# Deal or No Deal? Consumer Expectations and Competition in Daily Deals 

Completed Research Paper

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#### Abstract

Daily deals have emerged as an integral part of the marketing mix for retail merchants and have enjoyed wide acceptance by consumers. However, there is considerable ambiguity about the effects of deals on brand evaluation, and resulting electronic word-of-mouth (eWOM). In this paper, we propose that the effects of deals on eWOM are contingent on merchant heterogeneity and whether consumers perceive merchants' marketing efforts as desperate. We empirically model the effects of daily deals on eWOM for restaurants in Washington DC over 13 months. Results show that price segment, age, and competitive deal intensity strongly moderate the effect of deals on resulting eWOM. We also show that deals have significant spillover effects on neighboring merchants who do not offer deals. We confirm these effects using three controlled lab experiments, where similar results are obtained without the possibility of deal redemption.


Keywords: Bayesian, multi-level models, laboratory experiments, consumer behavior, econometric analysis, competition

## Introduction

A recent survey found that approximately four out of ten New Yorkers have used online coupons offered by firms such as Groupon and LivingSocial for redemption at assorted retail outlets (YouGov 2014). IBIS reports that between 2009 and 2014, platforms offering such social purchasing coupons have experienced a growth rate of over $140 \%$, with the majority of these deals focused on the services sector and retail consumer goods. Groupon, the market leader in daily deals (as these coupons are often referred to) has over 53 million active consumers, with over 200 million subscribers, and has sold over 400 million individual "deals" thus far in the United States and abroad. In the third quarter of 2014 alone, Groupon offered over 370,000 deals worldwide, with more than 160 million unique monthly visitors (Groupon 2015a). Broadly, daily deal platforms such as Groupon, LivingSocial and Google Offers operate doublesided markets, on which merchants offer deals (discounts) on one side, while individuals buy these deals, on the other side of the market. The platform appropriately extracts revenues from the merchant side of the platform, while subsidizing the consumer side of the market.

The numbers offered above would indicate that such platforms are unqualified successes. However, despite their popularity, online deals have remained a controversial subject, where opinions regarding their value to consumers and merchants have diverged significantly. The popular press provides several articles detailing the failures of many merchants' online deals (Clifford and Miller 2012; Agrawal 2013, Cohan 2012). In a recent survey of online deals merchants, Dholakia found that only $55 \%$ of merchants made a profit while $26 \%$ lost money (Dholakia 2010). A LivingSocial survey finds similar results, with only $54 \%$ of the respondents reporting a profit (BusinessInsider 2011). Given that a restaurant servicing a $\$ 50$ for $\$ 25$ deal receives an average of $\$ 12.50$, it is not surprising that some of these deals result in a loss for the merchant, since restaurants typically spend about $30 \%$ of their revenues on food preparation, more than the $25 \%$ revenues that such deals often provide (RestaurantReport 2012). However, daily deals can, in theory, lead to increased foot traffic, revenues and visibility for merchants at a lower customer acquisition cost (Dholakia 2011b).

Daily deals, thus, represent a dilemma for the merchant. On one hand, they can be valuable for generating awareness, entering the consideration set of customers and boosting sales by gaining access to the thousands of local subscribers in the daily deals site network (Dholakia 2011C). On the other hand, beyond potential short-term losses from such promotions, there are also long term considerations such as sustainability of the increase in the number of newly acquired customers as well as the retention of existing customers. One of the drivers of long-term effects is the impact of deals on quality perceptions. Prior academic work has shown that price changes do affect reported quality perceptions amongst consumers (Li and Hitt 2008, McGregor et al. 2007). The direction of the effects, however, depends on number of factors. In some cases, consumers may respond positively to such promotional activities, while in other contexts where such promotions may smack of desperation, the consumer's response is negative (Friestad and Wright 1994, Kirmani and Wright 1989).

Given this dichotomy about how online deals may influence the perception of service quality offered by the merchant, our first research question here is: do online deals affect a merchant's reported perceived quality? In other words, we explore what effects the release of a daily deal has on the perceived quality of the merchant's service offerings. Clearly, in the presence of competing expectations for how daily deals may affect the merchant's quality perceptions, we let the empirical analysis guide us. Prior work has also suggested that merchant heterogeneity may influence the responses to daily deals (Kirmani and Wright 1989). Therefore, our second research question is: what characteristics of the merchant moderate the effect of online deals on their perceived quality? Features such as merchant segment, age and prior reputation may affect the response to a daily deal - we explore these moderating factors here.

Finally, merchants do not operate in a vacuum, but within a competitive landscape that typically includes other merchants and their competitive actions that then cumulatively determine the options available to consumers. This brings into sharp focus the effect that competitors to the focal merchant may have, through their own decisions regarding offering deals. Specifically, by virtue of systematically offering heavily discounted daily deals, competitors to the focal merchant contribute towards shaping the experiences and opinions of consumers, thereby driving responses to deals offered by the focal restaurant. Thus, business owners are facing a critical dilemma - understanding how daily deals may influence
consumers and ultimately their market position. As long as these deals remain an important part of advertisement and, more generally, of the marketing budgets in small businesses ${ }^{1}$, understanding when deals may be affecting both promoted and non-promoted brand performance is critical as merchants attempt to increase the effectiveness of digital marketing campaigns. More formally: under what conditions are daily deals affecting the market position of participating and non-participating merchants? And perhaps more importantly, in environments where deals become the norm, how are nonparticipating merchants affected?
An important part of our analysis is on collecting data on quality perceptions of merchants. For the purposes of our study, we use online reviews provided by consumers on the merchants as indicators of perceived quality. Online reviews have often been used in the literature to gauge merchant or product quality. Indeed, anecdotally, $88 \%$ of the respondents to a recent survey said they do use online reviews to determine the quality of a business (BrightLocal 2013). Consumers routinely use online reviews to inform their purchasing decisions in both the online and offline contexts for a number of products and services. Apart from being used in informing consumer decisions, online reviews also have considerable influence in shaping common opinion about businesses. For example, $72 \%$ of surveyed consumers say that positive reviews make them trust a business or product more while $88 \%$ of consumers trust online reviews as much as personal recommendations (Cone 2011).
More formally, scholars have found that online reviews have a significant effect on outcomes like sales and consumer choice (Chevalier and Mayzlin 2006, Clemons et al. 2006, Duan et al. 2008, Chen and Xie 2008, Zhu and Zhang 2010). In the specific context of restaurants, which we study, Luca (2011) found that a one-star increase in Yelp rating leads to a 5-9 percent increase in revenue. Thus, inasmuch as recent literature indicates that online reviews are an important driver of a merchant's sales performance and also reflect customers' opinions about quality, we use online reviews as our measure of perceived quality of the merchant offering a daily deal.
We conduct our study using data collected from two sources. We focus on restaurants in our study, since there is considerable research indicating that online reviews are significantly associated promotional activities in this context (Lu et al. 2013). Our dataset is thus composed of daily deals offered by restaurants within a major metropolitan area in the United States over a 13 -month period. We collect data on daily deals offered by multiple platforms and their performance, i.e. the number of deals purchased, the discount rate and so on. Second, we collect online reviews for restaurants that offer these deals over a six-year period from Yelp.com, a popular online review site for restaurants. We augment this dataset with restaurants from the same geographical area that do not offer deals, to provide an apt control group.

We model the arrival and valence of reviews over time to identify the effect of engaging in a deal on the rating of the merchant over time. Further, we consider the effect of moderators, such as restaurant segment, age and cuisine, on the relationship between the deal and ex post reviews. Finally, we consider the effect of deals offered by local competitors on the reviews for the focal restaurant, ex post. Our findings suggest that daily deals indeed affect consumer quality evaluations in online reviews, but the direction of this effect depends strongly on merchant characteristics, such as the price segment, location, and cuisine type. For most restaurants, we find that the average effect of a daily deal is negative, i.e. ex post review valence is significantly lower, indicating lower quality perceptions. Surprisingly, we find clear evidence of a spillover effect - the presence of competing deals in the neighborhood affects the valence of reviews even for those restaurants that do not offer deals.
While our results indicate that deals tend to reduce online ratings, it is not clear whether this is because of ex post consumption, i.e. the consumer received poor service due to congestion or inadequate preparedness at the restaurant (Dholakia 2011b) when redeeming the deal, or if intrinsically, the offering of a deal reduced the perception of quality of the restaurant. In the latter case, reviewers may simply respond to the availability of a daily deal for a restaurant by lowering expectations, under the logic that deal-offering restaurants are likely to be "low quality" per se. To analyze this question, we extend our empirical models to a controlled setting through three lab experiments conducted on MTurk.

[^0]Through this work, we contribute to the literature at the intersection of information systems and marketing by explicating, using archival as well as experimental data, the effects of offering daily deals on the quality perceptions of restaurants. Our work here is easily generalized to those contexts where services or complex products are offered, and where online reviews are viewed as reasonable sources of quality information. Moreover, we expand our understanding of how the competitive environment affects the quality perception of merchants, by considering the competitive effects of deals specifically. Broadly, we add to the large and influential literature on electronic word of mouth (eWOM) by analyzing the effects of deals on online reviews, thereby extending existing models of eWOM.

