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Essays on Business Models and Empirical Analysis of the Online Daily Deal Industry

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Abstract

With the spread of information technology (IT), consumers can easily purchase products and spread opinions about their purchases. Social media has become a force in the marketplace. Not surprisingly, retailers have sought to develop and implement innovative strategies to leverage social media. In the online daily deal industry, coupon offerings are frequently linked with convenient access to social media to "spread the word" and enhance coupon sales. But the online daily deal industry is fairly new and little rigorous analysis has been directed at understanding the causal relationships between deal characteristics and deal outcomes, the causal factors leading to repeat daily deal promotions, or the causal interrelationships among daily deal promotions, social media commentary, and changes in firm ratings. This dissertation investigates all three questions in depth. Throughout, we link our investigations to an overall consideration of the implications for developing an empirically validated business model of the industry.

This thesis consists of three separate but related essays and employs a significant data set that we developed by accessing publicly available Groupon sites. At various points, this data set is paired with data we gathered electronically from Yelp and demographic data directly from the 2010 U.S. Census. The first essay focuses on the impacts of the minimum requirements, a unique deal characteristic of Groupon deals, on social media sharing and deal outcomes.

The second essay focuses on e-WOM and local competition factors on retailers' initial and return Groupon promotion decisions. The final essay focuses on the main effect of Groupon promotions on e-WOM, and investigates mediators and moderators of the main effect. Our study contributes to the literature of various areas, including e-WOM, local competition, business customer loyalty, and online daily deals. Our findings provide important implications for retailers and online daily deal platforms.

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Chapter 1 Introduction

Online daily deal sites, such as Groupon, provide a new marketing tool for retailers. Combining e-coupons and social media, the online daily deal e-market connects retailers with consumers. On the one hand, online daily deal sites provide consumers with a variety of deals and coupons. On the other hand, these sites may benefit retailers by attracting new consumers. This dissertation includes the investigations of business models of online daily deals by examining consumer economic behaviors and retailer decisions using the data collected from the largest daily deal site, Groupon.com.

The first essay focuses on the relationship between the deal design, social media sharing by consumers, and deal outcomes. We analyze the causal impacts of the existence of minimum requirements on Facebook likes and deal outcomes, including quantity of coupons sold and deal revenue. Using Groupon data we collected electronically, we find that the presence of a minimum requirement increases Facebook likes, quantity of coupons sold, and total deal revenue at the time point when the minimum requirement is met and at subsequent two-hour intervals over the deal horizon until the end of deal promotion. The findings suggest that minimum requirements is an effective way for retailers to engage their consumers in social media and to increase their revenues from coupon selling. Yet Groupon has decided to remove this option from all deals, a decision which is in rather sharp contrast to our findings.

The second essay focuses on the sustainability of Groupon's business model from its business customers' perspective. Despite significant literature highlighting the importance of both e-WOM and local competition on business strategies, we found no detailed empirical analysis of how these factors causally impact a restaurant's initial and return promotion

decisions. We address these questions for the Chicago-area restaurant segment of Groupon's business, utilizing a dataset we developed that combines promotion details, location factors, and e-WOM measures. Using our extended propensity score matching method, the analysis identifies the significant causal factors that impact a restaurant's promotion decisions. While some findings follow expectations, others indicate impacts that clearly differentiate the online daily deal arena from the historic discount coupon setting. Important implications for Groupon lie in identifying which restaurants to target for potential business, and developing a more strategic marketing plan.

The third essay focuses on the impact of Groupon promotions on a retailer's online reputation. Despite a decreasing trend in retailers' Yelp ratings after Groupon promotions, we know little of the causal factors which may explain the negative impact of Groupon promotions on online ratings. We also know little concerning whether the negative effect is similar for all types of retailers. In this essay, utilizing a dataset combing promotion data from Groupon, online review data from Yelp, and area demographics for restaurants in the Chicago area, we show that Groupon promotions have a negative impact on consumers' perceptions of food quality and service quality, which further cause a decline in Yelp ratings, i.e. food quality and service quality mediate the negative main effect of promotions on online ratings. We also find that Groupon promotions have a negative impact on online ratings only for higher rated restaurants, versus a positive impact for lower rated restaurants. Our results provide important implications for managers to make promotion decisions and to avoid potential damage to their firm's online reputation.

In sum, the results presented in this dissertation provide insight into the business models of online daily deal e-market and insights as to how the models can be improved. These studies

also contribute to the literature on e-WOM, social media, local competition, and business customer loyalty.

Chapter 2 Relationships among Minimum Requirements, Facebook likes, and Groupon Deal Outcomes

Daily-deal coupons have gained a prominent foothold on the web. The earliest and largest player is Groupon. Originally, Groupon deals were a mix of deals with a minimum requirement (MR) of coupon sales before a deal became effective and deals without a minimum requirement (NMR). Eventually, Groupon stopped using MR deals. For Groupon and its retailer customers, might this decision have actually resulted in negative impacts for both parties (fewer coupons sold and lower revenue)? The structure of Groupon deals (including a "Facebook like" option) together with electronic access to the necessary data offered the opportunity to empirically investigate these questions. We analyzed relationships among MR, Facebook likes (FL), quantity of coupons sold and total revenue, performing the analysis across the four largest retail categories. Using time-stamped empirical data, we completed a propensity score analysis of causal effects. We find that the presence of MR increases Facebook likes, quantity of coupons sold, and total revenue at the time point when the MR is met and at subsequent two hour intervals over the horizon of deals. A key finding is the initial differences observed when MR is met not only continue, but actually increase over the life of the deals.

2.1 Introduction

Given the interest in social media sites, it is not surprising that marketers have sought to develop and implement innovative strategies using such sites. Numerous retailers have launched promotions on their Facebook pages, promotions which are claimed to have increased sales significantly (SimplyZesty, 2011). Such "social commerce" has also been prominent on daily

deal sites such as Groupon, leading some to refer to daily deal sites as “social couponing websites.” Yet, to date, we know of no non-anecdotal, empirical investigation of the relationships among deal characteristics, usage of social media links, and deal outcomes.

Consider Groupon, the acknowledged daily deal industry leader. As many retailers do, Groupon prominently displays a clickable “Like” icon to link to a consumer’s Facebook postings. Once a consumer clicks the icon on a Groupon deal’s webpage, information about the deal, including the title, a picture, and a link to the deal, is shared with all of the individual’s Facebook friends, which may number into the thousands. This Facebook like (hereafter *FL*) spreading of a deal can positively impact the number of coupons sold for the deal and thus increase total deal revenue. In addition, some Groupon deals have included a minimum coupon sales requirement, a specified number of coupons that must be sold before any coupon is authorized for use. If the minimum requirement (hereafter *MR*) is 50 for a given deal, that deal would not become valid until 50 coupons had been sold. If the deal period ends before 50 coupons are sold, no one can take advantage of the deal (the deal becomes null and void). In legal terminology, an *MR* deal is a “contingent offer” that takes effect when and if at least a certain number of coupons are sold within a specified period.

Until an *MR* deal is confirmed (meets the required number of sales), customers have two incentives to hit the “Like” icon and share that deal with their Facebook friends. The first is what we term a social sharing incentive (hereafter *SI*), and the second is a personal incentive (hereafter *PI*) linked to helping ensure that the *MR* is met and the deal confirmed. Once the *MR* is met and the deal confirmed, customers still have the *SI*, but no longer the *PI*. Moreover, for Groupon deals that do not include an *MR*, “no *MR*” or *NMR* deals, customers have the *SI* but not the *PI*.

What is the effect of the *MR* and the associated *PI* to share the deal on deal performance (quantity of coupons sold, and revenue from coupon selling)? If the *MR* only makes deals with get confirmed more rapidly, then is the true impact may be negligible. Over 99% of deals meet their *MR*, on average, in roughly eight hours. However, if the *MR* results in a significant increase in sales and revenues across the whole promotion period, then *MR* matters. Practically, this issue has a particular poignancy. Groupon has stopped using *MR* in their deals. From the perspective of generating revenue from the promotion, Groupon and the retailers have apparently overlooked the positive effect of having an *MR*. Our analysis suggests that returning to using an *MR* could significantly increase the quantity of coupons sold and deal revenues from coupons sold.

To investigate possible causal impacts of the *MR* on *FL*, quantity of coupons sold, and total revenue, we use a propensity score analysis (hereafter *PSA*) (Mithas and Krishnan 2009) utilizing deal data we collected for three major cities, Chicago, Boston and New York, running across Groupon's four largest retail categories enabling analysis of possible categorically differential relationships. Our analysis includes comparisons at two-hour intervals from the time when *MR* are met until the end of a deal. The time dimensionality of our investigation sets it apart from previous *PSA*. To the best of our knowledge, our research is the first to study the causal impact of the *MR* feature on consumer responses on Groupon using longitudinal data. We find that the presence of an *MR* results in increased *FL*, greater quantity of coupons sold, and higher total deal revenue both when the *MR* is achieved and every two hours subsequently until the end of deal promotion. More interestingly, we find that the initial differences in *FL*, quantity of coupons sold, and total revenue caused by the *MR* do not just maintain after the *MR* is met, but actually increase over subsequent time intervals until the end of a deal. Additionally, the

longer it takes for the *MR* to be met, the longer the *PI* exists, leading to a greater impact of *PI,* which, in turn, results in greater differences in *FL*, quantity of coupons sold, and total revenue. As explained below, our results have important managerial implications for retailers and Groupon.

The remainder of this essay is as follows. Section 2.2 briefly summarizes related work-to-date, differentiates our analysis from previous work, and sets forth the scope of this research. Section 2.3 provides essential details on Groupon and our data collection process. Section 2.4 provides an initial data summary and a *PSA* to assess causal effects. Section 2.5 offers concluding remarks and next steps in our continuing analysis of the daily deal industry.

2.2 Literature Review

2.1.1 electronic-Word of Mouth (hereafter e-WOM)

On Groupon, a consumer can share the information about a deal with his/her Facebook friends by clicking the *FL* icon, providing e-WOM on that specific deal. Given the large body of literature on e-WOM, we limit our review to recent papers about the impact of e-WOM on product sales. Liu (2006) collected e-WOM messages on movies released during May and September in 2002 from Yahoo! Movie, finding, in a cross-sectional study, that most of the explanatory power of e-WOM information came from WOM volume, not its valence. In another analysis of e-WOM on movie box office revenues, Rui et al. (2013) collected data on movies from Twitter. While previous literature measured e-WOM through volume or dispersion, Rui et al. (2013) directly measured the number of recipients of each tweet using the unique social structural information on Twitter. The authors argued that their evidence indicated a causal effect of WOM on product sales. Other researchers have examined the effect of e-WOM on the sales of products such as books (Chevalier and Mayzlin 2006), music (Dhar and Chang 2009),

craft beers (Clemons et al. 2006), and digital cameras (Zhang et al. 2013). Through an experimental study, Benlian et al. (2012) examined the direct and positive influence of e-WOM on four consumer beliefs (perceived usefulness, perceived ease of use, perceived affective quality, and trust), which can further increase sales for e-retailers. To date, research in this stream has focused on attempting to identify the influence of social media on product sales in a single retail category, with no analysis across categories.

2.2.2 Social Promotion

Our work is also related to the growing literature on social promotion. With the development of IT facilitation of online collaboration through social media, such as Facebook, YouTube, and blogs, consumers now have the ability to spread ideas and recommendations more quickly, widely, and cheaply than ever before (Ferguson 2008). Byers et al. (2012a) empirically analyzed e-WOM (in this case, social sharing through Facebook) in the daily deal Groupon setting. They found that daily deal sites benefit from word-of-mouth effects during sales events, but did not examine underlying deal characteristics or differences across retail categories. Grounded in observational learning theory, Luo et al. (2014) empirically examined the influence of deal popularity on a consumer's deal purchase and redemption time decisions. Using consumer level data, the authors found that deal popularity increased consumers' purchase likelihood and decreased redemption time. Li and Wu (2014) utilized aggregate level data from Groupon and found a positive influence of observational learning and social media word-of-mouth on the quantity of coupons sold.

2.2.3 Summary

Our analysis differs from previous research in at least three key respects. First, we present a set of structured hypotheses concerning the relationships among deal characteristics,

usage of social media links, and deal outcomes. Utilizing *PSA* that enables the investigation of causal relationships, each hypothesis is empirically tested using time-stamped data we gathered electronically. Second, the empirical analysis and hypothesis testing are conducted for separate retail categories. Third, using time-stamped data, we completed our analysis at specified time points until the deals end.

2.3 Introduction to Groupon and Data Collection

2.3.1 Introduction to Groupon

Groupon was an early entrant into and is the current leader of the daily deal industry (Yipit report, 2011). Groupon began selling daily deal coupons for local retailers in Chicago in November 2008 and has continued to expand, now offering daily deals in 175+ geographic markets spanning the North American continent. Every day in each geographic market, Groupon provides multiple deals from multiple retailers dedicated to that geographic market. Individual deals can also specify an *MR* that must be reached for the deal to be valid, a unique characteristic of Groupon deals. Each Groupon deal page includes a *FL* icon through which consumers can share the deal information (including title, picture, and link to the deal) with all their Facebook friends.

Groupon's revenues come from its share (approximately half) of the coupon price (The Washington Times, July 2009).[1] There are at least two reasons for local retailers to share so much of the coupon price with Groupon. First, Groupon promotions provide opportunities for price discrimination, a new marketing tool for exposure to new customers, and a potential

[1] According to various ad-hoc discussions, including one with a Boston-based merchant who had used Groupon, the actual percentage of coupon revenue that Groupon shares is negotiable. Because the actual percentage of the share varies, we analyze total revenue. Thus, the size of the split is not relevant to our analysis.

“advertising” effect (Edelman et al. 2011). Second, compared with traditional TV advertising and Yellow page advertising, Groupon promotions offer retailers a direct and immediate influx of customers (Dholakia 2011).

2.3.2 Data Collection

We collected longitudinal data from Groupon through its public API[2] for three major cities (Chicago, Boston, and New York) from September 13, 2011 until July 31, 2012.[3] We monitored all deals in the three cities during the data collection period. However, to be sure that we captured the entire sales and revenue stream from the deals we studied, we focused on local deals. We operationally defined local deals as coupon offers with two key characteristics: 1) the offer is only provided to a specific region or market, and 2) the coupon can only be redeemed at the seller’s physical store (no online redemption). In making this choice, we ignored two other sets of Groupon deals: 1) “getaway deals” involving coupons for discounts on flights, hotel rooms, and/or cruise packages, deals provided by a nationwide partnering of Groupon and Expedia; and 2) “online deals” involving coupons that can only be redeemed online, deals gain that are likely nationwide rather than local. Both excluded deal types likely had sales beyond those in the three cities.

Each deal has a set of characteristics including: deal description, original or retail price, discount rate, discounted price (i.e. coupon price), the length of promotion on Groupon (promotion length), whether the deal is featured (featured), coupon duration, whether there is an

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[2] An application programming interface (API) is a source code based specification intended to be used as an interface by software components to communicate with each other.

[3] From December 23, 2011, to January 9, 2012, coupon sold information is not available, because Groupon changed its deal display policy. From February 17, 2012, to April 12, 2012, *FL* are not available in our data set, again because of a shift in API policy. We excluded deals in those date ranges and obtained data covering approximately ten months.

MR, and whether the deal has limited number of coupons for sale (limited supply). Each deal is associated with a retail category, such as "Arts & Entertainment," or "Beauty & Spas."

The data collection period was a transition time in which Groupon moved from all *MR* deals to all *NMR* deals, with the middle months having both *MR* and *NMR* deals.[4] Our focus in this essay is on the deal decision (whether or not to have *MR*) itself, not the characteristics of the retailer making the deal with Groupon. We do consider the retailer's business category, which we discuss below. Our analyses used the six deal decision characteristics that are objective and available: coupon price, discount rate, promotion length, featured, coupon duration, and limited supply. Thus, we assume that *MR* and *NMR* deals do not differ across other retailer characteristics, an assumption we test in our robustness checks. We had two other observable deal characteristics: 1) the city where the deal was offered and 2) day of the week the deals were offered. However, analyses including them indicated no significant difference in results, and thus, for simplicity, these variables were dropped.

During a deal's promotion period, Groupon displayed the amount of coupons that had been sold up to any given moment in time. With coupon price and the amount of coupon sales, we also obtained total deal revenue at each time point. Groupon also showed the number of users who had clicked the *FL* button to express their positive feedback at any given point during each deal's life yielding the number of *FL* for that deal at each time point. We monitored each deal's cumulative sales and *FL* every hour over the duration of the deal, although for brevity and clarity, all of our reporting in this manuscript is done for two hour periods.

[4] Groupon appeared to completely abandon *MR* after January, 2013. We contacted Groupon about the stop of usage of *MR*. They responded that most of the deals had no problem meeting the *MR* since Groupon had grown its consumer base very fast. It seems Groupon did not need to have the *MR*.

We focused on four major categories for our analysis: "Arts & Entertainment" (A&E), "Beauty & Spas" (B&S), and "Health & Fitness" (H&F), and "Restaurant" (REST). These categories were chosen because they accounted for: a) roughly 80% of total local deals, each with a minimum of 10%, and b) about 75% of total Groupon revenue from local deals. Over the data collection period, 79.1% of all local deals were from these four categories. During our entire data collection period, only 2.1% (23 out of 1082) of *MR* deals in the four categories failed to meet the *MR*. In the results presented below, we excluded failed deals. For completeness, we redid the analysis with all such deals included and report the results in Appendix A.4. In all but one statistically insignificant instance, in the A&E category, results are consistent with those where failed *MR* deals are not included.

2.4 Analysis

2.4.1 Minimum Requirement (MR) versus No Minimum Requirement (NMR) Deals

We suggest that there are two incentives for consumers desiring an *MR* deal. First, there is the *SI* (social incentive) of wanting their friends to have the opportunity to get a good deal. But second, until the *MR* is satisfied, consumers wanting to take advantage of the Groupon deal also have a *PI* (personal incentive) to trigger the contingency (i.e., get enough people to buy so that the *MR* is met). *NMR* deals also have the *SI* but not the *PI*. We examine *SI* and *PI* in turn.

We are not the first to suggest a social incentive for sharing. Snyder and Omoto (2000) and Peddibhotla and Subramani (2007) divide a person's incentives to share into "other-focused" incentives (including what they label as social affiliation, altruism, and reciprocity), and "self-focused" incentives (including what they label as self-expression, personal development, and

enjoyment). We included both categories in *SI*, because both are associated with the pleasure received from sharing with a friend.

In discussing self-interest, altruism, and incentives, Jensen (1994) (also see Jensen and Meckling 1994) put it another way:

> "It is inconceivable that purposeful action on the part of human beings can be viewed as anything other than responses to incentives. Indeed, the issue of incentives goes to the heart of what it means to maximize or optimize, indeed to the very core of what it means to choose. Rational individuals always choose the option that makes them better off as they see it. …. As Meckling and I make clear in our article, there is nothing inconsistent between self-interested and altruistic behavior. … To find extensive evidence of altruism, we need only look to the willingness of people to give to charity, and to help family, neighbors and even strangers."

Using Jensen's terminology (and that of economics), we argue that altruism, while it may contain, as Jensen suggests, self-interested motivation based on a positive response to the individual from others who note the altruistic behavior or from good feelings from having acted altruistically, exists throughout the deal offer period.

For *MR* deals, what we call the *PI* to share exists until the *MR* is satisfied and the deal is confirmed. *PI* relates to ensuring that the deal "makes" so that the individual is able to benefit from the deal. This additional, and self-interested, motive exists only for *MR* deal offers and only up to the point in time at which the *MR* is met. Thus, we separated our deals into *MR* deals and *NMR* deals and analyzed the time-linked patterns in deal sales and overall outcomes. Our first set of hypotheses (H1, H2 and H3) suggest that, because of the extra incentive, i.e. *PI*, *FL*, quantity of coupon sales, and total revenue will be higher for *MR* deals than for *NMR* deals at the time equivalent to when the *MR* deal is confirmed. However, there would be little value to *MR*'s if they only resulted in *MR* deals being confirmed a bit sooner, particularly when the vast majority of *MR* deals are confirmed quickly. We suggest that *MR* deals will have a long term advantage over *NMR* deals because of a social contagion effect. After the *MR* is met, more *FL*

will result in more people being aware of and (likely) positively disposed toward the deal leading to more sales and revenue. These additional sales also suggest additional people will make their friends aware of and (likely) positively disposed toward the deal, increasing the *FL*, coupon sales, and revenue in the next period. This pattern will continue in future periods until the deal reaches its end point, either its sales limit or its time limit. Thus, the "Ha" hypotheses below add a "virtuous" cycle of *FL*, coupon sales, and revenue that continue across the entire deal. Thus, all other factors equal,

H1: When the *MR* is met, *MR* deals have more *FL* than do *NMR* deals.
H1a: The advantage in *FL* for *MR* deals over *NMR* deals continues over subsequent time intervals.

H2: When the *MR* is met, *MR* deals have more coupons sold than do *NMR* deals.
H2a: The advantage in coupons sold for *MR* deals over *NMR* deals continues over subsequent time intervals.

H3: When the *MR* is met, *MR* deals have greater total revenue than do *NMR* deals.
H3a: The advantage in total revenue for *MR* deals over *NMR* deals continues over subsequent time intervals.

Before we proceed to causal analysis and testing, we first examine the attribute means to see if direct comparisons might suffice.

2.4.2 Attribute Mean Comparisons for MR and NMR Deals

We first tested for normality across the characteristics. Normality was rejected for all characteristics for all four retail categories, thus we used the Wilcoxon non-parametric test for differences. Table 1 summarizes median values with mean values in parentheses, and median comparisons for *MR* deals versus *NMR* deals on the six deal characteristics for the four retail categories. For example, in the A&E category, the median price of *MR* deals was $20, significantly lower than the median price, $25, of *NMR* deals. In all tables, significance levels are indicated using asterisks (*'s) with *** indicating significance greater than .01; **

significance greater than .05; and * significance greater than 0.10. As Table 1 shows, 14 points of significant difference exist among the 24 possible comparisons (six characteristics by four retail categories), suggesting that these factors differ across categories and deal characteristics.

Table 1. Summary of Wilcoxon Rank Sum Test for Larger Median of Two Groups of Deals (Group Means in Parentheses)

	A&E		B&S		H&F		REST	
	MR	*NMR*	*MR*	*NMR*	*MR*	*NMR*	*MR*	*NMR*
# of deals	216	494	295	413	195	313	353	325
Price ($)	20 (29.42)	25*** (37.87)	39 (61.14)	45*** (83.87)	45 (127.04)	40 (357.08)	20 (22.19)	20 (23.93)
Discount rate (%)	51 (53.26)	51 (52.97)	56 (60.38)	58 (61.51)	64 (66.27)	67 (67.63)	51 (53.71)	51 (54.30)
Promotion length (days)	3 (3.38)	3*** (3.81)	3 (3.36)	4*** (3.97)	3 (3.48)	4*** (4.05)	3 (3.10)	4*** (3.73)
Featured	0 (0.14)	0 (0.11)	0 (0.10)	0 (0.08)	0** (0.10)	0 (0.05)	0 (0.10)	0 (0.08)
Coupon duration (days)	124*** (131.84)	61 (95.94)	187*** (232.84)	186 (199.69)	186*** (200.15)	185 179.24	185*** (169.81)	152 (151.42)
Limited supply	1 (0.78)	1** (0.85)	1 (0.76)	1 (0.80)	1 (0.69)	1*** (0.81)	1*** (0.79)	1 (0.70)

This led us to seek an appropriate method to perform *MR*-*NMR* deal comparisons. Recently Mithas and Krishnan (2009), henceforth M&K, demonstrated the use of a causal analysis approach involving matching cases based on propensity scores. In the approach, a case from a control group (for us, an *NMR* deal) is matched with a case from the treatment group (for us, an *MR* deal) where the matching is based on the similarity of their propensity scores, defined as the likelihood of being in the treatment group. The next section explains the process and illustrates our utilization in the Groupon setting. As explained in detail below, our setting had a time dynamic that sets it apart from M&K's approach. This time dynamic aspect allowed us to observe changes in patterns of similarities or dissimilarities over time.

2.4.3 Propensity Score Approach and Causal Analysis

2.4.3.1. Propensity Score Analysis (PSA)

The six characteristics listed in Table 1 are the observable characteristics for each deal. Consistent with previous literature, we utilized a strong *ignorability* assumption "that underpins the *PSA*." This assumption implies that the observed characteristics are all that matter. However, unlike the M&K context, our context had few previous research efforts against which our variable set could be compared. Our variable set is consistent, however, with those used in the few studies reported in Section 2.2. Later, we report a sensitivity analysis which examined the effect of possible variable omission.

As noted above, we collected data each hour over the life of a deal. Due to occasional server glitches, outages, and/or downtime, missing values occurred for some deals. To avoid issues with interpolating or estimating missing values, we deleted any deal with one or more missing hourly observations from our analysis. Table 2 lists the number of *MR* and *NMR* deals in each category that had complete hourly data.

Table 2. Number of Deals (2604) with Complete Hourly Observations

	A&E	B&S	H&F	REST
MR	216	295	195	353
NMR	494	413	313	325

Analysis using propensity scores strives to compare two similar deals, one from the treatment group and one from the control group. The similarity is based on a probability estimate (or the propensity score) obtained using the six deal characteristics as predictive variables. The propensity score is defined as: "the conditional probability that a subject with X = x_i will be in the treatment group, where x_i is the observed vector of background variables" (Mithas and Krishnan 2009). We employed a caliper matching approach with the caliper set at 0.05.[5] The steps in caliper matching are:

[5] Though Mithas and Krishnan (2009) utilized a kernel matching estimator, we employed a caliper matching process, that is, a technique with a defined distance measure between an *MR* deal and a matching *NMR* deal. We

Step 1: sort *MR* and *NMR* deals in a given retail category according to estimated propensity score (from lowest to highest);

Step 2: determine the common range of propensity score for *MR* and *NMR* and discard deals outside the common range;

Step 3: begin with the lowest propensity score deal, say MR_i, from the propensity-score ordered list of *MR* deals; identify the *NMR* deal with propensity score closest to and within 0.05 of the propensity score of MR_i. If a match is found, select the two deals (that is, matched pairs are one-to-one). If no match within the caliper range is found, remove MR_i from the analysis;

Step 4: repeat step 3 until no *MR* deal remains on the ordered list; and,

Step 5: repeat steps 1 through 4 for each retail category.

Table 3 provides the common range (termed "support") for each category and the number of matches obtained within each category across the relevant range. Referring back to Table 2, we can see that the largest possible number of matched pairs for A&E is 216, for B&S 295, for H&F 195, and for REST 325. The actual matches obtained were 194, 219, 169, and 221, which we viewed as a reasonable proportion of possible matches for all four retail categories.[6]

Table 3. Common Support of Propensity Score before Matching and Number of Matched Pairs

	A&E	B&S	H&F	REST
Common range (called the "support") of propensity score	(0.196, 0.862)	(0.078, 0.881)	(0.056, 0.859)	(0.058, 0.917)
Number of matched pairs	194	219	169	221

The *PSA* method relies critically on the ignorability assumption. Based on this assumption, we estimated propensity scores from observable factors. Our matching method enabled us to find the closest matches for *MR* deals. After matching, the following percentages of *NMR* deals were included: 39.3% for A&E, 53.0% for B&S, 54.0% for H&F, and 68.0% for

investigated both a kernel matching process and a nearest neighbor estimation. Finding no significant difference, we report only the caliper marching process because, in our view, it is the clearest and easiest to understand.

[6] The use of *PSA* typically entails the loss of some observations. Increasing the size of the caliper will tend to increase the number of matches but the matches are not as close or as tight. We doubled the size of the caliper (from .05 to .1), but this resulted in only one more match for A&E, B&S, and REST, and two more matches for H&F. Thus, we stayed with the .05 caliper choosing the better matched pairs rather than adding a few, but less well matched, additional pairs.

REST. Though, as is typical in *PSA*, some observations are lost, we argue that the included deals are neither a trivial set of deals nor a small outlier subset. In addition, as shown in Table 4, there is no statistical difference for observable deal characteristics between the included pairs of *MR* deals and *NMR* deals. The only difference between the two groups is that one has *MR* (treatment group) whereas the other one (control group) does not (*NMR*). The purpose of matching is to limit observable difference in characteristics within each matched pair to *MR* or no *MR*. If we compared without matching, the influence of *MR* could be confounded with differences in the observable deal characteristics.

