. Ghose, B. Wiesenfeld. 2008. Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. *Information Systems Research* **19**(3) 291–313.

Friedman, J., T. Hastie, R. Tibshirani. 2001. *The elements of statistical learning*. Springer, Berlin.

Garen, J. 1984. The returns to schooling: A selectivity bias approach with a continuous choice variable. *Econometrica* **52**(5) 1199–1218.

Ghose, A. 2009. Internet exchanges for used goods: An empirical analysis of trade patterns and adverse selection. *MIS Quarterly* **33**(2) 263–291.

Gower, J. C. 1971. A general coefficient of similarity and some of its properties. *Biometrics* **27**(4) 857–874.

Ho-Dac, N. N., S. J. Carson, W. L. Moore. 2013. The effects of positive and negative online customer reviews: Do brand strength and category maturity matter? *Journal of Marketing* **77**(6) 37–53.

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

Hui, K. L. 2004. Product variety under brand influence: An empirical investigation of personal computer demand. *Management Science* **50**(5) 686–700.

Jedidi, K., C. F. Mela, S. Gupta. 1999. Managing advertising and promotion for long-run profitability. *Marketing Science* **18**(1) 1–22.

Jin, G. Z., A. Kato. 2006. Price, quality, and reputation: Evidence from an online field experiment. *RAND Journal of Economics* **37**(4) 983–1004.

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

Jolly, D. A. 1991. Differences between buyers and nonbuyers of organic produce and willingness to pay organic price premiums. *Journal of Agribusiness* **9**(1) 97–111.

Keller, K. L., D. R. Lehmann. 2006. Brands and branding: Research findings and future priorities. *Marketing Science* **25**(6) 740–759.

Kim, Y., R. Krishnan. 2015. On product-level uncertainty and online purchase behavior: An empirical analysis. *Management Science* **61**(10) 2449–2467.

Kirmani, A., A. R. Rao. 2000. No pain, no gain: A critical review of the literature on signaling unobservable product quality. *Journal of Marketing* **64**(2) 66–79.

Lattin, J., R. Bucklin. 1989. Reference effects of price and promotion on brand choice behavior. *Journal of Marketing Research* **26**(3) 299–310.

Li, H., C. Kuo, M. G. Rusell. 1999. The impact of perceived channel utilities, shopping orientations, and demographics on the consumer's online buying behavior. *Journal of Computer-Mediated Communication* **5**(2).

Li, X., L. M. Hitt. 2008. Self-selection and information role of online product reviews. *Information Systems Research* **19**(4) 456–474.

Li, X., L. Wu. 2013. Measuring effects of observational learning and social-network word-of-mouth (WOM) on the sales of daily-deal vouchers. *The 46th Hawaii International Conference on System Sciences*. IEEE, 2908–2917.

Liu, Y. 2006. Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing* **70**(3) 74–89.

Luo, X., M. Andrews, Y. Song, J. Aspara. 2014. Group-buying deal popularity. *Journal of Marketing* **78**(March) 20–33.

Magnusson, M. K., A. Arvola, U. K. Hursti, L. Aberg, P. Sjoden. 2001. Attitudes towards organic foods among Swedish consumers. *British Food Journal* **103**(3) 209–227.

Mayzlin, D. 2006. Promotional chat on the internet. *Marketing Science* **25**(2) 155–163.

Mayzlin, D., Y. Dover, J. Chevalier. 2014. Promotional reviews: An empirical investigation of online review manipulation. *American Economic Review* **104**(8) 2421–2455.

Mela, C. F., S. Gupta, D. R. Lehmann. 1997. The long-term impact of promotion and advertising on consumer brand choice. *Journal of Marketing Research* **34**(2) 248–261.

Mela, C. F., K. Jedidi, D. Bowman. 1998. The long-term impact of promotions on consumer stockpiling behavior. *Journal of Marketing Research* **35**(2) 250–262.

Miyazaki, A. D., D. Grewal, R. C. Goodstein. 2005. The effect of multiple extrinsic cues on quality perceptions: A matter of consistency. *Journal of Consumer Research* **32**(1) 146–153.

Nevo, A. 2000. A practitioner's guide to estimation of random-coefficients Logit models of demand. *Journal of Economics & Management Strategy* **9**(4) 513–548.

Overby, E., S. Jap. 2009. Electronic and physical market channels: A multiyear investigation in a market for products of uncertain quality. *Management Science* **55**(6) 940–957.

Ozpolat, K., G. Gao, W. Jank, S. Viswanathan. 2013. The value of third-party assurance seals in online retailing: An empirical investigation. *Information Systems Research* **24**(4) 1100–1111.

Pavlou, P. A., H. Liang, Y. Xue. 2007. Understanding and mitigating uncertainty in online exchange relationships: A principal–agent perspective. *MIS Quarterly* **31**(1) 105–136.

Rao, A. R. 2005. The quality of price as a quality cue. *Journal of Marketing Research* **42**(4) 401–405.

Rao, A. R., K. B. Monroe. 1989. The effect of price, brand name, and store name on buyers' perceptions of product quality: An integrative review. *Journal of Marketing Research* **26**(3) 351–357.

Rao, A. R., L. Qu, R. W. Ruekert. 1999. Signaling unobservable product quality through a brand ally. *Journal of Marketing Research* **36**(2) 258–268.

Rousseeuw, P. J. 1987. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics* **20** 53–65.

Schaninger, C. M. 1993. Social class versus income revisited: An empirical investigation. *Marketing Science* **12**(1) 73–87.

Shivendu, S., Z. Zhang. 2013. Economics of daily-deal websites: Advertising and sampling effects. *The 34th International Conference on Information Systems* .

Smith, R. E., C. A. Vogt. 1995. The effects of integrating advertising and negative word-of-mouth communications on message processing and response. *Journal of Consumer Psychology* **4**(2) 133–151.

Subramanian, U., R. C. Rao. 2016. Leveraging experienced consumers to attract new consumers: An equilibrium analysis of displaying deal sales by daily deal websites. *Management Science* **62**(12) 3555–3575.

Tirole, J. 1988. *The theory of industrial organization*. MIT press, Cambridge, MA.

Wang, J., X. Zhao, J. Li. 2013. Group buying: A strategic form of consumer collective. *Journal of Retailing* **89**(3) 338–351.

Wells, J. D., J. S. Valacich, T. J. Hess. 2011. What signal are you sending? How website quality influences perceptions of product quality and purchase intentions. *MIS Quarterly* **35**(2) 373–396.

Wolinsky, A. 1983. Prices as signals of product quality. *Review of Economic Studies* **50**(4) 647–658.

Wu, J., M. Shi, M. Hu. 2015. Threshold effects in online group buying. *Management Science* **61**(9) 2025–2040.

Zhang, J., H. Li, R. Yan, C. Johnston. 2017. Examining the signaling effect of e-tailers' return policies. *Journal of Computer Information Systems* **57**(3) 191–200.

Zhang, L., D. J. Chung. 2016. Strategic channel selection with online platforms: An empirical analysis of the daily deal industry. Working Paper, Harvard Business School.

Zhu, F., X. Zhang. 2010. Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of Marketing* **74**(2) 133–148.

