Effectiveness of Paid Search Advertising: Experimental Evidence*

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This draft: August 2018

Abstract

Paid search advertising has become increasingly common, comprising about half of all online advertising expenditures. To shed light on the effectiveness and mechanism of paid search advertising, we design and analyze a large-scale field experiment on the review platform Yelp.com. The experiment consists of roughly 18,000 restaurants and 500 million advertising exposures. Yelp's business search advertising packages are randomly assigned to more than 7,000 restaurants for a three-month period. We find that advertising increases a restaurant's Yelp page views and consumer purchase intentions, including getting directions, calling the restaurant, browsing the restaurant's website, and leaving reviews. The advertising effects decline continuing through the consumer's purchase funnel, indicating lower purchase conversion rate of marginal consumers brought to the page by search advertising compared with average consumers visiting the page via organic links. A back-of-the-envelope calculation suggests that advertising would on average produce a positive return for restaurants in our sample. In addition, we find larger advertising effects for newer and independent restaurants, consistent with the informative view of paid search advertising. We also find larger advertising effects for restaurants with higher ratings, suggesting the complementary role of online reputation.

*We thank Susan Athey, Garrett Johnson, Randall Lewis, Sridha Moorthy and participants at the NBER Summer Institute for valuable comments. We thank Yelp, and especially Geoff Donaker, Matt Halprin, Luther Lowe, Travis Brooks, Dan Frank, Brian Dean, and Stephen Lyons for providing support for this experiment. Dai and Luca have consulted for tech companies, including Yelp, but their compensation and ability to publish did not depend on the results of this paper. Please contact Daisy Dai (dai@lehigh.edu) or Mike Luca (mluca@hbs.edu) for correspondence.

1 Introduction

Internet advertising has been the fastest-growing marketing channel in recent years, accounting for roughly $60 billion of spending in the United States alone in 2015. The rise of digital advertising has been dramatic – more than doubling over the past five years alone. Paid search, in which advertisements are placed alongside search results, comprises the largest share of online advertising expenditures.

In the offline world, advertising has historically resembled a credence good, where the effectiveness of a product is taken largely on faith. Even after an advertising campaign is implemented, limited access to outcome data and endogenous variations in business advertising decision and consumer exposure have often made credibly estimating of the impact of advertising difficult. In principle, the digital age provides new opportunities to evaluate the effectiveness of advertisements, enabled by granular data about users(Goldfarb and Tucker, 2011).

Yet estimating the effectiveness of digital advertising remains challenging. First, correlations between advertising expenditure and revenue in observational data may yield biased estimates because advertising spending is often determined by the business' sales prospects. Second, causal interpretation of the traffic generated from search ads or banner ads may overestimate the effect of advertising since ads are more likely to be shown to consumers who are already interested and intended to make a purchase even without being exposed to the ads (Johnson et al., 2014; Blake et al., 2015; Gordon et al., 2016). In the context of paid search advertising, Blake et al. (2015) illustrate that showing a well-known brand's link in the paid search ads to consumers who search using the brand keyword has zero effect to lift demand. More generally, some consumers who visit the website by clicking on the paid search ads would have visited the website through organic links anyways, so such paid clicks are simply replacement of organic clicks and should not be counted as causing incremental increase in site traffic (Chan et al., 2011).

Lastly, the challenge lies in conducting experiments with adequate statistical power. Large sample sizes, often in the level of millions of impressions, are needed to estimate impacts of advertising with sufficient precision due to low conversion rates from ads to purchases (Lewis and Reiley, 2014; Lewis and Rao, 2015; Athey and Imbens, 2016). The need to conduct multiple hypothesis testing on outcomes often puts even more stringent requirement on sample sizes. Such sample size requirements makes it hard for a small business to test ads effects.

In this paper, we leverage the experimentation capacity Yelp.com facilitates to randomize search ads for thousands of restaurants to explore the effect of search advertising. Yelp is the largest review platform for local businesses in the US and is one of the most popular search engines for restaurants. A paid search experiment on Yelp allows us to test the effects of search advertising for a rich variety of local businesses with different characteristics, for example, restaurants with different review ratings and chain status. Furthermore, the effect of search advertising on Yelp has important implications on the competition of local businesses. The ability to search local businesses online has substantially lowered the search cost and could potentially affect the market structure(Bar-Isaac et al., 2012). The informative role of search advertising can help consumers find high-quality businesses that are not yet prominent online, and may make the market more competitive.

To explore the impact of paid search advertising on Yelp, we design and analyze a large-scale field experiment. On Yelp, businesses can purchase standardized search advertising packages at a fixed rate, which guarantee a minimum number of advertising impressions and page views each month. We randomly assign the as-is standard ads packages to more than 7,000 restaurants for a three-month period, sending out roughly 500 million total advertising impressions. We focus on restaurants that have not actively advertised on Yelp prior to the experiment. We then monitor business-level outcomes including page views of the business's Yelp page, a standard measurement of advertising effectiveness (Graepel et al., 2010; McMahan et al., 2013), as well as consumer clicks on the call-to-action buttons that generate additional measures of consumer intention to go to the restaurant–requests for directions, phone calls to the restaurant from Yelp's mobile page, and clicks on the restaurant's own URL on its Yelp page, which are also referred to as "leads".

Overall, we find that Yelp's search ads package increases a restaurant's Yelp page views by 19% on average. Search ads attract page views by placing a relevant business' Yelp link at the top of the search result page, but they have also replaced a small amount of page views that would have been led from organic links that causes a 0.09 standard deviation decrease in the click-through rate rate of organic links. The number of page views is often considered as a proxy for consumer demand by online platforms. Companies including Yelp, Bing, and Google design online ads with the objective of lifting page views in mind (Graepel et al., 2010; McMahan et al., 2013). Nonetheless, consumers who land on the business page through search ads links may have different probabilities to make a purchase compared with consumers coming through organic links, so the increase in page views caused by search advertising may not translate into the increase in demand at the same rate as organic clicks.

To gain insights into the conversion rate from page views to purchase, we select the experiment sample size large enough to detect the effects on the number of leads which conditions on consumer viewing the business page. We find that Yelp's search ads package results in a 7-14% increase in various measures of leads, a rate a increase lower than page views, suggesting that consumers drawn to the page by search ads are less likely to make a purchase than consumers visiting the page without seeing the search ads. Overall, paid search advertising lowers the conversion rate from page view to leads by 0.3 standard deviation.

As a final indicator of demand, we consider the number of reviews that are left during the advertising period. In principle, if paid search advertising lead more Yelp users to visit the restaurant, then one would expect to see an increase in the number of reviews. Consistent with this hypothesis, we find that advertising leads to a 5.1% increase in the number of reviews left for a restaurant. Examining the advertising effects over time, we find that the effects of paid search advertising stay the same during the three months of treatment period. However, the effects drop to zero immediately after the treatment ends, suggesting that search advertising temporarily raises the awareness of the advertised businesses. A back-of-the-envelope calculation suggests that advertising leads to an 6.2% increase in revenue, and would produce a positive return to advertising, on average, within our sample.

Lastly, we use the variation in restaurant characteristics that affect the advertising effectiveness to test whether the heterogeneous effects are consistent with the informative view of search advertising. If search advertising is mainly informative, its effect should be bigger when the search ads link features restaurants that consumers are less familiar with. More specifically, the informative view would predict that chain restaurants will gain less than the independent restaurants from search ads, and newer restaurants will gain more than older and more established restaurants from search ads. We estimate the heterogeneity in search advertising effectiveness by examining conversion rates based on different restaurant characteristics. We find evidence of greater search advertising effects for restaurants that are newer and independent, consistent with the informative view of search advertising. In addition, we provide novel results showing heterogeneous advertising effects based on review ratings. The click-through rate of search ads is 0.96 standard deviations higher for restaurants with 4.5- or 5-star ratings than restaurants with 3-star ratings. And the percentage loss in conversion rate from page views to leads due to search advertising is 40% lower for restaurants with 4.5- or 5-star rating than restaurants with 3-star ratings.

Our paper contributes to understanding the essential question of how advertising works to influence consumers demand. There are three classic views of the role of advertising (Bagwell, 2007;

Ackerberg, 2001). The persuasive view argues that advertising directly changes consumer preference for the advertised product. The informative view considers the role of ads that help firms to convey information to consumers. The third view is that advertising enters the consumer's utility as complementary to the consumption of the advertised product. Among the three views, the informative role of ads lowers consumer search cost and has pro-competitive implications. Recent literature has tried to test empirically the informative view and persuasive view of search advertising. For example, Blake et al. (2015) find that paid search advertising is ineffective for brand keywords targeting at the brand. For non-brand keywords, the paper finds that search ads are more effective in influencing new and infrequent consumers, supporting the informational view of paid search advertising. Narayanan and Kalyanam (2015) analyze the moderators driving heterogeneous position effects of search ads. They find that position is more important for small advertisers and for keyword phrases that are not usually linked to or targeted at the advertisers. Relatedly, Jeziorski and Moorthy (2017) show that paid search position and advertiser prominence are substitutes that prominent firm gains less from good paid search position than less prominent ones. While the above papers support the informational view, there are also papers that find evidence consistent with the persuasive view. Sahni and Nair (2018) design an experiment on a restaurant mobile search platform in India and find that search advertising serves as a signaling device which improves the consumer perception about the product quality. The experiment randomizes whether to disclose the advertising sign beside paid link and the experiment results show that consumer demand positively responds to the display of the advertising sign.[1] In an earlier paper, Yang and Ghose (2010) find that the average click-through rate of organic links at the presence of paid search ads is higher than the average click-through rate of organic links without paid search ads for the majority of keywords and proof that the effects are causal. This potentially could be explained by positive persuasive effects.