Table 4. Summary of Wilcoxon Rank Sum Test of Two Groups of Deals after Matching (Group Means in Parentheses)

	A&E		B&S		H&F		REST	
	MR	*NMR*	*MR*	*NMR*	*MR*	*NMR*	*MR*	*NMR*
# of matched pairs	194		219		169		221	
Price ($)	20 (30.26)	23.5 (31.11)	40 (65.54)	40 (67.01)	49 (140.09)	49 (162.47)	20 (23.21)	20 (23.04)
Discount rate (%)	51 (53.02)	51 (53.35)	56 (60.80)	58 (61.05)	67 (67.11)	64 (66.15)	54 (54.75)	51 (54.25)
Promotion length (days)	3 (3.40)	3 (3.43)	3 (3.61)	3 (3.63)	3 (3.57)	3 (3.63)	3 (3.53)	3 (3.52)
Featured	0 (0.14)	0 (0.15)	0 (0.11)	0 (0.10)	0 (0.07)	0 (0.08)	0 (0.09)	0 (0.09)
Coupon duration (days)	99 (110.14)	90 (115.30)	186 (208.90)	187 (220.32)	186 (186.68)	186 (194.51)	185 (156.47)	185 (157.24)
Limited supply	1 (0.84)	1 (0.77)	1 (0.74)	1 (0.77)	1 (0.72)	1 (0.70)	1 (0.72)	1 (0.76)

Earlier we indicated that our analysis had the added feature of a time dimension. Until an *MR* deal actually becomes valid (i.e., the *MR* is met), we explained earlier that there is both an *SI* and a *PI*. Once the *MR* is satisfied, only an *SI* remains. For *NMR* deals, there is only the *SI* throughout the time periods. Thus, for each matched set of an *MR* and an *NMR* deal, we began our comparisons at the point in time when the *MR* deal became valid (termed “time point 0”). The first point or “0” time comparison represents the endpoint of the period during which an *MR*

deal involves both an *SI* and *PI* while its matching *NMR* deal involves only *SI*. We continued our comparisons of paired deals every two hours across the next 40 hours (see discussion below on this choice of duration). This allowed us to analyze whether there are observed differences at the end of the period in which both *SI* and *PI* were present for the *MR* deals but only *SI* was present for the *NMR* deals, and whether any such differences continue, diminish, or expand over the period in which only an *SI* exists for both the *MR* and *NMR* deals. For thoroughness, we also completed our analysis using time 0 as 2 hours after the deal begins. Appendix A.3 provides the tables for that analysis (corresponding to Tables 5-8 below). We found no significant differences. We note that, for retailers and for Groupon, the differences at the end of the deal are the ones that matter for their bottom line. These are the same under either starting point.

In analyzing the data across the various two hour periods, we completed a test for symmetry (Mira 1999), an assumption inherent in the Wilcoxon test. The results were mixed in the sense that for 45 of the periods, symmetry was not rejected, but for 115 periods, symmetry was rejected. We decided to report the Wilcoxon test results but also to include tests results for the nonparametric sign test, a test that does not assume symmetry. In Tables 5-8 that follow, we used the following format for each data cell:

median	(mean)
significance of Wilcoxon test	significance of sign test

Figure 1. Example of Cell Structure for Tables 5-8

As noted earlier, we use *'s to indicate levels of significance for the Wilcoxon test, and +'s to indicate the corresponding significance levels for the sign test.

Tables 5-8 provide results for each of the four retail categories and run up to 40 hours after the *MR* deal met its minimum. The tables also include the "final results" at the end of the

promotions. For A&E deals, Table 5 presents details on all of the two-hour periods. For brevity, Tables 6-8 (B&S, H&F, and REST respectively) report results for periods 0, 10, 20, 30, and 40. Since some two-day deals might not meet the minimum until several hours have elapsed, some deals are over before the "deal makes plus 40 hours" time is reached. This resulted in a somewhat lower number of matched-pair observations for the last two periods. A&E, for example, had 194 observations through the 36th period, but 168 at the end of the 38th hour and 138 at the end of the 40th hour after the *MR* deal makes. Consider Table 5 which reports the set of average values on the output variables for *MR* and *NMR* matched deals for A&E deals. Time "0" is the point in time when the *MR* deal becomes valid. Time "2" is two hours after time "0" and so on through time "40". We stop at 40 because, in many cases, this would be at or near the endpoint of a two day deal. After this point (see discussion above), the number of (open) deals drops off sharply as many deals end. In the last row, we report the results at the end of the deal promotion.

Table 5. Comparison Results over Time for A&E Deals (Median Values with Mean Values in Parentheses)

Time point (number of pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
0 (194)	3 (6.34) * ++	2 (5.75)	15 (24.75) *** +++	6 (27.46)	306 (675.41) ** +++	135 (640.77)
2 (194)	10 (17.06) ** +++	5 (13.28)	33 (66.52) * +++	20 (71.80)	724 (1877.64) ++	551 (1668.76)
4 (194)	18 (28.79) *** ++	8 (19.66)	63 (119.59) ** +++	30 (104.42)	1363 (3136.39) * +++	910 (2451.47)
6 (194)	23 (38.62) *** +++	10 (24.09)	88 (159.89) *** +++	40 (126.56)	1800 (4317.52) ** +++	1200 (2993.52)
8 (194)	27 (47.29) *** +++	13 (27.45)	100 (190.25) *** +++	60 (161.90)	2088 (5187.85) ** ++	1400 (3688.21)
10 (194)	30 (54.09) *** +++	15 (30.18)	110 (232.00) *** +++	60 (174.25)	2375 (5939.69) ** +++	1600 (4020.59)
12 (194)	32 (58.96) *** +++	17 (32.70)	120 (248.61) *** +++	70 (185.09)	2563 (6395.95) ** +++	1800 (4314.63)
14 (194)	35 (63.42) *** +++	19 (35.04)	130 (263.70) *** +++	70 (195.73)	2875 (6815.11) ** ++	2000 (4588.40)
16 (194)	37 (66.39) *** +++	19 (36.32)	140 (274.01) *** +++	80 (202.32)	3045 (7076.64) ** +++	2065 (4757.62)
18 (194)	38 (67.98) *** +++	20 (37.29)	140 (279.12) *** +++	80 (205.13)	3120 (7210.75) ** +++	2225 (4817.96)
20 (194)	38 (68.93) *** +++	20 (37.69)	145 (281.62) *** +++	80 (206.46)	3120 (7265.95) ** +++	2225 (4853.66)
22 (194)	38 (69.80) *** +++	21 (38.02)	150 (283.56) *** +++	85 (208.35)	3120 (7324.94) ** +++	2225 (4894.57)
24 (194)	40 (71.79) *** +++	21 (39.33)	150 (289.35) *** +++	85 (214.77)	3170 (7530.16) ** ++	2245 (5072.18)
26 (194)	43 (75.72) *** +++	22 (41.77)	160 (326.07) *** +++	90 (226.43)	3465 (8663.37) ** ++	2400 (5401.41)
28 (194)	44 (79.87) *** +++	22 (44.07)	170 (341.98) *** +++	100 (235.07)	3725 (9131.25) ** ++	2610 (5637.28)
30 (194)	45 (83.32) *** +++	23 (45.61)	180 (355.02) *** +++	105 (243.84)	3900 (9476.21) ** ++	2790 (5880.81)
32 (194)	47 (86.29) *** +++	23 (46.93)	190 (365.54) *** +++	110 (250.21)	4150 (9736.28) ** ++	2890 (6054.76)
34 (194)	47 (88.57) *** +++	24 (48.12)	200 (373.68) *** +++	110 (256.03)	4350 (9964.07) ** ++	2913 (6225.46)
36 (194)	48 (90.76) *** +++	25 (49.55)	205 (380.78) *** +++	110 (262.72)	4400 (10173.04) ** ++	3175 (6423.99)
38 (168)	51 (97.70) *** +++	26 (51.62)	220 (418.73) *** +++	130 (285.71)	4940 (11273.62) ** ++	3390 (6982.30)
40 (138)	53 (102.45) *** +++	29 (56.07)	240 (448.82) *** +++	140 (299.79)	5235 (12035.22) * +	3600 (7701.41)
End of promotion length (194)	55 (111.23) *** +++	30 (68.23)	265 (496.50) ** ++	170 (360.41)	6170 (14074.00) * +	4935 (9487.40)

Table 6. Comparison Results over Time for B&S deals (Median Values with Mean Values in Parentheses)

Time point (number of pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
0 (219)	1 (1.24) * ++	0 (0.95)	13 (17.38) ** +++	8 (19.30)	594 (906.82) *** +++	300 (842.94)
10 (219)	6 (10.29) *** +++	4 (6.29)	100 (170.30) ** ++	82 (144.68)	4900 (8476.73) *** +++	3700 (6107.05)
20 (219)	8 (13.12) *** +++	5 (7.70)	120 (216.39) ** ++	110 (176.49)	6240 (10648.07) *** +++	4830 (7501.72)
30 (219)	10 (15.16) *** +++	6 (9.01)	150 (252.44) ** +	120 (206.49)	7650 (12444.93) *** +++	5880 (8923.71)
40 (196)	12 (17.24) *** +++	6 (10.17)	180 (309.03) ** ++	140 (228.25)	9035 (15967.07) *** +++	6410 (9769.00)
End of promotion length (219)	13 (20.57) *** +++	8 (12.24)	230 (365.95) ** +++	200 (286.40)	11200 (19502.10) **	9360 (13074.30)

Table 7. Comparison Results over Time for H&F Deals (Median Values with Mean Values in Parentheses)

Time point (number of pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
0 (169)	1 (3.72) *** +++	0 (2.37)	14 (17.88) *** +++	5 (15.40)	704 (1127.98) *** +++	190 (606.37)
10 (169)	10 (21.97) *** +++	5 (11.20)	84 (134.72) *** +++	50 (93.12)	4480 (6984.37) *** +++	2030 (4101.17)
20 (169)	12 (27.51) *** +++	6 (14.41)	110 (173.07) *** +++	60 (116.27)	5340 (8952.73) *** +++	2700 (5087.53)
30 (169)	15 (32.38) *** +++	7 (17.18)	140 (213.59) *** +++	80 (147.30)	6670 (11274.24) *** +++	3430 (6343.08)
40 (134)	16 (40.11) *** +++	7 (17.31)	145 (254.27) *** +++	90 (154.10)	7770 (13533.80) *** +++	3920 (7060.08)
End of promotion length (169)	20 (44.99) *** +++	10 (29.47)	220 (318.15) *** +++	140 (232.81)	11040 (23399.60) *** +++	6860 (12006.80)

Table 8. Comparison Results over Time for REST Deals (Median Values with Mean Values in Parentheses)

Time point (number of pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
0 (221)	2 (2.58)	1 (3.15)	25 (35.34) +++	20 (73.30)	506 (781.95) +++	336 (1237.25)
10 (221)	17 (21.87) *** +++	10 (19.24)	260 (344.70)	240 (346.17)	5600 (7577.81)	4900 (6912.62)
20 (221)	22 (28.51) *** +++	13 (23.12)	330 (432.75)	300 (409.64)	7350 (9546.90) ** +	6380 (8368.10)
30 (221)	26 (33.32) *** +++	15 (26.32)	410 (503.30)	360 (456.26)	8640 (11218.04) ** ++	7500 (9423.83)
40 (199)	28 (37.55) *** +++	17 (28.41)	460 (573.26) **	390 (480.60)	10080 (12809.79) *** +	8400 (10350.04)
End of promotion length (221)	32 (44.05) *** +++	21 (33.13)	570 (654.18) *	510 (560.77)	12000 (14909.40) *** +++	10000 (12038.70)

For A&E deals, the significant difference on *FL* favoring the *MR* deals existed when *MR* levels are met (period 0) and continued to spread and be significant across the remainder of the periods. The numerical differences were significant for both mean and median values, and expanded across the observed periods. The differences in coupons sold and revenue were also significant at period 0 and expanding until the 40th period and the end of the promotions. The results were consistent for B&S and H&F deals. Thus for A&E, B&S, and H&F deals, H1, H1a, H2, H2a, H3 and H3a are all supported.

REST deals showed a slightly different pattern. The significant difference of *FL* favoring the *MR* deals began in the two hour period after the *MR* levels were met and continued to spread and be significant across the remainder of the periods. The difference in the number of coupons sold did not show as significant until quite late (just prior to period 40), when there was a significant positive difference for the *MR* deals. Total revenue, however, showed a significant difference favoring the *MR* deals starting in the 12th period and expanded until the 40th period and until the end of the promotions. Thus for REST deals, H1a, H2a, and H3a were all

supported, whereas H1, H2, H3 were not. The results suggest that the advantages of having the *MR* feature for restaurant deals was not significant until the *MR* is met, but they became significantly positive towards the end of the deal period.

After *PSA* matching, deal characteristics (including coupon price) of the *MR* deals were not statistically significantly different from the deal characteristics of matched *NMR* deals. Hence, the greater revenues that *MR* deals generated resulted from the greater quantity of coupons sold. We used sensitivity analysis with respect to the *PSA* matching technique to test the possibility of significant impact from unobservable (or not included) variables. Our sensitivity analysis found that our results have low sensitivity to unobservable factors (in Section 2.4.3.3).

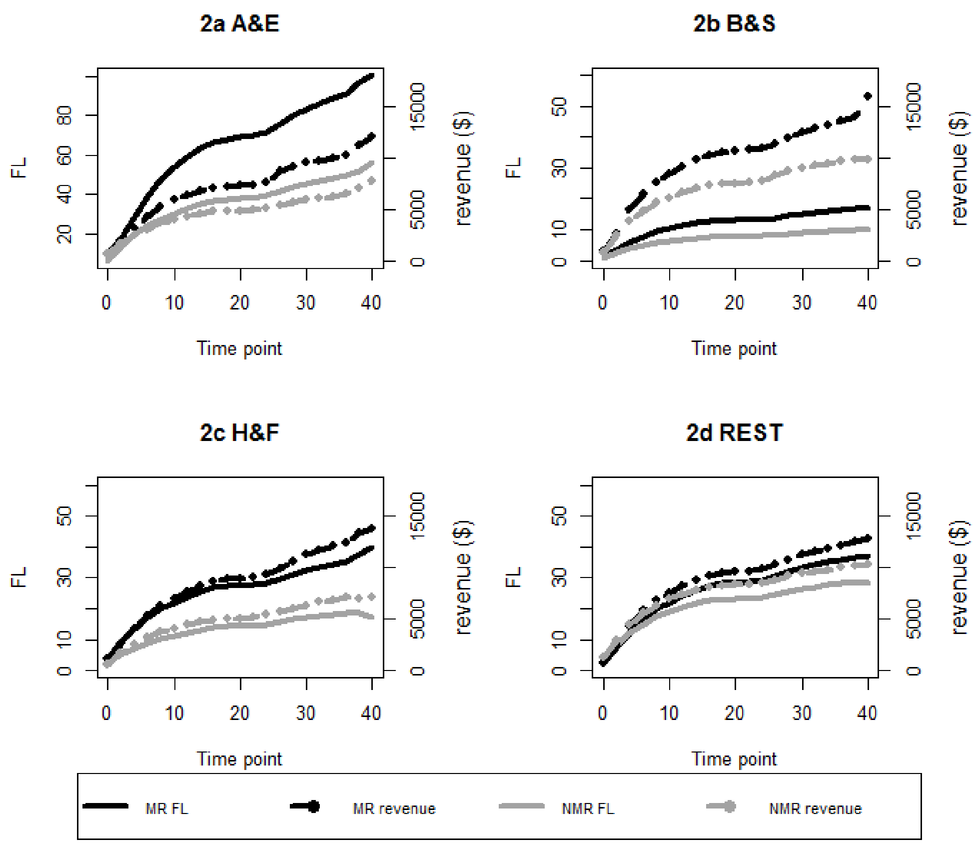

Figure 2. Average FL and Total Revenue Plotted across Time for Matched MR and NMR (T = 0 Represents the Time at Which the MR deal is Triggered, that is, PI Ceases)

Figures 2a-2d graphically illustrate the movement over time for *FL* and total revenue *after* the *MR* had been met (after time 0). For example, values at T = 4 represent average values at the end of four hours after the *MR* deal had met the *MR*. We note the close tracking between *FL* and total revenue for both the *MR* and *NMR* deals across time and retail category. Importantly, the figures also show that the gaps (for *FL* and total revenue) between *MR* and *NMR* deals all got larger over time for the four categories.

After an *MR* is met, the *PI* no longer exists. Only the *SI* remains for both the *MR* deals and the *NMR* deals. However, as Figures 2a-2d show, the initial impacts of the *PI* were magnified over time until the end of deal promotion. We suggest two likely reasons. First, because of the *PI*, the *MR* deals acquired a larger group of seed consumers than the *NMR* deals until the *MR* was met. This larger base of seed consumers provided more individuals who might have acted based on the *SI* and also shared the deal with more friends through Facebook. This social media contagion tended to reinforce deal purchases in a 'snowball' fashion over time (Kempe et al. 2003).

Second, later consumers may have used observational learning to infer the quality of the offers based on previous consumers' purchasing decisions (Hu et al. 2013). When consumers arrived at the Groupon site after the *MR* had been met, they likely took a positive view toward the deal from observing more *FL* and a greater quantity of coupons sold for *MR* deals. The positive impression could have strengthened their *SI* to share the deals and further facilitate purchasing decisions, perhaps resulting in a herding effect (Li and Wu 2014).

We also noticed that the *MR* had the smallest impact on REST deals in terms of increased *FL* and total revenue. *MR* deals for A&E acquired about 82.7% more *FL* and 45% more total revenue than A&E *NMR* deals. B&S *MR* deals totaled 69.5% more *FL* and 50% more total

revenue than their matched B&S *NMR* deals. The figures for H&F had *MR* deals with a 131.7% advantage in *FL* and a 98.2% advantage in total revenue. However, for REST deals, *MR* deals had 32.2% more *FL* and 20% greater total revenue. As we discussed in Section 2.4.1, *PI* only exists until the *MR* is met. Thus, the longer it is from the time the deal is posted until the *MR* is met, the longer the *PI* exists, which, in turn, should lead to a greater impact of *PI*. We note that the average time to reach the *MR* was shortest for REST deals, 7.3 hours, compared with 8.3 hours for A&E, 8.0 hours for B&S and 8.4 hours for H&F. Thus, the *MR* for REST deals was reached most quickly and, therefore, the impact of *PI* was likely to be the smallest. This is consistent with Figures 2a-2d, in that the increases of Facebook likes and revenue for REST deals were the smallest. Our results should encourage restaurants to consider raising their *MR* level, providing a longer period for the *PI* and, in turn, improved deal outcomes.

The results show that *MR* have a causal influence on *FL* and on total revenue. The results suggest that, for a local retailer considering Groupon as a promotion and advertising tool, *MR* are clearly an element to include. We should note that, while we observed similar movements over time in *FL* and total revenue in response to the presence or absence of *MR*, our analysis was not able to imply a causal link between *FL* and Revenue.

In the next two sections, we examine the robustness of our results. In the first section, we consider issues related to heterogeneity, that is, whether the results noted above hold consistently across the different levels of propensity scores. In the second, we analyze the sensitivity of estimated causal effects to potential violations of the strong *ignorability* assumption.

2.4.3.2 Heterogeneity Analysis

To test whether our results hold consistently across various levels of propensity scores, we divided deals into sub-groups according to the estimated propensity score, with each

subgroup covering 0.15 of the range of the propensity scores (i.e., 0 <0.15, 0.15 <0.30, 0.3 < 0.45, and so on). For each of the intervals within each of the four retail categories, we conducted Wilcoxon signed rank tests again for *FL*, quantity of coupons sold and total revenue for time points 0, 20 and 40. For brevity, we summarize the results here with the tables provided in Appendix A.1:

> 1) for each time point, the conclusions for sub-groups are not always the same as the overall results shown in Tables 5-8. However, for the three or four subgroups in each category that included the larger numbers of deals, we found general consistency with the overall results; and,
>
> 2) similar to the overall results discussed above, the effects of *MR* grew stronger over time. In the heterogeneity analysis, the number of range groups with significance increased over time and increased in level of significance over time.

The patterns of observed differences between *MR* and *NMR* deals across propensity level groupings supported the potential importance of *MR* to advertisers across the retail categories.

2.4.3.3 Sensitivity Analysis

Our *PSA* utilized the strong assumption that the observed deal characteristics fully accounted for differences between treatment group (*MR*) deals and control group (*NMR*) deals. Yet the decision whether to include an *MR* in a particular deal may have been based on retailer characteristics as well as the deal, that is, be endogenous. So, if the treatment and control groups actually differ on important unobservable factors, the ignorability assumption was not met and the strength of our conclusions about the impacts of *MR* on *FL*, quantity of coupons sold, and revenue may be restricted. However, retailer characteristics were not readily available in our data set. Thus, we performed an analysis to determine how sensitive our estimated causal effects were to potential violations of the assumption. We refer the reader to detailed discussions of sensitivity analysis in M&K (2009) and in Rosenbaum (1999), and summarize our results for the sake of brevity. Following M&K (2009), we use Γ to indicate “the log odds of differential

assignment to treatment because of unobserved factors." A larger value of Γ means that unobservable factors would need to have had a larger effect to undermine the influence of *MR*, that is, the initial outcomes are less sensitive to possible unobserved variables.

In Appendix A.2, we summarize the values of Γ where the observed significant positive effect of *MR* would become insignificant (at the .01 level). In both analyses, we see that in all or almost all cases, there is significance at levels above the initial level with larger values of Γ at the end of the promotion period providing the retailers' final coupon sales and revenue. Together, these results suggest that, for the large majority of our results, missing variables must have a relatively large effect to nullify the importance of *MR*. Thus, the calculated importance of *MR* does not appear to be an artifact of missing variables.

2.5 Summary, Conclusions and Implications

In the context of Groupon's promotions, we studied causal relations among *MR*, *FL*, quantity of coupons sold, and total revenue. We gathered data hourly, enabling a time-linked analysis of the persistence of differences between *MR* deals and *NMR* deals.

2.5.1 Summary and Conclusions

With a time dimension added, we utilized a *PSA* to analyze causality. Our results indicated that, consistent with our hypotheses, *MR* deals outperform matched *NMR* deals. *MR* deals had more coupons sold and greater total revenue. In addition, *MR* deals had significantly more *FL*, with the total revenue pattern closely following the *FL* pattern for the entire time periods studied. For three of the four retail categories, the differences were all significant when the *MR* were met and continued to be significant (or significant at higher levels) across the time period studied. The one exception, restaurants, did not have significant differences when *MR* were met, but did so later in the promotion period.

Though we utilized only a ten-month data period, it is possible that consumers' interests or attention on Groupon faded or altered over that time. If so, this could influence our conclusions. To check for any possible time trend, we analyzed the de-meaned (subtracting values for each *MR* (*NMR*) deal from the mean of all *MR* (*NMR*) deals) time trend for *FL* and for quantity of coupons sold for all four categories over the ten-month period. We found no significant overall trend or month-by-month difference.

Our research demonstrates, in the context studied, the existence of a *PI* before *MR* are met. The extra incentive provided consumers more motivation to share a deal through social media and before *MR* are met. Our analysis shows that the initial advantage from *PI* continued its impact until the promotion end, a type of social contagion or observational learning effect (Li and Wu 2014). We do not know why Groupon decided to end the use of *MR*. Perhaps this decision was based on the company's observation that virtually all *MR* were met and thus *MR* were viewed as unnecessary. Our results do raise questions about the wisdom of Groupon's decision and suggest a reconsideration of that decision. The evidence indicates positive causal impacts of an *MR* on coupon sales and revenue, both important to retailers and Groupon.

2.5.2 Generalizations and Implications

Our research has important theoretical implications in the e-WOM arena. While numerous studies have documented positive influences of e-WOM on sales or revenue, few studies have examined factors driving the generation of e-WOM (one example is Godes and Silva 2012). Our research: 1) found the presence of *MR* drives increasing social media sharing (*FL*) across the entire length of such deals; and, 2) demonstrated the importance of *PI* for increasing *FL*, coupon sales, and total revenue.

Our results have two significant areas of generalization. First, for daily deal sites that do not diverge significantly from the Groupon format, the results should directly generalize. Second, the demonstrated importance of *PI* should carry over to a myriad of market settings. We currently see many firms assimilating social media. Given what we found about the importance of *PI*, we posit that these firms should utilize some form of *PI* appropriate for their market activities. People do act altruistically in sharing, but we should not forget that they also can act in their own personal interest through sharing.

The impact of *PI* leads to an important managerial insight, but we offer a much broader and likely more important managerial insight. In terms of generating sales and revenue, Groupon apparently overlooked the positive effect of using *MR*. Perhaps because virtually every *MR* was met, Groupon might have thought the effort of tracking and reporting on the *MR* to be unnecessary. Interestingly, Groupon had all the data to analyze the value of *MR*, but there is no indication that they performed the analytics to do so. Our results offer a cautionary tale to those pondering an abrupt alteration of a market process – *do the analytics before you leap*!

As in all studies, there are certainly caveats. Our data, although a fairly large data set, was gathered from three cities over approximately ten months. Second, our data only included Groupon deals. Third, our analysis covered just four retail categories, albeit some 80% of Groupon's local deals. Finally, the utilization of *PSA* enabled us to analyze the causal relation between *MR* and *FL*, the causal relationship between *MR* and deal outcomes (quantity of coupons sold and total revenue), but not the causal relationship between *FL* and deal outcomes. Given the consistency in patterns among *FL* and the outcome variables, we see this as an interesting direction for a theory paper in future work.

Chapter 3 Who Will Come and Who Will Return? — An Empirical Investigation of Business Decisions to Pursue Initial and Return Groupon Promotions

Online daily deals provide a new marketing tool for local retailers. Despite significant literature highlighting the importance of both e-WOM and local competition on business strategies, we found no detailed empirical analysis of how these factors impact a restaurant's initial and return promotion decisions. The research reported here addresses these questions for the Chicago-area restaurant segment of Groupon's business, utilizing a dataset we developed that combines promotion details, location factors, and e-WOM measures. Utilizing an extended propensity score matching method, our analysis identifies the significant causal factors. While some findings follow expectations, others indicate impacts that clearly differentiate the online daily deal arena from the historic discount coupon setting. The set of results provide important implications for Groupon to develop a more strategic marketing plan.

3.1 Introduction

Sites such as Groupon enable consumers both to conveniently purchase products and to spread opinions (Ferguson 2008). A growing number of local retailers, such as the restaurants we examine in this essay, are choosing promotion strategies, such as Groupon, to conduct coupon promotions in lieu of traditional newspaper or flier promotions.

In the daily deal setting, consumers purchase coupons or deals from a website to redeem later at the retailers' physical locations. Customers can be expected to make their decisions as they do for any product, based on a combination of price and perceived quality. But what drives

businesses to pursue an initial Groupon promotion and, subsequently, to pursue or not pursue a second such promotion?

Each business faces a variety of factors that they cannot control, but in some cases, they can influence. Two such factors that we study in this essay are e-WOM and local competition. e-WOM activities, such as Yelp reviews, are not controlled by a restaurant, but may certainly be impacted by the restaurants' business operations. A restaurant cannot control local competitors, but can, by its business decisions, impact the competitive landscape. In the work detailed here, we address: 1) the impact of e-WOM and local competition on a business' (in our analysis, a restaurant's) decision about whether or not to pursue an initial Groupon promotion, and, 2) the impact of post-first-promotion shifts in e-WOM, the local competitive landscape, and the results of the first promotion on the decision on whether or not to pursue a second promotion.

We constructed a detailed dataset of Groupon promotions for restaurants in the Chicago area that includes data on 7008 restaurants over a period of three years. In order to investigate causal relationships, we employed propensity score analysis (PSA). In addition, we extended PSA in order to utilize continuous variables as treatment variables.

Interestingly, what we found was a mix of the expected and the unexpected. As expected, coupon revenue from the first Groupon promotion is the most important factor driving restaurants to return for a second Groupon promotion. However, some of the effects of e-WOM were counter to previous research. Restaurants that were highly rated were more likely to run a first Groupon promotion but less likely to run a second Groupon promotion than were those that were less highly rated. Restaurants with more reviews, generally considered a proxy for popularity in the marketing literature (Liu 2006), were more likely to run both a first and a return Groupon promotion. The effects of local competition were also interesting. Restaurants in more

competitive areas were surprisingly less likely to run an initial Groupon promotion but no less likely to return to Groupon. Restaurants were more likely to run both a first and a return Groupon promotion if nearby competitors had not run a Groupon promotion, suggesting that Groupon promotions are viewed more as creating a competitive advantage than as a competitive response. Note that, because we are using an extended PSA, all of the results reported here are based on comparisons across grouped pairs of restaurants in which the paired restaurants are determined to be statistically equivalent except for the indicated treatment variable.