Our work has also significant implications for practitioners. First, we help inform merchant owners (restaurateurs in our study) who seek to understand the conditions under which online deals may be beneficial to the restaurant. We find that certain merchant characteristics, such as a newness of the merchant and the price of a merchant might strongly moderate the direction (positive or negative) of the effect on the reputation of offering a deal. More importantly, we observe strong evidence of a deal competitive effect; the presence of competing deals in the neighborhood affects eWOM even for those restaurants that do not offer deals. Moreover, merchants in highly competitive deal environments suffer significantly less (and may even benefit) from offering a deal. In the following section, we briefly outline the prior literature before discussing the methodology in detail.

## Background and Theory

Online daily deals, also referred to as group-buying deals, social coupons or group discount vouchers (Luo et al. 2014, Kumar and Rajan 2012), are discount coupons posted online through a platform, such as Groupon or LivingSocial. These sites operate double-sided platforms (Parker and Van Alstyne 2005) on which merchants offer deals (on one side of the platform) while individuals buy the deals (on the other side of the platform). The platform appropriately extracts revenues from the merchant side of the platform, while subsidizing the consumer side. Platform owners typically work with merchants to offer deals for a specific period of time (usually 2 weeks). Once purchased, the deal's discounted price can be redeemed over a longer time-period (typically three months after the deal is posted) at the merchant, with some conditions applied on the bundling of coupons or on the specific form of services offered (Dholakia 2010). Once the coupon expires, the consumer can still typically redeem the original dollar value of the coupon without the discount.

Since the launch of online deals in 2008, they have experienced strong growth, with IBIS reporting that between 2009 and 2014, revenues have grown at an annual rate of $147.1 \%$, reaching $\$ 3.4$ billion in 2014 (2015). Groupon and LivingSocial are market leaders, totally accounting for roughly $60 \%$ of the deals market. In recent years alone, the number of global active deals offered daily has grown from 180,000 in the first quarter of 2014 to 425,000 in the first quarter of 2015 (IBIS 2015). Because of the continued popularity of daily deals with merchants, practitioner news outlets have argued that daily deals are a new and integral part of the online and mobile marketing mix for merchants (Tuten and Ashley 2011, Integreon 2012, Krasnova et al. 2013, Bharadwaj et al. 2013). However, and despite their popularity with customers as well, online deals have remained a contentious subject in practice (Agarwal 2013, Cohan 2012).

Within the academic literature, a small but growing body of work in marketing has focused on the extent to which deals affect firm performance. Specifically, scholars have provided insight into how offering a daily deal affects firm revenues (Dholakia 2010, Dholakia 2011a, Edelman et al. 2011, Dholakia and Kimes 2011, Dholakia 2012, Reiner and Skiera 2013, Shivendu and Zhang 2013). In addition to revenue, Dholakia (2010, 2011a, 2011b) surveyed merchants to investigate the profitability of daily deals. The results, largely consistent with the practitioner press, indicate that only $50 \%$ of merchants offering deals actually made any surplus. One of the primary reasons for this is based on the observation that most consumers often do not spend more than the deal value (Dholakia 2011b). However, on the positive side, daily deals have been found to provide many of the immediate benefits of price promotions observed in the literature (Guadagni and Little 1983, Neslin, Henderson, and Quelch 1985, Blattberg and Neslin 1990) by increasing foot traffic, revenues, and visibility for merchants, at a lower customer acquisition cost (Dholakia 2011a, 2012c). Beyond revenues and margins, how do daily deals influence the focal merchants' electronic word of mouth? We address this specific question next.

Recent work has attempted to quantify the extent to which daily deals may influence a merchant's brand attitudes and eWOM. In a survey of 931 U.S. consumers, Dholakia and Kimes (2011) examine consumer responses to daily deals and find there is no loss in brand equity for merchants offering deals. In fact, the authors comment: "To the contrary, respondents offered favorable comments about the restaurant and their dining experience" (p. 18). These authors also find that consumers are aware of the deals offered by multiple daily deal sites, with $50 \%$ or more of consumers reporting awareness of deals from Groupon, restaurant.com, LivingSocial, BuyWithMe, and TravelZoo. Alternatively, Byers et al. (2012a, 2012b) focus on a single platform, Groupon, and report that offering a Groupon leads to an average 0.2 star rating decrease in Yelp². Their study follows approximately 5,000 Groupons from many categories in the U.S, which were then linked to the online reviews for that merchant on Yelp. While Dholakia and Kimes (2011), by virtue of their design, do not account for the heterogeneity among merchants who offer deals, Byers et al. (2012a) include all retailers offering Groupon deals without accounting again for the heterogeneity of deal merchants. We argue that there is likely a middle ground here driven by heterogeneity of the merchants offering deals, and their competitive environments. Accounting for this heterogeneity will deliver, arguably, a more nuanced view of the effect of daily deals, suggesting that the negative or null effect from deals may not extend to all merchants. We consider the influence of these sources of heterogeneity below.
As a first step, we note that daily deals represent a new online mixture of price promotions and opt-in advertisements (Edelman et al. 2011). Daily deal subscribers typically need to sign up with the platform (such as Groupon or LivingSocial) to access the deals and receive email messages with the equivalent of advertising copy for the merchants, which typically contain positively framed images and endorsements; these are akin to advertisements for the focal merchant (Shivendu and Zhang 2013). Additionally, daily deals represent price promotions, since they offer deep price discounts. We use these two aspects of daily deals to theoretically motivate the moderating effects of heterogeneity and competition in their effects on eWOM.

Prior work has established that consumer expectations and attitudes are shaped by pricing strategies, more specifically, the promotional activities used by merchants (Mazumdar et al. 2005, Lynch and Ariely 2000, Yoon et al. 2014, Lee and Tsai 2015). Research has established that higher prices are associated with higher quality evaluations and more positive eWOM, all else being equal (McGregor et al. 2007, Li and Hitt 2010). We are, however, interested in how the marginal effect of the daily deal on the resulting eWOM may change depending on the merchant's characteristics, or more specifically, its price segment. Research studying the effects of price promotions on consumer attitudes and brand evaluations shows that the effect is driven largely by the discounted dollar amount (Blattberg et al. 1995). Winer (1986) first proposed that the larger the difference between the initial price and the purchase price, the greater the resulting consumer utility and the more positive the consumer attitude towards the merchant or product. He argued that this effect is predicated on the discounted dollar value rather than the discount rate per se; this effect has been empirically observed in various other product contexts as well (Della Bitta et al 1981, Grewal et al. 1998, Wu et al. 2004, Biswas et al. 2013).
Following this logic in the daily deals context, we argue that deep discounts offered by merchants in the low-price segment are likely to be viewed more negatively, given that the resulting dollar value of the discount is small. Additionally, if lower prices are already associated with lower quality, further price discounts in this context are likely to be viewed even more negatively by consumers. Alternatively, deals offered by high-price segment merchants start from an expectation of high quality (Li and Hitt 2010) and also offer consumers greater discounts in absolute value. Thus, merchants in the high-price segment may not experience the same negative effect on their eWOM as merchants operating in a lower-price segment. In fact, strong associations made between price and qualities, which benefit high-price merchants, may even lead to a positive response on eWOM for such merchants. These arguments suggest that the marginal effects of daily deals on ex post eWOM are likely to be significantly negative for low-price merchants (consistent with Byers et al. (2012a)) but not so for merchants in the premium segment.
To the extent that daily deals share features of opt-in advertisements, the persuasion knowledge model proposed by Friestad and Wright (1994) suggests that under certain conditions, the motivations behind

[^1]such promotional efforts are perceived as appropriate and reflect confidence in the product or service advertised. However, in other contexts, promotional or advertising efforts may smack of desperation and produce negative brand evaluations (Kirmani 1997, Chen and Kirmani 2015). Extending this argument to the daily deals context suggests that merchants providing daily deals under conditions that reflect confidence may not receive negative eWOM but may actually benefit from such daily deals. One such contingency in which it is viewed as legitimate to offer price promotions and invest in advertising effort is when the business is new (McDougall and Robinson 1990, Carter et al. 1994); anecdotal evidence also suggests that new businesses may find it advantageous to offer daily deals to recruit new customers (BizJournals 2013). In contrast, established merchants offering deals may lead to perceptions of weakness and desperation. Whether the merchant is truly in such a state may not matter; if offering a daily deal leads to some subset of consumers to draw such conclusions, brand perceptions are likely to suffer, leading to a higher probability of negative eWOM ex post. We thus expect that the age of the merchant to influence the extent to which daily deals affect eWOM, leading to a testable proposition.
Beyond sources of merchant heterogeneity, merchants do not operate in a vacuum, but within a competitive landscape that typically includes other merchants and their competitive actions, which cumulatively determines the options available to consumers. This competitive environment, in turn, contributes to setting reference prices for the merchant segment (Mazumdar et al. 2005, Bell and Lattin 2000). Moreover, it is well accepted that price changes affect the demand for other products, through cross-price elasticity (Sethuraman et al. 1999). Frequent price promotions on a segment within a geographical area can also lead to lower reference prices for that category, which affects price perceptions of all merchants in that category (Mayew and Winer 1992). Thus, if nearby competitors offer frequent daily deals, the reference price for similar products or services should shift downward along with consumer quality expectations, and the resulting eWOM, on average (Li and Hitt 2010). However, it is likely that those merchants that offer deals, as a response of high deal competition, will not experience a negative deal effect as they are in fact matching prices with its competitors (Raghubir and Corfman 1995, 1999). The eWOM literature has also documented how the competitive environment affects eWOM (Forman et al. 2009, Li et al. 2011, Jabr and Zheng 2013, Kwark et al. 2014). This reasoning brings into sharp focus the possibility that nearby deals might also negatively affect merchants who never offered deals, leading to a perverse and unexplored effect of daily deals within a competitive market. We thus test for the effect on a focal merchant's eWOM when its competitors offer daily deals but it does not.