Different from the methods used in the previous literature, we run a large-scale field experiment that tests the effectiveness of search advertising in thousands of treated businesses. The rich variation in business characteristics allows us to provide insights into the mechanism of when paid search advertising works. It also allows us to derive heterogeneous treatment effects based on business information consumers observe online, such as review ratings, that are of great practical interests to both the advertising platform and the advertisers.

Our paper also complements the recent surge of literature that estimate the effectiveness of

[1]Sahni and Nair (2016) experiment with existing advertisers on the search platform and design the experiment to uncover the average persuasive effect. We focus on a large set of non-advertise in our experiment and examine the role of search ads through heterogeneous effects of search advertising based on variation in restaurant characteristics.

online advertising using experiments. Due to the requirement to run experiments on large number of impressions to gain statistical power to assess the effects of online ads (Lewis and Rao, 2015), most experiments are run in collaborations with a single or a couple large companies, enabled by the large consumer base these companies can access or the experiment money they can afford. For example, Blake et al. (2015) run experiments using geographic pausing of ads to assess the effectiveness of search advertising for eBay. While the findings of the paper is compelling that search ads on eBay keywords have zero effects to lift demand. The conclusion shall not be generalized to any branded product lesser known than eBay. Similarly, Lewis and Reiley (2014) and Johnson et al. (2014) are based on experiments with major national retailers. At larger scales, Gordon et al. (2016) compare advertising effect estimates using experimental methods with estimates using observational methods involving 12 US advertisers on the Facebook platform. By contrast, our experiment sample consists of 7,210 restaurants in the treated group and 11,085 restaurants in the control group, a large set of representative restaurants in the market. We are able to obtain the average treatment effects for businesses typically unable to run their own experiments and provide estimates in contrast to the large-scale experiments run by individual advertisers.

It is well understood that counting all paid search clicks as incrementally caused by the search advertising overestimates the advertising effect (Chan et al., 2011). Chan et al. (2011) find that 89% of the paid ads clicks are truly incremental and the rest 11% of the paid ads clicks are merely replacing the loss in organic clicks that would not have happened without search ads. Blake et al. (2015) find that the effect of search ads for well-known branded advertisers is limited, implying that most of the paid clicks are not incremental. Somewhere in the middle, Chesnes et al. (2017) find that only one-third of paid clicks are incremental for Canadian online pharmacies advertising in the US. In our paper, we find very small substitution from organic clicks to paid clicks, and the majority of the paid clicks are incremental, similar to the conclusion in (Chan et al., 2011). More generally, our results demonstrate the potential of search advertising to drive outcomes – even among businesses that have opted not to advertise.

2 Experimental Design and Data

The experiment is conducted on the popular consumer review platform Yelp.com. Yelp allows consumers to search, browse, and review local businesses around the world. As of 2015, Yelp had roughly 163 million unique visitors monthly. Known as a restaurant review website, Yelp is also a powerful search engine for local businesses including restaurants, tailors, or hair salons. The search function enables Yelp to generate revenue from paid search advertising which is one of Yelp's main revenue sources.

Yelp's search function works similarly as other typical search engines. A consumer enters a keyword of the business or the type of businesses (for example, "italian") and the location she is looking for. The result page will return a list of businesses that best matches the search query and the links to the businesses' Yelp pages. Examples of the search result page are shown in Figure 1. The business featured in the paid search ad is listed on the top of the result page, followed by organic search results. For each search, Yelp allocates a single slot for the paid search ad. Which business to show in the paid search slot is determined by relevance. A yellow flag "Ad" is prominently shown beside the name of the business in the paid search link to distinguish it from organic search results. If there is no advertising business relevant to the consumer's search query, no paid search link appears in the result page.

Yelp's paid search ads are mainly sold through standard monthly advertising packages. Businesses buying the advertising package pays a $400 monthly fee and becomes an "advertiser" on Yelp. Advertisers can set the paid search advertising preferences such as the business categories and search keywords where their paid search ads should be placed. Yelp manages the placement of paid search ads in all three channels where paid search ads can appear–web browser, mobile website, and Yelp's mobile app. Yelp guarantees a minimum number of paid search impressions and page views for the advertiser.

2.1 Treatment and randomization

The experiment is designed to help Yelp understand the effectiveness of its paid search ad package. We choose to run the experiment in the category of US restaurants since the number of current advertisers is very small relative to the search volume in this category, so there is plenty of vacant capacity of search impressions to show ads. The experiment that treats a random set of businesses with search ad packages will have minimum effect on current advertisers and Yelp's revenue.

Since the goal is to evaluate how much businesses gain from Yelp's search ad packages, the treatment is the as is four-hundred dollar search ad package Yelp currently sells. We select a random set of eligible restaurants to be treated, with the treatment lasting for three months between August 1 and October 31, 2015.

The randomization is done in the following steps. First, we filter out businesses that are not actively operating (for example, temporarily closed) and businesses that are not qualified to place paid search ads. The qualification requires that the basic information on the restaurant listing (for example, address and phone number) is verified, the restaurant has a minimum number of trusted reviews with good ratings, and the restaurant's Yelp page has user- (or owner-) contributed photos. The first two requirements are to screen out low-quality businesses and businesses with fraudulent information, and the second requirement is to have a photo to feature in the paid search ad (see Figure 1).

Second, we exclude restaurants that have purchased paid ad packages in the past six months before the start of the experiment. We choose to exclude the active advertisers since they may be conducting other marketing activities we do not observe that impact demand. Since active advertisers account for only a tiny fraction of the restaurant population, excluding them from the experiment still leaves us with the majority of restaurant population to study the mean treatment effects.

Third, we focus on three subsamples of restaurants on which unique outcomes are tracked that facilitate the measurement of demand and one subsample of restaurants whose advertising effects are of interest to Yelp. The first subsample consists of Yelp Reservations restaurants. Yelp Reservations is an online reservation system hosted by Yelp that allows consumers to directly make reservations on the restaurant's Yelp page. With this subsample, we observe information about the reservations made on the restaurants. The second subsample of restaurants is similar to the Yelp Reservation restaurants. They have signed up to use OpenTable, an Internet booking platform, to manage their reservations. Yelp is interested in this set of restaurants since they are mid-range to high-end full-service restaurants, similar to Yelp's current active advertisers. The third subsample consists of restaurants that have signed up to use Yelp's delivery service, EAT24. On the Yelp page of EAT24 restaurants, consumers can directly order takeouts. With this subsample of restaurants, we can collect information on the number and value of take-outs ordered through Yelp. Among the restaurants that are not partners with Yelp or OpenTable, we choose to focus on the ad-qualified restaurants in Washington state since we can partially link the restaurants to historical revenue data obtained from the Washington state Department of Revenue. Non-partner restaurants in the Washington state consists of the fourth subsample. On Yelp, the majority of restaurants are non-partners. On average, they have lower online prominence than partner restaurants. As shown in Panel B of Figure 2, restaurants in the fourth subsample have considerably fewer consumer reviews than restaurants in other subsamples.

After performing the above steps, we are left with 18,295 restaurants in the four subsamples as described in Table 1. Because we are interested in the subsample treatment effects that are potentially heterogeneous, we randomize within each subsample. Randomizing treatment within groups of businesses with similar characteristics increases statistical power (Athey and Imbens, 2016; Imbens and Rubin, 2015). In particular, we treat 50% of the restaurants in subsample 1 to 3 and 20% of the restaurants in subsample 4. The subsample sizes and treatment ratio are listed in Table 1.

When choosing the fraction of restaurants to be treated, we take into account the potential general equilibrium effect into account and limit the fraction of treated restaurants. If a high proportion of restaurants is treated within a local market, the increased competition in the search ads bidding market will change the return of advertising. Also, treating a large number of restaurants in a local market may cause negative spillover to the control restaurants through business-stealing effects offline and affect the interpretation of the estimates. According to 2015 County Business Patterns, there are over 600,000 restaurants in the US.[2] There are only 11,914 restaurants in subsample 1-3 in the entire US, less than 2% in the entire US, so we are less concerned about the spillover effect by treating restaurants in subsample 1-3. We choose the treatment ratio to be 50%. However, in Washington state, Yelp records around 20,000 active restaurants and food places, but we have close to 7,000 restaurants in subsample 4 in WA, so we treat a much lower fraction of restaurants in subsample 4. At the zip code level, the mean fraction of restaurants treated within a zip code is 2.3% and the median is 1.4%. The mean number of businesses treated within a zip code is 2.8, and the median is 2.

The randomization test is shown in Appendix Table A1. We do not find any statistically significant difference between the treated and control restaurant consumer purchase intention outcomes before the experiment. We do randomization tests for subsample 4 separately since its treated ratio is 20%, different from the 50% treated ratio in subsample 1-3. With different treated ratio, comparing treated and control by simply pooling all subsamples together results in different subsample weights within the treated and control samples and invalidates the balance test. Similarly, we plot the restaurant characteristics of the treated and control units before the experiment for subsample 1-3 and subsample 4 separately in Figure 2. The figure shows similarity in the distribution of restaurant characteristics between the treated and the control.