The remainder of this essay is organized as follows. Section 3.2 includes our discussion of related literature and details of how our analysis differs from previous work. In Section 3.3 we develop our hypotheses based on previous literature. Section 3.4 is devoted to the definition of variables and details on how we compiled the dataset. Section 3.5 presents our extended PSA method along with the estimations of causal relationships, sensitivity analyses, and robustness checks. Section 3.6 is a summary of our conclusions and managerial insights.

3.2 Literature Review

We briefly review three fields of related research: 1) coupon and online daily deal promotions, 2) e-WOM and firm strategies, and 3) local competition.

3.2.1 Coupon and Online Daily Deal Promotions

Marketing research has shown that local retailers have used coupon promotions to generate short-term sales increases (Ehrenberg et al. 1994; Taylor 2001), to attract new consumers, that is, long-term sales increases (Chapman 1986; Varadarajan 1984), and to encourage repeat purchases of a brand (Taylor and Long-Tolbert 2002). Short-term sales and new consumers mostly come from brand switchers who are, by definition, prone to switch again (Gupta 1988).

Previous studies have shown that frequent coupon promotions tend to have two negative impacts. First, frequent promotions lead consumers to infer low product quality and/or inferior brand image (Yoo et al. 2000). Second, Jedidi et al. (1999) showed that frequent promotions cause resistance to buy at the normal price; loyal consumers begin to expect and wait for the next coupon promotion and lower price.

Online coupons introduced easier access for consumers and lower distribution cost for retailers (Chiou-Wei and Inman 2008; Lu et al. 2013). At first blush, daily deal coupons, such as those offered in Groupon promotions, may appear to be a simple extension of online coupons, but this is not the case. First, consumers must pay to get Groupon coupons, whereas the traditional coupons (hard copy or online versions) are free. Second, local retailers pay no up-front promotion costs or fees to Groupon. What the retailers do face is the requirement that they share the coupon sales revenue with Groupon. Thus the daily deal coupon environment shifts the paradigm from a fee-for-promotion-service to a revenue sharing tactic.

The online daily deal arena has begun to attract growing research interest. Research on the sustainability of the industry has not reached consistent findings. Arabshahi (2010) and Kumar and Rajan (2012) concluded that the approach in the industry is not ideally suited to acquire customers and generate profits for retailers. Others suggested particular niches for success. For example, Edelman et al. (2011) argued that the online daily deal promotion is more profitable for lesser known firms and firms with low marginal costs. Dholakia (2012) contended that daily deal promotions are most attractive for newer and relatively smaller businesses.

The studies discussed above are mostly based on analytical models or data from surveys or interviews data rather than actual empirical analysis. The lack of analyses utilizing empirical market data provides a research gap that we begin to fill.

3.2.2 e-WOM and Firm Strategies

Consumers frequently use e-WOM as part of their purchase decision processes. Thus it is not surprising that a large body of research literature on e-WOM has emerged. Numerous studies have shown that e-WOM has significant impact on sales and revenue for industries such as movies (Liu 2006; Rui et al. 2013), books (Chevalier and Mayzlin 2006; Li and Hitt 2008), music (Dhar and Chang 2009), and even craft beers (Clemons et al. 2006).

e-WOM also has significant impact on retailers' response strategies (Feng et al. 2014). Some retailers respond to consumers' comments directly. For example, Gu and Ye (2014) contended that retailers respond to consumers' comments directly to improve future consumer satisfaction for those consumers offering negative reviews. Dellarocas (2006) and Mayzlin et al. (2014) suggested that retailers can go a bit further and attempt to manipulate online comments through posting fake reviews. Other retailers respond to e-WOM through pricing strategies. Kuksov and Xie (2010) posited that retailers may respond to e-WOM by offering lower prices to early customers whose reviews may influence subsequent potential customers.

Chen and Xie (2005, 2008) offered a perspective that ties directly to the work we present here. Their analytical work suggests that it is more profitable for retailers to respond to e-WOM using advertising (that is, promotion) rather than pricing. We suggest and empirically analyze daily deal promotions as one marketing strategy by retailers in response to e-WOM.

3.2.3 Local Competition

A large percentage of online daily deals are from retailers, such as restaurants, whose competition is generally highly localized (Pinkse et al. 2002). Past studies have focused on the impact of local competition on three types of retailer decisions. First, local competition tends to have negative impact on prices. Thomadsen's study (2005) indicated that competition between

geographically close fast food stores drives prices lower than would be expected if the stores merged under a single franchise (see also, Davis 2006 demonstrating that price competition primarily impacts nearby retailers). Second, Dubé et al. (2005) and Pancras et al. (2012) demonstrated that local competition influences a retailer's entry and/or exit decision. Third, Zhu and Singh (2009), in their analysis of both entry and location selection decisions, maintained that the number of nearby retail stores exerts a negative effect on whether or not competitors enter, but the effect decreases with the location's distance from rival outlets.

Here, we extend the prior work on local competition to the arena of daily deal promotions. In particular, we focus on a local retailer's promotion decisions in the presence of social media, which to the best of our knowledge has not been examined in the previous literature.

3.3 Hypotheses Development

In this section, we develop our hypotheses related to restaurants' Groupon promotion decisions. As discussed in Section 3.2.1, a retailer must use repeated coupon promotions with great caution due to the potential negative impacts. Thus, we argue that a restaurant's second promotion is a very different decision from the initial one. Therefore, our hypotheses for a restaurant's two promotion decisions involve some overlapping but other distinct factors.

We first examine the influence of e-WOM factors and local competition factors on the decision to run an initial Groupon promotion (Figure 3). Then, we examine the influence of e-WOM factors, local competition factors, and coupon revenue from the initial Groupon promotion on the decision to return for a second Groupon promotion (Figure 4). Note that the operational definitions of factors listed in Figure 3 and Figure 4 will be fully discussed in Section 3.4.1.

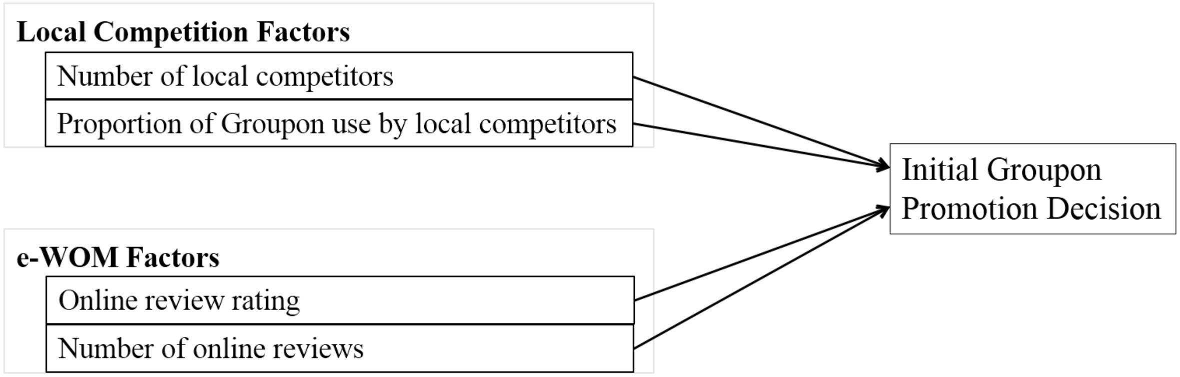

Figure 3. Conceptual Model for the Initial Groupon Promotion Analysis

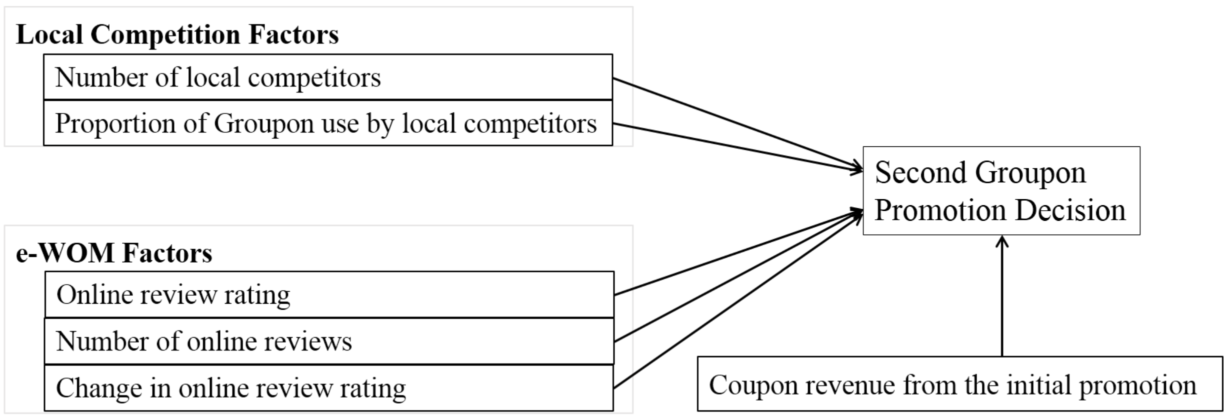

Figure 4. Conceptual Model for the Second Groupon Promotion Analysis

3.3.1 e-Word-of-mouth (e-WOM) Factors

Previous literature has focused mainly on two e-WOM factors: online review rating and number of online reviews. Liu (2006) suggested that, in a more general context, an online review rating can be thought of as the valence of e-WOM and the number of online reviews as the volume of e-WOM. We use online review rating and number of online reviews in our analysis because we are using an online review context.

3.3.1.1 e-WOM Factors and the Initial Groupon Promotion Decision

Anderson and Magruder (2012) argued that an online review rating is an indicator of a retailer’s online reputation and that a high rating has a positive influence on consumer demand. Byers et al. (2012a) noted that, in the online daily deal context, consumers need to pay for and

buy the coupons, providing revenue for the daily deal sites and retailers. The authors argued that higher rated retailers are better perceived by consumers, and therefore, can expect to sell more coupons and earn more revenue. In addition, some consumers will not just use the coupons, but also write reviews and spread a retailer's reputation online. Thus, higher rated restaurants should be more willing to get exposure through daily deal promotions, and expect that their good online reputation will be enhanced, which will attract more consumers in the future. This implies that higher rated restaurants would be more likely to run the initial Groupon promotion, which leads to the following hypothesis:

> **H1**: A higher rating has a positive influence on restaurants choosing whether to do an initial Groupon promotion.

However, restaurants without a good online reputation may suffer from attracting new consumers. Basic marketing theory suggests that lower rated restaurants need marketing tools, including promotion, to encourage new consumers to try their service. Hence, lower rated restaurants would be more likely to run an initial Groupon promotion, which leads to a competing hypothesis:

> **H1a**: A lower rating has a positive influence on restaurants choosing whether to do an initial Groupon promotion.

Number of online reviews is an indicator of popularity, such that more reviews have a positive influence on consumer demand (Liu 2006). Restaurants with more reviews are viewed by consumers as more popular, and therefore should attract more consumers. Restaurants with more reviews may be more likely to run an initial Groupon promotion for two reasons. First, restaurants with more reviews may expect to sell more coupons and earn more revenue. Second, when more Groupon coupons are sold, more coupon users will write online reviews, a positive for the restaurant. These two reasons lead to the following hypothesis:

> **H2**: Having more reviews has a positive influence on restaurants choosing whether to do an initial Groupon promotion.

However, both theoretical work (Edelman et al. 2011) and survey work (Dholakia 2012) have argued that online daily deal promotions are beneficial to unknown or newer local retailers. Restaurants with fewer reviews may be more likely to run an initial Groupon promotion, because they need promotions to encourage new consumers to try their service. This leads to the following competing hypothesis:

> **H2a**: Having fewer reviews has a positive influence on restaurants choosing whether to do an initial Groupon promotion.

3.3.1.2 e-WOM Factors and the Second Groupon Promotion Decision

Higher rated restaurants are likely to return for a second Groupon promotion because of two potential benefits. First, higher rated restaurants may expect to have a successful daily deal promotion and earn more revenue from selling coupons. Second, the high rating may get enhanced through new online reviews by Groupon coupon users. Thus, we hypothesize:

> **H3**: After an initial Groupon promotion, a higher rating has a positive influence on restaurants choosing whether to return.

However, as we discussed earlier, frequent promotions may have a negative impact. For example, a restaurant may suffer from damage to its brand image if it runs a second Groupon promotion (Yoo et al. 2000). It is also likely that a restaurant's loyal consumers will learn not to purchase without a discount, which will hurt the restaurant's revenue in the long run (Jedidi et al. 1999). Hence, a fear of potential damage to its brand image and harm to long-term revenue could well lead higher rated restaurants to avoid return promotions. In contrast, lower rated restaurants would suffer less from the negative impact because their online review ratings are already low. Therefore, a lower rated restaurant may be more likely to return for a second Groupon promotion, an argument leading to the following competing hypothesis:

> **H3a**: After an initial Groupon promotion, a lower rating has a positive influence on restaurants choosing whether to return.

The change in a restaurant's online review rating after the initial Groupon promotion may influence its decision on a second promotion. The initial Groupon promotion may bring in new consumers with different perceptions about food and service. These customers may post qualitatively different online reviews, which may lead to a change in a restaurant's online reputation (Byers et al. 2012a). If its online review rating is improved after the first Groupon promotion, the restaurant will evaluate the promotion as an effective tool. Hence, a restaurant with improved online review rating after the initial Groupon promotion is more likely to return for a second Groupon promotion, which leads to the following hypothesis:

> **H4**: After an initial Groupon promotion, improved online review ratings have a positive influence on restaurants choosing to return.

Restaurants with higher numbers of reviews are more likely to return for two reasons. Reflecting their popularity, such restaurants are more likely to be successful in selling coupons and obtaining greater revenue. An additional expectation is that such popular restaurants would again be more likely to receive even more reviews because they sell more coupons. These reasons lead to the following hypothesis:

> **H5**: After an initial Groupon promotion, having more reviews has a positive influence on restaurants choosing whether to return.

On the other hand, unpopular restaurants, i.e. those with fewer reviews, need promotions to encourage consumers to try their food and service. Hence, repeated daily deal promotions may benefit unpopular restaurants through advertising effects (Edelman et al. 2011), which leads to the following competing hypothesis:

> **H5a**: After an initial Groupon promotion, having fewer reviews has a positive influence on restaurants choosing whether to return.

3.3.2 Local Competition Factors

As discussed in Section 3.2.3, competition in restaurant markets is highly localized (see Pinske et al. 2002). In our analysis, we investigate two local competition factors: the level of local competition and Groupon usage by local competitors.

3.3.2.1 Local Competition Factors and the Initial Groupon Promotion Decision

Local competition was formally modeled by Hotelling (1929) in a highly simplified format, in which two firms located at the two extremes of a “linear city” sell the same physical good to consumers with transportation costs. The Hotelling model theoretically demonstrated that if transportation cost is small, the two firms will be involved in price competition. Empirical studies have shown that marginal transportation cost declines with distance and that price competition mostly impacts nearby retailers (Davis 2006). Further, restaurants close to each other very likely share the same set of potential consumers (Duan et al. 2009). Restaurants in a more competitive area are more likely to attract brand switchers and increase their short-term revenue through coupon promotion (Gupta 1988). These analyses lead to the following hypothesis:

> **H6**: A higher level of local competition has a positive influence on restaurants choosing whether to do an initial Groupon promotion.

However, another stream of literature on spatial concentration suggests that geographic proximity in a local area is also likely to increase demand (Klier and McMillen 2008). A competitive area, such as the downtown area, may be a “destination” place for more consumers because there are numerous options for consumers to choose from. Restaurants in an area with a higher level of local competition may have a bigger base of potential consumers. Hence, restaurants in a more competitive area do not need to run a Groupon promotion to increase demand, or:

> **H6a:** A higher level of local competition has a negative influence on restaurants choosing whether to do an initial Groupon promotion.

Duan et al. (2009) argued that consumers of retailers which are close to each other in a local area are similar. This suggests that nearby restaurants are competing for similar potential consumers. In competing for such similar customers, nearby restaurants may run Groupon promotions, that is, restaurant A may run a competing promotion if nearby restaurant B has just run such a promotion. Hence:

> **H7**: A higher proportion of Groupon use by local competitors has a positive influence on restaurants choosing whether to do an initial Groupon promotion.

On the flip-side, if a restaurant runs a Groupon promotion, consumers may notice and subsequently try nearby restaurants, providing a positive spillover effect (Wang et al. 2015). In contrast, if few or no competitors nearby are using Groupon promotions, a restaurant will not benefit from the spillover effect and may be more likely to pursue its own Groupon promotion. This leads to the competing hypothesis:

> **H7a**: A lower proportion of Groupon use by local competitors has a positive influence on restaurants choosing whether to do an initial Groupon promotion.

3.3.2.2 Local Competition Factors and the Second Groupon Promotion Decision

Here we also have two competing hypotheses for the level of local competition. On the one hand, restaurants in a more competitive area are more likely to return for a second Groupon promotion because: 1) nearby restaurants compete for the similar set of consumers, and 2) coupon promotions are one marketing tool to maintain a restaurant's market share. Hence, restaurants in an area with a higher level of local competition may be more likely to run a second or follow-up Groupon promotion, summarized in the following hypothesis:

> **H8**: After an initial Groupon promotion, a higher level of local competition has a positive influence on restaurants choosing whether to return.

On the other hand, based on the spatial concentration literature, a more competitive area is more likely to be a “destination” location and draw more consumers to the area. In contrast, restaurants in a less competitive area may suffer from acquiring new consumers, and be more likely to run a second Groupon promotion. This leads to the following competing hypothesis:

> **H8a**: After an initial Groupon promotion, a lower level of local competition has a positive influence on restaurants choosing whether to return.

A higher proportion of Groupon use by local competitors could be expected to make a restaurant more likely to return for a second Groupon promotion for two reasons: 1) promotions may intensify local competition and encourage “reaction” promotions, and 2) there can be “herding effects” that lead to imitating competitors’ promotion behavior (Bronnenberg and Mela 2004). Thus:

> **H9**: After an initial Groupon promotion, a higher proportion of Groupon use by local competitors has a positive influence on restaurants choosing whether to return.

On the other hand, a restaurant with a higher proportion of Groupon use by its competitors may be less likely to return due to the spillover effect. In contrast, facing lower or no use of Groupon promotions a restaurant may be more likely to run a follow-up promotion, leading to the competing hypothesis:

> **H9a**: After an initial Groupon promotion, a lower proportion of Groupon use by local competitors has a positive influence on restaurants choosing whether to return.

3.3.3 Coupon Revenue from the First Groupon Promotion

Loyal customers that provide a steady stream of revenue can have a powerful impact on company performance (Rust et al. 1993; Edvardsson et al. 2000; Lam et al. 2004, Ryals 2005). Many studies on customer loyalty have shown, not surprisingly, that satisfaction has a positive relationship with business customer loyalty (Vickery et al. 2004; Lam et al. 2004; and Bennett et al. 2005). In our setting, the relevant loyalty is whether a restaurant that has conducted an initial

Groupon promotion decides to return for a follow-up promotion. The greater the coupon revenue from the first Groupon promotion, the more likely the restaurant would evaluate the promotion as an effective marketing tool encouraging a return promotion. Although promotions may be "too successful," resulting in overcrowding, sell-outs, or other conditions (see, for example, http://www.yelp.com/topic/chicago-groupon-horror-stories-do-you-have-any), we conjecture that the coupon revenue from the first Groupon promotion generally has a positive influence on a restaurant's return decision. Thus:

> **H10**: After an initial Groupon promotion, greater coupon revenue of that initial promotion has a positive influence on restaurants choosing whether to return.

3.4 Variable Descriptions and Data Collection Processes

3.4.1 Variable Descriptions

The following variables, with their formal names in italics, appear in our hypotheses and must be operationally defined:

The online review rating: *Average Yelp Rating*
The number of online reviews: *Number of Yelp Reviews*
Level of local competition: *Number of Competitors Nearby*
Proportion of Groupon use by local competitors: *Proportion of Competitors Nearby Using Groupon*
Coupon revenue from the initial Groupon promotion: *Coupon Revenue from the First Promotion*
Change in online review rating: *Change in Average Yelp Rating*.

Table 9 below provides a brief operational definition of each variable along with the relevant data source. Data collection details are provided in the next subsection.

Table 9. Variable Descriptions/Definitions and Data Sources

Variables	Descriptions/Definitions	Data Sources
Groupon Restaurants	Restaurants that ran a Groupon promotion for the first time prior to the end of data collection.	Groupon
Non-Groupon Restaurants	Restaurants that had not run Groupon promotions prior to the end of data collection.	Identified from Groupon and Yelp
Groupon Return Restaurants	Restaurants that returned for a second promotion within 450 days after the first Groupon promotion. [a]	Groupon
Groupon One-Time Restaurants	Restaurants that had not returned for a second promotion within 450 days after the first Groupon promotion. [a]	Groupon
Average Yelp Rating	The average of all Yelp ratings when a restaurant either ran an initial Groupon, or ran a second promotion. [b]	Yelp
Number of Yelp Reviews	The number of all Yelp reviews when a restaurant either ran an initial Groupon or ran a second promotion. [b]	Yelp
Number of Competitors Nearby	The number of competitors (other restaurants) within a half mile from a particular restaurant.	Yelp
Proportion of Competitors Nearby Using Groupon	First, we obtain the number of a restaurant *A*'s competitors within a half mile that have run a Groupon promotion either before *A* ran an initial Groupon promotion (or between *A*'s initial and second Groupon promotions). Then we divide this number by *Number of Competitors Nearby*. [c]	Calculated from Groupon and Yelp
Coupon Revenue from the First Promotion	The quantity of coupons sold in the initial Groupon offering multiplied by the price of the coupon for a restaurant.	Groupon
Change in Average Yelp Rating	The value of *Average Yelp Rating* when a restaurant ran a second Groupon minus that when it ran an initial Groupon.	Yelp

Note: [a] We chose 450 days to define a Groupon return restaurant, because 90% of returning restaurants returned within 450 days. Our results are not sensitive to the choice of 450 days.

[b] For non-Groupon restaurants without a date of the initial Groupon promotion, we constructed the two e-WOM factors (*Average Yelp Rating* and *Number of Yelp Reviews*) on April 20, 2011, because April 20, 2011 is the median date at which Groupon restaurants ran the initial Groupon promotions. For those Groupon one-time restaurants without a return date, we constructed the two e-WOM factors using the date of 210 days after their initial Groupon promotion, because 210 is the median interval of days between the initial and second promotion for return restaurants.

[c] Similar to note b, for Groupon one-time restaurants, we calculated the Proportion of Competitors Nearby between their initial Groupon promotion and the date of 210 days after the initial Groupon promotions.

3.4.2 Data Collection

As shown in Table 9 above, the main sources for constructing the variables include Groupon and Yelp. From Groupon we collected all Groupon promotions run over the specified period by each restaurant including the specific date and coupon revenue from each deal. From

Yelp, we collected all online reviews for each restaurant along with the corresponding price level and location. The detailed processes of data collection follow.

3.4.2.1 Groupon Data Details

We first collected restaurant deals in the Chicago area via Groupon's website from September 1, 2011 through March 31, 2013. Each Groupon deal has a unique ID which differentiates it from other deals. Even deals from the same restaurant are given different deal IDs. Based on the ID patterns[7], we identified restaurants that were returning (restaurants that had a prior Groupon promotion), with some of the initial deals occurring before September 1, 2011. To capture the deals before September 1, 2011 (Groupon started its business in Chicago in November, 2008), we collected data from three other sources (Figure 5).

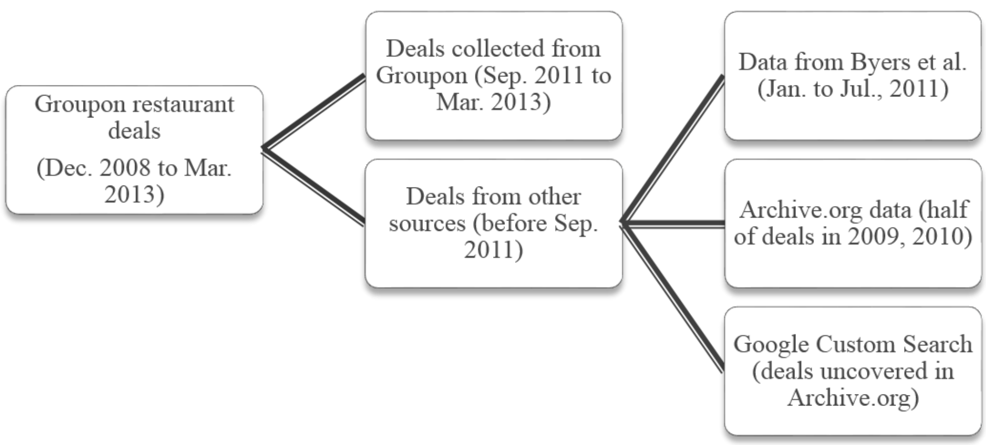

Figure 5. Data Collection Sources of Groupon restaurant Deals

First, we obtained a data set compiled by Byers et al. (2012a)[8], which covered all Groupon deals between January 1, 2011 and July 31, 2011. Second, we collected Groupon deal links from Archive.org, which scans Groupon's webpages and provides free access to the data. However, the Archive.org only scanned Groupon data on randomly selected days each month.

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[7] Deal IDs roughly follow a certain pattern. For example, 'delux-grill' would be the deal ID for a grill restaurant's first promotion, 'delux-grill -1' for the second deal, and 'delux-grill -2' as the third deal.
[8] http://people.bu.edu/zg/daily-deals-dataset.html

Overall, we determined that the Archive.org scanned Groupon deals in Chicago for 23 days during 2009 and 118 days during 2010. Third, for the days not covered by Archive.org, we searched Groupon deal links through Google Custom Search with key words being the physical addresses and/or phone numbers of the restaurants in question. Archive.org and Google Custom Search together provided 1143 restaurant deals for 2010 and earlier in the Chicago area.

Overall, the Groupon restaurant deal data span the period December 7, 2008, to March 31, 2013. However, we cannot guarantee that all the first-time deals from 2010 and earlier were captured by Archive.org and Google Custom Search. This is a caveat to our results.[9] We identified restaurants which had returned for a second promotion (*Groupon Return Restaurants*) and those which had not returned prior to March 31, 2013 (*Groupon One-Time Restaurants*). Wanting to allow a sufficiently long period for a restaurant to return, we set this period to be 450 days because our data show that 90% of identified return restaurants returned within 450 days. Thus a *Groupon Return Restaurant* is defined as one that returned for a second promotion within 450 days after the restaurant's first Groupon promotion.[10]

Through Groupon's public API[11], we obtained the information about each deal, including: 1) the date when the deal was issued, 2) the discounted coupon price, and 3) the quantity of coupons sold by the end of the promotion. Using the coupon price and the quantity of coupons sold, we calculated coupon revenue from the coupon promotion. From Groupon's public API, we also obtained each restaurant's longitude and latitude, physical address, and zip code. With the longitude and latitude for any restaurant, we determined Groupon usage by local

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[9] We indeed obtained every first deal for later deals like '*-1' or '*-2', i.e. we will not mistake a second promotion for a first-time promotion.
[10] We also used 420 days and 480 days, and find our main conclusions still hold (Appendix B.4).
[11] An application programming interface (API) is a source code based specification intended to be used as an interface by software components to communicate with each other.

competitors within a specified distance (e.g. half mile).[12] Regarding restaurant *A*'s decision whether to run an initial promotion at time *t*, we obtained *Number of Competitors Nearby using Groupon* by calculating the number of restaurants within half mile from *A* that had run Groupon promotions within 180 days[13] prior to time *t*. Regarding *A*'s decision whether to return for a second promotion at time *t'*, we obtained *Number of Competitors Nearby using Groupon* by calculating the number of restaurants within a half-mile that had run Groupon promotions between *t* and *t'*.

3.4.2.2 Yelp Data Details

As mentioned above, Yelp provides the necessary operationalizations of e-WOM (Yelp ratings) and price level for each restaurant (Yelp dollar signs). We collected Yelp information for all restaurants in the Chicago area. We then differentiated Groupon restaurants from non-Groupon restaurants as follows:

> 1) for some Groupon restaurants (58.2%), Groupon directly provided Yelp information;
>
> 2) for the remaining Groupon restaurants, using phone numbers, business names and physical addresses from Groupon listings, we searched for the necessary Yelp information. This yielded the necessary information for another 39.5% of the Groupon restaurants.

Overall, we matched 97.7% of those restaurants that had run Groupon with the necessary Yelp information specific to those restaurants. For each restaurant we collected all of the restaurant's individual reviews with corresponding numeric ratings (1-5 points) and review dates. We then constructed the average of individual Yelp ratings and the number of Yelp reviews for

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[12] As discussed in detail in Section 3.5.4, we performed robustness tests using different distances. Detailed results are provided in Appendix B.2.