Figure 1. Distribution of Discount Percentage

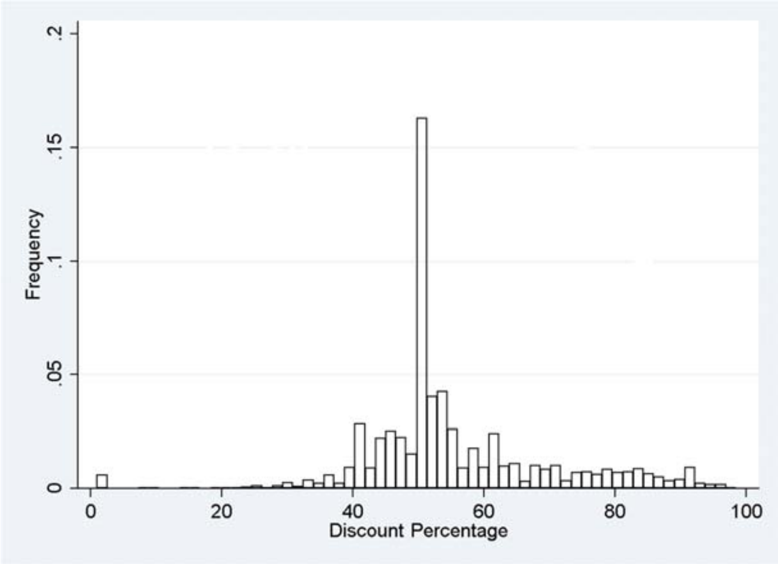
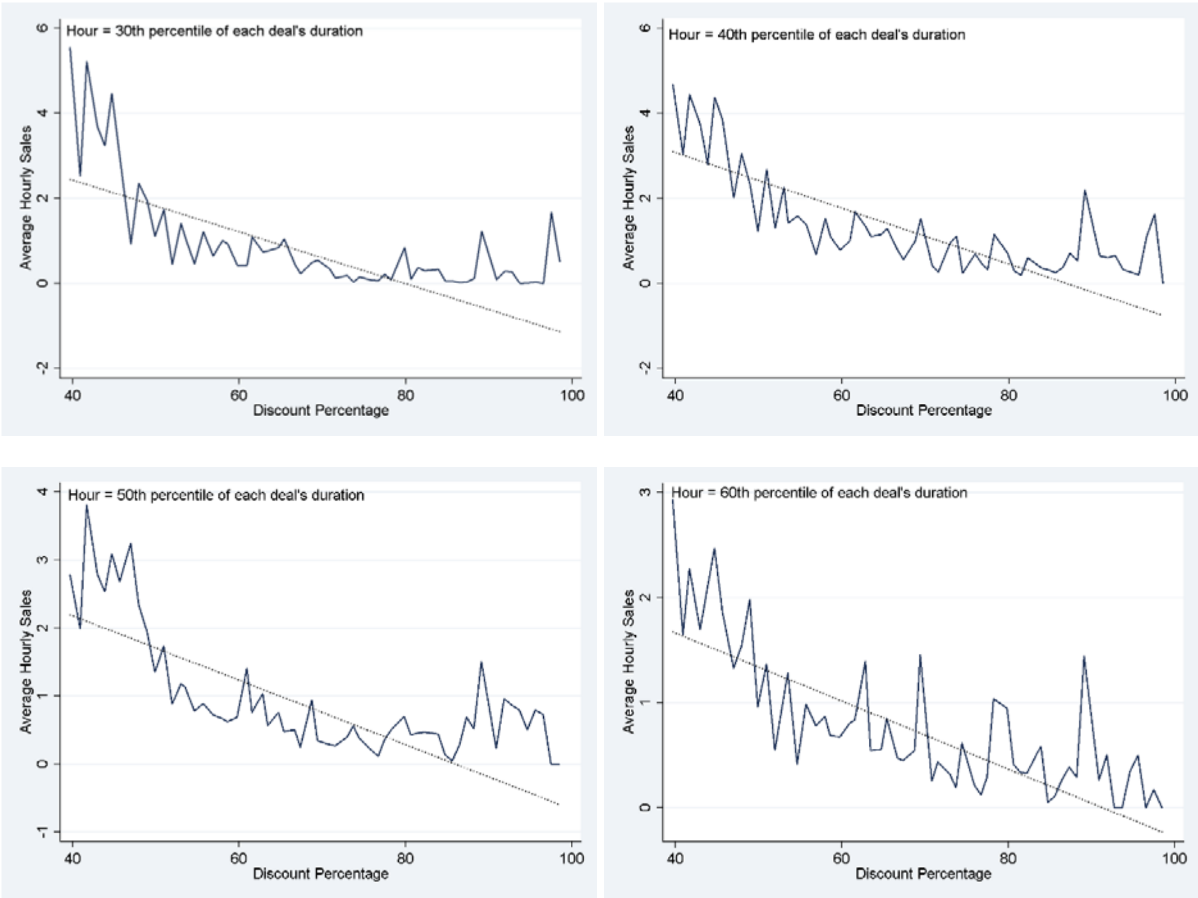


Figure 2. Deal Sales and Discount Percentage

(a)



(b)