[2]We searched the number of establishments in the NAICS code "722 - Food services and drinking places." using 2015 Census County Business Patterns.

The treatment–the Yelp paid ad package is given to the treated restaurants from August 1, 2015 to October 31, 2015. To avoid Hawthorne effects, we did not inform restaurants about the experiment and we removed the treated restaurants from the advertising sales list.[3]

The treatment is randomized at the business level, and the effects are also measured at the business level. The experiment design differs from search advertising experiments that randomize advertising exposure at the impression or consumer level–removing a business's ads from the search results or holding out a random set of consumers from being exposed to search ads. Such experiments are often carried out on a single advertiser to evaluate the advertiser's advertising effectiveness. The advantage of such experiments is the ability to learn heterogeneous effects based on the characteristics of the search sessions or different consumers (Blake et al., 2015; Zantedeschi et al., 2017). However, since such experiments are often conducted for a single business, it cannot answer questions about advertising effectiveness based on business characteristics. In addition, treated consumers may interfere with the untreated consumers if they discuss or share information about the advertising restaurants with consumers in the control group. The experiment we conduct assign search ads to a randomly chosen set of businesses and resolves the above two challenges.

2.2 Measures of consumer purchase intentions

The first key metric we use to assess the advertising effectiveness is the number of page views of a restaurant's Yelp page, a standard measure used by the online advertising industry. To get a better sense of the conversion rate from page views to demand, we trace consumer purchase interactions with call-to-action (CTA) buttons on the business's Yelp page. The CTA buttons allow consumers to request direction or request to browse the restaurant on the map, directly call the restaurant on mobile devices, and direct to the restaurant's own URL (external to the Yelp website). Clicks on the call-to-action buttons are also called "leads". Furthermore, consumers can click to place a reservation if the restaurant is a Yelp Reservations partner (in subsample 1) or order take-outs if the restaurant is an EAT 24 partner (in subsample 3). We track the number of reservations and take-outs in subsamples. We also use the number of reviews left on the restaurant as an indicator of purchase.

When analyzing the mechanisms of how search ads influence consumers, we focus on two conversion rates. The first one is the rate at which consumers click to view the restaurant's Yelp page

[3] The advertising sales list is a list of businesses that Yelp's marketing team calls to promote Yelp's paid search ad package.

after they are exposed to the restaurant's paid search link (ad) or organic link. We call the first measure the click-through rate (CTR). The second measure is the rate at which consumers click on the CTA buttons after they visit the restaurant's Yelp page. We call the second measure the CTA conversion rate. To construct the CTR of both organic and paid links, we collect data on organic and paid impressions–the number of times the business's link appears in the paid search and organic search results separately.

3 Conceptual Framework

3.1 Interpret the average treatment effect

We track the array of consumer purchase intention measures following consumers through their purchasing funnels where paid search advertising takes effects. Deriving and comparing treatment effects at each level of the funnel helps us understand the mechanism of paid search advertising.

At the top level of the funnel, the paid search ads promote visibility of the restaurant and increase traffic to the restaurant's Yelp page. After a consumer enters keywords to search, the paid link of an advertised restaurant relevant to the search is promoted to the top of the page. The consumer who browses the search results from top to bottom first sees the paid link and decides whether to click on it or continue browsing the organic links below. At the same time, the restaurant featured in the paid link may appear in the list of organic links in the same search session.

At the top funnel, the paid search ads affect page views through both paid clicks and organic clicks. The effect on paid clicks is positive as far as the paid link has a non-zero click-through rate (CTR). The effects on organic clicks work through two mechanisms in potentially opposite directions. The first mechanism is through substitution, and the sign of the effect is always negative (Chan et al., 2011; Blake et al., 2015; Chesnes et al., 2017). If the business appears in both organic and paid search results in the same search session, consumers who would have clicked on the business's organic link may instead click on the paid link since it appears at the top. The substitution between paid and organic clicks reflects the informational role of search advertising since after controlling for rank order bias, the organic link and the paid link are perfect substitutes in the role to inform consumers about the business.

What do we expect the size of the substitution effect on Yelp? Substitution happens if consumers click on the search ads when they could have found the business through organic links, so the substitution effect is large when the restaurant can be easily found in the organic result—prominent either in name or organic search ranking, such as eBay in the Blake et al. (2015) setting. Due to fierce competition among restaurants, none of the restaurants can dominate top positions in the organic search results, so we expect the substitution effects to be modest in size. In addition, to prevent businesses from spending on search ads when they already can obtain prominent positions in the organic search, Yelp would not place the business in the paid search link if the business can appear in the top three position in the organic result.

The second channel of the effect is through persuasion. If being the paid search advertiser improves the consumer perception about the quality of the restaurant, consumers who have been exposed to the restaurant's search ads perviously may also be more likely to click on its organic link regardless whether the restaurant appears in the paid link or not. However, on the contrary, if being the paid search advertiser decreases the perceived quality of the restaurant, search ads may negatively affect the organic CTR. In the Yelp search context, we expect the overall effect on organic CTR to be negative unless there exists a positive persuasive effect.

At the middle and final funnel, the consumer who lands on the restaurant's Yelp page through paid or organic link decides whether to respond to any call-to-action (CTA) button which potentially leads the consumers to a purchase. We call the probability that consumers click on CTA buttons conditional on landing on the page the CTA conversion rate. Conceptually, what do we expect comparing the CTA conversion rate of page views directed from organic links and from paid links? There are also two driving factors affecting the direction of the effects. The first factor is due to the change in the composition of consumers who visit the page when the business is placed in the paid link. The literature has documented declining CTR with search result position and argued that search is costly (Jeziorski and Moorthy, 2017). When the business appears in the organic link, potentially not always obtaining the top position in the search result, only consumers who are sufficiently interested in the restaurant would bear the search cost and reach the restaurant through organic link. When the business is placed in the paid link, more consumers will click on the link, but may be less interested in the restaurant. In order words, paid links attract consumers that are less well matched to the restaurants than consumers finding the restaurant through organic links, so we could expect lower CTA conversion rate for consumers attracted by the paid link. The second factor is again the persuasive effect of paid ads. If being an advertiser changes how consumers perceive the quality of the restaurant, it changes how likely consumers engage with the CTA buttons.

Overall, we expect search ads to negatively affect CTA conversion ratesunless the persuasive effect is positive and substantial.

In summary, how much paid search ads lift purchase depends on the conversion rate at each stage of the purchase funnel. We observe two key conversion rates at the top and middle funnel: CTR–the probability of search impressions converting to page views, and CTA conversion rate–the probability of page views converting to leads. Let κ_o and κ_p denote organic and paid CTR respectively, and ρ_o and ρ_p denote CTA conversion rate following an organic and paid page view respectively, the number of restaurant leads can be written as,

$$\begin{aligned} Leads &= PaidImpression \times \kappa_p \times \rho_p + OrganicImpression \times \kappa_o \times \rho_o \\ &= PaidPageView \times \rho_p + OrganicPageView \times \rho_o. \end{aligned} \tag{1}$$

We can directly calculate the CTR of paid and organic links using paid and organic search impression and click data, but we cannot directly calculate CTA conversion rates of paid and organic page views due to a data limitation–we only observe the total number of leads, but we cannot trace whether each lead is generated from an organic page view or a paid page view. However, the change in the overall CTA conversion rate, ρ_{all}, due to search ads provides information about the relative size of ρ_o and ρ_p. If $\rho_p = \rho_o = \rho_{all}$, by definition, $\rho_{all} = TotalLeads/TotalPageView$, implying that leads will increase at the same rate as page views. If $\rho_{paid} < \rho_{organic}$, after the business is treated with paid search ads, we expect the overall CTA conversion rate to fall, leading to a smaller increase in leads than in page views.

Furthermore, we can back out ρ_p and ρ_o for treated restaurants with the assumption that the search ads do not affect the CTA conversion rate of organic page views. Given equation (1), let η_p denote the percentage of page views generated from paid links, superscript 0 and 1 denote the period before and during the experiment, subscript 0 and 1 denote whether the restaurant is treated with search ads, then the change in overall CTA we observe can be expressed as,

$$\rho_{all,1}^{t=1} - \rho_{all,1}^{t=0} = \eta_p^{t=1}(\rho_{p,1}^{t=1} - \rho_{o,1}^{t=1}) + (\rho_{o,1}^{t=1} - \rho_{o,1}^{t=0}). \tag{2}$$

Assume that the trend in ρ_o does not differ between treated and control restaurants, and given that $\rho_o = \rho_{all}$ for the control restaurants, $\rho_{o,1}^{t=1} - \rho_{o,1}^{t=0} = \rho_{o,0}^{t=1} - \rho_{o,0}^{t=0} = \rho_{all,0}^{t=1} - \rho_{all,0}^{t=0}$. Equation (2) can be rewritten as

$$\rho_p^{t=1} - \rho_0^{t=1} = \frac{(\rho_{all,1}^{t=1} - \rho_{all,1}^{t=0}) - (\rho_{all,0}^{t=1} - \rho_{all,0}^{t=0})}{\eta_p^1} \tag{3}$$

where the numerator of the right-hand side of equation (3) is the DID estimate of the effect of search ads on the overall CTA conversion rate. Therefore, equation (3) gives us a simple formula to calculate the loss in CTA conversion rate when consumers visit the page from paid links instead of organic links.