[13] Its competitors' promotion behaviors within a period may influence a restaurant's promotion decision. We operationalize the period by choosing 180 days before it ran its initial Groupon promotion, because the median of coupon duration (days when a coupon buyer can use the coupon) is 180 days.

every restaurant available on the particular day when the restaurant ran the initial Groupon promotion and on the day of return for restaurants with a second promotion. We also collected the number of Yelp dollar signs ('$'), which indicates the price level of each restaurant.

For each restaurant, we used Yelp to identify the number of restaurants (i.e. number of competitors nearby) within a certain distance (e.g. a half-mile) based on latitude and longitude. This data provided the *Number of Competitors Nearby*. Using this information with corresponding information from Groupon on what restaurants conducted a promotion and when the promotion occurred, we constructed the *Proportion of Competitors Nearby Using Groupon.* We collected demographic information (average household income and average age) from the 2010 U.S. Census by zip code and used these variables as controls.

3.5 Data Analysis

3.5.1 Method

Earlier we laid out two research questions:

1) Are e-WOM factors and/or local competition factors significant drivers of a restaurant's decision to run an initial Groupon promotion?

2) Are e-WOM factors, local competition factors, and/or the outcome of an initial promotion significant drivers of a retailer's decision to return for a second promotion?

Given our interest in identifying accurate answers to these questions, we considered a variety of possible methods and settled on propensity score analysis (PSA), a quasi-experimental method where comparisons are performed over matched pairs of restaurants. As we analyze the impact of each factor in turn, the restaurants are paired for similarity on all other e-WOM and competition factors along with a set of control variables.

The analyses reported here are part of an eventual theory development effort in the arena of e-couponing. We strive to learn critical causal relationships to be later integrated in a formal

model. Thus SEM, which requires a formal model for estimation, would be premature. PLS-Path Modeling, sometimes referred to as a "soft modeling approach" might seem a likely choice, but even PLS-PM utilizes a path structure and involves a process to iteratively estimate the joint set of path coefficients. PSA, on the other hand, harkens back to controlled experimentation (along the lines of Smith 1976, 1982, and 1994) where a treatment measure is manipulated on a treatment group and the outcomes compared to those for a control group undergoing no treatment. Analysis is done on the causal impact of each individual treatment.[14]

We chose the PSA approach over either laboratory or field experimentation for a number of reasons. With respect to laboratory experimentation, we were able to collect actual micro-level data for more than 7000 real restaurants engaging in Groupon promotions. This use of real data enabled us to make comparisons on fairly large sets of matching pairs over long periods of time in direct contrast to the very limited observation sets over limited amounts of time that are typical of controlled laboratory experiments. Finally, because we used real restaurants, our data reflect the actual decision-making of a large number of real business owners and consumers rather than the actions of participants in a laboratory setting.[15] With respect to field experiments, similar factors argued for our approach. Constructing a field experiment generally requires the experimenter to limit the context to one or, at most, a few stimuli that may or may not be representative of the real environment created by the experimenters, not real participants in the environment, over a relatively limited time frame. Because we matched pairs of real deal offers

[14] Careful experimental design can, of course, utilize a factorial approach to lessen the overall number of necessary experiments.

[15] For a more thorough consideration of data source comparisons, see Bapna, R., Goes, P., Gopal, R., and Marsden, J. R. (2006). Moving from data-constrained to data-enabled research: experiences and challenges in collecting, validating and analyzing large-scale e-commerce data. Statistical Science, 116-130.

from real restaurants purchased by real consumers, none of these limitations affected our data. As a result, we see our results as both realistic and highly likely to be causally valid.

3.5.2 Extended Propensity Score Method

PSA involves identifying a variable (or combination of variables) for which a two-level separation is possible (e.g., low versus high, or zero value versus positive value). The set of observations is then divided into two groups, one called a treatment group (e.g., high value, positive value) and a control group (e.g., low value, zero value). A structured search is then conducted to identify corresponding members (matches), one from the control group and one from the treatment group, such that the likelihood of each paired observation being a member of the treatment group is "close" (within a specified ε). That is, given the observed values on all variables but the variable under causal analysis (the treatment variable), the propensity score or likelihood that the paired observation from the control group "is" in the treatment group is very close to the propensity score for the matching observation that actually is in the treatment group (see Mithas and Krishnan 2009, and Bai et al. 2015a, for in-depth explanation and details of alternative matching procedures). Once a set of such matched pairs is identified, the analysis focuses on examining the difference (or lack thereof) in the outcome variable of interest. The basic idea is to evaluate the differences in outcomes for two sets of observations that are matched on all but the variable being analyzed for a causal effect.

Here we add a twist, creating an Extended Propensity Score Analysis (EPSA), which allows us to perform causal analysis on each of the continuous variables appearing in our hypotheses. Past uses of PSA involved binary treatment variables (e.g., drug treatment versus no drug treatment in medicine, an MBA degree versus no MBA degree). The variables analyzed here are continuous or nearly continuous, such as *Average Yelp Rating*, *Number of Yelp Reviews*,

or *Coupon Revenue from the First Promotion*. Thus, we must dichotomize our explanatory variables.

Table 10 provides the range of values that we used to transform the variables of interest into binary variables. In seeking to create binary variables with separation, we ordered observations and then assigned the bottom third of observed values as a "0" or Control Group value and those whose values in the upper third of observed values as a "1" or Treatment Group value. The middle third were not assigned. Thus, in our propensity score analysis, matched pairs involve matching elements from the lowest one third to those in the upper one third, or, in treatment terms, high values of a variable are considered as treatments for those variables. Though the division into treatment and control groups does not involve a direct binary split (e.g., drug versus no drug), the basic approach is the same, though we must note that our decision to base divisions on "bottom third" (control) versus "upper third" (treatment) is certainly subjective in nature. To examine the "validity" of this decision, we also tested other possible splits, ranging from "bottom 20% versus top 20%" to "bottom 40% versus top 40%". The former splits resulted in significantly lowered numbers of matches, while the latter actually had negligible impact. Thus, we utilize the "bottom third" versus "upper third" splits for the EPSA.

Table 10 reports variable levels and the number of observations or matched pairs for all of our treatment/control groups. To aid clarity, we utilize a running example for the variable, *Number of Yelp Reviews*. As shown in Table 10, for the initial decision on a Groupon promotion (yes or no), there are 2338 observations in the control group, with a mean value of 2.59 and a standard deviation of 1.38, in contrast to 2335 observations in the treatment group, with a mean value of 102.48 and a standard deviation of 115.47.

Table 10. Variable Levels and Number of Observations for Control and Treatment

		Initial Groupon Promotion decision		Second Groupon Promotion decision	
		control group	treatment group	control group	treatment group
Average Yelp Rating	mean (Std. Dev.)	2.70 (0.60)	4.27 (0.32)	2.46 (0.51)	4.34 (0.30)
	N	2447	2336	196	138
Number of Yelp Reviews	**mean (Std. Dev.)**	**2.59 (1.38)**	**102.48 (115.47)**	**3.49 (1.79)**	**42.28 (25.53)**
	N	**2338**	**2335**	**246**	**221**
Number of Competitors Nearby	mean (Std. Dev.)	11.52 (5.31)	241.33 (199.00)	9.31 (4.64)	197.70 (175.73)
	N	2441	2326	242	229
Proportion of Competitors Nearby Using Groupon	mean (Std. Dev.)	0 (0)	0.05 (0.05)	0 (0)	0.10 (0.12)
	N	3511[a]	2320[a]	298[a]	230[a]
Coupon Revenue from the First Promotion	mean (Std. Dev.)	NA	NA	4689.57 (1885.27)	32966.00 (31762.81)
	N			232	227
Change in Average Yelp Rating	mean (Std. Dev.)	NA	NA	-0.81 (0.51)	0.73 (0.48)
	N			317[b]	135[b]

Note: N—indicates number of observations.
[a] Due to the distribution of Proportion *of Competitors Nearby Using Groupon*, 0 is both 1/3 quantile and median in the case of Groupon or not. That is why about 1000 more data are assigned into low level than high level. Similar reason for the case of return or not.
[b] To examine the same magnitude of *Change in Average Yelp Rating*, here instead of the one-third split method we take the restaurants with the value lower than -0.25 as the control group, and those with the value greater than 0.25 as the treatment group.

3.5.3 Analysis and Results

Our analysis follows the ordering of hypotheses set out earlier, except that we first consider the hypotheses related to an initial Groupon promotion (H1, H2, H6, and H7) followed by those related to a decision on a return or follow-up Groupon promotion (H3,H4, H5, H8, H9, and H10).

3.5.3.1 Initial Groupon Promotion Decision

The EPSA results for each variable are presented in Table 11.

Table 11. Proportion of Restaurants in Matched Pairs Running an Initial Groupon Promotion in Control and Treatment Groups

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.082	0.098**	1947	**H1 supported**
Number of Yelp Reviews	**0.075**	**0.117*** **	**1345**	**H2 supported**
Number of Competitors Nearby	0.132***	0.054	869	**H6a supported**
Proportion of Competitors Nearby Using Groupon	0.137***	0.108	1332	**H7a supported**

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***

To continue our running example, consider the bolded second row in Table 11. The EPSA results in a comparison across 1345 matched pairs, each pair containing an observation from the control group (low number of Yelp reviews) and from the treatment group (high number of yelp reviews). 11.7% of the treatment group restaurants in the matched pairs decided to conduct an initial Groupon promotion, whereas 7.5% of the control group restaurants in the matched pairs decided to do so. Based on the Wilcoxson signed rank test, this difference is significant at the .01 level (***). As noted below, this result supports H2. We now summarize results for each of the hypotheses related to whether to do an initial Groupon promotion.

H1 proposed that a higher average Yelp rating for a restaurant increases its likelihood to choose an initial promotion, whereas H1a proposed the alternative. Across the 1947 matched pairs, 9.8 % of the restaurants in the high Yelp rating treatment group pursue an initial Groupon promotion, while 8.2% of the restaurants in the low Yelp rating decide to conduct an initial Groupon promotion. The difference is significant at the .05 level and supports H1 and not H1a.

H2 proposed that more reviews for a restaurant increase its likelihood to choose an initial promotion, whereas H2a proposed the alternative. As explained above as part of our running example, the 11.7% versus 7.5% difference is significant ta the .01 level and supports H2.

H6 proposed that a higher level of local competition around a restaurant increases its likelihood to choose an initial promotion, whereas H6a proposed the alternative. The EPSA yielded 869 matched pairs. In this case, the restaurants in the low local competition settings were actually the ones more likely to conduct an initial Groupon promotion (13.2% versus 5.4%) and the difference was significant at the .01 level. This result supports H6a and not H6.

H7 proposed that a higher use of Groupon by a restaurant's local competition increases its likelihood to choose an initial promotion, whereas H7a proposed the alternative. In this case, EPSA identified 1332 matched pairs, with 13.7% of the restaurants facing low (actually 0) use of Groupon by local competitors deciding to do an initial Groupon promotion while 10.8% of those restaurants facing some Groupon use by local competitors decided to do an initial Groupon promotion. The difference is significant at the .01 level and supports H7a rather than H7.

3.5.3.2 Second Groupon Promotion Decision

Table 12 presents the EPSA results relating to hypotheses on restaurant decisions on whether or not to do a second or follow-up Groupon promotion. Since the results relate only to restaurants that did an initial promotion, the number of identified matched pairs is much smaller than the corresponding numbers in Table 11.

Table 12. Proportion of Restaurants in Matched Pairs Running a Second Groupon Promotion in Control and Treatment Group

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.377*	0.321	53	**H3a supported**
Number of Yelp Reviews	**0.408**	**0.461****	**76**	**H5 supported**
Number of Competitors Nearby	0.317	0.317	41	**Neither H8 nor H8a supported**
Proportion of Competitors Nearby Using Groupon	0.436***	0.390	172	**H9a supported**
Coupon Revenue from the First Promotion	0.253	0.434***	99	**H10 supported**
Change in Average Yelp Rating	0.361	0.421***	133	**H4 supported**

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***

Continuing our running example, we see in the second row of Table 12 that restaurants in the low number of Yelp review category are less likely (40.8% v. 46.1%) than their matched counterpart in the high number of Yelp reviews group do a follow-up Groupon promotion (remember that all the restaurants included here have done an initial promotion). The EPSA results are based on 76 matched pairs. We now summarize the results related to each of the hypotheses on the decision of whether or not to do a second Groupon promotion.

H3 proposed that restaurants with a higher rating are more likely to return for a second Groupon promotion; H3a proposed the alternative. 37.7% of restaurants in the lower Yelp rating group decided to pursue a follow-up Groupon promotion compared to 32.1% of the restaurants in the high Yelp rating group, a difference that is significant at the .1 level. EPSA supports H3a.

H4 proposed that an increase in average ratings for a restaurant after its first Groupon promotion increases the likelihood of it returning; there is no alternative hypothesis. Considering the results in the last row of Table 12, we see that restaurants in the high positive change in Yelp ratings return at a rate of 42.1% while those in the low category of this variable return at the

36.1% rate. The difference, based on 133 matched pairs, is significant at the .01 level and supports H4.

H5 proposed that more reviews for a restaurant lead to a greater likelihood that restaurant will return; H5a proposed the alternative. Using the results in the second row of Table 12, we see that 46.1% of the restaurants in the high number of reviews group return compared to 40.9% of their matched pair counterparts in the low number of reviews group. The difference is significant at the .05 level and supports H5.

H8 proposed that a higher level of local competition makes a restaurant's return more likely; H8a proposed the alternative. Based on the results in the third row of Table 12, the EPSA analysis indicates no significant impact on return decisions from the level of local competition. Thus, the results support neither H8 nor H8a.

H9 proposed that more use of Groupon by local competition would lead a restaurant to be more likely to return; H9a proposed the alternative. The results in Table 12, row 4, indicate that restaurants in the group with no local competitors using a Groupon promotion are actually more likely (43.6% vs. 39.0 %) to return for a second promotion than restaurants facing positive number of local competitors that have run a Groupon promotion. The EPSA results, based on comparing 172 matched pairs, are significant at the .01 level and support H9a.

H10 proposed that greater revenue for a restaurant from the first promotion increases its return likelihood. As suggested earlier, while H10 might be expected, it is important to complete the analysis. In fact, based on 99 matched pairs, restaurants that experience high coupon revenue during their first promotions are more likely to return (43.4% vs. 25.3%) than their matched pair restaurants that experience low coupon revenue in their first Groupon promotion. The results, significant at the .01 level, support H10.

In the next section we expand on our examination of the impact of *Coupon Revenue from the First Promotion* on the decision regarding whether to pursue a second Groupon promotion. This examination is brief and examines the strength of the initial promotion result versus various possible interaction effects.

3.5.3.3 The Interaction Effects

As detailed above, both *Coupon Revenue from the First Promotion* and *Change in Average Yelp Rating* affect a restaurant's decision whether to return. But the two factors are different in nature. *Coupon Revenue from the First Promotion* is received relatively immediately, whereas *Change in Average Yelp Rating* will typically take more time to be received by restaurants. Although both factors have a positive influence on the second Groupon promotion decision, it is unclear how the two factors will interact.

We divided the 99 matched pairs for *Coupon Revenue from the First Promotion* (see Table 12) into two groups, one group with positive *Change in Average Yelp Rating* and one with negative *Change in Average Yelp Rating*. We performed comparison tests and summarized the results in Table 13 below. As expected, when *Change in Average Yelp Rating* is positive, restaurants with high *Coupon Revenue from the First Promotion* are more likely to return (45.7% vs. 31.4%). Interestingly, even when *Change in Average Yelp Rating* is negative, that is, online reputation is damaged, restaurants with high *Coupon Revenue from the First Promotion* are still more likely to return (40.3% vs. 19.4%). These results suggest that *Coupon Revenue from the First Promotion* impacts the return decision more than does *Change in Average Yelp Rating*.

Table 13. Proportion of Return Restaurants of two types of *Change in Average Yelp Rating* within Matched Pairs of Analysis of *Coupon Revenue from the First Promotion*

	Low Coupon Revenue (Control)	High Coupon Revenue (Treatment)	Number of matched pairs
	Restaurants with increased *Average Yelp Rating*		
Proportion of Return Restaurants	0.314	0.457**	35
	Restaurants with decreased *Average Yelp Rating*		
Proportion of Return Restaurants	0.194	0.403***	62

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***

As shown in Table 12, there were 133 matches in our analysis of *Change in Average Yelp Rating*. We divided these 133 pairs into two groups, one with high *Coupon Revenue from the First Promotion* and the other with low *Coupon Revenue from the First Promotion*. We summarized the comparison results in Table 14. We see that increased *Average Yelp Rating* positively affects a restaurant's decision when *Coupon Revenue from the First Promotion* is relatively high and not when it is relatively low.

Table 14. Proportion of Return Restaurants of two types of *Coupon Revenue from the First Promotion* within Matched Pairs of Analysis of *Change in Average Yelp Rating*

	Decreased *Average Yelp Rating* (Control)	Increased *Average Yelp Rating* (Treatment)	Number of matched pairs
	Restaurants with high Coupon Revenue		
Proportion of Return Restaurants	0.379	0.545***	66
	Restaurants with low Coupon Revenue		
Proportion of Return Restaurants	0.343	0.299	67

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***

Overall, we find that *Coupon Revenue from the First Promotion* dominates *Change in Average Yelp Rating*. *Change in Average Yelp Rating* has an impact on the return decisions only when the revenue from the first promotion is high, whereas the *Coupon Revenue from the First*

Promotion positively impacts the return decisions regardless *Change in Average Yelp Rating* from the first promotion.

3.5.4 Sensitivity Analysis and Robustness Checks

3.5.4.1 Sensitivity Analysis

The EPSA method has its own limitations. The stringent assumption is that the differences between the treatment group and the control group can be fully captured by observable variables (the strong ignorability assumption, Rosenbaum 1999). Thus, conclusions may be sensitive to unobserved factors. Therefore, we conducted sensitivity analysis.

Following Mithas and Krishnan (2009), we define Γ to indicate "the log odds of differential assignment to treatment because of unobserved factors". If there are no hidden factors, Γ is equal to 1. If the potential hidden factors are underestimated, Γ is larger than 1. A larger Γ means a larger influence of potential unobservable factors on the assignment to the treatment group and the control group. If our conclusions hold when Γ is larger, we are more confident in our results. We computed the value of Γ at which test results of the hypotheses start to be insignificant (Appendix B.1). For almost all factors, there is significance at levels with relatively large values of Γ. These results suggest that, the calculated importance of each factor does not appear to be an artifact of missing variables.

3.5.4.2 Different Radii

Our local competition variables are operationalized using a half mile radius. The results may be sensitive to this definition, although a half mile is a reasonable measure for the restaurant industry. We also operationalized local competition variables using a quarter of a mile and one mile as the radii and ran the analysis for each (Appendix B.2). Results are generally not sensitive to the size of this radius, consistent with previous literature (Reinitz 1968).

3.5.4.3 Different Split Methods

Currently we divided our data into treatment group and control group by assigning the top 1/3 quantile of data to the treatment group and the bottom 1/3 to the control group. The results may be sensitive to this particular data split method. Thus, we reran our analysis using a 20% quantile split (bottom 20% versus top 20%) and a 40% quantile split (bottom 40% versus top 40%). Results show that our main conclusions still hold (Appendix B.3).

3.5.4.4 Different Interval of Days

In our analysis, we used 180 days to operationalize the *Proportion of Competitors Nearby using Groupon* for the initial Groupon promotion decision. To test whether this specification influences our results, we also used 150 days and 210 days. Results show that our main conclusions still hold (Table B.4.1 and Table B.4.2 in Appendix B.4).

In Table 9, we used 450 days to define *Groupon Return Restaurants*. To test whether this specification influences our results, we also used 420 days and 480 days. We find consistent results (Table B.4.3 and Table B.4.4 in Appendix B.4).

3.5.4.5 Areas with Tourist Attractions

The Chicago area is a large metropolitan area with significant tourist attractions in some areas. Tourist attractions in these areas may attract consumers from outside of the zip code. To examine whether tourist areas influence our results, we redid our analysis excluding restaurants from the key zip codes with tourist attractions (covering Navy Pier, Rush Street, Old Town, Gold Coast, and Uptown). The results show that out main conclusions still hold (Appendix B.5).

3.6 Summary and Conclusions

3.6.1 Theoretical Implications from Empirical Results

Our results make interesting theoretical implications with respect to how e-WOM and local competition affect both initial and return Groupon promotion decisions. Previous literature (e.g., Liu 2006) has suggested that there are two factors related to the influence of e-WOM: the valence (positivity or negativity) and the volume or amount of e-WOM. In our work, we operationalize volume as the number of reviews of a restaurant and valence as the average numeric rating of the reviews for that restaurant. With respect to the number of reviews, we find consistency across the two types of decision, that is, the greater the number of reviews for a restaurant, the more likely that restaurant was to engage in an initial and a subsequent promotion. These results suggest that decisions about Groupon promotions are contrary to many other promotion decisions; the more people who are interested in the product or service, the less necessary ordinary promotions are. The difference here probably revolves around the fact that Groupon promotions are not free to the consumer and thus result in a new and relatively immediate stream of revenue.

With respect to ratings, we find somewhat contrary results. That restaurants with higher ratings were more likely to decide to run initial Groupon promotions which suggests that the decision-makers or managers of these restaurants were both attracted to the revenues and confident that their good ratings would continue. But the fact that this positive impact of high ratings did not carry over for the return to a second Groupon promotion, suggests that managers of higher rated restaurants became aware of possibly negative issues associated with a significant increase in customers and thus were less likely to decide to run another Groupon promotion. To summarize, e-WOM did clearly impact both initial and return decisions, but quite differently.

We considered two local competition factors: 1) competitive density of restaurants in the area, and 2) proportion of restaurants in the area that had engaged in a Groupon promotion. That fewer restaurants in high competitive density areas ran Groupon promotions than in low competitive density areas indicated that Groupon promotions were initially seen by restaurant owners as a mechanism to draw customers when there were few competitive restaurants competing for those customers. Interestingly, competitive density was not seen as a significant issue in return decisions, suggesting that return decisions were more a function of the restaurant's results from the initial promotion, revenue generated and ratings changes than of the environment the restaurant inhabits. That restaurants are more likely to run a Groupon promotion when competitors have not, is evidence that Groupon promotions seem to be viewed by restaurant managers as a way for owners to create a competitive advantage by drawing in consumers, not simply acting as a response to competitors' running Groupon promotions. To summarize, we see that a lack of competitive density and a lack of competitors using Groupon promotions both tend to increase the likelihood that a restaurant will decide to use a Groupon promotion initially, but that it is performance that drives return decisions.

3.6.2 Methodological Contributions

Recall that all of our results are based on comparisons across matched pairs of restaurants in which the paired restaurants are determined to be statistically equivalent except for the indicated treatment variable. Our EPSA paired comparison analysis is based on PSA, but involves two extensions of the standard PSA approach. The first modification is that we do our propensity score matching by developing separate groupings, treatment and control variable combinations, individually for each of the set of independent variables we want to test. This allows us to test the causal relationship for each independent variable separately, rather than

building an analysis of multiple variables that might mask each other's true impacts. The second modification is relatively straightforward and relates to our focus of independent causal variables that are continuous. We create treatment versus control groups by dividing observations of a specific variable under analysis in almost all cases by means of quantiles (the bottom third of the independent variable is assigned to the control group and the top third of the same variable to the treatment group). In the case of Yelp ratings we used differing score levels that lead to separation between control and treatment groups (change in Yelp ratings below -0.25 were assigned to the control group and above 0.25 to the treatment group).

We note that the choice of our second modification is not cost free since it results in the loss of potential pairs from our analysis. This occurs because we seek to pair one restaurant from the lowest 1/3 of values on an independent variable with a restaurant from the group having the highest 1/3 of values on that variable. This requires that we ignore those restaurants having the middle third of values on variable. We thought it important to have the paired restaurants very different on the variable under analysis while being very close to the same on all other variables.

3.6.3 Managerial Contributions

Our results provide useful managerial implications for Groupon, suggesting opportunities to increase both the initial trial rate and the relatively low (approximately 38.1% in our data set) return rate for Groupon promotions. Our results suggest that Groupon may be better able to entice highly rated and heavily reviewed restaurants located in less competitive locations to try a Groupon promotion. This suggests a possible redeployment of their sales force and to emphasize on more likely customers. Perhaps more importantly, to entice more restaurants to return, Groupon needs to ensure that the first promotion works for its customers. The evidence is quite

clear that initial deal revenue has the greatest effect on the decision to return, followed by the effect on the restaurant's ratings.

3.6.4 Limitations

Our empirical test uses EPSA, a quasi-experimental method that allows for analysis of causation among the paired observations. However, there are costs to using this technique. First, using EPSA can result in small numbers of paired observations with which to carry out the causal tests, which, in turn, can lead to the inability to test some relationships or to false negative tests due to inflated standard errors. Second, EPSA runs the omitted variables risk, that other variables that are important to creating the matched groups are not included in the analysis, a risk that can be examined but not totally resolved by means of the sensitivity test that we employ in our robustness check. Finally, the technique entails acceptance of the risk that unpaired observations are inherently different from paired observations. All of these concerns suggest that, while our results are theoretically interesting, statistically significant, and empirically verified, further research using a different empirical method should be encouraged.

Any sampling decision involves trade-offs. Our need to create a data set that incorporated the full population of ratings data from Yelp, an online ratings service, location data from geographical information in Yelp, and promotion data from the Groupon website necessitated limiting our data set, such that it is comprised of one category, restaurants, and one Groupon city website, Chicago. Obviously, this may limit the generalizability of our results to some degree. This suggests the same call for different empirical analyses with broader category and location coverage.

3.6.5 Conclusions

We use extended propensity score analysis (EPSA) to provide a causal analysis of the effects of e-WOM and local competition on restaurant's decisions whether or not to engage in an initial Groupon promotion and whether or not to return for additional Groupon promotions. In terms of e-WOM, we find that restaurants with higher ratings on the reviews they receive are more likely to engage in initial promotions but less likely to return for additional promotions. We also find that restaurants with more reviews are more likely both to engage in initial promotions and to return for additional promotions. In terms of local competition, we find that the greater the local competition, the less likely restaurants are to engage in initial promotions, but that this variable does not affect additional promotions. In addition, we find that restaurants are more likely to engage in initial Groupon promotions, and additional Groupon promotions if their competitors are not engaged in Groupon promotions. These results have important implications for understanding the effects of e-WOM and local competition on online promotion decision making.

Chapter 4 The Impact of Daily Deal Promotions on Retailers' Online Reputation

Online daily deals are becoming a popular promotion tool for local retailers. Despite a decreasing trend in retailers' Yelp ratings after Groupon promotions, we know little of factors which may explain the negative impact of Groupon promotions on online ratings, or whether the negative effect is the same for all types of retailers. In this study, we addressed these questions utilizing a dataset combing promotion data from Groupon and online review data from Yelp for restaurants in the Chicago area. We showed that Groupon promotions decreased consumers' perceptions of food quality and service quality, which further caused a decline in Yelp ratings, i.e. food quality and service quality mediate the negative main effect of promotions on online ratings. Another interesting finding is that Groupon promotions had a negative impact on online ratings only for higher rated restaurants, versus a positive impact for lower rated restaurants. Our results provide important guidance for managers to make promotion decisions and to avoid potential damage to their firm's online reputation.

4.1 Introduction

Marketing research has well documented the separate roles of promotion tools and e-word-of-mouth (e-WOM) on customer demand. For example, coupon promotions are often used by retailers to accelerate short-term sales (Ehrenberg et al. 1994; Taylor 2001). On the other hand, e-word-of-mouth (e-WOM), such as online reviews, provides information about products or services and has a positive effect on sales (Chevalier and Mayzlin 2006; Liu 2006). Recognizing the effectiveness of promotions and e-WOM, retailers may rely on both strategies

simultaneously to reach their consumers (Lu et al. 2013). However, there are few studies investigating the interaction between promotions and e-WOM.

In recent years, online daily deal sites such as Groupon are a growing promotion tool for local retailers, such as restaurants. Daily deal coupon users sometimes post their opinions of their experiences online after their consumption, and these postings influence a retailer's online reputation after promotions. Byers et al. (2012a) showed a decreasing trend in retailers' Yelp ratings after they used Groupon promotions. However, the decline may not be caused by Groupon promotions. Even without promotions, online ratings also decline naturally (Godes and Silva 2012). Therefore, the first question addressed in this study is: What is the main causal effect of daily deal promotions on retailers' online ratings?