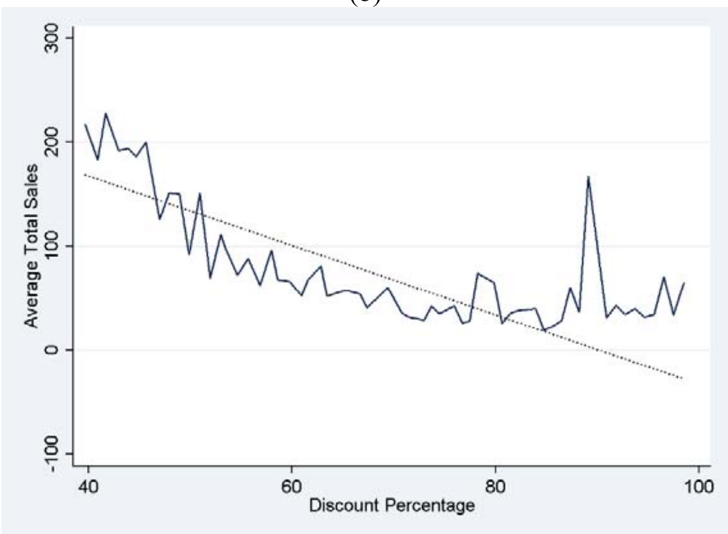


Figure 3. Discount Effects over Deal Life Cycle

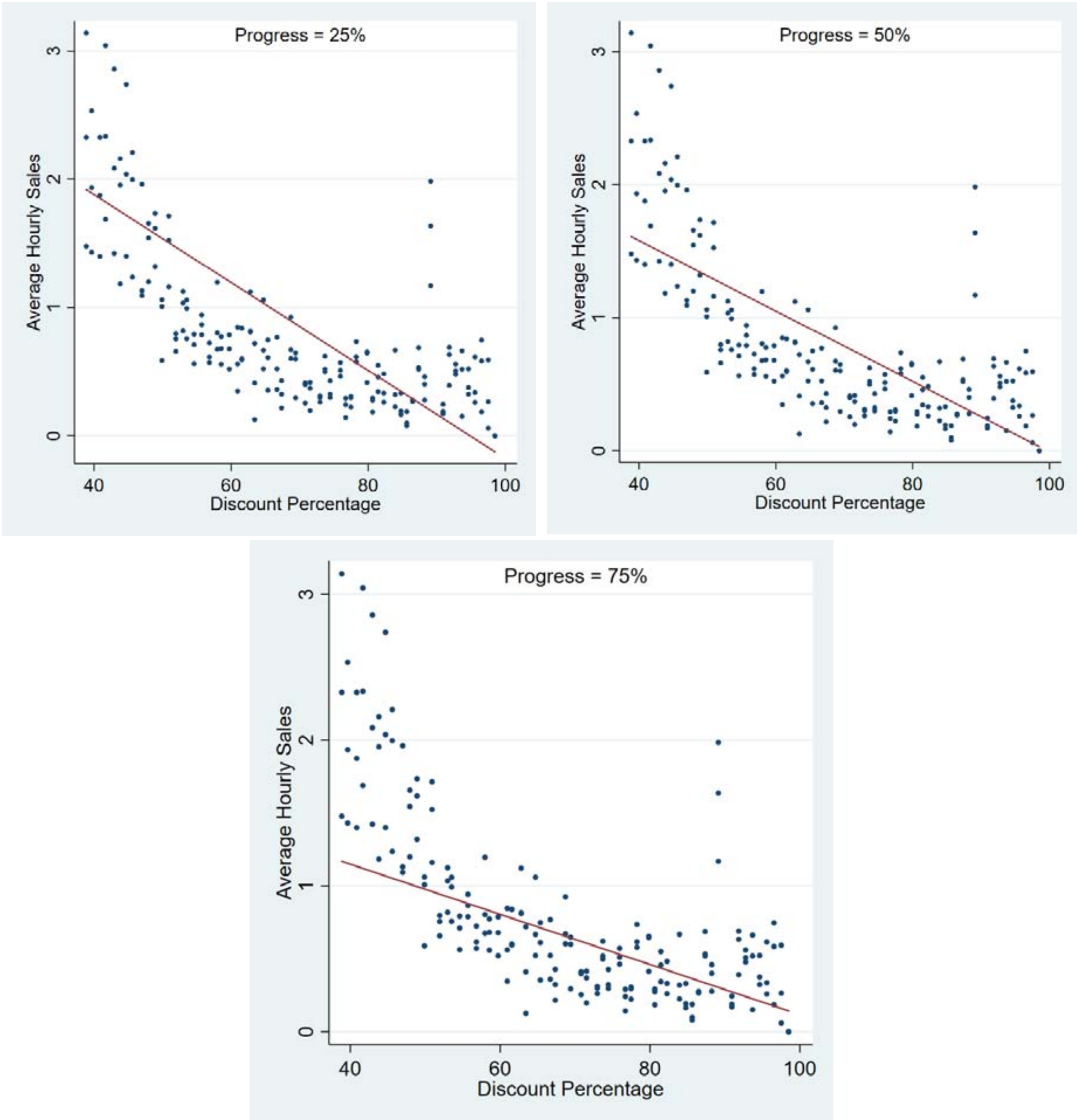


Figure 4. Perceived Quality Uncertainty, Perceived Quality, and WTB

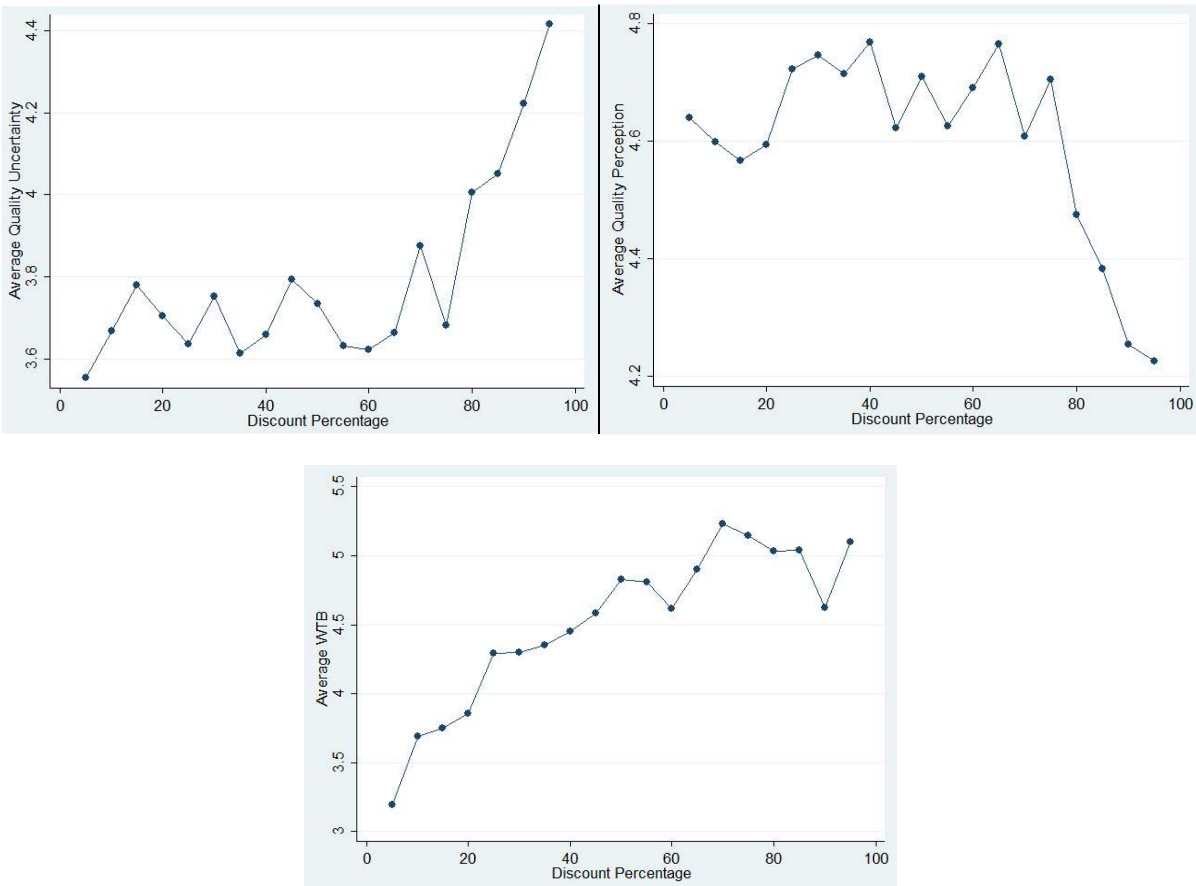


Table 1. Deal Distribution

Category	Freq.	Percent	Cum. percent
Automotive	271	1.36	1.36
Beauty & Spas	5,230	26.18	27.54
Education	691	3.46	30.99
Entertainment	6,524	32.66	63.65
Food & Drink	620	3.10	66.75
Health & Fitness	1,804	9.03	75.78
Home Services	226	1.13	76.91
Medical Treatment	558	2.79	79.71
Nightlife	60	0.30	80.01
Pets Services	90	0.45	80.46
Other Professional Services	734	3.67	84.13
Restaurants	3,170	15.87	100.00
Total	19,978	100.00	

Table 2. Summary Statistics

Variables	*N*	Nr. of deals	Unit	Mean	Std. dev.	Min	Max
Hourly sales	1,835,794	19,978		1.24	5.77	0	990
Lag cumulative sales	1,835,794	19,978		76.33	149.32	0	990
Total sales	19,978	19,978		113.81	194.39	0	990
Transaction price	1,835,794	19,978	USD	52.44	154.68	2	6,440
Original price	1,835,794	19,978	USD	142.74	364.00	5	12,582
Discount percentage	1,835,794	19,978	0~100	55.55	14.34	1	99
Maximum purchases allowed	1,835,794	19,978		5.49	21.16	1	540
Number of Facebook fans	1,835,794	19,978		190,781	1,589,734	0	51,136,036
Display review quotes (dummy)	1,835,794	19,978		0.02	0.12	0	1
Number of options	1,835,794	19,978		2.00	1.40	1	42
Number of competing deals	1,835,794	19,978		0.24	0.60	0	5
Use-restriction proxy	1,835,794	19,978		424.70	133.33	0	734
Sold out finally (dummy)	1,835,794	19,978		0.03	0.16	0	1
Merchant created deal (dummy)	1,835,794	19,978		0.03	0.16	0	1
Days before expiration	1,835,794	19,978		212.78	120.91	30	358
Online deal (dummy)	1,835,794	19,978		0.01	0.11	0	1
Multiregion deal (dummy)	1,835,794	19,978		0.33	0.47	0	1
Deal frequency	1,835,794	19,978		1.10	0.35	1	6
Duration	1,835,794	19,978	Hour	102.64	55.76	12	926
Review count	624,924	6,692		531.61	1623.73	1	8,778
Average rating	624,924	6,692	1~5	3.70	0.66	1	5
Credence-good deal (dummy)	1,835,794	19,978		0.04	0.18	0	1
Median household income, 2008--2012	1,704,202	18,553	1,000 USD	54.77	10.60	24.65	90.75
Bachelor's degree or higher, % of persons age 25+, 2008--2012	1,704,202	18,553	0~100	33.90	9.75	8.50	58.10
Average hourly wage (AHW)	1,704,202	18,553	USD	18.90	6.44	12.30	38.59
House price index (HPI)	1,704,202	18,553		212.19	20.20	177.10	262.10