3.2 Heterogenous treatment effects and the role of search advertising

Paid search advertising plays an informational role if it provides consumers with new information about the advertised restaurant. The informational effect could be merely informing consumers about the existence of the restaurant or providing other information about the restaurant that the consumers do not already know, for example, location, price range, or popular food items. If paid search ads are informative, we expect the conversion rate at each stage of the funnel to be larger for when search ads give more information to consumers. For example, chain restaurants are better known than independent restaurants, so we expect the conversion rates for the independent restaurants to be higher. Also, older restaurants are better known than newer restaurants, so we expect the conversion rate for newer restaurants to be higher.

We can also infer whether paid search ads play an informative role by examining whether consumers respond to the information posted on the paid search ads. As shown in Figure 1, the search ad link provides information about the restaurant review ratings, number of reviews, and the price level. Testing how restaurant characteristics featured in the ads affect conversion rates of paid search ads can offer insights into the role of search ads as well as practical perspectives on which advertisers benefit more.

Besides directly providing information, the online ads may influence consumer demand in positive or a negative ways through other mechanisms. Since Nelson (1974), the literature on advertising has postulated the role of advertising to signal the quality of the product and built models that rationalizes advertising choice of high-quality producers in separating equilibrium. Consumers in such models would also correctly believe that the quality is higher for advertisers (Milgrom and Roberts, 1986; Bagwell and Ramey, 1988). However, advertising may also negatively influence consumer demand. Contrary to the positive signaling effects, Feltovich et al. (2002) have discussed the possibility of an equilibrium in which the very best businesses do not signal to differentiate themselves apart from the good but not the very best businesses. The counter-signaling theory is possible when other noisy information about the business quality exists in which the best businesses do not need to rely on a single signal, such as advertising. If the current advertising equilibrium on the Yelp is consistent with counter-signaling, we may see the advertising effectiveness for the

5-star restaurants to be lower than the 4.5-star restaurants – a consumer may find it suspicious if she sees a 5-star restaurant advertise. Another potential negative effect of advertising is the result of the prevalence of online ads. As online ads penetrate into the consumer browsing experience, consumers have become increasingly weary of online ads. Seeing the business in the advertising link may negatively affect the consumer likelihood to click, especially if they find the ad distracting or believe that they have been tracked and targeted by the website (Goldfarb and Tucker, 2011).

4 Empirical Results

4.1 Empirical specifications

Using restaurant monthly data between January 2015 and December 2015, we estimate the average treatment effect using the difference-in-differences (DID) approach. Since the treated ratios differ in each subsample and the treatment effects are likely to differ among subsamples, we need to modify the typical DID specification. Use dummy variable T_ι, $\iota \in \{0, 1, 2\}$ to denote before experiment, during experiment, and post experiment regimes, dummy variable S_s, $s \in \{1, 2, 3, 4\}$ to denote each subsample, i to denote a restaurant, t to denote a month, and ω to denote the treatment status, we run regression using the following specification,

$$
\begin{aligned}
y_{it} =& \beta_0 + \sum_{\iota=1}^{2} \gamma_{1\iota} T_{\iota t} + \sum_{\iota=1}^{2} \sum_{s=2}^{4} \gamma_{2s\iota} T_{\iota t} \times S_{si} + \sum_{\iota=1}^{2} \alpha_\iota \frac{1}{\lambda_1} \omega_i T_{\iota t} S_{1i} \\
&+ \sum_{\iota=1}^{2} \sum_{s=2}^{4} \beta_{s\iota} (S_{si} - \frac{\lambda_s}{\lambda_1} S_{1i}) \omega_i T_{\iota t} + \mu_i + \delta_t + \epsilon_{it}
\end{aligned}
\tag{4}
$$

where λ_s is the percentage experiment sample in subsample s. In equation (4), α_1, α_2 consistently estimates the average treatment effects during and after the experiment; $\beta_{s\iota}$ ($s = 2, 3, 4$; $\tau = 1, 2$;) estimate the treatment effects for subsample 2-4 during and after the experiment; $\gamma_{1\iota}$, $\gamma_{2s\iota}$ control subsample specific time trends; μ_i and δ_t are restaurant and month fixed effects.

Since the absolute scale of the effect contains proprietary information, we report the effects in standardized levels and in percentages. The effects in standardized levels are calculated by regressing equation (4) using standardized outcomes that are scaled by their respective full-sample standard deviations before the experiment. For the average percentage effect, we first calculate the percentage effect within each subsample by dividing subsample treatment effects by their respective counterfactual treatment sample means during and after the experiment. We then take the weighted average of each subsample's percentage effect using subsample size as weights. When calculating the confidence interval for the percentage effects, we need to take into consideration that both treatment effects and the denominators are random variables and may be correlated with each other, so we calculate the confidence interval of the percentage effects using bootstrap.[4]

Equation (4) can be extended to calculate the heterogeneous treatment effects for restaurants with different characteristics. Use dummy variable X_z, $z \in \{1, ..., Z\}$ to denote categorial restaurant characteristics,

$$\begin{aligned} y_{it} =& \beta_0 + \sum_{\iota=1}^{2} \gamma_{1\iota} T_{\iota t} + \sum_{\iota=1}^{2}\sum_{s=2}^{4} \gamma_{2s\tau} S_{si} \times T_{\iota t} + \sum_{\iota=1}^{2}\sum_{z=2}^{Z} \gamma_{3z\iota} X_{zi} \times T_{\iota t} + \sum_{\iota=1}^{2}\sum_{z=2}^{Z}\sum_{s=2}^{4} \gamma_{4sz\iota} S_{si} \times X_{zi} \times T_{\iota t} \\ &+ \sum_{z=2}^{Z} [\sum_{\iota=1}^{2} \alpha_{z\iota} \frac{1}{\phi_1} \omega_i S_{1i} X_{zi} T_{\iota t} + \sum_{\iota=1}^{2}\sum_{s=2}^{4} \beta_{sz\iota} (S_{si} - \frac{\phi_s}{\phi_1} S_{1i}) \omega_i X_{zi} T_{\iota t}] + \alpha_i + \epsilon_{it} \end{aligned} \tag{5}$$

where

$$\phi_s = \frac{\lambda_s r_s^z}{\sum_{s=1}^{S} \lambda_s r_s^z}$$

where r_s^z is the share of restaurants with characteristics z in subsample s, so ϕ_s is the share of restaurants in subsample s with characteristics z among all restaurants with characteristics z. In regression equation (5), regressors of interests are α_{1z}, α_{2z} that estimate the treatment effect for restaurants with characteristics z during and after the experiment. In addition, $\beta_{s\iota z}$ ($s = 2, 3, 4$) estimate the heterogeneous treatment effects within each subsample.

4.2 Results on Average Treatment Effect

The percentage effects of Yelp's paid search advertising package on the spectrum of purchase intention measures are presented in the lower panel of Table 2. Overall, we find that advertising increases a restaurant's Yelp page views by 19%. Across the three additional measures of purchase intentions, advertising leads to an increase in map inquiries by 14%, calls by 6.5%, and clicks on restaurants' own URLs by 6.8%.[5] As a final indicator of demand, we examine the number of reviews. We find that advertising increases the monthly number of reviews left on the restaurant by 5.1%. While advertising generates more reviews, it has no significant impact on rating or length of the reviews written during the advertising period, it also has no impact on the percentage of reviews labeled as

[4]The randomization of the experiment is done within each subsample, so we implemented bootstrap draws within each subsample.

[5]The increase in percentage reported here are based on absolute counts and not on conversion rate conditional on search impressions or page views.

fake by Yelp (Luca and Zervas, 2016).

The top panel of Table 2 presents the average standardized treatment effects in the overall sample. Appendix Table A2 includes the effects in subsample 2-4[6] The cross products are weighted according to equation (4). The coefficients for the cross products of time period dummies and the treatment status dummy represent the overall experiment sample average treatment effects, and the coefficients for the cross products with the subsample dummies represent the treatment effects in each subsample. Column (1)-(4) in Table 2 show statistically significant increases in page views and leads when restaurants are treated with search advertising. Furthermore, since each outcome is scaled by the same constant common number, we can directly compare the absolute size of the effects across subsamples. Column (4)-(9) in Appendix Table A2 present subsample treatment effects on consumer purchase intentions. The absolute size of the effects on page views and map views are similar in subsample 2 and 3–restaurants that are also on the OpenTable reservation platform and restaurants on the EAT24 delivery platform. The effects are smallest in subsample 4–restaurants in WA that are non-partners. Smaller effects in absolute values do not necessarily mean smaller percentage effects. Comparing the Yelp page traffic (page views) before experiment for subsample 2-4, the traffic for OpenTable restaurants is 2.1 times that of EAT24 restaurants, and the traffic for EAT24 restaurants is 2.7 that of the non-partner restaurants. Comparing the base levels with the subsample treatment effects in Appendix Table A2, the percentage effects are higher for the subsample with smaller bases. Comparing the advertising effects on calls and external URL clicks, we see that the effects on calls are similar and the effects on external URL clicks is much larger for OpenTable restaurants than for EAT 24 restaurants. This is because OpenTable restaurants are more likely to have their own website.

Lastly, Column (5) and (6) in Table 2 show the effects on the number of reviews and take-out orders. More reviews are written due to advertising, indicating more visits. We only observe orders for EAT 24 restaurants, so we can estimate the effect using the typical DID specification, although the effects are positive, we cannot estimate the effects precisely due to limited sample size.