Although Byers et al. (2012b) showed the negative effect of promotions on online ratings, we still know little of the factors which may have caused these direct effects of promotions on online ratings. In this study we focus on consumers' perceptions of quality, because consumers' perception of their consumption experience is the main factor reflected in online reviews (Hu et al. 2009). A particular question addressed in this study is: Does consumer perceptions of quality mediate the main effect of daily deal promotions on online ratings?

Further, Li and Hitt (2008) showed that a retailer's initial ratings moderate the trend of future online ratings. That is, when initial ratings are relatively lower (higher), online ratings will increase (decrease) over time. Hence, we also examined the potential moderating effect of online ratings on the main effect of promotions on online ratings: Will the main effect be different for retailers with different levels of initial ratings?

To answer these questions, we constructed a data set including: 1) 936 restaurants (*Groupon Restaurants*) that ran one Groupon promotion and 6402 restaurants (*Non-Groupon*

Restaurants) that did not run a Groupon promotion over a three-year period in the Chicago area; and 2) online review data from Yelp for all restaurants. To investigate the main causal effect, we applied a propensity score matching (PSM) method and obtained a matched set of *Non-Groupon Restaurants* and *Groupon Restaurants*. We found that on average the Yelp ratings of *Groupon Restaurants* declined statistically significantly more than did their matched *Non-Groupon Restaurants*, i.e. we found a negative main effect.

We then sought to determine what caused the Groupon promotions to reduce consumers' on-line ratings. To do this we employed text mining techniques to the contents of Yelp reviews after promotions to isolate the two features most frequently mentioned by reviewers, their perceptions of food quality and service quality, and measures of sentiment that corresponded to the two measures of perceived quality. Through a formal test of the mediation and moderation effect models, we obtained two interesting findings. First, both food quality and service quality mediate the main effect of Groupon promotions on the Yelp ratings. Particularly, Groupon promotions decreased perceived food quality and service quality, which led to a decline in Yelp ratings. Second, regarding the moderation effect of pre-promotion ratings, Groupon promotions had a negative effect on Yelp ratings for relatively higher rated restaurants, but a positive effect on Yelp ratings for relatively lower rated restaurants. We also discuss important implications for retailers in Section 4.7.

The remainder of this essay is organized as follows. Section 4.2 discusses related literature and how our work differs from previous studies. In Section 4.3 we introduce our model. Section 4.4 includes the details of our data collection and variable definition. Section 4.5 presents our propensity score analysis and the results for the main effect. In Section 4.6 we

formally test mediators and moderators using text mining to identify the mediating variables. Section 4.7 summarizes the conclusions from our study and contains related managerial insights.

4.2 Literature Review

This study aims to examine the main causal influence of promotions on online reviews, and potential moderation and mediation effects on the main effect. In this section, we summarize three areas of related research: 1) drivers and dynamics of online reviews. The literature of this area provides us potential moderators and mediators in our research model; 2) the impacts of promotions[16] on e-WOM. Previous research has shown the influence of promotions on the volume of e-WOM. Our work complements the stream of literature by focusing on the valence of e-WOM (online ratings); and 3) online daily deals, which is a growing area in research. Online daily deals are becoming a new promotion tool for local retailers. Previous studies have shown us interesting trends, on which we build our model.

We also highlight the differences between our study and each stream of previous research.

4.2.1 Drivers and Dynamics of Online Reviews

Previous studies on online reviews have explored the generation of online reviews by consumers and the dynamics of online ratings over time.

First, many studies have shown that the generation of online reviews is driven by consumers' perception of the consumption. For example, consumers tend to write reviews only when they are either extremely satisfied or extremely dissatisfied about the products or services

[16] Promotions are traditionally defined as a marketing mix element comprising "a wide variety of tactical promotion tools of a short-term incentive nature designed to stimulate earlier and/or stronger target market response" (Lilien et al. 1992). Popular forms of sales promotions include coupons, price discounts, premiums, and free trials.

(Hu et al. 2009). Consumers are also more likely to post online reviews when satisfied than when dissatisfied (Dellarocas and Wood 2008).

Second, environmental factors, such as previously posted opinions, can influence the posting of online reviews. Wu and Huberman (2008) find that exposing potential reviewers to previously posted opinions leads to the increasingly extreme reviews because individuals tend to provide comments deviating from previous reviews. Moe and Schweidel (2012) further identified two types of reviewers: 1) expert reviewers, who are more active, more negative and more likely to differentiate from previous reviews; and, 2) non-expert reviewers, who are less active, more positive and more likely to show a consensus with previous opinions.

Regarding the dynamics of online ratings, Li and Hitt (2008) utilized book reviews from Amazon and showed that when the initial ratings are low, online ratings increase over time, whereas when the initial ratings are high, online ratings decrease over time. Godes and Silva (2012) established two processes to examine the dynamics of online ratings, one as the process of the amount of time (temporal pattern) and another as a process of the sequence of reviews (ordinal pattern). They showed an increasing temporal pattern of online ratings controlling for calendar dates, but a decreasing online ratings over the sequence. Through a simulation on the two types of reviewers (expert and non-expert), Moe and Schweidel (2012) argued an overall decreasing trend of online ratings over time.

Promotions may influence consumers' perception of consumption, which further impacts the posting of online reviews. For example, consumers with coupons tend to infer low product quality (Yoo et al. 2000). And the new consumers brought by promotions may also have different opinions from previous reviews, and therefore leave a higher (lower) rating if previous ratings are lower (higher). However, there are few research studies on the influence of

promotions on the dynamics of online reputation. In this study, we fill that gap by utilizing Groupon promotion data and Yelp review data of restaurants in the Chicago area.

4.2.2 Impacts of Promotions on e-WOM

Marketing studies have well documented the value of promotions and e-WOM separately. Retailers may apply promotions and e-WOM marketing simultaneously to increase sales (Lu et al. 2013). However, it is important to understand the impact of promotions on e-WOM, because the changed online reputation may impact retailers' sales or revenue in the future.

Current studies have shown that promotions can trigger the generation of WOM. Berger and Schwartz (2011) examined the psychological factors influencing immediate and ongoing WOM. They showed that promotional giveaways were associated with increased overall WOM. Godinho de Matos et al. (2015) found that price discounts increased the volume of e-WOM, which further boosted sales. From the perspective of the valence (positive or negative) of e-WOM, Feinberg et al. (2002) showed that selective targeted promotions will increase perception of unfairness for consumers without promotions, which generates negative e-WOM. However, this research focuses on a selective targeted promotion context, rather than a general coupon promotion situation as examined in our study.

Our study has three key differences from previous literature on e-WOM. First, our work focuses on the causal effect of promotions on the valence of e-WOM (indicated by online ratings) by utilizing empirical promotion data in the online daily deal context. Second, we further examined the moderation role of previous online ratings (before promotions) on the causal effect of promotions on online ratings. Third, we measured consumer perception of consumption implicitly by mining textual reviews and extracted perceived quality (food quality

and service quality) most frequently mentioned by reviewers. The perceived quality serves as a mediator between daily deal promotions and the change in online ratings.

4.2.3 Online Daily Deals

Online daily deals have drawn much attention in media and practice in recent years, but the area remains relatively new in academics (Smith Brain Trust 2015). Recent studies focused on the effect and/or profitability of daily deal promotions and reached inconsistent conclusions. Some studies argued that online daily deal promotions have a negative impact on retailers. Based on an analytical model, Kumar and Rajan (2012) concluded that the daily deal promotion is not ideally suited to acquire customers and generate profits for retailers. Utilizing empirical data, Byers et al. (2012a) showed that restaurant's Yelp ratings have a declining trend overall after Groupon promotions.

Other studies suggested that online daily deals are profitable for niche markets. Edelman et al. (2011) argued that the online daily deal promotion is more suitable for unknown firms and firms with low marginal costs. Based on a survey of restaurants having run daily deal promotions, Dholakia (2012) contended that daily deal promotions mostly benefit newer and relatively smaller businesses.

Current studies have rarely examined the daily deal promotions on retailers' online reputation. A study closest to our work is from Byers et al. (2012b), which also utilized Groupon promotion data and Yelp review data, and investigated the fact that Yelp ratings decreased on average after Groupon promotions from various aspects. We extend their study in two ways. First, we posit that previous ratings (prior to the Groupon promotions) are a moderator of the main effect of promotions on online ratings. Second, we suggest that consumer perceived

quality is a mediator, which may provide deeper understanding of the impact of promotions on online ratings.

4.3 Research Model

Figures 6 – 9 outline the models analyzed in this presentation. Figure 6 provides the basic main effect model. Using familiar marketing terms, Figure 7 provides the mediation effect model. In this model, the perceived quality of the restaurant during the promotion is expected to serve as a mediator of the impact of a Groupon promotion on online ratings. Figure 8 adds a separate moderation effect to the model in Figure 7. Existing ratings before a Groupon promotion are expected to moderate the direct impacts of the Groupon promotion on online ratings. Finally, the model in Figure 9 includes an additional moderating effect such that the pre-promotion ratings serve as a moderator to impact the mediation effect of perceived quality on the Groupon promotion effect on online ratings.

In the next four subsections, we detail and explain each of the four models.

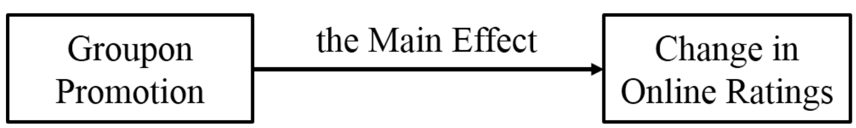

Figure 6. Main Effect Model

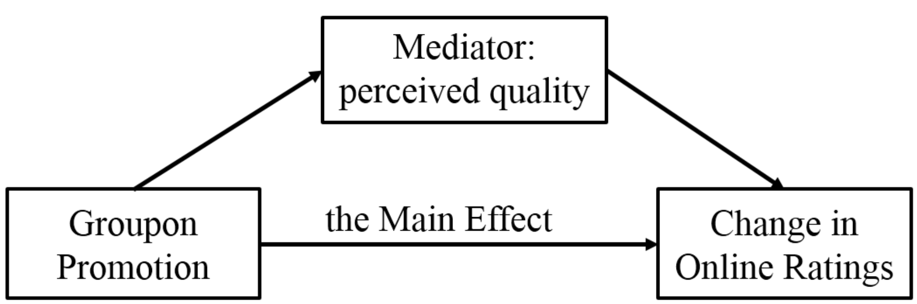

Figure 7. Mediation Effect Model

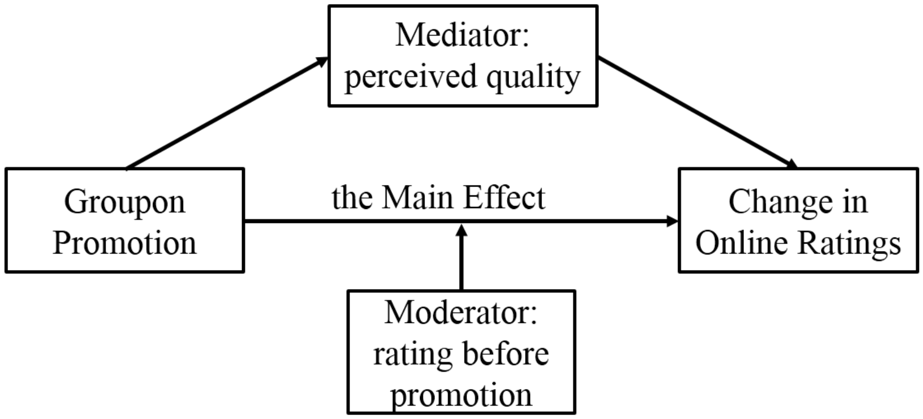

Figure 8. Separated Mediation Effect and Moderation Effect Model

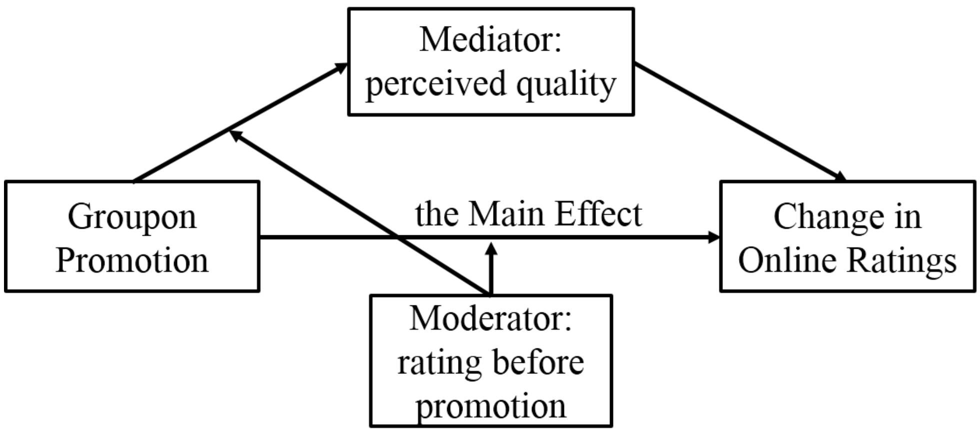

Figure 9. Moderated Mediation Effect Model

4.3.1 Main Effect

Byers et al. (2012a, 2012b) showed a declining trend of Yelp ratings on average after Groupon promotions. We start our analysis with the same basic question: What is the main effect of Groupon promotions on retailers' online ratings?

We expect a negative impact based on the studies by Byers et al (2012a, 2012b). As described in the next sections our work analyzes more complex relationships than those studied by Byers et al.

In the next section, we consider whether or not there is a mediation effect of perceived quality between the promotion and the evaluation.

4.3.2 Mediation Effect

As discussed in Section 4.2.1, the generation of online reviews is driven by consumers' post-purchase perception. If the perceived quality of products or services is high (or low), consumers tend to leave positive (or negative) reviews (Hu et al. 2008). Promotions may impact the online ratings through influencing such perceived quality. For example, consumers with coupons have been shown to infer low product quality (Yoo et al. 2000).

Groupon promotions may also change the environment in which consumers consume the products or services, which leads to a different perceived quality. For example, Groupon promotions may bring a larger volume of consumers to a restaurant in a short period of time (Kumar and Rajan 2012), and the crowded dinning environment may lower consumer perceived quality and lead to a lower rating. Using a survey based analysis, Dholakia (2010) found that Groupon promotions also influence employees' satisfaction Unsatisfied (satisfied) employees may probably provide a bad (good) service, which will decrease (increase) consumers' perceived service quality and therefore leads to negative (positive) reviews.

Hence, we posit that consumer perceived quality mediates[17] the main effect of Groupon promotions on the change in online ratings (Figure 7). Assuming the overall negative impact of Groupon promotions on online ratings, we expect Groupon to promotions have a negative influence on consumer perceived quality, which, in turn, causes the decreased online ratings. As shown in Section 4.6, we included two potential mediators in this study: food quality and service quality, because these two features are the most frequently mentioned by reviewers.

[17] A mediator (perceived quality in this study) is defined as a third variable that accounts for the relation between an independent variable (Groupon promotions) and a dependent variable (online ratings) (Baron and Kenny 1986).

4.3.3 Moderation Effect

Li and Hitt (2008) has shown that the change in online ratings over time without promotion varies according to the initial ratings. They argued that when initial ratings are high, online ratings will decrease over time, whereas when initial ratings are low, online ratings will increase over time. Some studies (Li and Hitt 2008; Godes and Silva 2012) based on self-selection theories examined the phenomenon from the aspect of the timing of the purchase and reviews. Consumers who are more likely to appreciate the products or services will come early and leave high initial ratings (Li and Hitt 2008). Godes and Silva (2012) indicated that the high initial ratings may lead to purchase errors for later consumers who are less likely to appreciate the products or services and therefore leave low ratings, which in turn leads to a declining trend in online ratings. On the other hand, Sun (2012) shows how low initial ratings can help later consumers to identify their niche market under a certain condition. Hence, later consumers with matched retailers with their preferences are more likely to leave high ratings, which leads to the increasing trend of online ratings.

Coupon promotions are a traditional marketing tool to attract new consumers for retailers (Chapman 1986; Varadarajan 1984). Dholakia (2012) claimed that, in the context of online daily deals, 80% of coupon users are new consumers. We posit that online ratings prior to Groupon promotions will directly moderate[18] the main effect of promotions on the change in online ratings (Figure 8). Based on the self-selection theories discussed above, we further expect that Groupon promotions will magnify the natural trend of online ratings due to the increased number of new

[18] A moderator (pre-promotion ratings in this study) is defined as a variable that affects the direction and/or strength of the relation between an independent variable (Groupon promotions) and a dependent variable (online ratings) (Baron and Kenny 1986).

consumers. That is, when the pre-promotion ratings are high (low), online ratings after promotion will decrease (increase) more than the case of no Groupon promotion.

4.3.4 Moderated Mediation Effect

As discussed in Section 4.2.1, Wu and Huberman (2008) and Moe and Schweidel (2012) argued that the generation of online reviews is also influenced by previous reviews, because later reviewers tend to differentiate their opinion from early reviews. We argue that if pre-promotion ratings are high, new consumers brought by promotions are more likely to perceive a relatively lower quality conditional on previous high ratings and hence leave lower ratings to differentiate themselves. In contrast, if pre-promotion ratings are low, new consumers are more likely to perceive a relatively higher quality than previous reviewers and leave higher ratings. On the other hand, exposed to higher (lower) pre-promotion ratings, new consumers are likely to have higher (lower) expectations. The higher (lower) reference points may lead to lower (higher) perceived quality, which further decrease (increase) the online ratings.

Therefore, we conjecture that there exists a moderated mediation effect (Figure 9). We expect to see that Groupon promotions increase (decrease) the perceived quality when pre-promotion ratings are low (high), which further increase (decrease) online ratings.

In the next section, we provide the details of the data collection.

4.4 Data Collection

To investigate the research models illustrated in Figures 6 – 9, we operationalized the required variables and constructed the appropriate data set. We gathered the data from Groupon through our own automated process, from Yelp's online reviews, and from the 2010 U.S. Census' detailed demographic information.

4.4.1 Groupon Promotion Data

Groupon, the current leader of the daily deal industry, started to provide daily deal couponing services for local retailers in Chicago in November 2008. Groupon expanded in the next few years to 175+ geographic markets (Byers et al. 2012a). Groupon deals are from a variety of retailers, including restaurants, beauty salons, and amusement parks (Gupta et al. 2012). In this study, we chose to focus on restaurants for two reasons. First, restaurant deals are one of the largest categories provided by Groupon (Gupta et al. 2012). Second, as discussed in the next subsection, Yelp ratings are also readily available for restaurants. Through Groupon's website (Bai et al., 2015b) we were able to collect the necessary data on all restaurants in the Chicago area that had run at least one Groupon promotion from January 7, 2008 to February 29, 2012. From this set, we identified 943 restaurants which had run one and only one Groupon promotion over the period January 7, 2008 through one year and one month after our last data collection from Groupon on February 29, 2012 (March 31, 2013). We used these one-time Groupon promotion restaurants (hereafter, *Groupon Restaurants*) for our analysis so that the impact of an initial Groupon promotion on online ratings will not be conflated with that of a second promotion.

Through Groupon's public API, we obtained information on each deal, including coupon price, discount rate, and quantity of coupons sold by the end of the deal offer. We also captured the start date when a coupon buyer could first redeem the coupon and the coupon duration.

4.4.2 Yelp Review Data

Yelp.com is a website for consumers to post their reviews for restaurants and other businesses[19]. Yelp provides both online ratings and restaurant-related information including four

[19] http://www.yelp.com/about

price level categories which indicate approximate cost level per person per meal. First, we used Yelp to identify all the restaurants in the Chicago area. For each restaurant we collected all of its individual reviews and each review's corresponding numeric rating (1-5 points), review texts, and review dates. Second, we matched the restaurants we collected from Groupon to those from Yelp by their names, physical addresses and/or phone numbers. This provided us with two restaurant sets: 1) *Groupon Restaurants*, and, 2) *non-Groupon restaurants* (see detailed definitions in Table 15). Information on each restaurant in each set included the necessary Yelp rating and Yelp data relate to the restaurant.

Yelp also provides one of the four price level categories for each restaurant (e.g. $, $$, $$$, $$$$). Finally, with the latitude and longitude details for each restaurant provided by Yelp, we could identify the number of local competing restaurants, the local competitive landscape if you will, within a specified distance of any restaurant in our set.

4.4.3 Census Data

As one would expect, the collection of data from the 2010 U.S. Census was straightforward and included average household income, average age, and population density data by zip code.

4.4.4 Variable Definition

To measure the change in Yelp ratings, the dependent variable in this study, we constructed a series of variables as follows.

Having numeric ratings and the corresponding review dates, we were able to construct *Average Yelp Rating* at any time point t, which is equal to the average of all Yelp numeric ratings prior to a particular date t. For each *Groupon Restaurant*, we first calculated *Average Pre-promotion Yelp Rating* using the date immediately prior to the start date of the promotion.

We then calculated *Average After-promotion Yelp Rating* using the end date of the promotion. Therefore, we constructed the *Change in Yelp Ratings* using the following formula:

Change in Yelp Ratings = *Average After-Promotion Yelp Rating* - *Average Pre-Promotion Yelp Rating.*

Please note that *Non-Groupon Restaurants* did not have a start date of the promotion. In this study, we conducted propensity score matching (PSM) analysis, which enabled us to find a *Non-Groupon Restaurant* having similar characteristics of a *Groupon Restaurant* as a matched pair. For each matched *Non-Groupon Restaurant*, we calculated the *Change in Yelp Rating* using the same period as the paired *Groupon Restaurant*. Please find details on the matching process in Section 4.5.

We also constructed *Number of Yelp Reviews*, *Number of Pre-promotion Yelp Reviews*, *Number of Competitors Nearby* and other variables. Table 15 below summarizes the definitions and data sources for variables used in this research.

Table 15. Variable Definitions and Data Sources

Variables	Definitions	Data Sources
Groupon Restaurants	Restaurants that ran one and only one Groupon promotion prior to the end of data collection, i.e. March 31, 2013.	Groupon
Non-Groupon Restaurants	Restaurants that had not run Groupon promotions prior to the end of data collection, i.e. March 31, 2013.	Identified by combining Yelp and Groupon data
Average Yelp Rating	The average of all Yelp numeric ratings prior to a particular date t.	Constructed using Yelp data
Average Pre-promotion Yelp Rating	The average of all Yelp numeric ratings immediately prior to the start date of the promotion.	Constructed using Yelp data
Average After-promotion Yelp Rating	The average of all Yelp numeric ratings prior to the end date of the promotion [a].	Constructed using Yelp data
Change in Yelp Rating	Equal to *Average After-promotion Yelp Rating* minus *Average Pre-promotion Yelp Rating*.	Constructed using Yelp data
Number of Yelp Reviews	The number of all Yelp reviews prior to a particular date t.	Constructed using Yelp data
Number of Pre-promotion Yelp reviews	The number of all Yelp reviews prior to the start date when coupon buyers can redeem the coupons.	Constructed using Yelp data
Number of Yelp Dollar Signs	Yelp measure indicating approximate cost per person per meal for a restaurant. There are 4 levels: 1 – less than $10, labeled ‘cheap’; 2 – $11-$30, labeled ‘moderate’; 3 – $31-$60, labeled ‘spendy’; 4 – more than $61, labeled ‘splurge’.	Yelp data
Number of Competitors Nearby	The number of competitors (other restaurants) within half mile from a particular restaurant.	Constructed using Yelp data
Average Household Income by Zip Code	Average yearly household income (thousand dollars) in the zip code where a restaurant is located.	2010 U.S. Census Data
Average Age by Zip Code	Average age of people living in the zip code where a restaurant is located.	2010 U.S. Census Data
Average Household Size by Zip Code	Average number of people in a household in the zip code where a restaurant is located.	2010 U.S. Census Data
Population Density by Zip Code	Number of people (thousand) per square mile in the zip code where a restaurant is located.	2010 U.S. Census Data

Note: [a] — we chose 210 days after the start date of the promotion as the end date of the promotion for all restaurants, because we wanted to use the same interval of days for all restaurants and a significant majority of coupon durations (86.6%) are 210 days or less.

4.5 Preliminary Analysis

4.5.1 Summary of Data

After data collection, we obtained 936 *Groupon Restaurants* and 6402 *Non-Groupon Restaurants* (as shown in Table 16). We see that the *Average Yelp Rating* under Groupon promotions declined by 0.08, i.e. the average of the *Change in Yelp Ratings* is -0.08. To examine the general trend of *Average Yelp Rating* without promotions, we chose June 1, 2011 as the hypothetical start date for *Non-Groupon Restaurants* to calculate the *Average Yelp Rating* at the starting point, because it is the median date of the Groupon restaurants' start dates. We then calculated the *Average Yelp Rating* using the date of 210 days after June 1, 2011 as the hypothetical end date. We find that *Average Yelp Rating* declined 0.02 on average without Groupon promotions, i.e. the average of the *Change in Yelp Ratings* is -0.02. The comparison test showed that the decline of *Average Yelp Rating* for *Groupon Restaurants* is statistically significantly larger than the decline for *Non-Groupon Restaurants*. However, we cannot necessarily conclude that Groupon promotions have a negative impact on online ratings, because there exist statistically significant differences between the two groups of restaurants in other variables. Therefore, to conclude the causal relationship between Groupon promotions and the change in Yelp ratings, we need to control the differences between *Groupon Restaurants* and *Non-Groupon Restaurants* in other variables.

Table 16. Comparisons between *Groupon Restaurants* and *Non-Groupon Restaurants* before Matching

Variables		*Groupon Restaurants*	*Non-Groupon Restaurants*
	Number of restaurants	936	6402
Change in Yelp Ratings	mean (Std. Dev.)	-0.08 (0.33)	-0.02*** (0.28)
Average Pre-promotion Yelp Rating [a]	mean (Std. Dev.)	3.61** (0.59)	3.51 (0.78)
Number Pre-promotion of Yelp Reviews [a]	mean (Std. Dev.)	56.41*** (74.49)	39.37 (84.80)
Number of Yelp Dollar Signs	mean (Std. Dev.)	1.90*** (0.57)	1.52 (0.63)
Number of Competitors Nearby	mean (Std. Dev.)	88.75 (142.42)	97.33** (157.14)
Average Household Income	mean (Std. Dev.)	77.08*** (21.08)	69.82 (21.58)
Average Age	mean (Std. Dev.)	37.16*** (4.57)	36.62 (4.56)
Average Household Size	mean (Std. Dev.)	2.39 (0.48)	2.42 (0.52)
Population Density	mean (Std. Dev.)	6.06 (6.54)	6.46*** (6.25)

Note: [a] — we calculated *Average Pre-promotion Yelp Rating* and *Number Pre-promotion of Yelp Reviews* for *Non-Groupon Restaurants* using June 1, 2011 as the hypothetical start date.

*'s denote significance level of Wilcoxon tests of larger means Groupon vs. non-Groupon restaurants, and <0.1 *; <0.05 **; <0.01***

4.5.2 Propensity Score Matching Process

To examine the causal impact of Groupon promotions on Yelp ratings, we applied a propensity score matching (PSM) method, a quasi-experimental method (Rosenbaum 2002). Through the PSM method, we obtained matched pairs of *Groupon Restaurants* (the treatment group) and *Non-Groupon Restaurants* (the control group) with similar control variables, i.e. the only significant difference between the two groups is that one has run Groupon promotions, whereas the other one has not. Then for each matched pair, we calculated the *Change in Yelp Rating* for the *Non-Groupon Restaurant* using the same start date of the promotion as the

Groupon Restaurant. The comparison of the *Change in Yelp Rating* over exactly the same period of time for each matched pair allowed us to conclude the causal relationship between Groupon promotions and online ratings.

However, please note that, before matching, we constructed *Average Pre-promotion Yelp Rating* (and *Number of Pre-promotion Yelp Review*) for each *Groupon Restaurants* using its specific start day of the promotion, whereas we use June 1, 2011 as the start date for *Non-Groupon Restaurants* as discussed in section 4.5.1. The challenge is, how to obtain the matched pair of a *Groupon Restaurants* and a *Non-Groupon Restaurant* with the same start date before knowing the potential matched *Non-Groupon Restaurants* having no start date. Facing the similar challenge in a labor market policy context, Lechner (2002) suggested drawing from the distribution of the observed start dates of all participants (*Groupon Restaurants*) for each non-participant (*Non-Groupon Restaurants*). Lechner's method may be sensitive to one-time simulation and might not make full use of non-participants information. Therefore, we used the following modified matching process:

Step 1: calculate the propensity score of being assigned to the treatment group, i.e. *Groupon Restaurants*, using values of *Average Pre-promotion Yelp rating* and *Number of Pre-promotion Yelp Review* based on June 1, 2011 for *Non-Groupon Restaurants*;

Step 2: sort *Groupon Restaurants* from smallest to largest by the estimated propensity score;

Step 3: for a *Groupon Restaurant*, take all *Non-Groupon Restaurants* within the 0.001 caliper of propensity score as potential options;

Step 4: calculate the new *Average Pre-promotion Yelp rating* and *Number of Pre-promotion Yelp Review* for selected *Non-Groupon Restaurants* using the same start date of promotion as the specific *Groupon Restaurant*;

Step 5: calculate the distance of all matching variables (normalized) between the *Groupon Restaurant* and the selected *Non-Groupon Restaurants*, and choose the *Non-Groupon Restaurant* with the smallest distance to a matched one. Take the matched pair off the list;

Step 6: repeat Step 3 to Step 5 until no *Groupon Restaurant* remains on the ordered list.