Table 3. Correlations

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*
1. Hourly sales	1.00																	
2. Lag cumulative sales	0.31	1.00																
3. Transaction price	-0.15	-0.46	1.00															
4. Discount percentage	-0.08	-0.16	0.06	1.00														
5. Maximum purchases	0.05	0.10	-0.06	-0.07	1.00													
6. Facebook fans	0.11	0.25	-0.14	-0.12	0.30	1.00												
7. Review quotes	0.02	0.05	-0.00	-0.01	-0.00	-0.02	1.00											
8. Number of options	-0.09	-0.23	0.04	0.15	-0.17	-0.27	-0.00	1.00										
9. Competing deals	-0.00	0.00	0.02	-0.02	-0.02	0.00	0.01	-0.02	1.00									
10. Use-restriction proxy	0.01	0.04	0.04	-0.05	0.12	0.13	-0.01	0.03	0.04	1.00								
11. Sold out finally	0.12	0.19	-0.05	-0.05	0.13	0.25	-0.01	-0.16	0.05	0.07	1.00							
12. Merchant-created deal	0.03	0.08	-0.01	-0.07	0.17	0.15	-0.01	-0.16	0.01	0.12	0.02	1.00						
13. Days before expiration	0.09	0.19	0.00	-0.19	0.36	0.35	0.01	-0.29	-0.02	0.12	0.15	0.18	1.00					
14. Online deal	-0.02	-0.05	0.08	0.04	-0.01	-0.06	-0.01	-0.03	-0.04	0.02	-0.01	-0.02	-0.03	1.00				
15. Multiregion deal	0.04	0.08	-0.00	-0.05	0.37	0.42	-0.02	-0.21	-0.07	0.07	0.13	0.08	0.35	0.02	1.00			
16. Deal frequency	-0.01	-0.03	0.04	-0.00	0.03	0.02	0.00	0.01	0.04	0.03	-0.01	0.11	0.04	-0.00	0.02	1.00		
17. Duration	-0.05	0.11	-0.01	-0.03	0.09	0.11	0.01	-0.06	0.00	0.05	-0.07	0.10	0.09	-0.02	0.11	0.03	1.00	
18. Credence-good deal	-0.04	-0.12	0.14	0.11	-0.05	-0.07	-0.01	-0.02	-0.07	0.01	-0.03	-0.03	-0.06	0.15	-0.03	-0.02	-0.04	1.00

Table 4. Estimation Results

	(1) Whole Sample	(2) Sub-sample with Review	(3) Entertainment	(4) Beauty & Spas	(5) Restaurants
price	-0.0103**	-0.0274***	-0.0134**	-0.0143***	-0.0290***
	(0.0040)	(0.0077)	(0.0056)	(0.0030)	(0.0082)
discount	-0.0195***	-0.0295***	-0.0192**	-0.0187	-0.0266**
	(0.0070)	(0.0110)	(0.0088)	(0.0141)	(0.0107)
lag cumulative sales	0.1071***	0.1227***	0.1289***	0.0443***	0.1348***
	(0.0061)	(0.0041)	(0.0059)	(0.0044)	(0.0045)
days before expiration	0.0330***	0.0523***	0.0241***	0.0245***	0.0738***
	(0.0057)	(0.0065)	(0.0071)	(0.0060)	(0.0061)
merchant-created deal	0.0702***	0.0833***	0.0693***	0.1671***	0.2363**
	(0.0208)	(0.0235)	(0.0200)	(0.0350)	(0.0838)
facebook fans	0.0049***	0.0039***	0.0048***	0.0046***	0.0070***
	(0.0008)	(0.0013)	(0.0015)	(0.0007)	(0.0010)
has review quotes	0.0448**	0.0306*	0.0205	0.0136	0.0951***
	(0.0175)	(0.0171)	(0.0195)	(0.0129)	(0.0301)
sold out finally	0.2247***	0.1294***	0.1859***	0.0931**	0.2771***
	(0.0280)	(0.0226)	(0.0351)	(0.0330)	(0.0609)
duration	-0.2382***	-0.3517***	-0.2955***	-0.0586***	-0.3294***
	(0.0280)	(0.0277)	(0.0315)	(0.0145)	(0.0289)
options	-0.0169***	-0.0213***	-0.0105	-0.0137*	-0.0164
	(0.0055)	(0.0081)	(0.0094)	(0.0068)	(0.0150)
competing deals	-0.0214***	-0.0274***	-0.0378***	-0.0085***	-0.0095
	(0.0053)	(0.0099)	(0.0061)	(0.0025)	(0.0112)
maximum purchases allowed	0.0005	0.0162***	0.0054	0.0096*	0.0108
	(0.0040)	(0.0052)	(0.0055)	(0.0055)	(0.0087)
use restriction proxy	0.0017	-0.0019	-0.0044	0.0015	0.0054
	(0.0032)	(0.0069)	(0.0098)	(0.0018)	(0.0079)
online deal	-0.0404	-0.0542	-0.0594	0.0000	--
	(0.0579)	(0.0621)	(0.1052)	(0.0175)	
multi-region deal	0.0105	0.0015	0.0215*	0.0198**	-0.0107
	(0.0086)	(0.0144)	(0.0118)	(0.0076)	(0.0149)
deal frequency	-0.0084	-0.0306**	-0.0322**	0.0111	-0.0200
	(0.0092)	(0.0130)	(0.0134)	(0.0080)	(0.0263)
review count	--	0.0241***	--	--	--
		(0.0036)			
average rating	--	0.0054	--	--	--
		(0.0069)			
count × rating	--	-0.0013	--	--	--
		(0.0033)			
division fixed effects	Yes	Yes	Yes	Yes	Yes
subcategory fixed effects	Yes	Yes	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,835,794	624,924	620,317	469,746	287,932
R-squared	0.159	0.176	0.179	0.066	0.160