Table 2 presents results that are scaled by the standard deviation of the overall sample, however, the standard deviation differs by subsample. To show the size of the advertising effect in each subsample relative to the subsample standard deviation, we plot the outcomes for the treated and control samples scaled by the standard deviation within each subsample in Appendix Figure A1-

[6] Subsample 1 (Yelp Reservation restaurants) is used as the base category and the treatment effect on this subsample is not presented separately since the sample size of subsample 1 is small (1.7% of the full sample) and the treatment effect of this subsample is often imprecisely measured (see Figure 3 and A2).

A4. Appendix Figure A1 and A2 show that subsample 3 and 4 experience bigger advertising effects relative to their own subsample standard deviations. Overall, the differences in effect sizes across different samples suggest there exists substantial heterogeneity in treatment effects. We will explore them in the next subsection.

Table 7 presents results for organic impressions and clicks. As detailed in the discussion in Section 3.1, we expect a negative but small substitution effect that reduces the CTR of organic links. The substitution effect reduces the click-through rate of organic links unless it is counteracted by positive persuasive effects that lifts the organic click-through rate. The results in Column (1) and (3) show that the search ads have no impact on organic impressions but reduces CTR of organic links and hence reduces the organic page views. Consistent with our expectation, the substitution effects is relatively small, suggesting that the searches on Yelp is in general not highly targeted.

We discuss in Section 3.1 the reasons why we expect that consumers landing on the page through paid links are less likely to click on the CTA buttons than consumers through organic links. This will lead to slower increase in leads than page views. Percentage results in Table 2 confirm our prediction. The smaller CTA conversion rate of paid page visits will lower the overall conversion rate from page views to leads. Panel A of Table 3 shows the effect of search ads on overall CTA conversion rate. The loss is prevalent across all subsamples and browsing channels. Furthermore, we can calculate the difference between conversion rate through paid page views and organic page views using Eq (3). The results are presented in Panel B of Table 3. The CTA conversion rate of paid page views is 26-43% lower than that of organic page views. In general, this reflects that the matching between consumer and the restaurant is worse for visitors coming from paid link. The result is similar to the findings in Johnson et al. (2017). They conduct a meta-study of online display advertising experiments and examine consumer conversions in different levels of the marketing funnel. They find that incremental site visitors from paid clicks are less likely to convert than baseline visitors, a result consistent with our findings.

Lastly, we examine the treatment effects overtime. Figure 3 show the overall sample month-by-month treatment effects treating the first month in the sample, January 2015, as the base month. As shown in the figure, during the experiment, the lifts in purchase intention measures stay the same. In addition, the treatment effects disappeared immediately after the experiment ends. Table 2 shows that search advertising has no carry-over effects on the outcomes we track.[7] However,

[7] In an unreported table, we examine the advertising carry-over in the first and second month after the experiment separately, we do not find significant carry-over effect.

these patterns are not sufficient to reject the existence of the carry-over effects of search advertising. If converted consumers visit the restaurant again after the experiment without visiting with the restaurant's Yelp page, our measures are not able to track these consumers.

Robustness checks Besides linear specification with standardized outcomes. We checked other choices of specifications for robustness. Using the linear regression framework, we drop the business level fixed effect μ_i and replace it by the treatment indicator, the results are unaffected. We also run the generalized linear regression with Poisson link and we get similar results. For alternative hypothesis testing methods of advertising effects, we run the Fisher exact test of the average effects to confirm that we can reject the null at each equation level (Young, 2015; Athey and Imbens, 2016).

Return to advertising Since sales are not directly observed, we conduct a back-of-envelope calculation of sales increase by putting dollar values on the marginal increase of page views. From the Washington State Department of Revenue, we obtain historical tax revenue on Washington restaurants for the first half of 2015.[8] We were able to match 835 Washington state restaurants with restaurants in our experiment sample (13% of subsample 4). From the historical data, we examine the relationship between sales and page views, which we use to approximate the change in revenue when page views increases. Specifically, we conduct the following regression to associate revenue with page views:

$$Ln(Revenue_{it}) = \beta Log(Pageview_{it}) + \alpha_i + \delta_t + \epsilon_t$$

where i indicates for a restaurant and t indicates for a quarter. We add restaurant fixed effects to examine the revenue change related to within restaurant changes in page views and we add quarterly dummies to control for common time trends. The estimate for β is 32.54% significant at 1% level with standard errors clustered at the business level.

The estimates suggests that a 10% increase in quarterly page views is correlated with a 3.3% increase in quarterly revenue. Yelp's search advertising package leads to an average increase of 18.8% in total page views according to our experiment, and this correlates with an increase of roughly 6.2% in revenue. For example, for a business with $96,000 in quarterly sales (the median revenue in Washington state), take the marginal profit margin for additional sales at around 70%,[9]

[8] Unfortunately, we are not able to obtain revenue data during the period of the experiment.

[9] According to accounting firm Baker Tilly (http://www.bakertilly.com/uploads/restaurant-benchmarking.pdf), the variable cost (food cost, or in other words, the cost of goods sold) is roughly 28-32% of total sales.

the return on advertising would be 247%.[10] An important limitation of this calculation is the fact that marginal page views generated from search ads may have differential impacts on sales compared with page views from organic links. If we apply the 43.3% loss of conversion rate of paid search ads in non-partner Seattle restaurants (Panel B of Table 3), the ROI reduces to 97%. Nonetheless, the back-of-envelop ROI calculation suggests that paid search advertising can be a profitable investment for an average restaurant that is not currently advertising.

4.3 Heterogeneous treatment effects

We are interested in the informational role of advertising since it is pro-competitive (Bagwell, 2007). To examine the informational role of search advertising, we focus on the heterogeneous advertising effects in the dimensions of restaurant age and chain status that affect the informational value of search ads. We also examine heterogeneous effects in the dimensions of restaurant review rating, the number of reviews, and price range to test whether consumers respond to the information listed in the search ads. Regarding advertising effects, we focus on two key conversion rates that determine the effects of search ads—the conversion rate from paid ads to page views (paid CTR) and the conversion rate from page views to leads (CTA conversion rates).

We use information on Yelp to construct restaurant characteristics. The restaurant age is determined by the number of years the restaurant has been listed on Yelp. Yelp is established in 2005. It obtains information on new restaurant openings from user and partner reports and annual updates of other informational sources, such as the Yellow Page.[11] For restaurants listed on Yelp since the launch of Yelp, we add a dummy variable indicating that they have been around for more than ten years. To determine the chain status of restaurants, we first generate a list of potential chains that have three or more establishments with the same name in a city. We then ask research assistants to label the restaurants they recognize as chains and check the website of the restaurant they are not sure if it is a chain. For restaurants commonly recognize as chains, we call them "national chains," for other lesser known chains which often operate locally, we call them "local chains." For restaurant review information, we use the review rating and the number of reviews posted on the restaurant's Yelp page at the beginning of the experiment.

We first examine how restaurant characteristics affect the CTR of its search ads by regressing

[10] Gain from advertising is ($\$96,000 \times 6.2\% \times 70\% =)\$4,166$ per quarter, and the cost of advertising is $1,200 per quarter.

[11] The patterns of business churning calculated using Yelp data roughly match those using census data (Glaeser et al., 2018).

the standardized CTR of paid search link on restaurant characteristics. Since we observe paid search ads only in the experiment period, the paid CTR is standardized by its standard deviation during the experiment.

Panel A of Table 4 presents the effects of restaurant characteristics on paid CTR As expected, consumers are less likely to click on paid search ads featuring older restaurants and chain restaurants whereas consumers are more likely to click on search ads featuring restaurants with higher review ratings and with more reviews. Paid CTR of best-known chain restaurants is 0.4 standard deviations lower than non-chain restaurants, and restaurants with review rating 4.5 stars or higher have CTR almost one standard deviation higher than the restaurants with 3 stars or lower. In addition, restaurants with two dollar signs (price ranging between \$11 and \$30 per meal) gain the highest attraction.

The effect of the number of reviews is mixed, Overall, having more reviews is associated with higher paid CTR, but we may not expect the number of reviews to always play a positive role. For a restaurant with a high average review rating, the more reviews it has, the more assured consumers are of its quality. If a restaurant has a low average rating, while more reviews suggest that the restaurant is popular, it also reduces the uncertainty that the restaurant quality is low, so it might deter the consumer from clicking. Column (3)-(5) of Table 4 present the effect of the number of reviews conditional on the average rating of the restaurant. It shows the CTR of paid link reduces with the number of reviews if the restaurant has an average rating of 3-star or lower and increases with the number of reviews if the restaurant has an average rating of 4-star or higher.

The CTR of paid links is the crucial factor in determining how much more page views the restaurant can get from paid search advertising, but the total page view is also affected by how many organic clicks got substituted by paid clicks and the number of paid impressions the restaurant receives from Yelp's search ads package. As shown in and Table 7 and Appendix Figure A4, the average negative effects of search ads on organic page views are small, so we don't expect to detect statistically significant heterogeneous effects on organic CTR. We show the heterogeneous effects on organic CTR and total page views in Appendix Table A5 and A5. The heterogeneous effects on organic CTR are in general statistically insignificant. The heterogeneous effects on total page views are consistent with our prediction from the information role of search ads. Note that the differences in the treatment effects on the total number of page views are smaller than the differences in the effects on paid CTR. This is due to the higher number of paid search impressions Yelp gives to the restaurants with lower paid CTR to help them reach the number of paid page views that the Yelp ads package promises.