Beyond these theoretical mechanisms, and from an operations management perspective, some firms are better equipped to react to the demand fluctuations created by online deals. Previous work in the pricepromotions and marketing literatures has shown that promotions can have a sudden and unpredictable effect on demand (Blattberg et al. 1995, Pauwels et al. 2002, Alvarez and Vázquez Casielles 2005). Moreover, it is well established that resource flexibility, and in particular workforce flexibility, are important firm attributes to handle demand changes (Paul and Jonathan 1991). For example, Ebben and Johnson (2005) show that flexible firms have very specific characteristics and that not all firms are able to achieve operational flexibility. Thus, it is plausible that certain merchants will be able to successfully accommodate the increased demand that results from online deals, while others will not. The practitioner press contains many such anecdotes, with a business owner recently stating: "We had thousands of orders pouring in that really we hadn't expected to have" (BBC 2011, 2012). However, these effects should only be observable after the deal is redeemed and not necessarily before consumption. This highlights that there may be pre-consumption as well as post-consumption effects of daily deals on eWOM. While these differences are not directly observable using archival data, we address this question in more detail later in the paper.
In summary, there is theoretical and anecdotal support for the notion that the effects of daily deals on eWOM are likely to be moderated by sources of merchant heterogeneity (price segment and merchant age) as well as competition. Given the multiple possible mechanisms for the effects of daily deals, rather than provide formal hypotheses, we allow the analysis to provide us with guidance. We next detail the data and methodology used to test for these effects.

## Methodology

## Data

We focus on online reviews and online deals for restaurants in a large U.S. metropolitan area, Washington D.C. Prior work in online reviews (Mangold et al. 1999; Gu et al. 2012) suggests that restaurants provide a suitable context for studying eWOM, given the high-involvement nature of food. Existing research studying daily deals have also focused on services, particularly on restaurants, to understand their appeal within this sector (Farahat et al. 2012). Thus, the choice of restaurants as a context for studying the quality implications of daily deals is particularly suitable. The online reviews for the restaurants in our sample were collected from Yelp.com, which has over 14 million online reviews for restaurants, over 135 million monthly visitors, and is the market leader in North American online reviews (Yelp 2015). For the purposes of this study, we collected data on 2,012 restaurants operating in Washington, D.C., roughly comparable to 2,035 operating restaurants reported by the National Restaurant Association's estimate in D.C. for 2012, the focal year of our data collection. Each Yelp restaurant listing contains general information on restaurant characteristics, such as location, cuisine, price point and ambience, and online review information, such as the average rating and number of reviews. Furthermore, for each restaurant we collected each individual review, which resulted in 143,745 reviews collected between 2004 (Yelp's initial release) and 2012. Each review has a numerical rating, text comments, and timestamp.
We match this data with the data for Washington, D.C. provided by Yipit.com, a service provider aggregating deal data across multiple online daily deal platforms, for a 13 -month period between December 2011 and December 2012. We chose Yipit.com because it aggregates transaction data from over $97 \%$ of daily deal sites (Yipit.com 2015). Unlike prior research focused on measuring the effect a single daily deals vendor (Byers et al. 2012a), we observe deal offers from 31 vendors, such as Groupon, LivingSocial, GoogleOffers, Yelp Deals, and so on. In total we observe 2,425 deals corresponding to 935 restaurants in Washington D.C. Each deal listing contains information about the merchant, such as phone number, name and geographical location; deal characteristics, such as price, discount and duration; and deal performance metrics, such as quantity sold and revenues generated from the deal. Unfortunately, this dataset does not provide data on how many purchased deals were redeemed at the merchants over time.
These two data sources-Yelp and Yipit-form the core of our empirical data collection strategy. To aggregate these into a single and dynamic panel data set, we first summarize the review and deal data for each restaurant into two-week periods. We choose a two-week period because the majority of deals sell for two weeks (Mean=2.01 weeks). Thus, our unit of analysis is the restaurant-period. As our primary interest is modeling the deal-review relationship, we discard any periods beginning before the start date of our daily deals data set. Thus, our panel contains aggregated information for 28 two-week time periods covering 13 months (from December 1, 2011 to December 31, 2012). Moreover, since the release of the deal for a particular merchant in the two-week period may not be the same, we create a dynamic panel where each merchant with a deal has a two-week period after the deal. Of the initial 2,012 restaurants in the reviews dataset, we find 1,390 unique restaurants with reviews in this time period matching to 922 merchants offering online deals (of the 935 merchants with deals collected for the time period). After aggregating and collating the dataset into two-week periods, we have 19,691 restaurant-period observations in the panel.

Our dependent variable of interest, Rating $_{i t}$, is the average numerical rating of the reviews for restaurant $i$ arriving in time period $t$. Our primary independent variables of interest are Deals ${ }_{i t}$ (equal to 1 if restaurant $i$ is engaging in one or more online deals during time period $t$ and o otherwise) and DealsInZip it (the number of competitors of restaurant $i$ offering a deal during time period $t$ ). A competitor is defined as a restaurant that has the same cuisine type and price-point in the same geographical area, defined by zip code. A deal is considered offered during time period $t$ if that period overlaps with the deal sales period. Additionally, we control for all the observable characteristics of the restaurant and the deal offered, such as location, price point, cuisine, and all other characteristics listed in Yelp, such as ambience and noise level. A full description of the variables used in our models can be found in Table 1. Summary statistics and a correlation table for the resulting panel data set can be seen in Table 2 and Table 3, respectively. We now describe our econometric model.

## Empirical Model

We model the effect of deals offered by a merchant and its nearby competitors on the ratings of that merchant over time. We control for baseline Yelp metrics (average rating and number of reviews at the deal period start date) and the competitive landscape (the number of restaurants in the same geographical area) and propose a hierarchical model. First, to capture heterogeneity of longitudinal dynamics across restaurants, we allow the effect of each of the predictors to vary by restaurant. As such, the first-level model in the hierarchy is:

$$
\begin{align*}
& \text { Rating }_{i t}=b_{i 0}+\beta_{0}+\beta_{1 \mathrm{i}} \text { Deal }_{i t}+\beta_{2 \mathrm{i}} \text { BaseNumReviews }_{i}+\beta_{3 \mathrm{i}} \text { BaseRating }_{i}+\beta_{4 \mathrm{i}} \text { RestInZip }_{i}+ \\
& \beta_{5 \mathrm{i}} \text { DealsInZip }_{i t}+\epsilon_{i t}, \tag{1}
\end{align*}
$$

where $i$ indexes restaurants and $t$ indexes time periods. Furthermore, we argue that deal and competition effects might systematically vary based on restaurant characteristics. Hence, the second level in our hierarchy regresses each predictor's coefficient in the first level on all the observable characteristics of the restaurant captured in Yelp. Thus the second-level model is:
$\hat{\beta}_{j i}=\gamma_{0}+\gamma_{j 1}$ PricePoint $_{i}+\gamma_{j 2}$ Age $_{i}+\gamma_{j 3}$ Location $_{i}+\sum_{q=1}^{17} \gamma_{j 4}^{(q)}$ Cuisine $_{i}^{(q)}+\sum_{r=1}^{16} \gamma_{j 5}^{(r)}$ Char $_{i}^{(r)}$, (2)
where $j \in\{1, \ldots, 5\}$ indexes the predictors in the first level (i.e. Deal ${ }_{i t}$, BaseNumReviews $_{i}$, BaseRating $_{i}$, RestInZip $_{i}$, DealsInZip $_{i t}$ ); $q$ indexes cuisine types and Cuisine $_{i}^{(q)}$ are dummy variables equal to 1 if restaurant $i$ has cuisine type $q$; and $r$ indexes other restaurant characteristics (e.g. ambience, noise level, parking options, etc.).

We model this specification using a Hierarchical Bayes model (Gelman et al. 2014, Rossi and Allenby 2003) that allows us to account for the observable and unobservable heterogeneity of the merchants. Hierarchical Bayes (HB) models have been highly popular in marketing research as a useful tool to model multi-faceted, non-linear phenomena (Rossi et al. 2012). Bayesian methods are particularly appropriate to the decisions modeled in marketing problems where there are many units of analysis (e.g. customers or sites), each with multiple observations, and there is a desire to account for individual differences (Rossi and Allenby 2003). HB models consist of two main steps: first, a model is written in a hierarchical form, such as the model specified above. Second, the model is estimated using Bayesian methods, such as Markov chain Monte Carlo (MCMC) (Rossi et al. 2012).
Previous work both in marketing and IS have used Bayesian methods to study the dynamics and effects of online reviews (e.g. Zhao et al. 2013; Trusov et al. 2010; Moe and Trusov 2011). For example, both Dellarocas et al. (2007) and Dickinger and Mazanec (2008) analyze how online reviews affect firm performance using hierarchical models. Similarly, Zhou and Duan (2010) model the impact of user reviews and professional reviews, in the context of software downloads, using a Bayesian framework. Thus, there is a significant body of work in the extant literature supporting the use of Bayesian methods to model the effects of online reviews. We base our Bayesian analyses on these accepted methods.