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.*

Table 5. Identification

	(1) 2SLS Enter- tainment	(2) 2SLS Restaurants	(3) 2SLS (AHW and HPI as instruments)	(4) 2SLS (AHW as instrument)	(5) Self- selection by popularity
price	-0.0236***	-0.0745***	-0.0130***	-0.0132***	-0.0106***
	(0.0052)	(0.0096)	(0.0038)	(0.0038)	(0.0040)
discount	-0.1021***	-0.4859***	-0.0610	-0.0650*	-0.0185**
	(0.0223)	(0.0899)	(0.0379)	(0.0381)	(0.0079)
popular deals	--	--	--	--	-0.0065
					(0.0463)
popular deals× discount	--	--	--	--	-0.0018
					(0.0112)
lag cumulative sales	0.1286***	0.1377***	0.1078***	0.1078***	0.1070***
	(0.0022)	(0.0015)	(0.0015)	(0.0015)	(0.0061)
days before expiration	0.0177***	0.0547***	0.0308***	0.0307***	0.0349***
	(0.0063)	(0.0052)	(0.0035)	(0.0035)	(0.0057)
merchant-created deal	0.0703***	0.2261***	0.0668***	0.0667***	0.0720***
	(0.0135)	(0.0853)	(0.0140)	(0.0140)	(0.0204)
facebook fans	0.0051***	0.0065***	0.0052***	0.0052***	0.0049***
	(0.0007)	(0.0006)	(0.0005)	(0.0005)	(0.0008)
has review quotes	0.0211	0.1003***	0.0523***	0.0523***	0.0447**
	(0.0223)	(0.0111)	(0.0148)	(0.0148)	(0.0175)
sold out finally	0.1907***	0.2527***	0.2361***	0.2362***	0.2241***
	(0.0157)	(0.0222)	(0.0156)	(0.0156)	(0.0287)
duration	-0.2960***	-0.3465***	-0.2405***	-0.2405***	-0.2386***
	(0.0157)	(0.0072)	(0.0141)	(0.0141)	(0.0282)
options	-0.0082	-0.0202***	-0.0160***	-0.0159***	-0.0173***
	(0.0071)	(0.0053)	(0.0041)	(0.0041)	(0.0055)
competing deals	-0.0380***	0.0004	-0.0226***	-0.0226***	-0.0214***
	(0.0091)	(0.0059)	(0.0045)	(0.0045)	(0.0053)
maximum purchases allowed	0.0025	0.0088***	0.0004	0.0004	0.0009
	(0.0038)	(0.0034)	(0.0021)	(0.0022)	(0.0039)
use restriction proxy	-0.0075	-0.0015	0.0019	0.0019	0.0025
	(0.0072)	(0.0051)	(0.0028)	(0.0029)	(0.0031)
online deal	-0.0152	--	-0.0216	-0.0207	-0.0403
	(0.0708)		(0.0444)	(0.0444)	(0.0578)
multi-region deal	0.0181***	-0.0643***	0.0106**	0.0106**	0.0190
	(0.0066)	(0.0120)	(0.0048)	(0.0048)	(0.0131)
deal frequency	-0.0306**	-0.0047	-0.0103	-0.0104	-0.0084
	(0.0119)	(0.0120)	(0.0071)	(0.0071)	(0.0092)
division fixed effects	Yes	Yes	Yes	Yes	Yes
subcategory fixed effects	Yes	Yes	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	615,036	287,913	1,704,202	1,704,202	1,835,794
R-squared	0.177	0.136	0.159	0.159	0.159

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*

Table 6. Tests of Candidate Explanations

	(1) Test of local congestion I	(2) Test of local congestion II	(3) Incorporate deal progress	(4) Experience vs. credence goods	(5) Effect of displaying large sales	(6) Income effect	(7) Education effect
price	-0.0104**	-0.0574***	0.0158***	-0.0106***	-0.0155***	-0.0103**	-0.0101**
	(0.0040)	(0.0165)	(0.0045)	(0.0040)	(0.0032)	(0.0042)	(0.0043)
discount	-0.0077	-0.0382**	-0.0791***	-0.0190***	-0.0220**	-0.0155*	-0.0136
	(0.0066)	(0.0168)	(0.0140)	(0.0071)	(0.0092)	(0.0083)	(0.0086)
days before expiration × discount	-0.0231**	--	--	--	--	--	--
	(0.0108)						
progress	--	--	-0.9618***	--	--	--	--
			(0.1128)				
progress × discount	--	--	0.1240***	--	--	--	--
			(0.0261)				
credence × discount	--	--	--	-0.0696**	--	--	--
				(0.0343)			
salesAbove300	--	--	--	--	0.3651***	--	--
					(0.0266)		
salesAbove300 × discount	--	--	--	--	0.0479***	--	--
					(0.0112)		
income × discount	--	--	--	--	--	-0.0593***	--
						(0.0193)	
education × discount	--	--	--	--	--	--	-0.0410***
							(0.0126)
lag cumulative sales	0.1071***	0.1425***	0.1484***	0.1071***	0.0793***	0.1077***	0.1077***
	(0.0062)	(0.0072)	(0.0094)	(0.0061)	(0.0046)	(0.0063)	(0.0063)
days before expiration	0.0339***	0.0646***	0.0224***	0.0330***	0.0289***	0.0324***	0.0323***
	(0.0054)	(0.0091)	(0.0051)	(0.0057)	(0.0046)	(0.0055)	(0.0055)
merchant-created deal	0.0702***	0.1127	0.0582***	0.0703***	0.0590***	0.0666***	0.0665***
	(0.0208)	(0.1469)	(0.0187)	(0.0208)	(0.0196)	(0.0209)	(0.0209)
facebook fans	0.0050***	0.0053**	0.0031***	0.0049***	0.0045***	0.0052***	0.0052***
	(0.0008)	(0.0023)	(0.0007)	(0.0008)	(0.0007)	(0.0009)	(0.0009)
has review quotes	0.0446**	0.0754**	0.0327**	0.0448**	0.0311**	0.0526***	0.0523***
	(0.0175)	(0.0318)	(0.0149)	(0.0175)	(0.0157)	(0.0184)	(0.0184)
sold out finally	0.2251***	0.1479***	0.1759***	0.2246***	0.1828***	0.2343***	0.2344***
	(0.0280)	(0.0484)	(0.0284)	(0.0280)	(0.0258)	(0.0302)	(0.0301)
duration	-0.2382***	-0.4154***	-0.2582***	-0.2383***	-0.2370***	-0.2402***	-0.2402***
	(0.0280)	(0.0462)	(0.0294)	(0.0280)	(0.0272)	(0.0290)	(0.0290)
options	-0.0172***	-0.0236	-0.0048	-0.0171***	-0.0183***	-0.0171***	-0.0172***
	(0.0055)	(0.0198)	(0.0053)	(0.0055)	(0.0048)	(0.0055)	(0.0055)
competing deals	-0.0215***	0.0532	-0.0138**	-0.0215***	-0.0208***	-0.0229***	-0.0229***
	(0.0053)	(0.0420)	(0.0054)	(0.0053)	(0.0049)	(0.0055)	(0.0055)
maximum purchases allowed	0.0001	0.0053	0.0007	0.0006	0.0011	0.0005	0.0003
	(0.0040)	(0.0158)	(0.0034)	(0.0040)	(0.0035)	(0.0042)	(0.0042)
use-restriction proxy	0.0017	-0.0040	-0.0012	0.0018	0.0029	0.0028	0.0029
	(0.0032)	(0.0268)	(0.0033)	(0.0032)	(0.0027)	(0.0033)	(0.0033)
online deal	-0.0414	0.0178	-0.0184	-0.0400	-0.0445	-0.0321	-0.0318
	(0.0577)	(0.0861)	(0.0586)	(0.0580)	(0.0466)	(0.0666)	(0.0664)

multiregion deal	0.0099	0.0378**	0.0084	0.0107	0.0080	0.0113	0.0115
	(0.0087)	(0.0166)	(0.0068)	(0.0085)	(0.0071)	(0.0087)	(0.0087)
deal frequency	-0.0083	0.0905	-0.0029	-0.0085	-0.0007	-0.0104	-0.0105
	(0.0092)	(0.0562)	(0.0081)	(0.0092)	(0.0079)	(0.0094)	(0.0094)
division fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
subcategory fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,835,794	97,200	1,835,794	1,835,794	1,835,794	1,704,202	1,704,202
R-squared	0.159	0.210	0.184	0.159	0.169	0.160	0.160