We then examine the heterogeneous effects on the second key conversion rate—CTA conversion from page views to leads. On average, we find a decline in the overall CTA conversion rate due to search ads driven by the lower CTA conversion rate for paid page views compared with organic ones. The decreases in overall CTA conversion rates due to search ads for businesses with different characteristics are not directly comparable since the baseline level of CTA conversion rate is different for different businesses. More importantly, the fall in overall CTA conversion rate due to search ads depends not only on paid and organic CTA conversion rates, but also the share of page views led from paid links. So in addition to directly comparing the effects on overall CTA conversion rates as shown in Panel A of Table 5 and 6, we also examine the percentage reduction in the CTA conversion rate of paid page visit is compared with organic page visits in Panel B of Table 5 and 6.

Summarizing the heterogeneous effects on CTA conversion rates, Panel B of Table 6 shows that relative to CTA conversion rate of organic page views, the percentage decrease in conversion rate of paid page visits is greater for older restaurants and chain restaurants. Panel B of Table 5 shows that the percentage decrease is smaller for restaurants highly rated and with more reviews.

Among all restaurant characteristics we analyze, the factor that has the biggest influence on conversion rate is the posted review rating of the restaurants. Comparing the restaurants with 4.5-star or above with restaurants with 3-star or below, the paid CTR is almost one standard deviation higher, and the loss of CTA conversion rate for paid page views is almost half smaller. This suggest that the business's reputation on the platform plays a key role in affecting the conversion rate of search ads. Furthermore, we find that the advertising effects monotonically increase with review ratings, suggesting that the counter-signaling does not apply in the search ads setting.

Although the comparison of advertising effects between chain and independent restaurants are consistent with the informational view of search ads, the differences may be less stark than we expected given the chain restaurants are well known. Why chain restaurants such as KFC that everyone knows about can still gain from paid search advertising? Let's first think about the scenario in which the effects of search ads would be precisely zero. As discussed in Blake et al. (2015), if the consumer intends to go to KFC and use the query "KFC" in the neighborhood she intends to go, the consumer will go to KFC regardless whether a paid search ad for KFC is shown or not. Such scenarios where search ads have no effect is unlikely to happen on Yelp since Yelp avoids listing restaurant in the paid search link if the restaurant would appear in the top three positions of the organic search results. Given the most relevant KFC will appear top in the organic result, paid search ads will not appear in such searches. Instead, KFC may appear in the paid search ads if the consumer searches for "fried chicken" or "fast food", even though the consumer knows about KFC, she may not have it in mind when she searches and she may not know there is a KFC in the neighborhood she searches, so the paid search ads for a well-known chain restaurant still provide information to consumers that both remind them the existence of the choice and informs them the restaurant location.

Besides the characteristics we have discussed, another dimension worth examining is the volume of organic page views the restaurant's Yelp page has before the experiment. Jeziorski and Moorthy (2017) use the ranking of a website's total unique visitors and page views in the last three months (provided by Alexa.com) to approximate website prominence and they find that more prominent websites gain less in CTR when they improve their ranking in the paid search results. Similarly, we can use the total page views of a restaurant's Yelp page in the last three months before the experiment to approximate the restaurant prominence. What do we expect for the return of paid search ads for prominent restaurants? On the one hand, restaurant prominence manifests its popularity and prominent restaurants are more likely to be good matches for consumers. On the other hand, as shown in Jeziorski and Moorthy (2017), if a restaurant is so popular that the consumers already know the restaurant, the informational value of being shown in the search ads would to be low and so does the effect of search ads. However, due to Yelp's setting of not showing the restaurant in the paid search ads if it ranks top three in the organic search, the prominent restaurants will only appear in the search ads following search keywords that do not often lead to the restaurant. Narayanan and Kalyanam (2015) show that websites gain more from keywords that consumers do not often use to search for the website. So the prominent restaurants may not be familiar to the consumers who see it in the search ads. The relationship between prominence and CTR of search ads is also complicated by the cases in which the restaurant appear in both paid search ads and organic links (although not in the top three organic results). Given consumers do not click strictly sequentially Jeziorski and Moorthy (2017), they may notice two links in the search results and randomly choose which one to click. So looking only at the CTR of paid links and the effect on organic links may yield biased picture of the effect of paid search ads, we will check the effect on the organic and paid CTR as well as on the overall clicks.

We present the heterogeneous effects with respect to prominence for paid and organic CTR, overall page views, and CTA conversion rate. We approximate the prominence of a restaurant's Yelp page by its total page views in the three months before the start of the experiment. We then examine the distribution of the total page views and put the restaurants into five prominence categories using the 50th, 75th, 90th, and 99th percentile of the total page view as cutoffs.

The heterogeneous effects of prominence on paid CTR is shown in Appendix Table A3. For the overall paid CTR, restaurants that are more prominent enjoy higher paid CTR. In particular, the most prominent restaurant (above 99th percentile in the distribution of pre-experiment page views) has the paid CTR 0.9 standard deviation higher than those for restaurants in the bottom 50th percentile. Check the results jointly with the effects of search ads on organic CTR (Appendix Table A6), the loss in organic CTR are insignificant across all groups, and the effect sizes are small for the most prominent restaurants, search ads reduce the organic CTR by 0.04 standard deviation. Overall, the results show that more prominent restaurants gains more page views from paid search ads. The heterogeneous effects on CTA conversion rate are shown in Table 6. Panel A shows that the absolute loss in conversion rate is smaller for more prominent restaurants, and relative to the CTA conversion rate of organic page visits, the percentage loss of conversion rate of paid page visits does not have a monotonic relationship with prominence. The loss is relatively small for the restaurant with page views in the 75-90th percentile, and there is no loss for the restaurant with page views above the 99th percentile. In summary, the gain from search advertising is the greatest for the most prominent restaurant.

Given two forces that drives the results with respect to prominence—informational value and the potential of being a good match to consumers—the value of being a good match dominates according to the result on prominence. The findings with respect to prominence looks different from Jeziorski and Moorthy (2017) on the surface, but there are key differences in the settings. Both papers focus on clicks into seller websites, restaurants in our case and retailers selling cameras in Jeziorski and Moorthy (2017).[12] When consumers search for camera retailers, they do not need to rely on seeing the paid search ads to reach the retailer website, they can directly search retailer names, such as "bestbuy", "amazon", "ebay" or visit the seller website directly. They may have already done so before seeing the website in the paid search or plan to do so afterwards. So for prominent retailers, paid search ads add little information. But for retailers that are not prominent, consumers probably will not visit their websites unless they appear in search ads, so interested consumers who do not know these retailers can reach these sites through search ads. In the restaurant setting, consumers are unlikely to directly search for the popular restaurant's name, so even for the most prominent restaurant, it is useful to appear in the search ads to remind consumers of their existence.

[12] In Jeziorski and Moorthy (2017) footnote 12, the advertisers bidding on the product brand keywords are retailers.

5 Conclusion and Discussions

Overall, our results shed light on the effectiveness of paid search advertising for small businesses. To our knowledge, this is the largest scale advertising effectiveness study in terms of the number of businesses involved. For a common restaurant on Yelp and similar platforms, we show that search advertising does have a large impact. We find larger percentage increase in page views than leads due to search advertising, suggesting consumers visiting the page through paid search ads have lower conversion rate into leads than consumers visiting the page through organic links. It also implies that the incremental consumers acquired from the paid search may be systematically different from the average consumers visiting the restaurant page through organic search. There are rooms for future studies to explain the differences in consumer search and purchase behavior if the individual-level search and purchase data is available.

While we do not have the sales information required to directly estimate the impact of advertising on revenue, we obtain historical sales data for a sample of restaurants in Washington state. Establishing the relationship between changes in revenue and changes in page views, we estimate the impact of advertising on sales using this proxy. As we show below, the return of paid search advertising is positive, on average, for our sample of restaurants - which consists of restaurants that were not advertising on Yelp, and one might expect a larger return for businesses that are advertising.

In addition, we test whether the mechanism of paid search advertising is consistent with the information. We find that paid search advertising is in general more effective for businesses that could deliver more new information being featured in the search ads, for example, restaurants that are newer and independent. The heterogeneous effect of search advertising also yield new insights into role of consumer review ratings on the search ads. We find high quality restaurant—highly rated by consumers or have high page views—enjoy greater advertising effects.