## Model Estimation and Results

We estimate the specified model using a Bayesian MCMC sampling methodology. All priors are standard conjugate diffuse priors. Starting values were taken from the maximum likelihood parameter estimates from independent linear models estimated on the same dataset. The MCMC chain was run for 10,000 , after an initial burn-in period of 1,200 iterations [converges fast]. The posterior distributions of the coefficients of 5,000 draws were extracted and analyzed.
Table 4 summarizes the posterior distributions of the model coefficients for the longitudinal model of review rating over time for each restaurant. Below, we report the posterior mean for each coefficient of interest, followed by the $95 \%$ high probability density (HPD) interval. In agreement with previous work (Byers et al. 2012a), we find a negative effect of offering an online deal. In particular, we find that offering a daily deal results in a decrease in mean rating during the same period of 0.902 [ $0.672,1.436]$. However, we also find two strong moderators to this effect: price point and restaurant age. We find that restaurants with a one-level higher price point experience a reduction of the "deal effect" by 0.539 [0.211,
o.567]. We also find that younger restaurants are less negatively affected by deals, with a 1 -standard deviation reduction in age implying a reduction in the deal effect of 0.665 [ $0.333,0.748$ ]. Thus, premium restaurants, as well as new ventures, experience less negative fallout from the offering of a deal. However, how does the presence of daily deals within the competition affect the restaurant? The results show a significant negative effect of deal competition on the average review rating for all restaurants. For every proximal competitor offering a deal, we find a decrease in mean rating during the same period of 0.235 [ $0.152,0.368$ ]. The surprising effect here is that this result extends even to those restaurants that do not offer deals; the presence of deals in their neighborhood negatively affects their review ratings as well. We do not observe any significant moderation of this "deal competition effect" by characteristics of the focal restaurant - this effect is entirely based on the presence of deals in proximal competition, defined as within price point, cuisine and geographical area. This effect is new in the literature and has not been examined before.

## Discussion

Our empirical analysis of the restaurant reviews and online deals demonstrates that offering a deal has an overall negative effect on the reviews arriving within the 2-week period during which the deal was offered. However, we observe certain moderators of this effect, namely the price point and age of the restaurant, suggesting systematically weaker negative effects for premium and new restaurants. Most notably, we also find evidence for a deal competition effect. That is, all merchants (even those who never offer online deals) are negatively affected by nearby competing merchants offering deals.
These conclusions are based on a large data set and an unconstrained modeling framework that allows coefficient estimates to vary by merchant and controls for a range of factors that may affect the rating of the restaurant. However, there is still a possibility that our findings are driven by unobserved variables, selection issues, and/or endogeneity between the decision to offer a deal and the quality of a restaurant. That is, merchants exhibiting poor performance that is not reflected in their previous online reviews and therefore, unobservable to us, may seek to influence their short-term online ratings by offering an online deal. However, we note that any such effort may see a delayed effect, since online deals in large cities typically go live several months after the terms of the deal are finalized (Groupon 2015b, LivingSocial 2015, GrouponWorks 2014, Zabranova 2012). In other words, the gap in time between the restaurant opting for a deal and the eventual offering of the deal is often separated by several months, which is significantly longer than the 2-week (4-week in robustness tests) period we model. Therefore, the effects of reverse causality, in terms of lower ratings driving the decision to offer a daily deal, are muted here given the design of the analysis.
One limitation of the negative "deal effect" identified by our empirical model is that we are unable to distinguish between a reduction in ratings due to a decrease in performance of the merchant during the deal period and a decrease in quality expectations by the customer prior to consumption. That is, a negative effect on the restaurant's rating could be because the consumer redeemed the coupon in this period and experienced reduced service quality. Alternatively, the negative response could be due to the impression formed in potential consumers that the focal restaurant offering a deal is "in distress" as suggested by Friestad and Wright (1994), thereby leading to lower reviews even amongst regular customers or those without coupons. Even in the case of the "deal competition" effect, we cannot differentiate between the case where the reduction in review ratings emerges from deal consumption in the presence of multiple available proximal deals, or whether the overall expectations of the consumer for service quality in a geographical area where daily deals are common is lower, thereby leading to lower expectations and ratings in general. These effects cannot be teased out using our secondary data. To address these issues, we augment our econometric analyses with three lab experiments, specifically to tease out these confounding effects and provide cleaner identification. In the first two studies, we test for the possible effect of offering an online deal on consumer quality expectations without any possibility of actual deal redemption, and evaluate the moderating influence of prices (Lab Study 1) and restaurant age (Lab Study 2). We follow these up with Lab Study 3, where we test for the competitor deals effect. We describe these experiments in detail next.

## Experimental Testing

## Lab Study 1: Deals and the Price Points of Restaurants

Procedure, Data and Measures

Lab Study 1 tests whether consumers' online evaluations of a merchant's services are affected if the merchant offers an online deal and whether the price point of the merchant moderates this effect. Recall that evidence of this effect was observed in the Bayesian analyses reported earlier. For the purposes of the experiment, four hundred respondents ( 191 women) from Amazon's Mechanical Turk (MTurk) were recruited for pay in this study. Respondents were randomly assigned to one of four 2 (deal offered: yes vs. no) x 2 (price point: high vs. low) between subjects conditions.
The stimuli were developed by selecting a restaurant from our Yelp data set with the most popular cuisine, an average number of reviews, and an average numerical ratings and using the information displayed in Yelp.com. To avoid providing any biasing cues, we withheld any review text in the description of the restaurant. To create the deal condition (treatment), we showed that the restaurant is offering a Yelp online deal (one of the daily deal vendors in our deals dataset) using the same user interface shown by Yelp. Further, to create the high and low price conditions, we changed the price point of the restaurant from one (\$) to four (\$\$\$). In all four conditions, the restaurant was renamed to "Italian Kitchen" and given a new address to control for possible familiarity with the actual restaurant. We were also careful to maintain the user interface of Yelp.com by using the exact same fonts and colors. Participants were first asked to read the information in the webpage for the restaurant and then assess the quality of the restaurant, followed by a manipulation check on the price of restaurant to ensure that the price treatment had worked.
We measured brand evaluation, which is a composite of purchase intention and perceived quality. Purchase intention and perceived quality load to the same factor, with $\mathrm{r}=0.87$. We adapted purchase intention from Jamieson and Bass (1989): "If you were thinking about going to an Italian restaurant, how likely would you be to visit this restaurant?" ( $1=$ "very unlikely" to $7=$ "very likely"). We adapted perceived quality from Kirmani and Wright (1989): "Given the information provided about this restaurant, please rate the likely overall quality of this restaurant" ( $1=$ "very low" to $7=$ "very high"). Finally, and as a manipulation check, we ask respondents to rate the restaurant in regards to pricing ( $1=$ "low-priced to $7=$ "high-priced").

## Results and Discussion

We first ensure that the results from the Bayesian model were replicated in the lab. We find a significant deal $x$ price point interaction effect $(F(1,400)=6.31, p<0.01 ;$ see Figure 1). A first set of planned contrast show that for non-deal restaurants, a higher price point had no significant direct effect on perceived quality $\left(M_{n o}\right.$ deals-low $=5.14$ vs. $\left.M_{n o d e a l s-h i g h ~}=5.28 ; F(1,400)=2.12, p=0.33\right)$. For deal restaurants, however, having a higher price point significantly increased quality perceptions ( $\mathrm{M}_{\text {deal-low }}=3.94 \mathrm{vs}$. $\mathrm{M}_{\text {deal-high }}=5.6 ; \mathrm{F}$ $(1,400)=3.59, p<0.05)$. A different set of planned contrasts show that for restaurants associated with a lower price point, there is a significant decease in perceived quality when a deal is offered ( $\mathrm{M}_{\text {low-non deal }}=$ 5.14 vs. $\left.\mathrm{M}_{\text {low-deal }}=3.94 ; \mathrm{F}(1,400)=4.11, \mathrm{p}<0.05\right)$. However, this effect becomes "marginally significant" and positive for restaurants with a high price point restaurants ( $\mathrm{M}_{\text {high-non deal }}=5.28 \mathrm{vs}$. $\mathrm{M}_{\text {high-deal }}=5.6 ; \mathrm{F}$ $(1,400)=3.71, \mathrm{p}=0.07)$. The manipulation check on the pricing of restaurants was also successful. Those in the deal condition indicated that the restaurant was lower priced, showing that the treatment was effective.
As in our empirical model, we observe that the price point of the restaurant moderates the negative effect of the deal in a controlled experimental setting with no consumption possibility. These results suggest that even before visiting the restaurant and experiencing the service provided, there is a decrease in perceived quality and purchase intentions for certain merchants who offer online deals. More specifically, this finding adds further evidence that certain merchants are likely to be perceived as "desperate" (in our case the low-priced merchants, representing the non-premium segment) whereas other merchants will be perceived as "confident" (in our case the high-priced or premium merchants), as first suggested by

Kirmani (1990). Beyond the segment of the restaurant, is it possible that daily deals offered by new restaurants are viewed less negatively? We explore this contrast in the next experiment.