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*

Table 7. Descriptive Statistics: Groupon Goods

Variables	*N*	No. of deals	Unit	Mean	Std. dev.	Min	Max
Hourly sales	17,692	382		3.16	19.41	0	930
Lag cumulative sales	17,692	382		25.00	80.58	0	930
Transaction price	17,692	382	USD	208.41	90.79	6	1449
Original price	17,692	382	USD	425.58	320.46	12	6300
Discount percentage	17,692	382	0~100	51.59	9.26	1	95
Maximum purchases allowed	17,692	382		4.95	0.40	1	5
Number of options	17,692	382		1.20	1.21	1	12
Sold out finally (dummy)	17,692	382		0.01	0.01	0	1
Duration	17,692	382	Hour	101.14	45.64	2	291
Number of Competing Deals	17,692	382		0.23	0.65	0	4

Table 8. Falsification and Robustness Tests

	(1) Falsification: Groupon Goods	(2) Total Sales	(3) RE model	(4) Linear specification	(5) Add lag cumulative sales squared	(6) Excluding price outliers	(7) Excluding duration outliers
price	-0.4625***	-0.6760***	-0.0976***	-0.0004***	-0.0221***	-0.0383***	-0.0063
	(0.0268)	(0.0127)	(0.0085)	(0.0001)	(0.0028)	(0.0065)	(0.0039)
discount	0.3714***	-0.1415***	-0.0270**	-0.0045**	-0.0213*	-0.0291***	-0.0281**
	(0.0898)	(0.0275)	(0.0134)	(0.0021)	(0.0108)	(0.0098)	(0.0114)
lag cumulative sales	0.1796***	--	-0.0242***	0.0084***	0.1035***	0.1019***	0.0933***
	(0.0139)		(0.0056)	(0.0005)	(0.0031)	(0.0072)	(0.0055)
lag cumulative sales squared	--	--	--	--	0.0322***	--	--
					(0.0014)		
days before expiration	--	0.2461***	0.0753***	0.0012***	0.0261***	0.0276***	0.0278***
		(0.0179)	(0.0096)	(0.0002)	(0.0039)	(0.0051)	(0.0047)
merchant-created deal	--	0.1849**	0.1065***	0.1129	0.0213	0.0895***	-0.0162
		(0.0773)	(0.0373)	(0.1070)	(0.0163)	(0.0240)	(0.0198)
facebook fans	--	0.0475***	0.0122***	0.0003***	0.0029***	0.0049***	0.0040***
		(0.0025)	(0.0017)	(0.0001)	(0.0006)	(0.0012)	(0.0006)
has review quotes	--	0.3708***	0.0839***	0.1880*	0.0291**	0.0607**	0.0395**
		(0.0741)	(0.0298)	(0.1087)	(0.0144)	(0.0275)	(0.0184)
sold out finally	-0.2254	1.3725***	0.4500***	2.0767***	0.1390***	0.2290***	0.2554***
	(0.1769)	(0.0460)	(0.0276)	(0.2163)	(0.0223)	(0.0385)	(0.0584)
duration	-0.5742***	0.6722***	-0.2010***	-0.0060***	-0.2433***	-0.2240***	0.0206
	(0.0257)	(0.0325)	(0.0343)	(0.0013)	(0.0261)	(0.0417)	(0.2092)
options	-0.4320***	-0.3206***	-0.0561***	-0.0090	-0.0031	-0.0166***	-0.0214***
	(0.0423)	(0.0213)	(0.0094)	(0.0110)	(0.0052)	(0.0060)	(0.0054)
competing deals	0.3425***	-0.0524***	-0.0165***	-0.0777***	-0.0237***	-0.0297***	-0.0130***
	(0.0994)	(0.0122)	(0.0050)	(0.0232)	(0.0057)	(0.0083)	(0.0041)
maximum purchases allowed	-0.0334	0.0237*	0.0007	0.0001	0.0008	0.0016	-0.0033
	(0.0860)	(0.0129)	(0.0061)	(0.0001)	(0.0033)	(0.0041)	(0.0043)
Use-restriction proxy	--	0.0385**	0.0138***	-0.0003**	-0.0015	0.0030	0.0002
		(0.0150)	(0.0049)	(0.0001)	(0.0032)	(0.0028)	(0.0032)
online deal	--	-0.2504	-0.1578*	0.0280	0.0109	-0.0706***	-0.0211
		(0.2173)	(0.0822)	(0.2885)	(0.0308)	(0.0233)	(0.0401)
multiregion deal	--	0.0712***	0.0188	0.1706***	0.0098	0.0160*	0.0047
		(0.0260)	(0.0174)	(0.0616)	(0.0061)	(0.0096)	(0.0069)
deal frequency	--	-0.1192***	-0.0310*	-0.0083	-0.0083	-0.0101	-0.0081
		(0.0433)	(0.0175)	(0.0334)	(0.0071)	(0.0092)	(0.0081)
holiday percentage	--	0.0749*	--	--	--	--	--
		(0.0426)					
division fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
subcategory fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
time fixed effects	Yes	No	Yes	Yes	Yes	Yes	Yes
Observations	17,692	19,978	1,835,794	1,835,794	1,835,794	1,069,385	1,180,785
R-squared	0.808	0.233	--	0.111	0.173	0.157	0.132

Notes. Except column (2), the dependent variable is log hourly sales and all independent variables except dummies are specified in logs. In column (3), we rescale *facebook fans* by dividing it by 10,000 for easier interpretation. Robust standard errors clustered by product subcategory in parentheses, except column (1). Heteroskedasticity-robust standard errors used in column (1). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 9. Impact of Third-Party Support