4.5.3 Preliminary Results on Main Effect

After the matching process above, we obtained 896 matched pairs of *Groupon Restaurants* and *Non-Groupon Restaurants*. We summarize the results of comparison tests in Table 17 below.

We see that there is no statistically significant difference between *Groupon Restaurants* and *Non-Groupon Restaurants* in all control variables. Hence the only significant difference is that one group has already run Groupon promotions, whereas the other one has not. The comparison test in *Change in Yelp Ratings* shows that *Average Yelp Rating* of *Groupon Restaurants* decreased 0.07 after Groupon promotions, statistically significantly larger than the decrease (0.01) of *Non-Groupon Restaurants*. Therefore, we conclude that on average Groupon promotions have negative impact on Yelp ratings.

Table 17. Comparisons between *Groupon Restaurants* and *Non-Groupon Restaurants* after Matching

Variables		*Groupon Restaurants*	*Non-Groupon Restaurants*
	Number of matched pairs	896	
Change in Yelp Ratings	mean (Std. Dev.)	-0.07 (0.29)	-0.01*** (0.18)
Average Pre-promotion Yelp Rating	mean (Std. Dev.)	3.61 (0.57)	3.62 (0.54)
Number of Pre-promotion Yelp Reviews	mean (Std. Dev.)	57.04 (73.91)	56.40 (80.48)
Number of Yelp Dollar Signs	mean (Std. Dev.)	1.87 (0.54)	1.85 (0.55)
Number of Competitors Nearby	mean (Std. Dev.)	89.88 (143.88)	85.80 (137.09)
Average Household Income	mean (Std. Dev.)	75.91 (19.82)	75.69 (18.24)
Average Age	mean (Std. Dev.)	37.16 (4.57)	36.62 (4.56)
Average Household Size	mean (Std. Dev.)	2.39 (0.48)	2.38 (0.46)
Population Density	mean (Std. Dev.)	6.10 (6.51)	5.77 (6.11)

Note: *'s denote significance level of Wilcoxon tests of larger means between Groupon vs. non-Groupon restaurants, <0.1 *; <0.05 **; <0.01***

4.6 Mediation and Moderation Analysis

In this section, we report the results for the mediation, moderation, and moderated mediation analyses to test the effects discussed in section 4.3. In order to create our mediating variables, we conducted text mining analysis, which provided us with text based measures of consumer's perceptions of perceived quality and their sentiments about that perceived quality. We begin by describing the process by which we extracted the features from which we developed the measures of perceived quality and sentiment.

4.6.1 Feature and Sentiment Extraction through Text Mining

Text mining techniques have been used to extract important information from the texts of online reviews in marketing and other business areas (Lee and Bradlow 2011; Bai 2011; Netzer et al. 2012). In this study the text mining analysis involves two components: 1) identifying features (from which we derive consumers perceptions of quality) most frequently mentioned by reviewers; and 2) identifying the consumers' sentiments about the sentences containing those features.

4.6.1.1 Extracting Important Features

We adopted one of the well-established techniques (see Hu and Liu 2004) for feature identification to extract nouns and noun phrases as candidates, because the most frequently described features have been shown to be nouns and noun phrases.

The steps we used of features extraction include:

1) applied *POS* tagging and obtained nouns and noun phrases for each review. This yielded more than 9,000 nouns and noun phrases from Yelp reviews;

2) manually pre-defined five categories of features and built our own dictionary (see Table 18) to reduce the dimensionality of features;

3) classified each sentence into one of the 5 categories according to the dictionary; and,

4) selected food quality and service quality as the two key potential mediators because they were the most frequently mentioned features as detailed in Table 19.

Table 18. Feature Categories, Definitions and Example Words in the Dictionary

Feature Categories	Definitions	Example words
Food quality	Perceived quality related to food, including various types of food and drink.	'salad', 'chicken', 'ice tea', 'wine'
Service quality	Perceived quality related to service in a restaurant from various servers, such as waiter and waitress.	'waiter', 'waitress', 'manager'
Ambiance	Perceived quality related to the dinning environment, such as atmosphere.	'ambiance', 'atmosphere', 'music'
Social setting	A feature indicating whom the reviewers dine with.	'husband', 'wife', 'boyfriend', 'girlfriend'
Others	Any other feature which does not belong to any category above.	The rest of noun phrases

Table 19. Frequency Distribution of Features

Feature Categories	Matched Groupon Restaurants		Matched Non-Groupon Restaurants	
	Number of Reviews	Frequency	Number of Reviews	Frequency
Food quality	15336	99.0%	9661	98.9%
Service quality	6410	41.4%	3430	35.1%
Ambiance	263	1.7%	168	1.9%
Social setting	3511	22.7%	1895	19.4%
others	6255	40.4%	3852	39.4%
Total Reviews	15487	-	9765	-

4.6.1.2 Extracting Sentiments

Focusing on the two types of perceived quality detailed above we identified the sentiment for each sentence that mentioned food quality and/or service quality. We applied the corpus-based machine learning method, which enabled us to capture the contextual structure and domain-related knowledge (see Pang and Lee 2002).

The steps of sentiment identification included:

1) randomly selected 100 reviews and split them into 946 sentences;

2) manually assigned the sentiment (positive, negative or neutral) to each of the 946 sentences;

3) assigned 80% (757) of sentences as the training set and the remaining 20% (189) of sentences as the test set;

4) trained various machine learning models (including naïve Bayes, Support Vector Machine, and Logistic Regression) using the training set;

5) applied the trained model to the test set, and selected the model with the highest prediction rate, Logistic Regression; and,

6) utilized trained Logistic Regression model and obtained the sentiment of each sentence mentioning food quality and/or service quality.

To categorize the sentiments, we assigned -1 to indicate negative sentiment, 0 for neutral, and 1 for positive and then calculated the average sentiment of food quality (service quality) over all sentences mentioning food quality (service quality) for matched *Groupon Restaurants* and *Non-Groupon Restaurants*.

4.6.1.3 Preliminary Evidence of Mediation and Moderation Effects – Food Quality and Service Quality

Table 20 below summarizes the comparisons of average sentiment of food quality and *Change in Yelp Rating* for the matched pairs. Please note that we excluded any matched pair in which one or both restaurants in the matched pair did not mention food quality. Hence, we have 751 matched pairs for analysis.

The average sentiment of food quality for *Groupon Restaurants* is statistically significantly lower than that of *Non-Groupon Restaurants*, which potentially explains the overall declining trend of Yelp ratings. Hence, food quality is a potential mediator of the main effect.

We then divided the matched pairs into three groups according to pre-promotion ratings: 1) low rating, [1, 2.5); 2), 2) medium rating, [2.5, 3.5); and 3) high rating, [3.5, 5]. In all three

cases the average sentiment of food quality for *Groupon Restaurants* is statistically significantly lower than that of *Non-Groupon Restaurants*. However, regarding the *Change in Yelp Ratings*, the decline in Yelp Rating for *Groupon Restaurants* is statistically significantly larger than that of *Non-Groupon Restaurants* only for high rated restaurants. There is no statistically significant difference in *Change in Yelp Ratings* between *Groupon Restaurants* and *Non-Groupon Restaurants* for medium and low rated restaurants.

These results provide some direct evidence for the potential moderation role of pre-promotion ratings on the effect of Groupon promotions on Yelp ratings.

Table 20. Comparisons of Average Sentiment of Food Quality and *Change in Yelp Ratings*

Pre-promotion Rating	Number of Matched Pairs	Average Sentiment of Food Quality		*Change in Yelp Ratings*	
		Groupon Restaurants	*Non-Groupon Restaurants*	*Groupon Restaurants*	*Non-Groupon Restaurants*
Total	751	0.52	0.58***	-0.07	-0.01***
Low	15	0.40	0.66**	0.30	0.39
Medium	262	0.48	0.53***	-0.0004	0.002
High	474	0.55	0.60***	-0.12	-0.03***

Note: *'s denote significance level of Wilcoxon tests of larger means between Groupon vs. non-Groupon restaurants, <0.1 *; <0.05 **; <0.01***

Similarly, Table 21 summarizes the comparisons of average sentiment for service quality and *Change in Yelp Ratings* for the matched pairs. We excluded any matched pair in which one or both restaurants in the matched pair did not mention service quality. Because service quality was mentioned than food quality, we obtained fewer matched pairs (527) than for food quality.

The average sentiment for service quality for *Groupon Restaurants* is statistically significantly less than that of *Non-Groupon Restaurants*, which suggests that service quality is also a potential mediator for the overall decline of Yelp ratings after Groupon promotions.

We divided the matched pairs into three groups based on the three pre-promotion ratings. As detailed in Table 21, the average sentiment of service quality for *Groupon Restaurants* is less

than that of *Non-Groupon Restaurants* for all three groups, although the difference for low rated restaurants is not statistically significant.

Regarding the *Change in Yelp Ratings*, for the medium and high rated restaurants, the decline of Yelp ratings for *Groupon Restaurants* is statistically significantly larger than that of *Non-Groupon Restaurants*. However, the difference of the *Change in Yelp Ratings* between *Groupon Restaurants* and *Non-Groupon Restaurants* is 0.027 for the medium rated restaurants compared to 0.08 for the high rated restaurants. For the low rated restaurants, Yelp ratings for *Groupon Restaurants* increased more than *Non-Groupon Restaurants*. Because we only have 7 matched pairs for this group, statistical significance for the comparison test is not considered.

The results above also suggest the potential for moderation role of pre-promotion ratings on the effect of Groupon promotions on Yelp ratings.

Table 21. Comparisons of Average Sentiment of Service Quality and *Change in Yelp Ratings*

Pre-promotion Rating	Number of Matched Pairs	Average Sentiment of Service Quality		*Change in Yelp Ratings*	
		Groupon Restaurants	*Non-Groupon Restaurants*	*Groupon Restaurants*	*Non-Groupon Restaurants*
Total	527	0.51	0.56***	-0.07	-0.02***
Low	7	-0.18	0.14	0.37	0.34
Medium	184	0.17	0.28*	-0.03	-0.003**
High	336	0.25	0.34***	-0.11	-0.03***

Note: *'s denote significance level of Wilcoxon tests of larger means between Groupon vs. non-Groupon restaurants, <0.1 *; <0.05 **; <0.01***

In the next sections, we test the formal models of the mediation effect and moderation effect that we proposed in Section 4.3. In subsection 4.6.2 and subsection 4.6.3, we test the models for food quality and service quality separately. In subsection 4.6.4, we combined both food quality and service quality in the analysis. Please note that, because we do not have enough marched pairs for low rated restaurants, the analyses are limited to the matched pairs of the medium (relatively lower) and high (relatively higher) pre-promotion rated restaurants.

4.6.2 Mediation and Moderation Effects – Food Quality

4.6.2.1 Separated Mediation and Moderation Effect – Food Quality

We tested a separated mediation and moderation effect model (Figure 8 in Section 4.3, hereafter Model I) for food quality. In this model, food quality is expected to mediate the main effect of Groupon promotions on the *Change in Yelp Ratings*, while pre-promotion ratings are expected to moderate the main effect. The formal test is based on the following regression equations:

$$Change\_in\_Ratings = \alpha_{I\cdot 1} + \beta_{I\cdot 1} * Groupon + \mu_{I\cdot 1} \tag{I·1}$$

$$Food\_sentiment = \alpha_{I\cdot 2} + \beta_{I\cdot 2} * Groupon + \mu_{I\cdot 2} \tag{I·2}$$

$$Change\_in\_Ratings = \alpha_{I\cdot 3} + \beta_{I\cdot 3} * Groupon + \gamma_{I\cdot 3} * Pre\_Rating + \delta_{I\cdot 3} * Pre\_Rating * Groupon + \rho_{I\cdot 3} * Food\_sentiment + \mu_{I\cdot 3} \tag{I·3}$$

where $Change\_in\_Ratings$ indicates the dependent variable in this study, *Change in Yelp Ratings*. $Groupon$ is the binary independent variable indicating whether a restaurant has run a Groupon promotion or not; $Food\_sentiment$ is the mediator and the measure of the average sentiment of food quality for each restaurant; Pre_Rating is the binary moderator, indicating whether the level of pre-promotion rating is relatively higher or not. We also use $\alpha_{\mathrm{I}\cdot n}$ to indicate the intercept for equation n of Model I, where $n \in \{1,2,3\}$. We use the same format of β's to indicate the coefficients of $Groupon$, γ's for the coefficients of the moderator Pre_Rating, δ's for the coefficients of the interaction term of between $Groupon$ and Pre_Rating, ρ's for the coefficients of the mediator variable ($Food\_sentiment$), and μ's for the error terms (please see detailed notation of parameters in Table C.1 of Appendix C).

We summarize the regression estimation results in Table 22 using bold font for those coefficients of main interest in this study. We also illustrate the corresponding coefficients in

Figure 10. We see that the mediation effect of food quality is -0.013[20], and is statistically significant. This indicates that Groupon promotions had a negative impact on consumer perceived food quality which had a negative causal impact on Yelp ratings. Hence, food quality mediates the main effect of Groupon promotions on the *Change in Yelp Ratings*. Because the coefficient of the independent variable ($Groupon$) is still significant when we include the mediator ($Food\_sentiment$) in Equation (I·3), the mediation effect of food quality is categorized as a complementary mediation (Zhao et al. 2010).

The estimation results of Equation (I·3) also show a significant moderation effect for pre-promotion ratings. Groupon promotions have a statistically significantly negative impact (-0.07) on the *Change in Yelp Ratings* for higher rated restaurants, whereas a statistically significantly positive impact (0.01[21]) for lower rated restaurants.

Table 22. Results of Separated Mediation and Moderation Effect – Food Quality (Model I)

Dependent Variables	Change in Ratings	Food Sentiment	Change in Ratings
Regression Model	(I·1)	(I·2)	(I·3)
$Groupon$	-0.06***	**-0.05*** **	**-0.07*** **
$Food\_sentiment$	-	-	**0.26*** **
Pre_Rating	-	-	-0.74***
$Pre\_Rating * Groupon$	-	-	**0.08*** **
Number of restaurants	1472	1472	1472
Adjusted R square	0.02	0.02	0.11

Note: *'s denote significance level, <0.1 *; <0.05 **; <0.01***

[20] The formula to calculate the mediation effect here is -0.05*0.26=-0.013.

[21] In Equation (I·3), 'Pre-Rating' is a dummy variable, indicating whether pre-promotion ratings are higher or not. The coefficient of the interaction term: Pre-Rating*Groupon measures the difference between higher and lower level. To obtain the Groupon promotions on online ratings for the lower level, the formula is: -0.07+0.08=0.01.

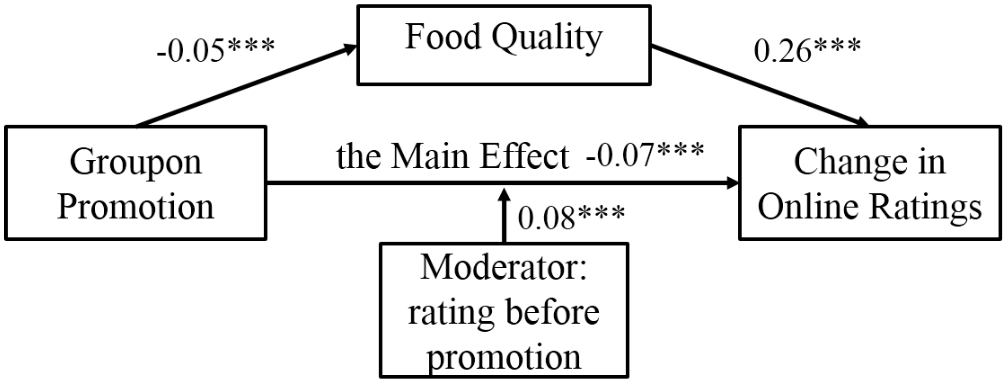

Figure 10. Results of Separated Mediation and Moderation Effect – Food Quality (Model I)

4.6.2.2 Moderated Mediation Effect – Food Quality

We next tested the moderated mediation effect model (Figure 9 in Section 4.3, hereafter Model II) for food quality. In this model food quality is still expected to mediate the main effect of Groupon promotions on the change in online ratings, while the pre-promotion ratings are expected to moderate both the main effect and the mediation effect.

The formal test for this model is based on a similar set of equations:

$$Change\_in\_Ratings = \alpha_{II\cdot1} + \beta_{II\cdot1} * Groupon + \mu_{II\cdot1} \qquad \text{(II·1)}$$

$$Food\_sentiment = \alpha_{II\cdot2} + \beta_{II\cdot2} * Groupon + \gamma_{II\cdot2} * Pre\_Rating + \delta_{II\cdot2} * Pre\_Rating * Groupon + \mu_{II\cdot2} \qquad \text{(II·2)}$$

$$Change\_in\_Ratings = \alpha_{II\cdot3} + \beta_{II\cdot3} * Groupon + \gamma_{II\cdot3} * Pre\_Rating + \delta_{II\cdot3} * Pre\_Rating * Groupon + \rho_{II\cdot3} * Food\_sentiment + \mu_{II\cdot3} \qquad \text{(II·3)}$$

where variables $Change\_in\_Ratings$, $Groupon$, $Food\_sentiment$, and Pre_Rating here in Model II have the same meanings as Model I. Consistently, $\alpha_{\mathrm{II}\cdot n}$ indicates the intercept for equation n of Model II, and $n \in \{1,2,3\}$. Again, we use β's to indicate the coefficients of $Groupon$, γ's for the coefficients of the moderator Pre_Rating, δ's for the coefficients of the interaction term of between $Groupon$ and Pre_Rating, ρ's for the coefficients of the mediator

variable ($Food\_sentiment$), and μ's for the error terms (please see detailed notation of parameters in Table C.1 of Appendix C).

We summarized the regression estimation results in Table 23 and bolded the coefficients of key interest. We also illustrate the corresponding numbers in Figure 11. The mediation effect of food quality on the main effect of Model 2 is the same as Model 1, which is equal to -0.013 and statistically significant. The mediation effect of food quality on the main effect is also a complementary mediation.

We obtained the same moderation effect on the main effect, which is that Groupon promotions have a statistically significantly negative impact on the *Change in Yelp Ratings* for higher rated restaurants, but a statistically significantly positive impact for lower rated restaurants. However, we do not see a significant moderated mediation effect, because the estimated coefficient of the interaction term $Pre\_Rating * Groupon$ in equation (II·3) is not significant.

Table 23. Results of Moderated Mediation Effect – Food Quality (Model II)

Dependent Variables	Change in Ratings	Food Sentiment	Change in Ratings
Regression Model	(II·1)	(II·2)	(II·3)
$Groupon$	-0.06***	**-0.05*** **	**-0.07*** **
$Food\_sentiment$	-	-	**0.26*** **
Pre_Rating	-	-0.07***	-0.74***
$Pre\_Rating * Groupon$	-	**-0.005**	**0.08*** **
Number of restaurants	1472	1472	1472
Adjusted R square	0.02	0.05	0.11

Note: *'s denote significance level, <0.1 *; <0.05 **; <0.01***

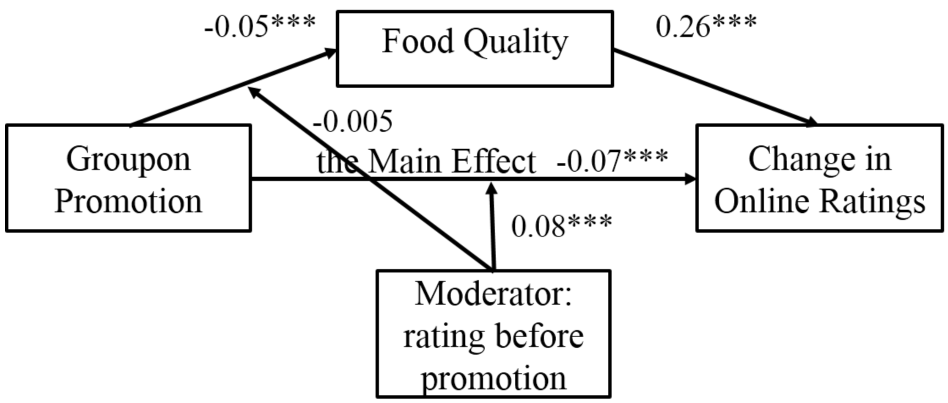

Figure 11. Results of Moderated Mediation Effect – Food Quality (Model II)

Overall, we conclude that food quality mediates the main effect of Groupon promotions on the change in ratings directly and that pre-promotion ratings moderate the main effect directly. However, there is no moderated mediation effect of pre-promotions on food quality's mediating effect on change in ratings.

4.6.3 Mediation and Moderation Effects – Service Quality

In this subsection, we examined the mediation and moderation effects for service quality.

4.6.3.1 Separated Mediation and Moderation Effect – Service Quality

Similar to the food quality, first we tested the separated mediation and moderation effect model (Figure 8 in Section 4.3, i.e. Model III) for service quality. In this model service quality is expected to mediate the main effect of Groupon promotions on the *Change in Yelp Ratings,* while the pre-promotion ratings are expected to moderate the main effect.

The formal test is based on the following regression equations:

$$Change\_in\_Ratings = \alpha_{III\cdot 1} + \beta_{III\cdot 1} * Groupon + \mu_{III\cdot 1} \quad \text{(III·1)}$$

$$Service\_sentiment = \alpha_{III\cdot 2} + \beta_{III\cdot 2} * Groupon + \mu_{III\cdot 2} \quad \text{(III·2)}$$

$$Change\_in\_Ratings = \alpha_{III\cdot 3} + \beta_{III\cdot 3} * Groupon + \gamma_{III\cdot 3} * Pre\_Rating + \delta_{III\cdot 3} *$$

$$Pre\_Rating * Groupon + \rho_{III\cdot 3} * Service\_sentiment + \mu_{III\cdot 3} \quad \text{(III·3)}$$

where variables $Change\_in\_Ratings$, $Groupon$, and Pre_Rating here in Model III have the same meanings as previous models. $Service\_sentiment$ is the mediator and indicates the measure of the average sentiment of service quality for each restaurant. Consistently, $\alpha_{\mathrm{III}\cdot n}$ indicates the intercept for equation n of Model III, and $n \in \{1,2,3\}$. We also use β's to indicate the coefficients of $Groupon$, and γ's for the coefficients of the moderator Pre_Rating, δ's for the coefficients of the interaction term of between $Groupon$ and Pre_Rating, ρ's for the coefficients of the mediator variable ($Service\_sentiment$), and μ's for the error terms (please see detailed notation of parameters in Table C.1 of Appendix C).

We summarized the estimation results in Table 24 and bolded the coefficients of key interest. We also illustrated the corresponding numbers in Figure 12. The calculated mediation effect of service quality is -0.005 and is statistically significant. This indicates that Groupon promotions had a negative impact on consumer perceived service quality, and that the reduced service quality further caused the decline of Yelp ratings. Hence, service quality mediates the impact of Groupon promotions on the *Change in Yelp Ratings* directly. Because the coefficient of the independent variable for $Groupon$ is still significant when we include the mediator ($Service\_sentiment$) in Equation (III·3), we classify the mediation effect of service quality as a complementary mediation (Zhao et al. 2010).

The estimation results of Equation (III·3) also show a significant moderation effect for pre-promotion ratings. Although Groupon promotions have a statistically significantly negative impact on the *Change in Yelp Ratings* for both higher rated and lower rated restaurants, the impact is larger for higher rated restaurants (-0.07) than that of lower rated restaurants (-0.02).

Table 24. Results of Separated Mediation and Moderation Effect – Service Quality (Model III)

Dependent Variables	Change in Ratings	Service Sentiment	Change in Ratings
Regression Model	(III·1)	(III·2)	(III·3)
$Groupon$	-0.06***	**-0.09*****	**-0.07*****
$Service\_sentiment$	-	-	**0.06*****
Pre_Rating	-	-	0.04**
$Pre\_Rating * Groupon$	-	-	**0.05****
Number of restaurants	1040	1040	1040
Adjusted R square	0.04	0.01	0.09

Note: *'s denote significance level, <0.1 *; <0.05 **; <0.01***

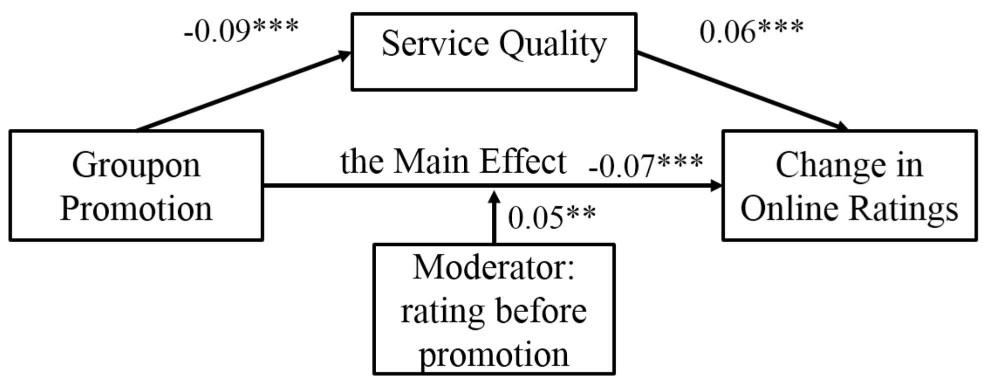

Figure 12. Results of Separated Mediation and Moderation Effect – Service Quality (Model III)

4.6.3.2 Moderated Mediation Effect – Service Quality

We also tested the moderated mediation effect model (Figure 9 in Section 4.3, i.e. Model IV) for service quality. In this model, service quality is expected to mediate the main effect of Groupon promotions on the change in online ratings directly, while the pre-promotion ratings are expected to moderate both the main effect and the mediation effect.

The formal test for this model is based on estimations of the following equations:

$$Change\_in\_Ratings = \alpha_{IV\cdot 1} + \beta_{IV\cdot 1} * Groupon + \mu_{IV\cdot 1} \quad \text{(IV·1)}$$

$$Service\_sentiment = \alpha_{IV\cdot 2} + \beta_{IV\cdot 2} * Groupon + \gamma_{IV\cdot 2} * Pre\_Rating + \delta_{IV\cdot 2} * Pre\_Rating * Groupon + e_{IV\cdot 2} \quad \text{(IV·2)}$$

$$Change\_in\_Ratings = \alpha_{IV\cdot3} + \beta_{IV\cdot3} * Groupon + \gamma_{IV\cdot3} * Pre\_Rating + \delta_{IV\cdot3} * Pre\_Rating * Groupon + \rho_{IV\cdot3} * Service\_sentiment + \mu_{IV\cdot3} \quad \text{(IV·3)}$$

where variables $Change\_in\_Ratings$, $Groupon$, $Service\_sentiment$ and Pre_Rating here have the same meanings as Model III. Consistently, we use α's to indicates the intercepts for the three equations, and use β's to indicate the coefficients of $Groupon$, and γ's for the coefficients of the moderator Pre_Rating, δ's for the coefficients of the interaction term of between $Groupon$ and Pre_Rating, ρ's for the coefficients of the mediator variable ($Service\_sentiment$),and μ's for the error terms (please see detailed notation of parameters in Table C.1 of Appendix C).

We summarize the estimation results in Table 25 with the coefficients of key interest in bold. We illustrate the corresponding numbers in Figure 13. The calculated mediation effect of service quality on the main effect is still -0.005 and statistically significant, which indicates a complementary mediation.

Regarding the moderation effect on the main effect, Groupon promotions have a statistically significantly negative impact on the *Change in Yelp Ratings* for both higher rated restaurants and lower rated restaurants. But the impact for the higher rated restaurants is stronger than that of lower rated restaurants. Similar to the case of food quality, we do not see a significant moderated mediation effect for service quality, indicated by the statistically insignificant coefficient of the interaction term $Pre\_Rating * Groupon$ in Equation (IV·2).