## Lab Study 2: Daily Deals and Restaurant Age

## Procedure, Data, and Measures

Lab study 2 tests whether consumers' brand evaluations are affected by the offering of a daily deal and whether the newness (age) of the restaurant moderates this effect. 398 respondents ( 175 women) from Amazon's Mechanical Turk (MTurk) participated for pay in this study. Respondents were randomly assigned to one of four 2 (deal offered: yes vs. no) x 2 (new restaurant: yes vs. no) between subjects conditions. Stimuli were identical to study 1, except that for the new condition, we added a banner showing that the restaurant opened recently using existing Yelp's user interface, displayed prominently as it is in Yelp's content webpage. As in the previous study, participants first read the information in the webpage for the restaurant and then assess the quality of the restaurant followed by a manipulation check on the price of restaurant. The measures are the same as in the first study: brand evaluation, which is a composite of purchase intention and perceived quality. Purchase intention and perceived quality load to the same factor with $\mathrm{r}=0.88$ with these subjects as well.

## Results and Discussion

Replicating our results from our empirical model, we find a significant deal x new interaction ( $\mathrm{F}(1,398$ ) $=$ 6.44, p <0.02; see Figure 2). A first set of planned contrast show that for non-deal restaurants, being new had no significant effect on brand evaluation $\left(\mathrm{M}_{\text {no deal-established }}=5.84 \mathrm{vs} . \mathrm{M}_{\text {no deal-new }}=5.17 ; \mathrm{F}(1,398)=1.15\right.$, $\mathrm{p}=0.28$ ). For deal restaurants, however, being new significantly increased brand evaluations ( $\mathrm{M}_{\text {deal-estabished }}$ $=4.03$ vs. $\left.\mathrm{M}_{\text {-deal-new }}=6.13 ; \mathrm{F}(1,398)=4.59, \mathrm{p}<0.05\right)$. A different set of planned contrasts show that for already established restaurants, there is a significant decrease in behavioral intentions when a deal is offered $\left(M_{\text {established-no deal }} \mathrm{l}=5.84\right.$ vs. $\left.\mathrm{M}_{\text {established-deal }}=4.02 ; \mathrm{F}(1,398)=5.32, \mathrm{p}<0.05\right)$. However, this effect becomes "marginally significant" and positive for newly established restaurants ( $\mathrm{M}_{\text {new-no-deal }}=5.16 \mathrm{vs}$. $\left.\mathrm{M}_{\text {new-deal }}=6.13 ; \mathrm{F}(1,398)=3.40, \mathrm{p}=0.06\right)$. Again, the manipulation of the pricing of the restaurant was successful. Those in the deal condition indicated that the restaurant was lower priced.

Replicating the results of our empirical model, we observe that the newness of the restaurant does indeed moderate the negative effect of the deal in a controlled experimental setting. These results also add credence to the notion that brand evaluations (perceived quality and purchase intentions) decrease even before consumption only by offering an online deal. New restaurants are expected to offer daily deals as a way to incentivize new consumers to take a chance on the merchant (Dholakia 2012); thus, offering a deal does not reduce the perceptions of quality in such cases. We test for the effect of competition next.

## Lab Study 3: Daily Deals and Deal Competition

## Procedure, Data, and Measures

Lab study 3 tests whether consumers' brand evaluations are affected if the focal merchant offers an online deal and if nearby competitors also offer online deals. 404 respondents ( 187 women) from Amazon's Mechanical Turk (MTurk) participated for pay in this study. Respondents were randomly assigned to one of four 2 (deal offered: yes vs. no) x 2 (deal competition: high vs. none) between subjects conditions. Stimuli were identical to study 1, except that for the deal competition condition, we added a measure of the degree of deal competition for similar restaurants nearby. More specifically, a restaurant with high nearby competition a graphic that showed, consistent with Yelp's user interface, : "There are 20 deals for similar restaurants in this area." As in the previous study, participants first read information about the restaurant and then assess the quality of the restaurant followed by a manipulation check on the price of restaurant. The measures are the same as in study 1; brand evaluation, which is a composite of purchase intention and perceived quality. Purchase intention and perceived quality load to the same factor, $\mathrm{r}=0.91$.

## Results and Discussion

Expanding the results of our empirical model, we find a significant deal x deal competition interaction ( F $(1,404)=6.74, p<0.01$; see Figure 3). A first set of planned contrast show that for non-deal restaurants, having a high deal competition had a significant negative effect on brand evaluation ( $\mathrm{M}_{\text {no deal-no deal competition }}$ $=5.78$ Vs. $\mathrm{M}_{\mathrm{no}}$ deal-deal competition $\left.=4.19 ; \mathrm{F}(1,404)=5.92, \mathrm{p}<0.02\right)$. For deal offering restaurants, however, high deal competition marginally increased brand evaluations ( $\mathrm{M}_{\text {deal-no deal competition }}=3.78 \mathrm{vs} . \mathrm{M}_{\text {deal-deal }}$ competition $=4.33 ; \mathrm{F}(1,404)=4.59, \mathrm{p}<0.07)$. A different set of planned contrasts show that for restaurants with no nearby deal competition, there is a significant decease in behavioral intentions when a deal is offered $\left(\mathrm{M}_{\mathrm{no}}\right.$ deal competition-no deal $=5.78$ vs. $\mathrm{M}_{\mathrm{no}}$ deal competition-deal $\left.=3.78 ; \mathrm{F}(1,404)=4.92, \mathrm{p}<0.05\right)$. However, this effect is not significant for restaurants with high nearby deal competition ( $\mathrm{M}_{\text {deal competition-no deal }}=4.19$ vs. $\left.\mathrm{M}_{\text {deal competition-deal }}=4.33 ; \mathrm{F}(1,404)=1.46, \mathrm{p}=0.22\right)$. The manipulation of the restaurant price was also successful, and those in the deal condition indicated that the restaurant was lower priced.

As previously found in our empirical model, we observe evidence of a deal competition effect. That is, even merchants who do not offer deals are affected by nearby competitors offering online deals. In this study, however, we go beyond this finding and show that for merchants without nearby deal competition, offering a deal would lead to a significant decrease in brand evaluations. However, for merchants with high deal competition, we do not find evidence of any change in brand evaluations as a result of offering a deal. The results show that in environments with high daily deal intensity, the negative effects associated with a deal are muted, and that offering a deal here is viewed as standard practice. We discuss these results in more detail in the next section.

## General Discussion and Implications

The revenues from online deals are expected to climb to $\$ 5.5$ billion in 2016 according to industry analysts (BIA Kelsey 2014). However, these figures notwithstanding, the offering of daily deals in services raises several questions about their effects on merchants, consumer responses and platforms in the literature. Our study aims to shed light on how online deals and the competitive deal landscape are affecting consumer perceptions in specific within the restaurant sector, where daily deals are popular and their effects may be gauged in good measure through online reviews on Yelp. In this work, we show that under certain conditions, offering online deals can indeed negatively affect consumer perceptions, captured as review rating on ex post Yelp reviews for the focal restaurant. More importantly, this effect, however, might be positive or negative depending on the merchant's characteristics.
In a longitudinal analysis of restaurants reviews from Yelp.com and a data set covering online deals offered by the same restaurants, we find evidence that restaurants' short-term ex post ratings are negatively affected by offering a deal. However, we find that certain restaurant characteristics, such as the price point and the newness, i.e. age, of the restaurant, are strong moderators of this deal effect. In the case of premium restaurants operating in the higher priced segment, we see that the response of consumers ex post appears to be less negative, suggesting that these restaurants are viewed as offering deals from a position of confidence. Alternatively, lower-rated restaurants and those in the lower price ranges are viewed as being "distressed" and receive negative quality feedback to daily deals. We add credence to the notion that customers perceive the online deal efforts of restaurants as desperate or confident depending on their particular circumstances. We also see an intriguing spillover effect from daily deals to proximal restaurants that do not offer any deals but see their quality perceptions reduce. That is, by including in our analysis the deals offered by nearby competitors, we also observe a decrease in their short-term review ratings when competitors offer deals.