	(1) Whole sample & interaction effects	(2) Subsample with online review	(3) Subsample with online review & review count ≥ 30	(4) Matched sample	(5) Matched sample & interaction effects
price	-0.0110***	-0.0278***	-0.0500***	-0.0160***	-0.0164***
	(0.0039)	(0.0077)	(0.0114)	(0.0057)	(0.0057)
discount	-0.0146***	-0.0262**	-0.0334***	-0.0145*	-0.0124*
	(0.0044)	(0.0114)	(0.0111)	(0.0080)	(0.0070)
discount × facebook fans	-0.0030***	--	--	--	-0.0023
	(0.0011)				(0.0024)
discount × has review quotes	-0.1114***	--	--	--	-0.2258***
	(0.0190)				(0.0769)
discount × review count	--	-0.0059	-0.0177**	--	--
		(0.0060)	(0.0087)		
discount × average rating	--	-0.0183	-0.0591***	--	--
		(0.0136)	(0.0198)		
lag cumulative sales	0.1068***	0.1227***	0.1320***	0.1149***	0.1148***
	(0.0061)	(0.0042)	(0.0044)	(0.0056)	(0.0056)
days before expiration	0.0333***	0.0522***	0.0646***	0.0458***	0.0460***
	(0.0057)	(0.0065)	(0.0098)	(0.0057)	(0.0057)
merchant-created deal	0.0696***	0.0819***	0.0790***	0.0816***	0.0800***
	(0.0207)	(0.0237)	(0.0277)	(0.0275)	(0.0277)
facebook fans	0.0048***	0.0039***	0.0060***	0.0024**	0.0024**
	(0.0008)	(0.0012)	(0.0019)	(0.0010)	(0.0009)
has review quotes	0.0395**	0.0309*	0.0713***	0.0109	0.0133
	(0.0164)	(0.0171)	(0.0270)	(0.0229)	(0.0226)
sold out finally	0.2238***	0.1293***	0.0834***	0.2269***	0.2271***
	(0.0283)	(0.0227)	(0.0186)	(0.0295)	(0.0291)
duration	-0.2385***	-0.3517***	-0.4272***	-0.2569***	-0.2573***
	(0.0280)	(0.0279)	(0.0179)	(0.0202)	(0.0202)
options	-0.0172***	-0.0215***	-0.0266**	-0.0210**	-0.0213**
	(0.0055)	(0.0080)	(0.0112)	(0.0087)	(0.0087)
competing deals	-0.0216***	-0.0274***	-0.0474***	-0.0167**	-0.0169**
	(0.0053)	(0.0100)	(0.0132)	(0.0073)	(0.0074)
maximum purchases allowed	0.0011	0.0161***	0.0186***	0.0076*	0.0079*
	(0.0040)	(0.0052)	(0.0067)	(0.0041)	(0.0040)
use-restriction proxy	0.0013	-0.0020	-0.0118	0.0092*	0.0091*
	(0.0032)	(0.0069)	(0.0132)	(0.0051)	(0.0051)
online deal	-0.0418	-0.0533	-0.1309	-0.0747**	-0.0756**
	(0.0586)	(0.0618)	(0.0995)	(0.0364)	(0.0368)
multiregion deal	0.0087	0.0009	0.0027	0.0085	0.0074
	(0.0081)	(0.0142)	(0.0223)	(0.0087)	(0.0084)
deal frequency	-0.0076	-0.0303**	-0.0439*	-0.0212**	-0.0206**
	(0.0091)	(0.0130)	(0.0256)	(0.0100)	(0.0101)
review count	--	0.0238***	0.0303***	--	--
		(0.0035)	(0.0055)		
average rating	--	0.0060	0.0024	--	--
		(0.0070)	(0.0144)		
count × rating	--	-0.0020	-0.0172*	--	--
		(0.0033)	(0.0100)		
division fixed effects	Yes	Yes	Yes	Yes	Yes
subcategory fixed effects	Yes	Yes	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,835,794	624,924	329,089	770,619	770,619
R-squared	0.159	0.176	0.191	0.156	0.156

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

Table 10. Threshold Effect of Discount

	(1) Perceived quality uncertainty	(2) Perceived quality	(3) WTB
discount (<60%)	-0.0011	0.0027*	0.0276***
	(0.0016)	(0.0015)	(0.0020)
discount (≥60%)	0.0189***	-0.0145***	-0.0006
	(0.0031)	(0.0026)	(0.0033)
deal fixed effects	Yes	Yes	Yes
subject fixed effects	Yes	Yes	Yes
order fixed effects	Yes	Yes	Yes
Observations	4,123	4,123	4,123
R-squared	0.265	0.264	0.310

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

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

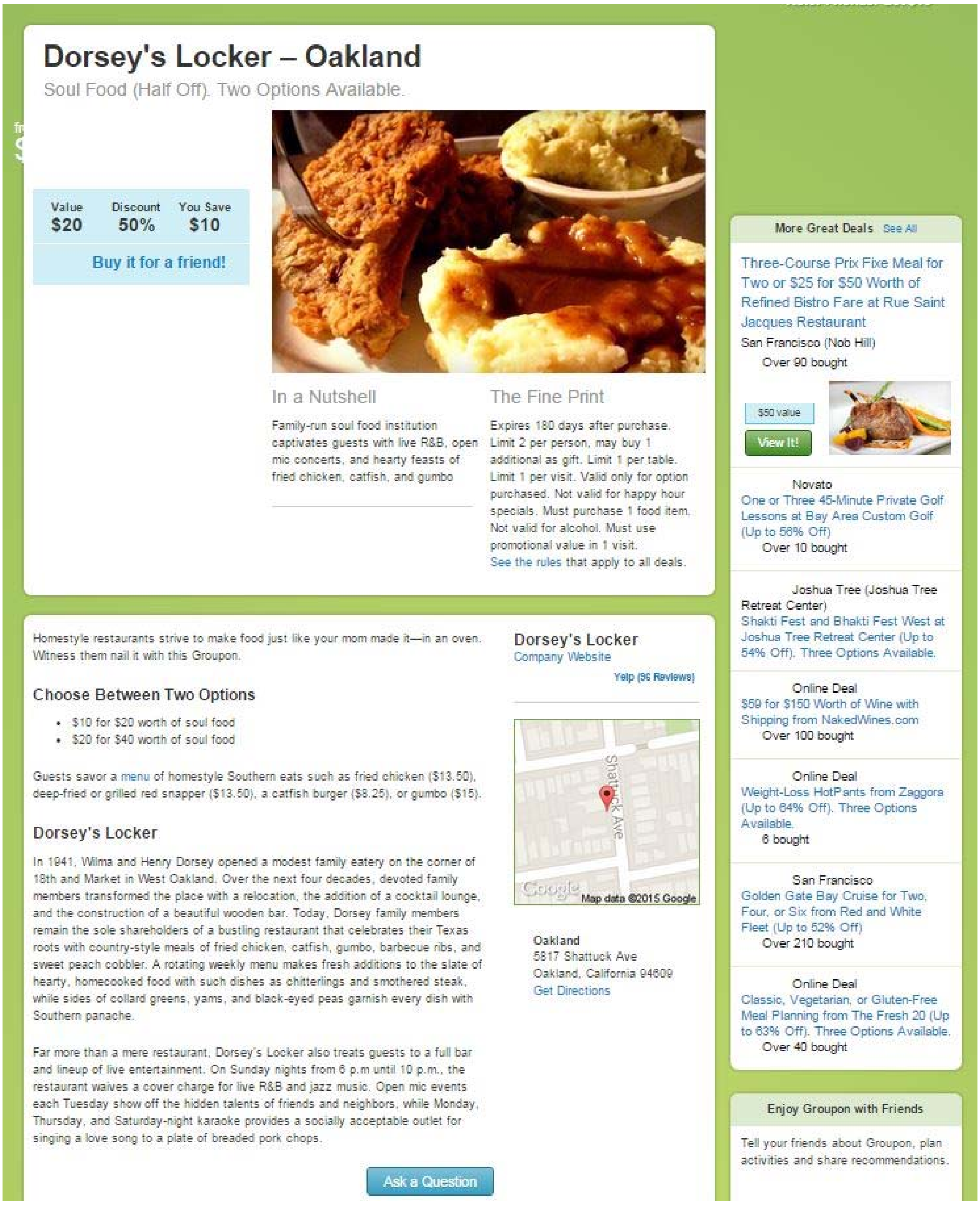


Table A.1. List of the subcategories

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.

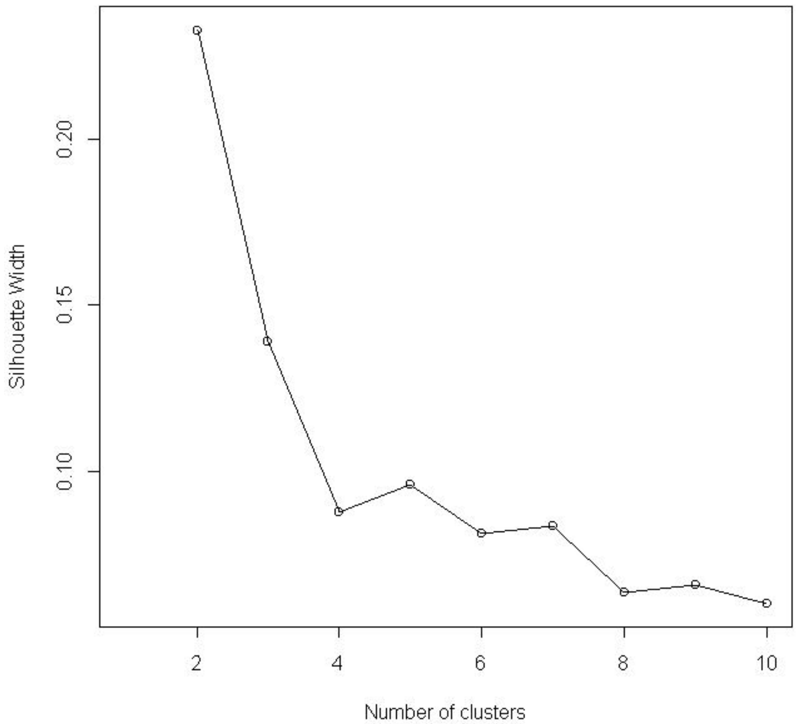
Because the deal characteristics do not vary over time, we use the cross-sectional deal data to perform the clustering. We compute the number of competing deals as the total number of deals that have ever overlapped with the focal deals during their entire lifespans. Furthermore, to account for "seasonality" 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
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**of t-tests**
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.