Table 25. Results of Moderated Mediation Effect – Service Quality (Model IV)

Dependent Variables	Change in Ratings	Service Sentiment	Change in Ratings
Regression Model	(IV·1)	(IV·2)	(IV·3)
$Groupon$	-0.06***	**-0.09*** **	**-0.07*** **
$Service\_sentiment$	-	-	**0.06*** **
Pre_Rating	-	-0.08	0.04**
$Pre\_Rating * Groupon$	-	**-0.02**	**0.05** **
Number of restaurants	1040	1040	1040
Adjusted R square	0.04	0.02	0.09

Note: *'s denote significance level, <0.1 *; <0.05 **; <0.01***

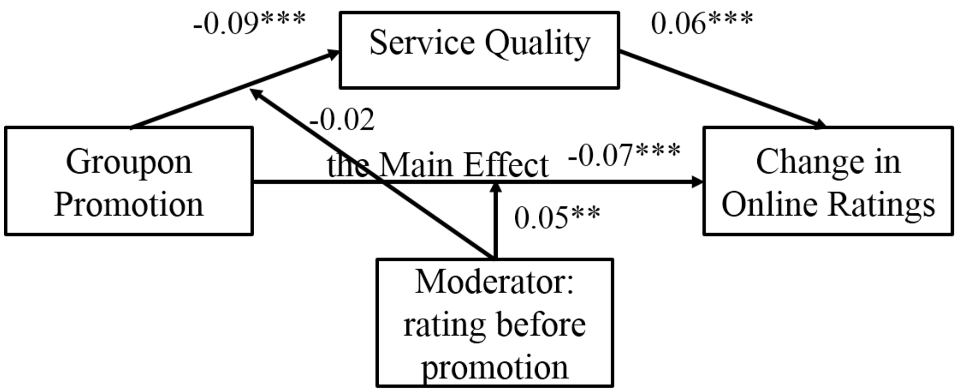

Figure 13. Results of Moderated Mediation Effect – Service Quality (Model IV)

Overall, the examination of the service quality shows that service quality mediates the main effect of Groupon promotions on the change in ratings directly and that pre-promotion ratings moderate the main effect directly. However, there is no moderated mediation effect of pre-promotions on service quality.

4.6.4 Joint Mediation and Moderation Effects – Food Quality and Service Quality

Previously we examined the mediation and moderation effect for food quality and service quality separately. In this subsection, we conducted the joint analysis of the two types of

perceived quality. We assume that the food quality and service quality are independent mediators, because the correlation of average sentiment between them is relatively low (0.28).

4.6.4.1 Separated Mediation and Moderation Effect – Food Quality and Service Quality

First we tested the separated mediation and moderation effect model (Figure 8 in Section 4.3, i.e. Model V) for the two types of perceived quality. In this model, food quality and service quality are both expected to mediate the main effect of Groupon promotions on the *Change in Yelp Ratings* independently, while the pre-promotion ratings are expected to moderate the main effect only.

The formal test for this model is based on estimations of the following equations:

$$Change\_in\_Ratings = \alpha_{V\cdot1} + \beta_{V\cdot1} * Groupon + \mu_{V\cdot1} \quad \text{(V·1)}$$

$$Food\_sentiment = \alpha_{V\cdot2} + \beta_{V\cdot2} * Groupon + \mu_{V\cdot2} \quad \text{(V·2)}$$

$$Service\_sentiment = \alpha_{V\cdot3} + \beta_{V\cdot3} * Groupon + \mu_{V\cdot3} \quad \text{(V·3)}$$

$$Change\_in\_Ratings = \alpha_{V\cdot4} + \beta_{V\cdot4} * Groupon + \gamma_{V\cdot4} * Pre\_Rating + \delta_{V\cdot4} * Pre\_Rating * Groupon + \rho^{f}_{V\cdot4} * Food\_sentiment + \rho^{s}_{V\cdot4} * Service\_sentiment + \mu_{V\cdot4} \quad \text{(V·4)}$$

where the variables and coefficients above are still consistent with previous models. Please note that, $\rho^{f}_{V\cdot4}$ indicates the coefficient of $Food\_sentiment$ in equation 4 for Model V, and similarly $\rho^{s}_{V\cdot4}$ indicates the coefficient of $Service\_sentiment$ in equation 4 for Model V. For the detailed notation of parameters, please see Table C.1 of Appendix C.

We summarize the estimation results in Table 26 and bolded the coefficients of key interest. We illustrate the corresponding numbers in Figure 14. The calculated mediation effect of food quality is -0.02 and is statistically significant. The calculated mediation effect of service quality is -0.003 and is also statistically significant. This suggests that Groupon promotions had a negative impact on consumer perceived food quality and service quality which in turn caused

the decline in Yelp ratings. Therefore, both food quality and service quality mediate the impact of Groupon promotions on the *Change in Yelp Ratings*. The two mediation effects are both complementary mediations.

The estimation results of Equation (V·4) also show a significant moderation effect for pre-promotion ratings. Groupon promotions have a statistically significantly negative impact (-0.058) on the *Change in Yelp Ratings* on for higher rated restaurants, whereas they have a statistically significant positive impact (0.005) on lower rated restaurants.

Table 26. Results of Separated Mediation and Moderation Effect – Food Quality and Service Quality (Model V)

Dependent Variables	Change in Ratings	Food sentiment	Service Sentiment	Change in Ratings
Regression Model	(V·1)	(V·2)	(V·3)	(V·4)
$Groupon$	-0.06***	**-0.05*** **	**-0.09*** **	**-0.058*** **
$Food\_sentiment$		**-**	**-**	**0.37*** **
$Service\_sentiment$	-	-	-	**0.03*** **
Pre_Rating	-	-	-	0.05***
$Pre\_Rating * Groupon$	-	-	-	**0.063*** **
Number of restaurants	1040	1040	1040	1040
Adjusted R square	0.04	0.03	0.01	0.17

Note: *'s denote significance level, <0.1 *; <0.05 **; <0.01***

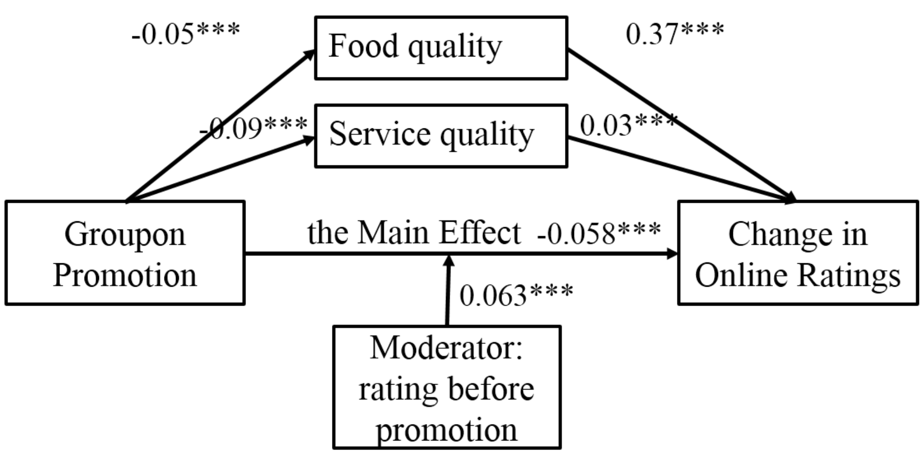

Figure 14. Results of Separated Mediation and Moderation Effect – Food Quality and Service Quality (Model V)

4.6.4.2 Moderated Mediation Effect – Food Quality and Service Quality

Next, we tested the moderated mediation effect model (Figure 9 in Section 4.3, i.e. Model VI) for the two types of perceived quality. In this model food quality and service quality are still expected to mediate the main effect of Groupon promotions on the change in online ratings independently, while the pre-promotion ratings are expected to moderate both the main effect and the mediation effects.

The formal test is based on the following regression equation:

$$Change\_in\_Ratings = \alpha_{VI\cdot 1} + \beta_{VI\cdot 1} * Groupon + \mu_{VI\cdot 1} \quad \text{(VI·1)}$$

$$Food\_sentiment = \alpha_{VI\cdot 2} + \beta_{VI\cdot 2} * Groupon + \gamma_{VI\cdot 2} * Pre\_Rating + \delta_{VI\cdot 2} * Pre\_Rating * Groupon + e_{VI\cdot 2} \quad \text{(VI·2)}$$

$$Service\_sentiment = \alpha_{VI\cdot 3} + \beta_{VI\cdot 3} * Groupon + \gamma_{VI\cdot 3} * Pre\_Rating + \delta_{VI\cdot 3} * Pre\_Rating * Groupon + e_{VI\cdot 3} \quad \text{(VI·3)}$$

$$Change\_in\_Ratings = \alpha_{VI\cdot 4} + \beta_{VI\cdot 4} * Groupon + \gamma_{VI\cdot 4} * Pre\_Rating + \delta_{VI\cdot 4} * Pre\_Rating * Groupon + \rho^{f}_{VI\cdot 4} * Food\_sentiment + \rho^{s}_{VI\cdot 4} * Service\_sentiment + \mu_{VI\cdot 4} \quad \text{(VI·4)}$$

where the variables and coefficients above are still consistent with previous models. Please note that, $\rho^{f}_{VI\cdot 4}$ indicates the coefficient of $Food\_sentiment$ in equation 4 for Model VI, and similarly $\rho^{s}_{VI\cdot 4}$ indicates the coefficient of $Service\_sentiment$ in equation 4 for Model VI. For the detailed notation of parameters, please see Table C.1 of Appendix C.

We summarized the regression estimation results in Table 27 and bolded the coefficients of key interest. We illustrated the corresponding numbers in Figure 15. The calculated mediation effects of food quality and service quality on the main effect are -0.03 and -0.005 respectively and both are statistically significant, which is the same as the separated mediation and moderation effect model.

Estimation results from Equation (VI·4) show that Groupon promotions have a statistically significantly negative impact (-0.058) on the *Change in Yelp Ratings* on for higher rated restaurants, whereas a statistically significantly positive impact (0.005) on lower rated restaurants. Therefore pre-promotion ratings moderate on the main effect directly. However, we do not see significant moderation effects on the mediation effect of food quality or service quality, indicated by the statistically insignificant coefficient of the interaction term $Pre\_Rating * Groupon$ in Equation (VI·2) and Equation (VI·3).

Table 27. Results of Moderated Mediation Effect – Food Quality and Service Quality (Model VI)

Dependent Variables	Change in Ratings	Food sentiment	Service Sentiment	Change in Ratings
Regression Model	(VI·1)	(VI·2)	(VI·3)	(VI·4)
$Groupon$	-0.06***	**-0.04*** **	**-0.09*** **	**-0.058*** **
$Food\_sentiment$	-	-	-	**0.37*** **
$Service\_sentiment$	-	-	-	0.03***
Pre_Rating	-	-0.04***	-0.08	0.05***
$Pre\_Rating * Groupon$	-	**-0.03**	**-0.02**	**0.063*** **
Number of restaurants	1040	1040	1040	1040
Adjusted R square	0.04	0.05	0.02	0.17

Note: *'s denote significance level, <0.1 *; <0.05 **; <0.01***

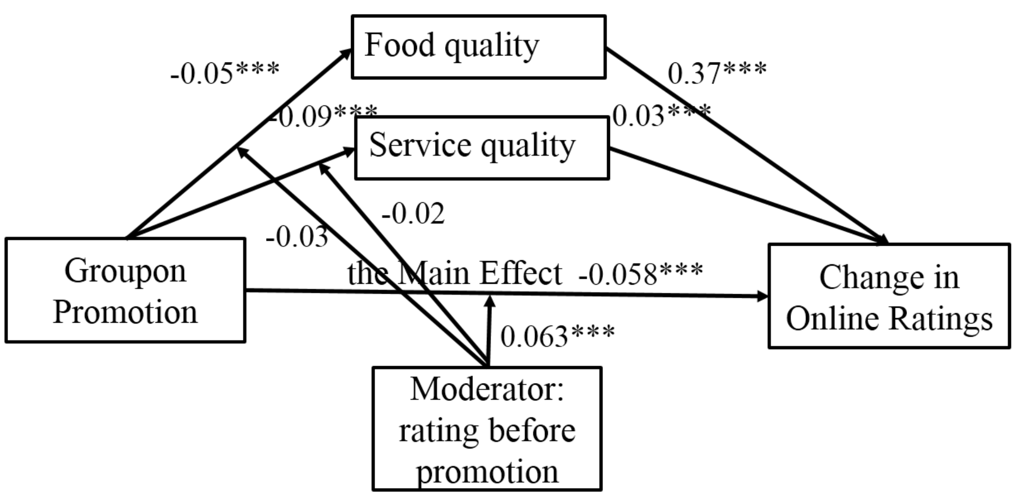

Figure 15. Results of Moderated Mediation Effect – Food Quality and Service Quality (Model VI)

Overall, we conclude that food quality and service quality both mediate the main effect of Groupon promotions on the change in ratings directly, and that pre-promotion ratings moderate the main effect directly. However, there is no moderation effect of pre-promotion ratings on the mediating effects of food quality or service quality on change in online ratings. Thus, the separated mediation and moderation effect model fits our data better.

4.7 Discussion and Future Work

In this essay, we examine the impact of Groupon promotions on its change in online ratings. We begin by exploring main impact of promotions on the change in online ratings through propensity score matching process. We then analyze the mediation effects of food and service quality factor and moderation effect of pre-promotion rating on the main effect. We utilize the text and sentiment extraction techniques and obtain food and service quality features and their associated sentiment through the period of promotion. We tested a range of causal relationship models using the data compiled from Groupon, Yelp, and the US Census. We find that mediation effects of food quality and service quality are both significant. Particularly, Groupon promotions decreased perceived food quality and perceived service quality, which cause the decrease in Yelp ratings. The moderation effect of pre-promotion ratings is found to be significant. Groupon promotions had a negative effect on Yelp ratings for relatively higher rated restaurants, while for lower rated restaurants Groupon promotions had a positive effect on Yelp ratings.

4.7.1 Summary of Theoretical Contributions

Our study makes two major theoretical contributions to the literature on the influence of retailer promotion strategies on e-WOM. First, we empirically examine the impact of retailers' promotions on the valance of e-WOM. Previous studies have shown that promotions can trigger

the generation of e-WOM and hence have a positive impact on the volume of e-WOM (Berger and Schwartz 2011; Godinho de Matos et al. 2015). Our analysis showed that Groupon promotions had a negative impact on online ratings on average, i.e. the online ratings after Groupon promotions declined more than that of without promotions. We operationalized valence with the average numeric ratings of retailers' online reviews. To identify the influence of Groupon promotions on online ratings from the natural trend of ratings over time, we applied a modified propensity score matching (PSM) method to *Groupon Restaurants* (the treatment group) and *Non-Groupon Restaurants* (the control group).

Second, we investigated consumer perceived quality as a mediator and pre-promotion ratings as a moderator of the main effect. Through text mining techniques, we extracted food quality comments and service quality comments from the textual contents of reviews and determined the corresponding sentiment (positive, negative or neutral). Interestingly, we found that food quality and service quality both mediated the main effect of Groupon promotions on online ratings. Specifically, Groupon promotions decreased consumers' perception of food quality and service quality, which further decreased online ratings. Another interesting finding is that Groupon promotions had a negative influence on online ratings for higher rated restaurants on average but a positive influence on online ratings for lower rated restaurants on average.

4.7.2 Discussion of Managerial Implications

Our results have important managerial implications for retailers. First, our results provide guidance for restaurant managers who are considering whether or not to run a daily deal promotion. Particularly for higher rating restaurants, the managers should take the potential damage to online ratings into account, because the changed online reputation may impact the future demand (Anderson and Magruder 2012). However, for lower rating restaurants, Groupon

promotions will likely not hurt their online reputation, and may be an effective marketing tool to reach more consumers who are likely to find them (Sun 2012).

Second, our findings suggest that restaurant managers who decide to run a Groupon promotion should pay special attention to the food quality and service quality during the promotion period. Managers may take appropriate actions, such as, for example, increasing training for wait staff before engaging in Groupon promotions, to avoid any decline in online ratings after promotions.

4.7.3 Limitations and Future Work

Our study, like all studies, has certain limitations. First, our main mediation and moderation effect analysis is based on matched *Groupon Restaurants* and *Non-Groupon Restaurants* with similar observable characteristics, that was the result of a modified propensity score matching process. However, it is possible that unobservable factors might influence the generation of matched pairs, which might impact our results. Although we employed a sensitivity analysis, there is still a caveat to, as in all analyses, relate to the potential for omitted factors.

Second, we conducted our analysis using online review data from one retail category, restaurants. Therefore the two mediators (food quality and service quality) obtained in this study likely restrict the generalizability of our results to other retail categories. However, our method is applicable for any type of retailer, if review data are available. Our future work will focus of the analysis to other retail categories and the possible generalization of our initial results.

Third, to obtain the mediators (average sentiment of perceived quality), we implicitly assumed that the three types of sentiment (positive, negative, and neutral) have equal weights. However, in reality, reviewers (and review readers) may have different weights for different

types of sentiment. For example, negative sentiment may have more impacts on final ratings than positive sentiment. Some advanced measures, such as a 5-score scale, might be useful in a future study.

4.7.4 Conclusions

We apply a propensity score matching (PSM) analysis to provide a causal analysis of the main effect of Groupon promotions on the change in online ratings. Consistent with previous empirical evidence, Groupon promotions have a negative effect on online ratings on average. Regarding the mediation effect, we find that food quality and service quality are two mediators of the main effect, i.e. Groupon promotions decrease consumers' perceived food quality and service quality, which further causes the decline of online ratings. Regarding the pre-promotion ratings as the moderator of the main effect, we find that Groupon promotions have negative effect on online ratings for higher rated restaurants, versus a positive impact for lower rated restaurants. These results provide important insights into the impact of promotions on retailers' online reputation.

Chapter 5 Conclusions and Future Research

This dissertation provides a systematic investigation of the online daily deal industry utilizing data collected from the industry leader, Groupon, complemented Yelp data and U.S. Census data. The results from the three essays enable us to understand business models of online daily deals from various angles, including consumer purchasing decisions and social media sharing, retailer initial and repeat promotion decisions, and characteristics of the e-platforms.

The first essay identifies the positive influence of minimum requirements on deal outcomes and social media sharing, and demonstrates that retailers and daily deal sites gain by including minimum requirements. The second essay provides a causal analysis of the effects of e-WOM and local competition on restaurants' decisions whether or not to engage in an initial Groupon promotion and whether or not to return for additional Groupon promotions. Interesting findings include: 1) restaurants with higher ratings on the reviews they receive are more likely to engage in initial promotions but less likely to return for additional promotions; 2) the greater the local competition, the less likely restaurants are to engage in initial promotions, but this variable does not affect additional promotions; and 3) restaurants are more likely to engage in initial Groupon promotions and additional Groupon promotions if their competitors are not engaged in Groupon promotions. The third essay investigates the effect of Groupon promotions on retailers' online reputation. We find that Groupon promotions have a negative main effect on the change in online ratings on average. We also find that consumers' perception of food quality and service quality mediates the main effect. Another interesting finding is that Groupon promotions had a negative impact on online ratings only for higher rated restaurants, versus a positive impact

for lower rated restaurants. Our results provide important guidance for managers to make promotion decisions and to avoid potential damage to their firm's online reputation.

Although there are rich findings from the three essays, there are still many interesting questions that deserve rigorous studies. For example, data we have gathered indicates that the proportion of bankruptcy for restaurants which have run Groupon promotions is 23.5%, significantly higher than the 6% rate for restaurants which have not run Groupon promotions. There are two potential explanations. One is that Groupon promotions exerted a negative influence on a restaurant’s performance, perhaps because of negative online reviews, and thus Groupon promotions caused the restaurant’s bankruptcy. The other explanation is that restaurants that were more close to bankruptcy were more likely to try Groupon promotions. A future study will examine the relationship between Groupon promotions and a restaurant’s bankruptcy. Other interesting future research directions include: 1) the investigation of other retail categories; and 2) formal theory development and related theory testing informed by the current empirical analyses.

In summary, we hope this dissertation and future research will inspire more studies on the online daily deals area, contribute to the IS literature and provide practical insights for consumers, and managerial implications for retailers and daily deal sites in the daily deal e-market.

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Appendix

Appendix A. Tables for Heterogeneity Analysis, Sensitivity Analysis and Robustness Tests (Chapter Two)

Appendix A.1 Tables for Heterogeneity Analysis

Table A.1.1 Heterogeneity analysis at time point 0 for A&E deals

Propensity score range (No. of matched pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
<0.15 (11)	4 (10.73)	3 (7.82)	15 (19.91)	4 (46.18)	1170 (2043.55)	447 (1607.91)
0.15-0.30 (55)	3 (5.09)	2 (6.07)	12 (16.67) ** ++	5 (23.07)	340 (559.18) * +++	90 (562.53)
0.30-0.45 (101)	3 (7.22) ** +++	1 (5.21)	15 (30.35) *** +++	5 (23.46)	228 (649.86) *** +++	117 (506.95)
0.45-0.60 (27)	3 (3.81)	3 (6.26)	17 (22.26)	20 (43.78)	343 (450.37)	236 (906.70)
0.60-0.75 (0)	-	-	-	-	-	-
>0.75 (0)	-	-	-	-	-	-

Table A.1.2 Heterogeneity analysis at time point 20 for A&E deals

Propensity score range (No. of matched pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
<0.15 (11)	59 (144.00) ***	24 (31.64)	100 (211.91)	90 (166.91)	11060 (22485.36)	4900 (6626.73)
0.15-0.30 (55)	32 (60.53) *	15 (43.18)	106 (198.07) ** ++	50 (154.02)	3015 (8132.67) ** +++	1450 (4296.42)
0.30-0.45 (101)	38 (69.27) *** +++	18 (32.64)	170 (345.45) *** +++	80 (202.44)	2800 (6027.78) ** +	2000 (4207.22)
0.45-0.60 (27)	34 (54.19)	31 (47.81)	160 (241.44)	260 (344.48) * +	3480 (3931.56)	5200 (7684.59) **
0.60-0.75 (0)	-	-	-	-	-	-
>0.75 (0)	-	-	-	-	-	-

Table A.1.3 Heterogeneity analysis at time point 40 for A&E deals

Propensity score range (No. of matched pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
<0.15 (11)	103 (202.55) ***	37 (48.82)	220 (322.00)	110 (249.18)	20826 (34850.18)	7450 (10297.18)
0.15-0.30 (51)	41 (90.47) *	20 (59.84)	154 (279.90) * ++	80 (215.59)	3900 (10177.37) * ++	2159 (6182.22)
0.30-0.45 (61)	52 (96.70) ** +	29 (49.48)	300 (625.84) *** +++	160 (340.16)	5250 (10751.61)	4000 (7291.85)
0.45-0.60 (15)	30 (93.13)	43 (75.40)	220 (396.27)	430 (459.00)	5220 (6841.00)	12000 (12628.67) *
0.60-0.75 (0)	-	-	-	-	-	-
>0.75 (0)	-	-	-	-	-	-

Table A.1.4 Heterogeneity analysis at time point 0 for B&S deals

Propensity score range (No. of matched pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
<0.15 (6)	2 (1.17)	0(1.17)	8 (9.50)	4 (8.33)	693 (1482.17) *	225 (735.00)
0.15-0.30 (33)	0 (1.30)	0 (1.00)	10 (12.06) * ++	4 (9.09)	825 (948.09) *** +++	180 (386.82)
0.30-0.45 (73)	1 (1.58) *** +++	0 (0.60)	16 (17.59) *** +++	7 (16.14)	590 (836.37) *** +++	273 (628.11)
0.45-0.60 (86)	1 (1.13)	0 (1.08)	14 (18.36) +	10 (20.65)	536 (819.59)	350 (1039.03)
0.60-0.75 (19)	0 (0.37)	0 (1.37)	17 (24.11)	20 (39.58)	750 (1289.63)	490 (1403.68)
>0.75 (2)	0 (1.00)	2 (3.00)	15 (15.00)	50 (85.00)	875 (1185.00)	1950 (2775.00)

Table A.1.5 Heterogeneity analysis at time point 20 for B&S deals

Propensity score range (No. of matched pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
<0.15 (6)	5 (5.67)	5 (8.83)	56 (87.67)	40 (60.00)	9453 (10097.67) *	3447 (3842.33)
0.15-0.30 (33)	10 (12.58) *** +++	3 (4.45)	90 (135.06) ** +	50 (82.27)	9000 (10607.03) *** +++	2400 (3947.30)
0.30-0.45 (73)	7 (11.78) *** ++	4 (6.64)	150 (189.90) *** +++	80 (140.62)	4640 (9427.96) *** +++	3960 (5729.11)
0.45-0.60 (86)	9 (13.28) *** +++	6 (8.52)	140 (246.86)	135 (211.33)	5805 (10953.47)	5390 (9621.45)
0.60-0.75 (19)	13 (21.21)	9 (12.32)	220 (350.21)	190 (312.00)	8250 (13563.63)	7410 (10826.42)
>0.75 (2)	2 (9.50)	8 (17.00)	39 (329.50)	210 (605.00)	11661 (16680.50)	8199 (19095.00)

Table A.1.6 Heterogeneity analysis at time point 40 for B&S deals

Propensity score range (No. of matched pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
<0.15 (6)	7 (9.67)	5 (11.50)	72 (117.17)	70 (96.00)	12637 (13489.50) *	4822 (6027.33)
0.15-0.30 (33)	12 (15.45) ** ++	4 (6.79)	132 (177.64) ** +	70 (117.36)	12250 (14918.27) *** +++	3400 (5633.76)
0.30-0.45 (72)	13 (15.53) *** +++	5 (8.53)	185 (253.51) *** ++	120 (185.57)	6633 (12626.42) *** +++	5630 (7829.57)
0.45-0.60 (71)	11 (17.46) ** ++	9 (11.89)	210 (344.77)	240 (294.00)	7840 (15861.58)	8400 (13102.11)
0.60-0.75 (13)	18 (33.38)	12 (16.00)	220 (794.08)	280 (388.69)	10050 (37521.62)	10780 (12974.38)
>0.75 (1)	20	34	950	1000	33250	30000

Table A.1.7 Heterogeneity analysis at time point 0 for H&F deals

Propensity score range (No. of matched pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
<0.15 (1)	6	0	3	0	8985	0
0.15-0.30 (35)	1 (3.03)	0 (2.94)	10 (13.00) ** +++	3 (9.14)	714 (1636.74) *** +++	147 (496.80)
0.30-0.45 (63)	1 (4.49)	1 (2.21)	12 (17.52) *** +++	4 (8.71)	500 (797.32) *** +++	160 (325.05)
0.45-0.60 (59)	1 (2.90) ** +	0 (1.98)	16 (20.14)	8 (24.80)	725 (1058.88) *** +++	300 (873.31)
0.60-0.75 (11)	2 (5.73) * +	0 (3.82)	18 (24.73)	20(24.64)	900 (1059.36)	1290 (1189.55)
>0.75 (0)	-	-	-	-	-	-

Table A.1.8 Heterogeneity analysis at time point 20 for H&F deals

Propensity score range (No. of matched pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
<0.15 (1)	12	0	7	1	20965	2999
0.15-0.30 (35)	12 (19.06) ** ++	4 (13.71)	77 (124.54) * +	41 (76.71)	5070 (11457.03) ** ++	2610 (7053.29)
0.30-0.45 (63)	12 (33.24) *** +++	6 (11.70)	110 (165.16) *** +++	50 (103.29)	4818 (6973.52) *** +++	2450 (3725.03)
0.45-0.60 (59)	11 (26.95) *** ++	6 (16.03)	140 (213.31) **	100 (145.86)	5880 (9684.80) *** +++	3000 (5060.54)
0.60-0.75 (11)	16 (26.00)	5 (24.73)	160 (172.09)	60 (168.27)	5950 (7301.36)	6650 (6970.82)
>0.75 (0)	-	-	-	-	-	-

Table A.1.9 Heterogeneity analysis at time point 40 for H&F deals

Propensity score range (No. of matched pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
<0.15 (1)	12	0	7	1	20965	2999
0.15-0.30 (34)	16 (23.88) ** +++	5 (19.09)	115 (178.74) *	70 (128.53)	8060 (16705.09) *** ++	3765 (10530.68)
0.30-0.45 (55)	13 (44.91) *** ++	9 (16.04)	150 (244.51) *** +++	80 (149.93)	6840 (10245.04) *** +++	3510 (5432.27)
0.45-0.60 (39)	19 (47.21) *** ++	8 (18.36)	190 (326.08) *	130 (195.13)	8400 (15003.23) *** +	4200 (6637.08)
0.60-0.75 (5)	8 (48.00)	8 (14.40)	260 (364.60) +	92 (84.40)	11700 (15197.60) *	5200 (5477.60)
>0.75 (0)	-	-	-	-	-	-