We proceed to replicate these findings in a controlled setting. In Lab Study 1 and 2, we find support for our empirical findings that there is a general decrease in the purchase intentions and perceived quality of restaurants that offer deals, and find that this effect is strongly moderated by the price of the restaurant and restaurant newness. This is consistent with Kirmani and Wright's (1989) assertion that "many people spontaneously assume high advertising expense implies managerial confidence and high quality unless [...] desperation undermine is salient to them." Further, we are able to rule out that the decrease in rating observed in our empirical models is solely attributable to poor performance of the restaurant, as some customers have claimed in their dealings with the restaurant during the redemption period. Indeed, we find that even before there is any product or service consumption (as is the case with our lab subjects),
there is a decrease in brand evaluations simply by offering an online deal. These results actually have very important implications for restaurants that offer daily deals as well as platforms that offer them. Furthermore, in Lab Study 3, we replicate our empirical model's finding that nearby competitors offering online deals are also affecting the rating of merchants.
Taken together, our results present a more complete view of how the recent and highly popular phenomenon of online deals is affecting consumer quality perceptions, leading to several theoretical contributions to the literature. First, building on early work on daily deals by Dholakia (2012) and Byers et al. (2012a) suggesting that online deals affect firm performance and online reviews, we provide specific conditions under which online deals affect online reviews and consumer perceptions. The nuances in how deals affect consumer perceptions are important in being able to assess the true value of such programs. Second, our work extends the work of Wright (1986) and Kirmani and Wright (1989) in understanding how consumers interpret a marketer's efforts, motives, and tactics. We show that in the current information-rich environment from online sources, consumers do form quality attributions based on the cues found in online reviews, online deals, and the particular conditions characterizing each merchant. In fact, since consumers are keenly aware of the deep discounts found in online deals, they may be using the information about the marketing campaigns of the merchant over time as indicators of the risks taken by the merchant (i.e. customer acquisition cost). Moreover, our results suggest that consumers do not interpret marketing efforts in a vacuum. In fact, by examining the promotional actions of nearby competitors, our work suggests that the consumer's "schema" in evaluating merchants proposed by Wright (1986) is more complex than previously thought of. To our knowledge, we are the first to outline the conditions under which market-specific quality determinants, such as the presence of proximal daily deals within the competition, affect an individual's quality attributions. One possible explanation for the deal competitions effect is that a higher number of nearby competitors offering deals leads to a reduction in reference prices for the restaurant's services. That is, a drastic reduction in the price of some services might affect quality attributions for all other merchant in that market. This is important since it suggests that online review for firms or merchants are likely to be affected by the actions of others, a form of crossmarket elasticity that has not been addressed in detail as yet. Finally, we also contribute to the price promotions literature by suggesting that there are actually two layers in the effect promotions have on brand evaluations -a pre-consumption effect and a post-consumption effect. Our empirical testing through MTurk shows, for the first time, that such pre-consumption effects are not only possible but also actually salient and likely reflect a combined influence of media, anecdotal evidence and offline word of mouth.

Apart from these contributions, there are significant implications from our work for practice, especially for merchants and platform owners. While there has been significant recent media attention to the failures of daily deals merchants, we find conditions under which daily deals can be beneficial in terms of online reputation to merchants, which is a key question for both merchants and platform owners. For platform owners, such as Google and LivingSocial our work also raises many pertinent issues. First, since consumers appear to be interpreting online deals either as a signal of high confidence or desperation, the daily deals platform might want to highlight the cues signaling high confidence, through the selection of the merchant or the structuring of the promotion itself. Additionally, we believe that deal platforms could actually benefit from using and reporting the information available on the merchant in online reviews platforms, such as Yelp.com and Foursquare.com. For example, if some reviewers mention the words "deals, Groupon, or Living Social" in the text and seem to be pleased with the service and deal provided by the merchant, then the customers making quality inferences could take this information into account. Another interesting perspective raised by our work is the possibility of offering deals only for consumers on-demand. That is, offering deals to consumers around a particular area and the possibility of buying deals only when consumers are actually at the merchant's place. Using the geographical location from mobile devices, for example, might allow daily deal vendors to showcase offers at the right time (i.e. just before consumption). These represent fruitful avenues for further research.
Our study also has some important limitations. In regards to our empirical model, we are limited in our ability to generalize our findings since our data is for a single major city in the United States. However, we observe the population of online deals for over a year, which allows us to account for seasonality effects during the year. Further, while we are able identify a deal competition effect in our empirical model and confirm this effect in a controlled setting, we cannot rule out or specifically test individual mechanisms that might drive a decrease in ratings for focal merchants under high deal competition. Future work
should address the specific mechanisms behind the deal competition effect to understand consumer choice given a range of different competitive environments. This would be a more accurate representation of the current state of daily deal vendors and restaurants in many cities in the U.S.

Table 1. Variable Descriptions

| Variable Name | Description |
| :--- | :--- |
| Rating $_{i t}$ | Average rating of reviews arriving during time period t for restaurant i |
| Deal $_{i t}$ | Binary variable indicating whether a deal was initialized by restaurant $i$ during time <br> period $t$. Also used in lagged form. |
| BaseNumReviews $_{i}$ | Number of reviews in Yelp for restaurant $i$ prior to Dec. 1, 2011 |
| BaseRating $_{\mathrm{i}}$ | Rating in Yelp for restaurant i prior to Dec. 1, 2011 |
| RestInZip $_{i}$ | Number of restaurants listed in Yelp in the same zip code as restaurant $i$ |
| DealsInZip $_{i t}$ | Number of deals being offered during time period $t$ in the same zip code as <br> restaurant $i$ |
| Price $_{i}$ | Price point of restaurant i equal to the number of Yelp dollar signs (1-4) |
| Age $_{i}$ | The number of days from the first review for restaurant $i$ prior to Dec. 1, 2011 |
| Cuisine $_{i}$ | Binary variable indicating whether a cuisine (16 cuisines in total) is listed in the <br> cuisine type for restaurant $i$ |
| OtherChars $_{i}$ | Categorical variables describing other restaurant characteristics, such as: payment <br> methods, parking, attire, group-friendly, kids-friendly, waiter, Wi-Fi, alcohol, etc. <br> (15 in total) |
| Location $_{i}$ | The zip code of the restaurant (12 in total) |

Table 2. Summary Statistics

| Variables $^{\|l\|}$ | Mean (SD) | Range |
| :--- | :--- | :--- |
| Rating $_{\text {it }}$ | 3.43 (1.07) | 1,5 |
| Deal $_{\text {it }}$ | o.03 (o.16) | o,1 |
| Price $_{i}$ | 1.89 (o.72) | 1,4 |
| Age $_{i}$ | 560.14 | $11,2920.85$ |
| BaseNumReviews $_{i}$ | $165.40(129.24)$ | 0,1963 |
| BaseRating $_{i}$ | $3.47(0.53)$ | 1,5 |
| Cuisine $_{i}$ | NA | NA |
| OtherChars $_{i}$ | NA | NA |
| Location $_{i}$ | NA | NA |
| RestInZip $_{i}$ | $206.31(88.27)$ | 86,330 |
| DealsInZip $_{i t}$ | $2.43(2.13)$ | 0,12 |

Table 3. Correlation Table

|  | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Rating | 1 |  |  |  |  |  |  |  |
| Deal | -0.03 | 1 |  |  |  |  |  |  |
| Price | 0.02 | 0.03 | 1 |  |  |  |  |  |
| Age | 0.13 | 0.05 | 0.01 | 1 |  |  |  |  |
| BaseNumReviews | 0.1 | 0.02 | 0.15 | 0.22 | 1 |  |  |  |
| BaseRating | 0.35 | -0.04 | 0.01 | 0.02 | 0.19 | 1 |  |  |
| RestInZip | 0.01 | -0.02 | -0.05 | 0.07 | 0.03 | 0.01 | 1 |  |
| DealsInZip | -0.02 | 0.08 | -0.03 | 0.05 | 0.01 | -0.01 | 0.14 | 1 |

Table 4. Multi-level Hierarchical Bayesian Results

|  | Mean (SD) | HPD (Lower) | HPD (Upper) |
| :---: | :---: | :---: | :---: |
| First Level |  |  |  |
| Intercept | 0.845 (0.73) | 0.785 | 0.922 |
| Deal | -0.902 (0.07) | -1.436 | -0.672 |
| Deal (lag 1) | -0.461 (0.15) | -0.911 | -0.193 |
| Deal (lag 2) | -0.098 (0.51) | -0.476 | 0.223 |
| BaseNumReviews | 0.000 (0.00) | -0.001 | 0.001 |
| BaseRating | 0.855 (0.02) | 0.798 | 0.986 |
| RestInZip | 0.000 (0.00) | 0.000 | 0.000 |
| DealsInZip | -0.235 (0.04) | -0.368 | -0.152 |
| Second Level: Deal ${ }_{\text {it }}$ |  |  |  |
| Intercept | 0.055 (0.08) | 0.017 | 0.222 |
| Pricepoint | 0.539 (0.00) | 0.211 | 0.567 |
| Age | -0.665 (0.00) | -0.748 | -0.333 |


| ${\text { Second Level: } \text { DealsInZip }_{\text {it }}}^{\text {Intercept }}$ |  |  |  |
| :--- | :--- | :--- | :--- |
| Pricepoint | 0.111 (0.04) | 0.051 | 0.287 |
| Age | 0.001 (0.41) | -0.112 | 0.241 |
| OtherChars (15 in total) | Included | -0.054 |  |
| Cuisines (16 in total) | Included | -0.211 | 0.099 |
| Location (12 in total) | Included |  |  |
| Sample size (unique restaurants) | $\mathrm{N}=19,691(1,390)$ |  |  |
| BIC | 4783.4 |  |  |

Figure 1. Brand Evaluation as a Function of Deal Offered and the Price of Merchants


Figure 2. Brand Evaluations as a Function of Deals Offered and the Newness of Merchants