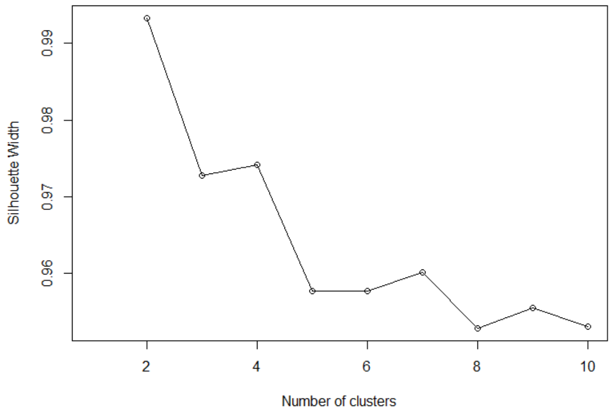
We use the one-to-one nearest neighbor without replacement matching method. In our setting, if no caliper (i.e., the maximum permitted difference between matched subjects) is set, the matched sample is quite unbalanced in the covariate distributions. Therefore, based on trial and error, we use 0.01 as 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 $K \in \{2,3,\ldots,10\}$. 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)

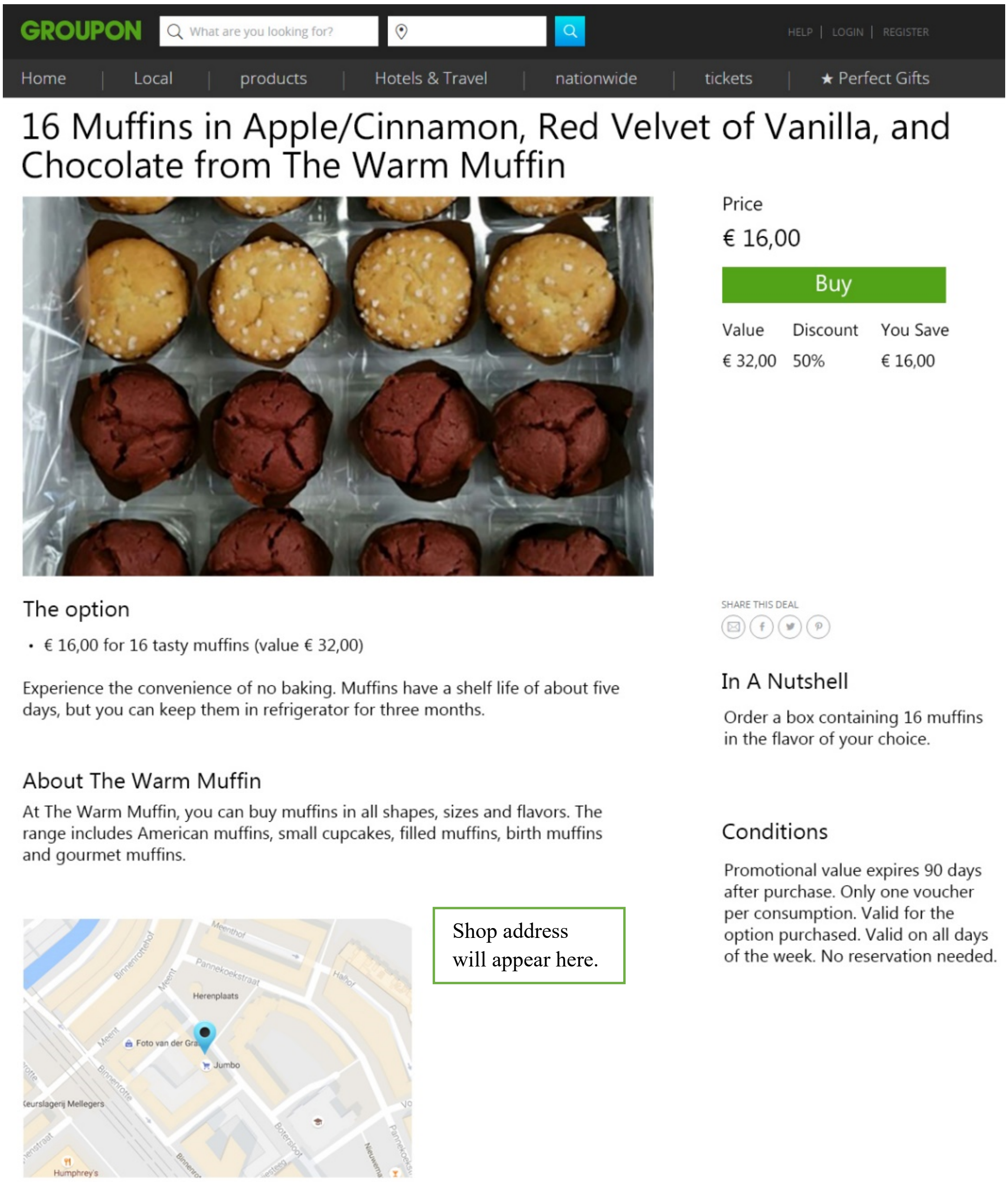
We create the experimental deals based on the distribution of deals in the Groupon data shown in Table 1. We create multiple deals for several categories because they are more often offered on Groupon. For these categories with multiple deals, we create one experimental deal for each of their top subcategories.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

References

Arellano, Manuel, Stephen Bond. 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies* **58**(2), 277--297.

Dice, Lee R. 1945. Measures of the amount of ecologic association between species. *Ecology* **26**(3), 297--302.

Dimoka, A., Y. Hong, P. A. Pavlou. 2012. On product uncertainty in online markets: Theory and evidence. *MIS Quarterly* **36**(2), 395--426.

Garen, John. 1984. The returns to schooling: A selectivity bias approach with a continuous choice variable. *Econometrica* **52**(5), 1199--1218.

Kirmani, Amna, Peter Wright. 1989. Money talks: Perceived advertising expense and expected product quality. *Journal Consumer Research* **16**(3), 344--353.

Pavlou, P. A., H. Liang, Y. Xue. 2007. Understanding and mitigating uncertainty in online exchange relationships: A principal--agent perspective. *MIS Quarterly* **31**(1), 105--136.

Peterson, Robert A., Alain J. Jolibert. 1976. A cross-national investigation of price and brand as determinants of perceived product quality. *Journal of Applied Psychology* **61**(4), 533--536.

Rousseeuw, Peter J. 1987. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics* **20**, 53--65.

Wooldridge, Jeffrey M. 2015. Control function methods in applied econometrics. *Journal of Human Resources* **50**(2), 420--445.

Zhang, Juanjuan, Peng Liu. 2012. Rational herding in microloan markets. *Management Science* **58**(5), 892--912.