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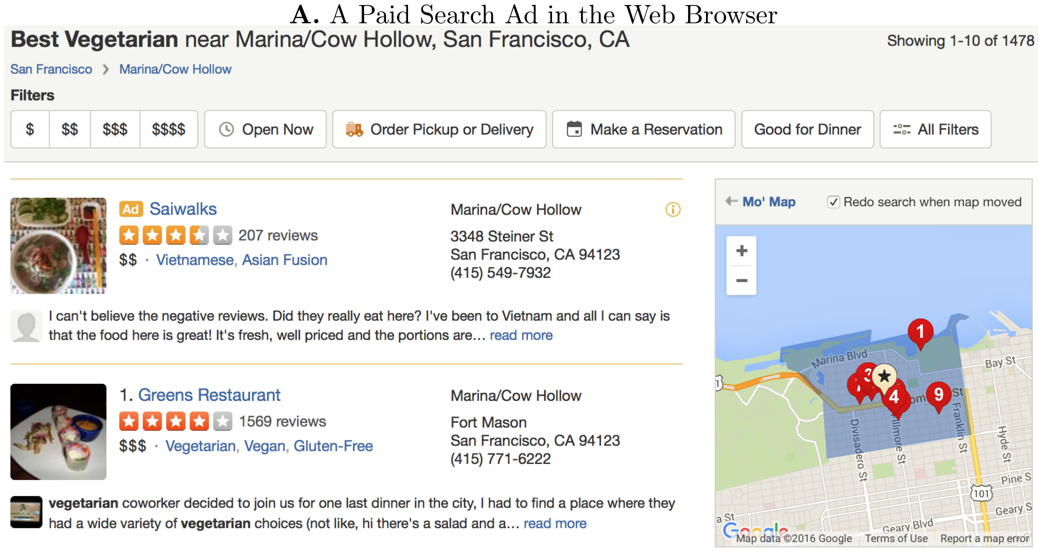
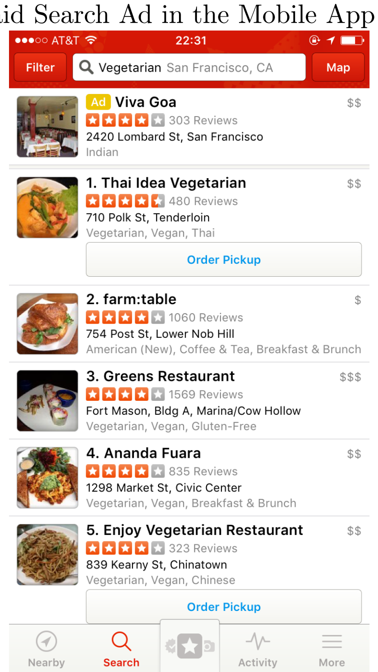
Figures and Tables

Figure 1: Snapshots of Paid Search Ads

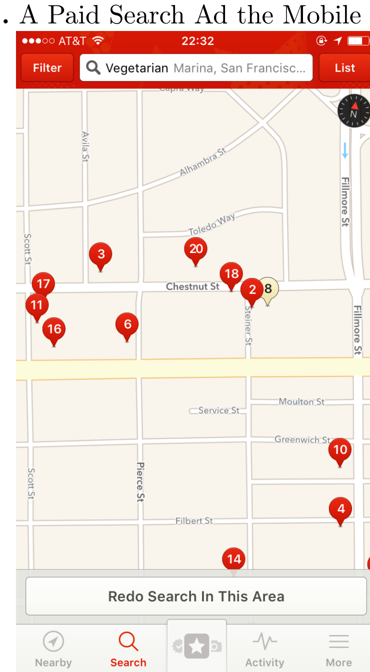
A. A Paid Search Ad in the Web Browser



B. A Paid Search Ad in the Mobile App



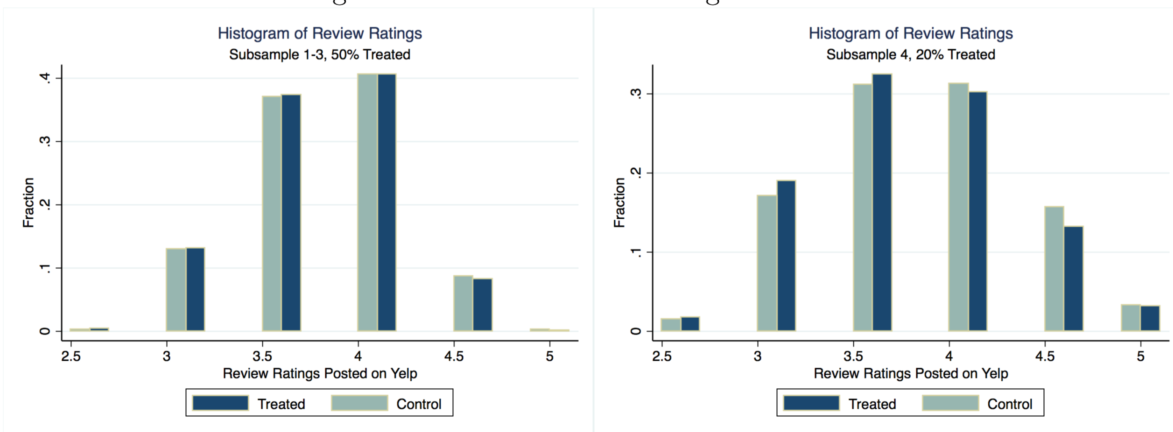
C. A Paid Search Ad the Mobile App Map



Notes: The above figures show examples of result screens following the search for "Vegetarian" near Marina, San Francisco, CA. The advertised restaurant is shown in the paid search slot (the first link) on the page. A yellow flag "Ad" is shown next to the advertised restaurant's name that distinguishes the paid link from the organic links. During the period of our data collection, at most one slot is allocated to paid search ads in a search session.

Figure 2: Baseline Restaurant Review Characteristics of the Treated and Control Samples

A. Histogram of Posted Review Ratings of Each Restaurant

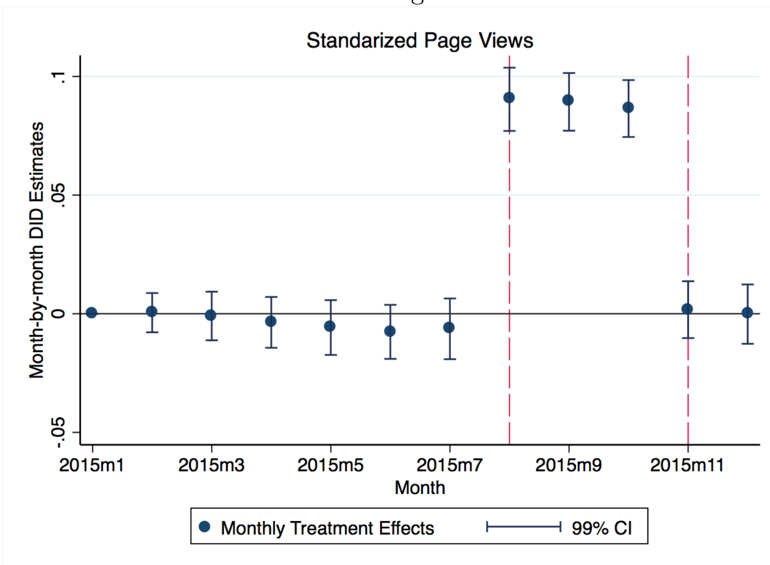


B. Histogram of the Number of Reviews of Each Restaurant

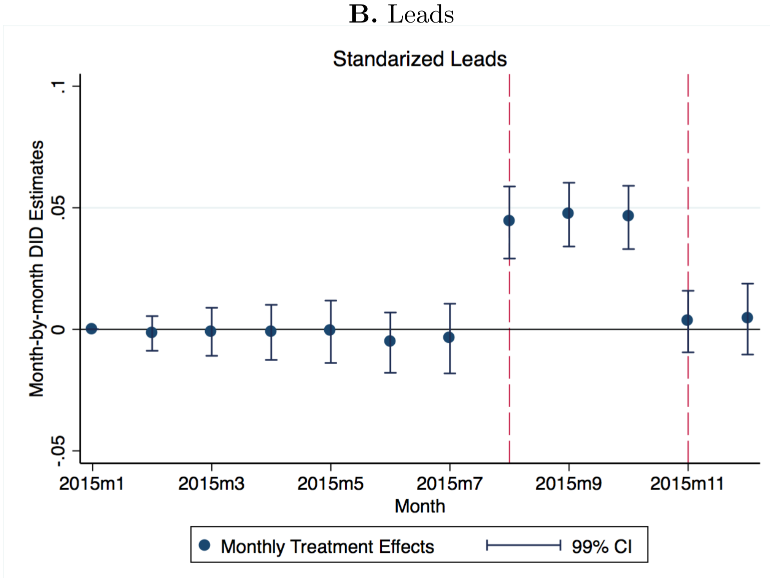
Notes: **1** Figure A plots the distribution of restaurant ratings before the experiment by treatment status . **2** Figure B plots the distribution of the number of reviews of the restaurants before the experiment by treatment status. Due to the sparse long right-tail, the distribution of number of reviews is truncated at 1,000. **3** Subsample 4 is plotted separately since its treated ratio is 20%, different from the 50% treated ratio in subsample 1-3. With different treated ratio, comparing treated and control by simply pooling all subsamples together results in different subsample weights within the treated and control samples and invalidates the balance test. **4** The plots show the balance in restaurant characteristics between the treated the control samples. The randomization test of outcome variables is shown in Appendix Table A1.