Figure 3. Brand Evaluation as a Function of Deal Offered and Deal Competition


## References

Agrawal, R. 2013. The rapid rise and fall of daily deal Web sites. Retrieved April 10, 2015, http://www.washingtonpost.com/blogs/innovations/wp/2013/11/22/the-rapid-rise-and-fall-of-daily-deal-web-sites/
Alvarez, B., and Vázquez Casielles, R. 2005. Consumer evaluations of sales promotion: the effect on brand choice. European Journal of Marketing 39(1/2) pp. 54-70.
Archak, N., Ghose, A., and Ipeirotis, P. G. 2011. "Deriving the Pricing Power of Product Features by Mining Consumer Reviews," Management Science 57(8) pp. 1485-1509.
BBC. 2012. Groupon voucher deal 'cost Hove firm thousands'. Retrieved April 10, 2015, http://www.bbc.com/news/uk-england-sussex-16679683
BBC. 2011. Groupon vouchers decision cost Berkshire business thousands. Retrieved April 10, 2015, http://www.bbc.com/news/uk-england-berkshire-15791507
Bell, D.R., and Lattin, J.M. 2000. Looking for loss aversion in scanner panel data: the confounding effect of price response heterogeneity. Marketing Science 19(2) pp. 185-200.
Bharadwaj, A., O.A. El Sawy, P.A. Pavlou, N. Venkatraman. 2013. Digital business strategy: toward a next generation of insights. Mis Quarterly 37(2) pp. 471-482.
BIA/Kelsey. 2014. Local Commerce Monitor Report. Retrieved April 10, 2015, http://www.biakelsey.com/Research-and-Analysis/SMB-and-Consumer-Research/Local-CommerceMonitor/
Biswas, A., Bhowmick, S., Guha, A., Grewal, D. 2013. Consumer evaluations of sale prices: role of the subtraction principle. Journal of Marketing 77(4) pp. 49-66.
BizJournal. 2013. How to decide to use ‘daily deal’ sites. Retrieved, April 10, 2015. http://www.bizjournals.com/bizjournals/how-to/marketing/2013/10/how-to-decide-to-use-daily-deal-sites.html?page=all
Blattberg, R. C., and Neslin, S. A. 1990. Sales promotion: concepts, methods, and strategies, Englewood Cliffs, NJ: Prentice Hall,
Blattberg, R. C., Briesch, R., and Fox, E. J. 1995. "How Promotions Work," Marketing Science 14(3) pp. G122-G132.
Blattberg, R. C., and Wisniewski, K. J. 1989. "Price-induced patterns of competition," Marketing science 8(4) pp. 291-309.
BrightLocal. 2013. Local Consumer Review Survey 2013. Retrieved April 10, 2015, https://www.brightlocal.com/2013/o6/25/local-consumer-review-survey-2013/
BusinessInsider. 2011. Internal LivingSocial Survey: Vast Majority Of Businesses Profit Or Break Even On Daily Deals. Retrieved April 10, 2015, http://www.businessinsider.com/living-social-survey-2011-8
Byers, J. W., Mitzenmacher, M., and Zervas, G. 2012a. "Daily deals: Prediction, social diffusion, and reputational ramifications," in Proceedings of the Fifth ACM International Conference on Web Search and Data Mining, New York, New York, USA, pp. 543-552.
Byers, J. W., Mitzenmacher, M., and Zervas, G. 2012b. "The groupon effect on yelp ratings: a root cause analysis," in Proceedings of the 13th ACM Conference on Electronic Commerce, New York, New York, USA, pp. 248-265.
Carter, N.M., Stearns, T.M., Reynolds, P.D., Miller, B.A. 1994. New venture strategies: Theory development with an empirical base. Strategic Management Journal 15(1) pp. 21-41.
Chen, Y.J., and Kirmani A. 2015. Posting strategically: The consumer as an online media planner. Journal of Consumer Psychology.
Chen, Y., and Xie, J. 2008. "Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix," Management Science 54(3) pp. 477-491.
Chevalier, J. A., and Mayzlin, D. 2006. "The Effect of Word of Mouth on Sales: Online Book Reviews," Journal of Marketing Research 43(3), pp. 345-354.
Clemons, E. K., Gao, G. G., and Hitt, L. M. 2006. "When Online Reviews Meet Hyperdifferentiation: A Study of the Craft Beer Industry," Journal of Management Information Systems 23(2) pp. 149-171.
Clifford, S., and Miller, C. C. 2012. Ready to Ditch the Deal. Retrieved April 10, 2015, http://query.nytimes.com/gst/fullpage.html?res=9Fo1E7DF153AF93BA2575BCoA9649D8B63
Cohan, P. 2012. Why Groupon Is Over and Facebook And Twitter Should Follow. Retrieved April 10, 2015, http://www.forbes.com/sites/petercohan/2012/o8/20/why-groupon-is-over-and-facebook-and-twitter-should-follow/

Cone. 2011. Online Influence Trend Tracker. Retrieved April 10, 2015, http://www.conecomm.com/2011coneonlineinfluencetrendtracker
Decker, R., and Trusov, M. 2010. "Estimating aggregate consumer preferences from online product reviews," International Journal of Research in Marketing 27(4) pp. 293-307.
Della Bitta, A.J., Monroe, K.B., and McGinnis, J.M. 1981. Consumer perceptions of comparative price advertisements. Journal of Marketing Research pp. 416-427.
Dellarocas, C., and Narayan, R. 2006. "A Statistical Measure of a Population's Propensity to Engage in Post-Purchase Online Word-of-Mouth," Statistical Science 21(2) pp. 277-285.
Dellarocas, C., Zhang, X. M., and Awad, N. F. 2007. "Exploring the value of online product reviews in forecasting sales: The case of motion pictures," Journal of Interactive Marketing 21(4) pp. 23-45.
Dholakia, U. M. 2010. "How Effective are Groupon Promotions for Businesses?," SSRN Electronic Journal.
Dholakia, U. M. 2011a. "How Businesses Fare with Daily Deals: A Multi-Site Analysis of Groupon, Livingsocial, Opentable, Travelzoo, and BuyWithMe Promotions," SSRN Electronic Journal.
Dholakia, U. M. 2011b. "What Makes Groupon Promotions Profitable?," SSRN Electronic Journal .
Dholakia, U. M. 2011c. "A Startup's Experience Running a Groupon Promotion," SSRN Electronic Journal.
Dholakia, U. M. 2012. "How Businesses Fare with Daily Deals as They Gain Experience: A Multi-Time Period Study of Daily Deal Performance," SSRN Electronic Journal.
Dholakia, U. M., and Kimes, S. E. 2011. "Daily Deal Fatigue or Unabated Enthusiasm? A Study of Consumer Perceptions of Daily Deal Promotions," SSRN Electronic Journal.
Dickinger, A., and Mazanec, J. 2008. "Consumers' preferred criteria for hotel online booking," Information and Communication Technologies in Tourism pp. 244-254.
Duan, W., Gu, B., and Whinston, A. B. 2008. "Do online reviews matter? - An empirical investigation of panel data," Decision Support Systems 45(4) pp. 1007-1016.
Ebben, J.J., and Johnson, A.C. 2005. Efficiency, flexibility, or both? Evidence linking strategy to performance in small firms. Strategic management journal 26(13) pp. 1249-1259.
Edelman, B., Jaffe, S., and Duke S. 2011. "To groupon or not to groupon: The profitability of deep discounts," Marketing Letters pp. 1-15.
Farahat, A., Ahmed, N. and Dholakia, U. 2012. "Does a Daily Deal Promotion Signal a Distressed Business? An Empirical Investigation of Small Business Survival," arXiv preprint arXiv pp. 1211.1694.

Forman, C., Ghose, A., and Goldfarb, A. 2009. "Competition Between Local and Electronic Markets: How the Benefit of Buying Online Depends on Where You Live," Management Science 55(1) pp. 47-57.
Friestad, M. and Wright, P. 1994. "The Persuasion Knowledge Model: How People Cope with Persuasion Attempts," Journal of Consumer Research 21(1) pp. 1-31.
Gelman, A., Carlin, J. B., Stern, H. S., Rubin, D. B. 2014. Bayesian data analysis (Vol. 2), Chapman \& Hall/CRC.
Godes, D. and Mayzlin, D. 2004. "Using Online Conversations to Study Word-of-Mouth Communication," Marketing Science 23(4) pp. 545-560.
Grewal, D., Krishnan, R., Baker, J., Borin, N. 1998. The effect of store name, brand name and price discounts on consumers' evaluations and purchase intentions. Journal of retailing 74(3) pp. 331-352.
GrouponWorks. 2014. Get the Most Effective Local Advertising Available. Retrieved April 10, 2015, https://www.grouponworks.com/benefits-of-advertising-with-groupon
Groupon. 2015a. Groupon - About. Retrieved April 10, 2015, http://www.groupon.com/press/aboutgroupon
Groupon. 2015b. Groupon - Terms of Use. Retrieved April 10, 2015, http://www.groupon.com/terms
Gu, B., Park, J., and Konana, P. 2012. "Research Note-The Impact of External Word-of-Mouth Sources on Retailer Sales of High-Involvement Products,"Information Systems Research 23(1) pp. 182-196.
Guadagni, P.M., and Little, J.D. 1983. A logit model of brand choice calibrated on scanner data. Marketing science 2(3) pp. 203-238.
Ibis. 2015. Report of Online Daily Deals Marketplace. Retrieved April 19, 2015, http://clients1.ibisworld.com/reports/us/
Integreon. 2015. The Groupon Effect. Retrieved April 20, 2015, http://www.integreon.com/pdf/Blog/Grail-Research-The-Groupon-Effect_238.pdf
Ipsos. 2015. New Tools Proving Successful in Restaurant Marketing Mix. Retrieved March 20, 2016. http://www.ipsos-na.com/knowledge-ideas/loyalty/articles/?q=daily-deals