Table A.1.10 Heterogeneity analysis at time point 0 for REST deals

Propensity score range (No. of matched pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
<0.15 (4)	4 (4.25) ** +	0 (0.25)	41 (47.25) * +	9 (9.50)	1383 (1452.50) * +	145 (181.25)
0.15-0.30 (18)	2 (3.17)	1 (1.44)	24(35.39)	25(30.28)	433 (839.44)	475(1002.56)
0.30-0.45 (54)	2 (2.94) *	0 (1.76)	25 (35.93) +++	10 (44.96)	500 (731.33) +	200 (949.72)
0.45-0.60 (86)	1 (2.29)	1 (2.19)	21 (33.71) ++	13 (58.03)	466 (714.71) * ++	320 (940.29)
0.60-0.75 (55)	2 (2.40)	2 (6.82) **	25 (36.93)	37 (141.89) **	620 (841.20)	600(2116.98)
>0.75 (4)	2 (2.25)	1 (3.00)	22 (28.50)	89 (98.25)	2216 (1167.25)	851 (1519.25)

Table A.1.11 Heterogeneity analysis at time point 20 for REST deals

Propensity score range (No. of matched pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
<0.15 (4)	26(45.00) * +	10 (8.75)	575 (625.00) * +	290 (242.50)	17100 (17860.00) * +	5150 (4750.00)
0.15-0.30 (18)	15 (20.89)	12 (15.17)	388 (404.89)	260 (356.89)	8425 (8581.17)	6815 (12452.78)
0.30-0.45 (54)	18 (27.46) ** +	13 (17.17)	330 (465.26) *	250 (320.91)	6910 (9680.02) *	5675 (7436.56)
0.45-0.60 (86)	22 (28.57) ** +	13 (20.51)	325 (436.48)	260 (395.30)	6750 (9444.34)	6195 (7861.80)
0.60-0.75 (55)	26 (31.02) +	23 (36.69)	320 (398.15)	430 (538.93) *** ++	7000 (9222.75)	8340 (8816.36)
>0.75 (4)	22 (24.75) *	24 (23.00)	285 (322.50)	645 (542.50)	10050 (10445.00)	10930 (10902.50)

Table A.1.12 Heterogeneity analysis at time point 40 for REST deals

Propensity score range (No. of matched pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
<0.15 (4)	37 (58.00) * +	13 (11.00)	970 (907.50) * +	375 (325.00)	24750 (27302.50) * +	6700 (6437.50)
0.15-0.30 (18)	19 (27.61)	16 (19.33)	500 (524.94)	315 (440.28)	10750 (11252.83)	9408 (15328.72)
0.30-0.45 (54)	24 (36.06) *** ++	16 (21.56)	497 (594.50) **	349 (399.63)	10040 (12711.17) ** +	7455 (9444.78)
0.45-0.60 (83)	27 (37.90) ** ++	20 (26.41)	460 (576.88) *	377 (476.70)	8960 (12598.13) *	8400 (9887.46)
0.60-0.75 (28)	34 (42.13) +	22 (49.00)	453 (534.87)	610 (640.58) *	10400 (12943.13)	10000 (10560.47)
>0.75 (2)	25 (24.50)	22 (21.50)	345 (345.00)	464 (463.50)	6750 (6750.00)	13008 (13007.50)

Appendix A.2 – Sensitivity Analysis Tables

Table A.2.1 The value of Γ where positive effect of the *MR* becomes insignificant (based on Wilcoxon signed rank test)

	FL	Quantity of coupons sold	Total revenue
Time point when deals meet the *MR*			
Arts&Entertainment	1.1	1.3	1.2
Beauty&Spas	1.2	1.2	1.3
Health&Fitness	1.3	1.7	2.3
Restaurant	-	-	-
20 Hours after meeting the *MR*			
Arts&Entertainment	1.6	1.3	1.2
Beauty&Spas	1.7	1.2	1.4
Health&Fitness	1.9	1.7	2.2
Restaurant	1.5	-	1.1
40 Hours after meeting the *MR*			
Arts&Entertainment	1.5	1.3	1.1
Beauty&Spas	1.7	1.2	1.6
Health&Fitness	2.0	1.8	2.6
Restaurant	1.6	1.1	1.3
At the end of promotion length			
Arts&Entertainment	1.5	1.5	1.5
Beauty&Spas	1.8	1.8	1.8
Health&Fitness	1.5	1.5	1.5
Restaurant	1.5	1.5	1.5

Table A.2.2 The value of Γ where positive effect of the *MR* becomes insignificant (based on sign test)

	FL	Quantity of coupons sold	Total revenue
Time point when deals meet the *MR*			
Arts&Entertainment	1.2	1.6	1.4
Beauty&Spas	1.2	1.4	1.6
Health&Fitness	1.3	1.7	2.1
Restaurant	-	1.2	1.3
20 Hours after meeting the *MR*			
Arts&Entertainment	1.3	1.3	1.2
Beauty&Spas	1.5	1.1	1.4
Health&Fitness	1.6	1.5	1.6
Restaurant	1.3	-	1.1
40 Hours after meeting the *MR*			
Arts&Entertainment	1.2	1.4	1.1
Beauty&Spas	1.6	1.1	1.4
Health&Fitness	1.7	1.5	1.6
Restaurant	1.4	-	1.1
At the end of promotion length			
Arts&Entertainment	1.4	1.2	1.1
Beauty&Spas	1.6	1.2	-
Health&Fitness	1.4	1.4	1.9
Restaurant	1.3	-	1.2

Appendix A.3 Tables for Starting Time Point Set at Two Hours after Deal Offer Begins (same starting point for all)

Table A.3.1 Comparison Results for A&E deals based on hours after a deal being posted (median values with mean values in parentheses)

Hours after a deal being posted (number of pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
2 (194)	0 (0.63)	0 (0.74)	1 (3.19) **	0.5 (2.74)	12 (66.05) **	3 (67.14)
12 (194)	16 (31.05) *** +++	8 (17.63)	57 (134.9) *** +++	30 (97.65)	1202 (3543.16) ** +++	800 (2188.80)
24 (194)	36 (67.43) *** +++	19 (36.45)	140 (274.15) *** +++	80 (200.74)	2980 (7070.67) ** ++	2065 (4694.65)
36 (194)	43 (79.84) *** +++	23 (43.24)	170 (340.59) *** +++	100 (231.92)	3707 (8947.76) ** ++	2580 (5533.32)
48 (183)	48 (95.06) *** +++	28 (52.84)	210 (392.38) *** +++	130 (280.92)	4600 (10668.68) ** +++	3600 (6938.58)
60 (122)	50 (104.6) **	30 (63.7)	225 (424.69) +	165 (337.15)	5050 (14014.87)	4535 (8935.2)
72 (113)	54 (118.19) ** +	31 (71.92)	250 (478.69)	200 (422.43)	6110 (16360.54)	5510 (10793.73)
End of promotion length (194)	55 (111.23) *** +++	30 (68.23)	265 (496.50) ** ++	170 (360.41)	6170 (14074.00) * +	4935 (9487.40)

Table A.3.2 Comparison Results for B&S deals based on hours after a deal being posted (median values with mean values in parentheses)

Hours after a deal being posted (number of pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
2 (219)	0 (0.27)	0 (0.32)	1 (1.70)	1 (1.75)	16 (71.17)	34 (65.80)
12 (219)	3 (6.22) *** +++	2 (3.82)	61 (103.08) ** +++	50 (93.60)	2750 (4981.47) * +	2100 (3759.63)
24 (219)	8 (12.71) *** +++	4 (7.42)	120 (207.85) ** +++	100 (171.30)	6000 (10098.37) **	4500 (7279.40)
36 (219)	10 (14.62) *** +++	5 (8.56)	140 (241.68) ** +++	120 (197.98)	7020 (11695.48) **	5520 (8522.13)
48 (212)	12 (17.23) *** +++	6 (9.9)	175 (272.79) ** +++	140 (228.15)	8457 (14055.09) ** +	6750 (10063.35)
60 (187)	12 (17.8) *** +++	6 (10.33)	180 (292.7) ** +	150 (229.9)	9360 (16319.47) *** +++	6900 (10366.34)
72 (164)	14 (19.67) *** +++	7 (11.74)	200 (325.72) ** ++	170 (252.85)	10245 (18520.41) *** +++	7595 (10879.98)
End of promotion length (219)	13 (20.57) *** +++	8 (12.24)	230 (365.95) ** +++	200 (286.40)	11200 (19502.10) **	9360 (13074.30)

Table A.3.3 Comparison Results for H&F deals based on hours after a deal being posted (median values with mean values in parentheses)

Hours after a deal being posted (number of pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
2 (169)	0 (0.37)	0 (0.60)	1 (3.63) ** +++	0 (1.21)	39 (143.34) *** +++	0 (41.06)
12 (169)	6 (13.04) *** +++	3 (6.56)	49 (81.82) *** +++	20 (55.51)	2520 (3981.93) *** +++	1110 (2219.35)
24 (169)	11 (26.91) *** +++	5 (13.79)	100 (166.22) *** +++	50 (111.89)	5040 (8552.69) *** +++	2610 (4900.76)
36 (169)	14 (31.04) *** +++	6 (16.30)	120 (201.32) *** +++	70 (136.17)	6321 (10499.31) *** +++	3190 (5903.80)
48 (165)	16 (37.30) *** +++	8 (20.05)	150 (248.97) *** +++	90 (169.12)	8000 (12964.89) *** +++	4100 (7408.88)
60 (133)	16 (42.96) *** +++	8 (18.78)	160 (271.8) *** +++	100 (168.27)	8260 (14410.67) *** +++	4410 (7549.46)
72 (118)	16 (46.71) *** +++	9 (20.33)	185 (300.69) *** +++	120 (197.78)	10195 (17031.96) *** +++	5305 (9013.44)
End of promotion length (169)	20 (44.99) *** +++	10 (29.47)	220 (318.15) *** +++	140 (232.81)	11040 (23399.60) *** +++	6860 (12006.80)

Table A.3.4 Comparison Results for REST deals based on hours after a deal being posted (median values with mean values in parentheses)

Hours after a deal being posted (number of pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
2 (221)	0 (0.56)	0 (0.38)	3 (5.23)	3 (5.93)	66 (102.95)	60 (111.65)
12 (221)	10 (13.88) *** +++	6 (11.98)	160 (217.77)	150 (249.96)	3300 (4706.82)	3200 (4769.99)
24 (221)	22 (27.89) *** +++	13 (22.73)	320 (416.12)	290 (401.45)	7000 (9237.98) ** ++	6240 (8171.81)
36 (221)	24 (32.45) *** +++	15 (25.52)	390 (483.91)	350 (445.62)	8320 (10824.43) *** ++	7200 (9175.31)
48 (218)	29 (37.61) *** +++	17 (28.92)	460 (559.22) **	400 (484.82)	9850 (12608.39) *** +++	8405 (10240.41)
60 (191)	28 (37.98) *** +++	19 (30.24)	500 (592.38) **	410 (493.66)	10650 (13473.44) *** ++	8800 (10835.13)
72 (164)	31 (41.57) *** +++	20 (32.34)	525 (635.8) ***	435 (509.21)	11450 (14917.04) *** ++	9000 (11487.32)
End of promotion length (221)	32 (44.05) *** +++	21 (33.13)	570 (654.18) *	510 (560.77)	12000 (14909.40) *** +++	10000 (12038.70)

Appendix A.4 Tables for Analysis of All Deals Including Failed MR Deals

Table A.4.1 Summary of Wilcoxon Rank Sum test for larger median of two groups of deals (group means in parentheses) with failed deals included

	A&E		B&S		H&F		REST	
	MR	*NMR*	*MR*	*NMR*	*MR*	*NMR*	*MR*	*NMR*
# of deals	228	494	303	413	197	313	354	325
Price ($)	20 (34.26)	25*** (37.87)	39 (63.19)	45*** (83.87)	45 (126.91)	40 (357.08)	20 (22.17)	20 (23.93)
Discount rate (%)	51 (53.00)	51 (52.97)	56 (60.24)	58 (61.51)	64 (66.21)	67 (67.63)	51 (53.70)	51 (54.30)
Promotion length (days)	3 (3.43)	3*** (3.81)	3 (3.34)	4*** (3.97)	3 (3.47)	4*** (4.05)	3 (3.11)	4*** (3.73)
Featured	0 (0.14)	0 (0.11)	0 (0.10)	0 (0.08)	0** (0.10)	0 (0.05)	0 (0.10)	0 (0.08)
Coupon duration (days)	111*** (129.21)	61 (95.94)	187*** (231.87)	186 (199.69)	186*** (200.03)	185 179.24	185*** (169.84)	152 (151.42)
Limited supply	1 (0.77)	1** (0.85)	1 (0.76)	1 (0.80)	1 (0.69)	1*** (0.81)	1*** (0.79)	1 (0.70)

Table A.4.2 Comparison results over time for all A&E deals including failed deals (median values with mean values in parentheses)

Hours after meeting *MR* (number of pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
0 (201)	3 (6.19) * ++	2 (5.61)	15 (24.16) *** +++	5 (26.77)	300 (658.44) ** +++	126 (624.67)
10 (201)	29 (52.95) *** +++	14 (29.37)	100 (225.25) *** +++	50 (169.4)	2241 (5761.5) ** ++	1535 (3915.39)
20 (200)	38 (68.02) *** +++	19 (36.9)	140 (273.42) *** +++	80 (201.31)	2930 (7047.97) ** ++	2030 (4751.89)
30 (199)	44 (82.46) *** +++	23 (44.84)	180 (346.30) *** +++	100 (238.61)	3700 (9238.12) ** +	2720 (5769.23)
40 (143)	52 (100.8) *** ++	28 (54.84)	220 (433.41) ** ++	130 (291.2)	4977 (11614.41) *	3600 (7505.77)
End of promotion length (201)	54 (109.31) *** +++	30 (66.96)	250 (479.20) ** ++	170 (353.28)	5890 (13583.90)	4920 (9375.40)

Table A.4.3 Comparison results over time for all B&S deals including failed deals (median values with mean values in parentheses)

Hours after meeting *MR* (number of pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
0 (225)	1 (1.20) * ++	0 (0.93)	13 (16.92) ** +++	8 (18.80)	585 (882.64) *** +++	290 (821.31)
10 (225)	6 (10.04) *** +++	4 (6.16)	100 (165.84) ** ++	80 (141.69)	4800 (8250.68) *** ++	3570 (5985.68)
20 (225)	8 (12.81) *** +++	4 (7.53)	120 (210.80) ** +	100 (173.97)	5976 (10364.12) *** +++	4810 (7402.78)
30 (225)	10 (14.80) *** +++	5 (8.81)	150 (245.90) **	120 (203.39)	7200 (12113.07) *** ++	5880 (8798.63)
40 (202)	11 (16.79) *** +++	6 (9.95)	175 (300.16) ** +	140 (225.10)	8695 (15492.8) *** +++	6410 (9646.59)
End of promotion length (225)	13 (20.08) *** +++	8 (12.00)	220 (356.19) ** ++	200 (282.85)	10890 (18982.04) *	9360 (12959.08)

Table A.4.4 Comparison results over time for all H&F deals including failed deals (median values with mean values in parentheses)

Hours after meeting *MR* (number of pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
0 (171)	1 (3.68) *** +++	0 (2.35)	14 (17.67) *** +++	5 (15.22)	700 (1114.79) *** +++	190 (599.27)
10 (171)	10 (21.73) *** +++	5 (11.08)	84 (133.20) *** +++	48 (92.06)	4350 (6902.68) *** +++	2030 (4057.15)
20 (171)	12 (27.20) *** +++	6 (14.30)	110 (171.12) *** +++	60 (115.03)	5340 (8848.02) *** +++	2610 (5043.11)
30 (171)	14 (32.06) *** +++	7 (17.05)	130 (211.18) *** +++	80 (145.69)	6650 (11142.37) *** +++	3330 (6283.98)
40 (136)	15 (39.61) *** +++	7 (17.16)	140 (250.65) *** +++	85 (152.05)	7445 (13334.77) *** +++	3920 (6986.92)
End of promotion length (171)	19 (44.54) *** +++	10 (29.23)	210 (314.43) *** +++	140 (230.44)	11040 (23125.95) *** +++	6670 (11915.12)

Table A.4.5 Comparison results over time for all REST deals including failed deals (median values with mean values in parentheses)

Hours after meeting *MR* (number of pairs)	Facebook likes *MR*	Facebook likes *NMR*	Quantity of coupons sold *MR*	Quantity of coupons sold *NMR*	Total revenue *MR*	Total revenue *NMR*
0 (222)	2 (2.57)	1 (3.14)	25 (35.18) +++	20 (72.97)	503 (778.43) +++	336 (1231.74)
10 (222)	17 (21.77) *** +++	10 (19.19)	260 (343.29)	240 (344.96)	5550 (7543.68)	4900 (6886.75)
20 (222)	22 (28.38) *** +++	13 (23.09)	330 (431.15)	300 (408.69)	7185 (9503.90) ** +	6370 (8343.91)
30 (222)	26 (33.17) *** +++	15 (26.28)	405 (501.41)	360 (455.28)	8633 (11167.51) ** ++	7470 (9397.60)
40 (200)	28 (37.37) *** +++	17 (28.36)	460 (570.84) **	390 (479.65)	10040 (12745.74) *** +	8300 (10320.03)
End of promotion length (222)	32 (43.86) *** +++	22 (33.09)	570 (651.23) *	505 (559.96)	11950 (14842.20) *** ++	10000 (12010.14)

Appendix B. Tables for Sensitivity Analysis and Robustness Tests (Chapter Three)

Appendix B.1 Sensitivity Analysis

Table B.1.1 Γ Values in Sensitivity Analysis

Variables	Initial Groupon Promotion decision	Second Groupon Promotion decision
Average Yelp Rating	1.1	1.9
Number of Yelp Reviews	34.0	2.5
Number of Competitors Nearby	41.4	-
Proportion of Competitors Nearby Using Groupon	23.7	4.9
Coupon Revenue from the First Promotion	NA	11.0
Change of Average Yelp Rating	NA	4.9

Appendix B.2 Different Radii for Local Competition Measures

We used a quarter of a mile to operationalize our local competition variables and summarized the results in Table B.2.1 and Table B.2.2 below.

Table B.2.1 Proportion of Restaurants in Matched Pairs Running an Initial Groupon Promotion in Control and Treatment Groups

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.080	0.099**	1929	H1 supported
Number of Yelp Reviews	0.079	0.117***	1360	H2 supported
Number of Competitors Nearby	0.121***	0.076	1135	H6a supported
Proportion of Competitors Nearby Using Groupon	0.135***	0.102	1513	H7a supported

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***

Table B.2.2 Proportion of Restaurants in Matched Pairs Running a Second Groupon Promotion in Control and Treatment Group

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.323*	0.274	62	H3a supported
Number of Yelp Reviews	0.370	0.466**	73	H5 supported
Number of Competitors Nearby	0.337	0.314	86	Neither H8 nor H8a supported
Proportion of Competitors Nearby Using Groupon	0.349	0.343	175 [a]	Neither H9 nor H9a supported
Coupon Revenue from the First Promotion	0.313	0.458**	96	H10 supported
Change in Average Yelp Rating	0.328	0.432***	125	H4 supported

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***
[a] p value is 0.50.

We used a distance of one mile to operationalize our local competition variables and summarized the results in Table B.2.3 and Table B.2.4 below.

Table B.2.3 Proportion of Restaurants in Matched Pairs Running an Initial Groupon Promotion in Control and Treatment Groups

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.089	0.099*	1940	H1 supported
Number of Yelp Reviews	0.072	0.125***	1295	H2 supported
Number of Competitors Nearby	0.128***	0.051	752	H6a supported
Proportion of Competitors Nearby Using Groupon	0.137***	0.105	1350	H7a supported

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***

Table B.2.4 Proportion of Restaurants in Matched Pairs Running a Second Groupon Promotion in Control and Treatment Group

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.385**	0.269	52	H3a supported
Number of Yelp Reviews	0.380	0.437**	71	H5 supported
Number of Competitors Nearby	0.229	0.257	35	Neither H8 nor H8a supported
Proportion of Competitors Nearby Using Groupon	0.392	0.376	189 [b]	Neither H9 nor H9a supported
Coupon Revenue from the First Promotion	0.237	0.474***	97	H10 supported
Change in Average Yelp Rating	0.333	0.434***	129	H4 supported

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***
[b] p value is 0.38.

Appendix B.3 Different Split Methods

We applied the 20%-quantile split method. That is, we take the top 20% quantile as the treatment group and the bottom 20% quantile as the control group. We summarized the results in Table B.3.1 and Table B.3.2.

Table B.3.1 Proportion of Restaurants in Matched Pairs Running an Initial Groupon Promotion in Control and Treatment Groups

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.081	0.096**	1089	H1 supported
Number of Yelp Reviews	0.064	0.118***	707	H2 supported
Number of Competitors Nearby	0.146***	0.047	451	H6a supported
Proportion of Competitors Nearby Using Groupon	0.157***	0.112	1147	H7a supported

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***

Table B.3.2 Proportion of Restaurants in Matched Pairs Running a Second Groupon Promotion in Control and Treatment Group

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.385	0.423	26 [a]	Neither H3 nor H3a supported
Number of Yelp Reviews	0.455	0.409	22 [a]	Neither H5 nor H5a supported
Number of Competitors Nearby	0.211	0.211	19	Neither H8 nor H8a supported
Proportion of Competitors Nearby Using Groupon	0.405*	0.357	126	H9a supported
Coupon Revenue from the First Promotion	0.209	0.488***	43	H10 supported
Change in Average Yelp Rating	0.297	0.484***	91 [b]	H4 supported

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***
[a] the 20% quantile split method leads to significantly fewer matched pairs. For *Average Yelp Rating* and *Number of Yelp Reviews*, we do not have enough matched pairs to draw any conclusion.
[b] here instead of the 20% quantile split method we take the restaurants with the value lower than -0.40 as the control group, and those with the value greater than 0.40 as the treatment group.

We also applied the 40%-quantile split method. That is, we take the top 40% quantile as the treatment group and the bottom 40% quantile as the control group. We summarized the results in Table B.3.3 and Table B.3.4.

Table B.3.3 Proportion of Restaurants in Matched Pairs Running an Initial Groupon Promotion in Control and Treatment Groups

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.089	0.098*	2297	H1 supported
Number of Yelp Reviews	0.077	0.127***	1767	H2 supported
Number of Competitors Nearby	0.125***	0.055	1145	H6a supported
Proportion of Competitors Nearby Using Groupon	0.138***	0.107	1338	H7a supported

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***

Table B.3.4 Proportion of Restaurants in Matched Pairs Running a Second Groupon Promotion in Control and Treatment Group

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.400*	0.356	115	H3a supported
Number of Yelp Reviews	0.302	0.427**	96	H5 supported
Number of Competitors Nearby	0.379	0.368	87	Neither H8 nor H8a supported
Proportion of Competitors Nearby Using Groupon	0.400**	0.351	185	H9a supported
Coupon Revenue from the First Promotion	0.348	0.455**	132	H10 supported
Change in Average Yelp Rating	0.337	0.386**	184 [c]	H4 supported

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***
[c] here instead of the 40% quantile split method we take the restaurants with the value lower than -0.10 as the control group, and those with the value greater than 0.10 as the treatment group.

Appendix B.4 Different Intervals of Days

Table B.4.1 Proportion of Restaurants in Matched Pairs Running an Initial Groupon Promotion in Control and Treatment Groups (using 150 days)

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.086	0.099*	1949	H1 supported
Number of Yelp Reviews	0.075	0.137***	1300	H2 supported
Number of Competitors Nearby	0.129**	0.088	318	H6a supported
Proportion of Competitors Nearby Using Groupon	0.127***	0.090	747	H7a supported

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***

Table B.4.2 Proportion of Restaurants in Matched Pairs Running an Initial Groupon Promotion in Control and Treatment Groups (using 210 days)

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.084	0.098*	1949	H1 supported
Number of Yelp Reviews	0.077	0.135***	1298	H2 supported
Number of Competitors Nearby	0.148***	0.093	270	H6a supported
Proportion of Competitors Nearby Using Groupon	0.126***	0.098	725	H7a supported

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***

Table B.4.3 Proportion of Restaurants in Matched Pairs Running a Second Groupon Promotion in Control and Treatment Group (using 420 days)

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.359*	0.302	53	H3a supported
Number of Yelp Reviews	0.416	0.442	77 [a]	Neither H5 nor H5a supported
Number of Competitors Nearby	0.319	0.298	47	Neither H8 nor H8a supported
Proportion of Competitors Nearby Using Groupon	0.416***	0.376	173	H9a supported
Coupon Revenue from the First Promotion	0.242	0.462***	91	H10 supported
Change in Average Yelp Rating	0.333	0.411***	129	H4 supported

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***
[a] p value is 0.34.

Table B.4.4 Proportion of Restaurants in Matched Pairs Running a Second Groupon Promotion in Control and Treatment Group (using 480 days)

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.340*	0.264	53	H3a supported
Number of Yelp Reviews	0.408	0.474**	76	H5 supported
Number of Competitors Nearby	0.383	0.340	47	Neither H8 nor H8a supported
Proportion of Competitors Nearby Using Groupon	0.391	0.408	169 [b]	Neither H9 nor H9a supported
Coupon Revenue from the First Promotion	0.277	0.468***	94	H10 supported
Change in Average Yelp Rating	0.354	0.431***	130	H4 supported

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***
[b] p value is 0.97.

Appendix B.5 Areas without Tourist Attractions

Table B.5.1 Proportion of Restaurants in Matched Pairs Running an Initial Groupon Promotion in Control and Treatment Groups

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.082	0.097**	1808	H1 supported
Number of Yelp Reviews	0.078	0.121***	1304	H2 supported
Number of Competitors Nearby	0.136***	0.057	722	H6a supported
Proportion of Competitors Nearby Using Groupon	0.142***	0.110	1309	H7a supported

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***

Table B.5.2 Proportion of Restaurants in Matched Pairs Running a Second Groupon Promotion in Control and Treatment Group

	Control group	Treatment group	Number of matched pairs	Hypotheses
Average Yelp Rating	0.319	0.298	47 [a]	Neither H3 nor H3a supported
Number of Yelp Reviews	0.384	0.465***	86	H5 supported
Number of Competitors Nearby	0.413	0.326	46	Neither H8 nor H8a supported
Proportion of Competitors Nearby Using Groupon	0.380	0.399	158 [b]	Neither H9 nor H9a supported
Coupon Revenue from the First Promotion	0.269	0.419***	93	H10 supported
Change in Average Yelp Rating	0.344	0.427***	131	H4 supported

Note: *'s denote significance level of Wilcoxon signed rank test: <0.1 = *; <0.05 = **; <0.01= ***

[a] p value is 0.50.

[b] p value is 0.73.

Appendix C. Tables of Notation (Chapter Four)

Table C.1 Notation of Parameters in Mediation and Moderation Effect Analysis

Parameters	Definitions
$\alpha_{\mathrm{M}\cdot n}$	The intercept for equation n of Model M [*].
$\beta_{\mathrm{M}\cdot n}$	The coefficients of $Groupon$ for equation n of Model M.
$\gamma_{M\cdot n}$	The coefficients of Pre_Rating for equation n of Model M.
$\delta_{M\cdot n}$	The coefficients of the interaction term $Pre\_Rating * Groupon$ for equation n of Model M.
$\rho_{M\cdot n}$	The coefficients of the mediator for equation n of Model M.
$\mu_{M\cdot n}$	The error terms for equation n of Model M.
$\rho_{M\cdot 4}^{f}$	The coefficient of $Food\_sentiment$ in equation 4 for Model M, where $\mathrm{M} \in \{\mathrm{V}, \mathrm{VI}\}$.
$\rho_{M\cdot 4}^{s}$	The coefficient of $Service\_sentiment$ in equation 4 for Model M, where $\mathrm{M} \in \{\mathrm{V}, \mathrm{VI}\}$.

Note: [*] — M indicates a model, and $\mathrm{M} \in \mathrm{I}, \mathrm{II}, \mathrm{III}, \mathrm{IV}, \mathrm{V}, \mathrm{VI}\}$; n indicate an equation, $n \in \{1,2,3\}$ when M $\in \{\mathrm{I}, \mathrm{II}, \mathrm{III}, \mathrm{IV}\}$; and $n \in \{1,2,3,4\}$ when $\mathrm{M} \in \{\mathrm{V}, \mathrm{VI}\}$.