Jabr, W., and Zheng, E. 2013. "Know Yourself and Know Your Enemy: An Analysis of Firm Recommendations and Consumer Reviews in a Competitive Environment," MIS Quarterly 38(3) pp. 635-654
Jamieson, L. F., and Bass, F. M. 1989. "Adjusting stated intention measures to predict trial purchase of new products: A comparison of models and methods," Journal of Marketing Research pp. 336-345.
Kalwani, M. U., and Yim, C. K. 1992. "Consumer price and promotion expectations: An experimental study," Journal of Marketing Research pp. 90-100.
Kirmani, A. 1990. "The effect of perceived advertising costs on brand perceptions," Journal of Consumer Research 17(2) pp. 160-171.
Kirmani, A. 1997. Advertising repetition as a signal of quality: If it's advertised so much, something must be wrong. Journal of advertising pp. 77-86.
Kirmani, A., and Wright, P. 1989. "Money Talks: Perceived Advertising Expense and Expected Product Quality," Journal of Consumer Research 16(3) pp. 344-53.
Krasnova, H., Veltri, N.F., Spengler, K., Günther, O. 2013. "Deal of the Day" Platforms: What Drives Consumer Loyalty? Business \& Information Systems Engineering 5(3) pp. 165-177.
Kumar, V., and Rajan, B. 2012. "Social coupons as a marketing strategy: a multifaceted perspective," Journal of the Academy of Marketing Science 40(1) pp. 120-136.
Kwark, Y., Chen, J., and Raghunathan, S. 2014. "Online Product Reviews : Implications for Retailers and Competing Manufacturers," Information Systems Research 25(1) pp. 93-110.
Lattin, J. M., and Bucklin, R. E. 1989. "Reference effects of price and promotion on brand choice behavior," Journal of Marketing research pp. 299-310.
Lee, I., and Lee, K. 2012. "Social shopping promotions from a social merchant's perspective," Business Horizons 55(5) pp. 441-451.
Lee, L., and Tsai, C.I. 2014. How price promotions influence postpurchase consumption experience over time. Journal of Consumer Research 40(5) pp. 943-959.
Li, X., and Hitt, L. M. 2008. "Self-Selection and Information Role of Online Product Reviews," Information Systems Research 19(4) pp. 456-474.
Li, X., and Hitt, L. 2010. "Price Effects in Online Product Reviews: An Analytical Model and Empirical Analysis," MIS Quarterly 34(4) pp. 8o9-831.
Li, X., Hitt, L. M., and Zhang, Z. J. 2011. "Product Reviews and Competition in Markets for Repeat Purchase Products," Journal of Management Information Systems 27(4) pp. 9-42.
LivingSocial. 2015. Living Social - Terms of Use. Retrieved April 10, 2015, https://www.livingsocial.com/terms
Lu, X., Ba, S., Huang, L., Feng, Y. 2013. "Promotional Marketing or Word-of-Mouth? Evidence from Online Restaurant Reviews," Information Systems Research 24(3) pp. 596-612.
Luca, M. 2011. "Reviews, Reputation, and Revenue: The Case of Yelp.Com," SSRN Electronic Journal.
Luo, X., Andrews, M., Song, Y., Aspara, J. 2014. "Group-buying deal popularity," Journal of Marketing 78(2) pp. 20-33.
Lynch Jr, J.G., Ariely, D. 2000. Wine online: Search costs affect competition on price, quality, and distribution. Marketing Science 19(1) pp. 83-103.
Mangold, W. G., Miller, F., and Brockway, G. R. 1999. "Word-of-mouth communication in the service marketplace," Journal of Services Marketing 13(1) pp. 73-89.
Mayhew, G. E., and Winer, R. S. 1992. "An empirical analysis of internal and external reference prices using scanner data," Journal of consumer Research pp. 62-70.
Mazumdar, T., Raj, S., and Sinha, I. 2005. Reference price research: Review and propositions. Journal of marketing 69(4) pp. 84-102.
McDougall, P., and Robinson Jr, R.B. 1990. New venture strategies: An empirical identification of eight" archetypes" of competitive strategies for entry. Strategic Management Journal 11(6) pp. 447.
McGregor, J., Jespersen, F. F., Tucker, M., Foust, D. 2007. "Customer Service Champs," Business Week pp. 52-64.
Moe, W. W., and Trusov, M. 2011. "The Value of Social Dynamics in Online Product Ratings Forums," Journal of Marketing Research 48(3) pp. 444-456.
Moorthy, S., and Hawkins, S. A. 2005. "Advertising repetition and quality perception," Journal of Business Research 58(3) pp. 354-360.
Moriarty, M. 1985. "Retail Promotional Effects on Intra-and Interbrand Sales Performance," Journal of Retailing 61(3) pp. 27.

National Restaurant Association. 2012. 2012 Restaurant Industry Forecast. Retrieved April 10, 2015 http://www.restaurant.org/News-Research/Research/Forecast-2012
Netzer, O., Feldman, R., Goldenberg, J., Fresko, M. 2012. "Mine your own business: Market-structure surveillance through text mining," Marketing Science 31(3) pp. 521-543.
Olson J, C. 1977. "Price as an Informational Cue: Effects in Product Evaluation," Consumer and Industrial Buying Behavior pp. 267-286.
Neslin, S.A., Henderson, C., and Quelch, J. 1985. Consumer promotions and the acceleration of product purchases. Marketing science 4(2) pp. 147-165.
Parker, G.G., and Van Alstyne, M.W. 2005. Two-sided network effects: A theory of information product design. Management Science 51(10) pp. 1494-1504.
Parsons, A. G., Ballantine, P. W., Ali, A., Grey, H. 2014. "Deal is on! Why people buy from daily deal websites," Journal of Retailing and Consumer Services 21(1) pp. 37-42.
Paul, H., and Jonathan, Z. 1991. Flexible specialization versus post-Fordism: theory, evidence and policy implications. Economy and Society 20(1) pp. 5-9.
Pauwels, K., Hanssens, D.M., and Siddarth, S. 2002. The long-term effects of price promotions on category incidence, brand choice, and purchase quantity. Journal of marketing research 39(4) pp 421-439.
Raghubir, P., and Corfman K. 1999. When do price promotions affect pretrial brand evaluations? Journal of Marketing Research pp. 211-222.
Reiner, J. and Skiera, B. 2013. "An Analysis of the Profitability of Deal-of-the-Day Promotions." Working paper.
RestaurantReport. 2012. Restaurant Accounting: For Profit's Sake, Inventory Your Food Cost! Retrieved April 10, 2015, http://www.restaurantreport.com/features/ft_inventory.html
Rossi, P. E., and Allenby, G. M. 2003. "Bayesian statistics and marketing," Marketing Science 22(3) pp. 304-328.
Rossi, P. E., Allenby, G. M., and McCulloch, R. 2012. Bayesian statistics and marketing. John Wiley \& Sons.
Sethuraman, R., Srinivasan, V., and Kim, D. 1999. "Asymmetric and neighborhood cross-price effects: Some empirical generalizations," Marketing science 18(1) pp. 23-41.
Shivendu, S., and Zhang, Z. 2013. Economics of Daily-deal Websites: Advertising and Sampling Effects. ICIS 2013 Proceedings.
Trusov, M., Bodapati, A. V., and Bucklin, R. E. 2010. "Determining influential users in internet social networks," Journal of Marketing Research 47(4) pp. 643-658.
Tuten, T.L., and Ashley, C. 2011. Promotional strategies for small businesses: group buying deals. Small Business Institute Journal 7(2) pp. 15-29.
Yelp.com. 2015. About. Retrieved April 10, 2015, http://www.yelp.com/about
Yipit.com. 2014. Yipit Data. Retrieved March 29, 2015, Yipit.com
Yoon, S., Oh, S., Song, S., Kim, K.K., Kim Y. 2014. Higher quality or lower price? How value-increasing promotions affect retailer reputation via perceived value. Journal of Business Research 67(10) pp. 2088-2096.
YouGov. 2014. Daily Deal: What New Yorkers Want. (n.d.). Retrieved March 29, 2015, https://today.yougov.com/news/2014/10/o6/discount-massages-what-new-york-women-want-theird/
Winer, R.S. 1986. A reference price model of brand choice for frequently purchased products. Journal of consumer research 250-256.
Wright, P. 1986. "Schemer Schema-Consumers Intuitive Theories About Marketers Influence Tactics," Advances in consumer research 13 pp. 1-3.
Wu, B., Petroshius, S., and Newell, S. 2004. The Impact of Store Image, Frequency of Discount, and Discount Magnitude on Consumers' Value Perceptions and Search Intention. Marketing Management Journal 14(1) pp. 14.
Zabranova, N. 2012. Daily Deal Guide - How to run a daily deal. Retrieved March 10, 2015, https://www.gosquared.com/blog/daily-deal-guide
Zhao, Y., Yang, S., Narayan, V., Zhao, Y. 2013. "Modeling consumer learning from online product reviews," Marketing Science 32(1) pp. 153-169.
Zhou, W. and Duan, W. 2010. "Online User Reviews and Professional Reviews: A Bayesian Approach to Model Mediation and Moderation Effects," in ICIS 2010 Proceedings, Paper 256.

Zhu, F., and Zhang, X. M. 2010. "Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics," Journal of Marketing 74(2) pp. 133-148.


[^0]:    ${ }^{1}$ Indeed, in a recent small business survey by the National Restaurant Association, daily deals was the most popular marketing tool for Restaurants (Ipsos 2015).

[^1]:    ${ }^{2}$ The authors refer to this as the "Groupon effect" in their analysis (Byers et al. 2012a).