Figure 3: Monthly Diff-in-diff Estimates for Standardized Page Views and Leads

A. Total Page Views



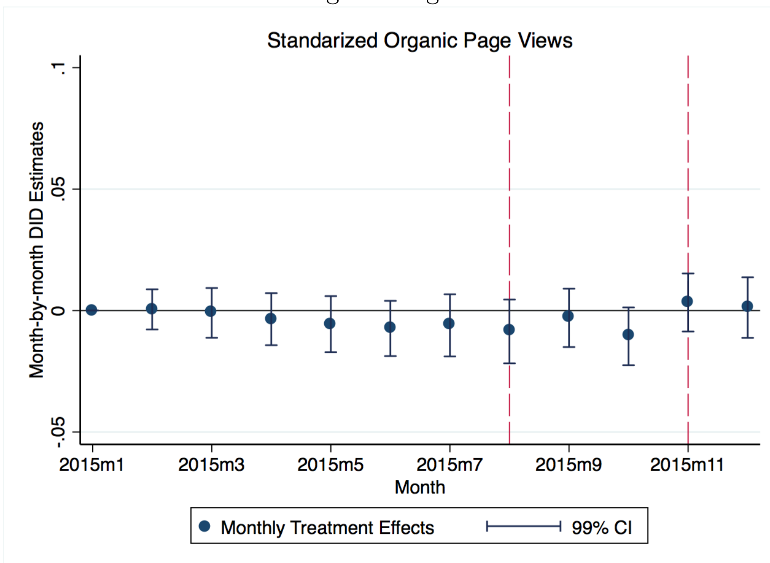
B. Leads



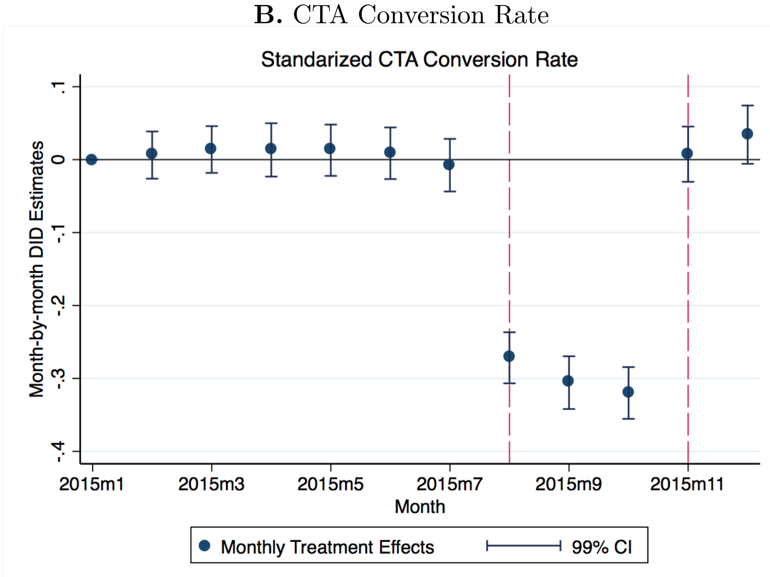
Notes: **1** The figures plot the differential changes in treated and control sample using monthly difference-in-differences estimates treating the first month as the baseline. More specifically, we run regression according to equation 4 and replace time dummies by month dummies. **2** Each outcome is standardized by its sample mean and standard deviation before the experiment. **3** The two dashed vertical lines indicate the first month the experiment starts and ends. **4** See Appendix Figure A1 and A2 for plots of standardized total page views and leads in subsamples.

Figure 4: Monthly Diff-in-diff Estimates for Standardized Organic Page Views and CTA Conversion Rates

A. Organic Page Views



B. CTA Conversion Rate



Notes: **1** The figures plot the differential changes in treated and control sample using monthly difference-in-differences estimates treating the first month as the baseline. More specifically, we run regression according to equation 4 and replace time dummies by month dummies. **2** Each outcome is standardized by its sample mean and standard deviation before the experiment. **3** The two dashed vertical lines indicate the first month the experiment starts and ends. **4** See Appendix Figure A4 and A3 for plots of standardized organic page views and CTA conversion rates in subsamples.

Table 1: Subsamples in the Experiment

Subsample	Description	Size	Treated	Control
1. Yelp Reservation Restaurants	Restaurants on Yelp that have partnered with Yelp's reservation service.	307	50%	50%
2. OpenTable Restaurants	Restaurants on Yelp that have also partnered with the OpenTable reservation service.	5,740	49%	51%
3. EAT24 Restaurants	Restaurants on Yelp that have partnered with Yelp's delivery service.	5,867	50%	50%
4. Non-partner Restaurants in WA	Restaurants on Yelp that are non-partners and are in Washington.	6,381	20%	80%
	Total:	18,295	7,210	11,085

Notes: **1** Mutually exclusive subsamples of restaurants listed on Yelp are selected before the randomization. We divide the full experiment sample into subsamples since certain outcomes of interests are only available in subsamples. For example, data on reservation is only available for restaurants that have signed up to use Yelp's reservation platform (subsample 1). Data on takeout orders are only available for restaurants that have signed up to use Yelp's EAT24 delivery platform (subsample 3). Historical restaurant revenue data are only available for Washington restaurants (subsample 4). **2** The restaurants in the experiment are chosen in the following steps: (1) take all US restaurants that belong to each subsample; (2) if a restaurant falls in two or more subsamples, randomly assign it to one subsample; (3) exclude all restaurants that are not currently operating or are not ad-qualified (e.g. does not have enough good review ratings or miss key information or photo.); (4) exclude restaurants that have actively advertised on the Yelp platform (less than 10% of the sample); (5) randomly exclude restaurants if a marketing market is over sampled. This leaves us with the sample size listed in the above table. **3** Within each subsample, the treatment is randomly assigned to restaurants. The restaurants treated receives the Yelp business ad package for free for three months between August and October 2015.

Table 2: Average Treatment Effects on Consumer Demand Proxies

[Outcomes Standardized]

Weighted Regressors[a]	(1) Page Views	(2) Map Views	(3) Calls from Mobile	(4) External URL Clicks	(5) Reviews	(6) Orders
Treated×ExprOn	0.092***	0.064***	0.031***	0.032***	0.027***	0.017
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.018)
Treated×PostExpr	0.004	0.008*	0.004	0.003	0.002	0.023
	(0.004)	(0.00415)	(0.0054)	(0.00482)	(0.00627)	(0.024)
Other Controls & Business FE, Month FE	x	x	x	x	x	x
N	218,831	218,831	218,831	218,831	218,831	70,294
Mean effects in percentages and their 95% confidence intervals						
During Experiment	18.8%	13.8%	6.5%	6.8%	5.1%	1.42%
	[17.7%,19.9%]	[12.4%,15.1%]	[5.1%,7.9%]	[4.5%,9.5%]	[3.1%,6.9%]	[-1.86%,4.56%]
Post Experiment	0.1%	2.8%	1.2%	0.3%	1.1%	0.02%
	[-0.5%,2.5%]	[.04%,2.0%]	[-0.5%,2.9%]	[-2.6%,3.2%]	[-1.9%,4.1%]	[-0.02%,0.06%]

* p<0.05, ** p<0.01, *** p<0.001. Standard errors in parentheses, clustered at the business level.

[a]Regressors are weighted according to regression equation (4). Coefficients of Treated×ExprOn and Treated×PostExpr reflect the overall sample average treatment effects during the experiment and after the experiment.

Notes: **1** The table shows the results of the regression equation (4) that estimates the average treatment effects on various outcomes. The observation is at the business×month level, and the outcomes are standardized by the standard deviation of each subsample in the sample period before the experiment (Jan-Jul, 2015). **2** The second half of the table reports the effects of paid ads in percentage terms. The 95% confidence interval of the percentage estimates are calculated using bootstrap.

Table 3: Average Treatment Effects on Call-to-action (CTA) Conversion Rates

Panel A. *Effect of Paid Search Ads on Overall CTA Conversion Rates*

[Standardized Outcomes]	CTA Conversion Rate
Treated×ExprOn	-0.306***
	(0.009)
Treated×ExprOn×SS2	-0.186***
	(0.008)
Treated×ExprOn×SS3	-0.362***
	(0.013)
Treated×ExprOn×SS4	-0.366***
	(0.023)
Treated×PostExpr	0.014
	(0.01095)
Treated×PostExpr×SS2	0.011
	(0.01)
Treated×PostExpr×SS3	-0.001
	(0.016)
Treated×PostExpr×SS4	0.031**
	(0.026)
Other Controls & Business FE, Month FE	x
N	218,680

a. Standard errors in parentheses, clustered at the business level. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

b. The regressions follow the specification in equation (4). Other control variables include the full sets of period dummy, subsample dummy, treatment dummy, and their interactions. Coefficients of Treated×ExprOn and Treated×PostExpr reflect the overall sample treatment effects during and after the experiment. The coefficients interacted with the subsample dummies SS2 - SS4 represent the treatment effects in subsample 2-4.

Panel B. *Proportional Reduction in the Probability of Converting from Page Views to an Action (CTA Conversion Rate) from Organic Views to Paid Views*

(% Loss in Overall Conversion Rate of Paid Views)	
Rating	Ads On
Subsample1	32.0%
Subsample2	26.4%
Subsample3	41.6%
Subsample4	43.3%

Note: Panel A reports the average treatment effects of the call-to-action conversion rate. Panel B reports results converted to the absolute value of the reduction to a percent of the CTA conversion of organic views. Apply subsample weight, we find that the the CTA conversion rate for paid page visits decreases by 37.25% compared with organic page visits in the overall sample.

Table 4: Heterogeneous Click-through Rate (CTR) of Paid Links

[Outcome Standardized]	(1)	(2)	(3)	(4)	(5)
	Paid CTR (Overall)	Column(1) in %	Paid CTR (<3.5 Star)	Paid CTR (3.5 Star)	Paid CTR (≥4 Star)
$Age(Year)\|Age < 10$	-0.006*	-0.4%	-0.032***	-0.006	-0.012**
	(0.003)		(0.006)	(0.004)	(0.005)
$I(Age \geq 10Yrs)$	-0.058**	-3.5%	-0.23***	-0.083**	-0.102***
	(0.02)		(0.045)	(0.03)	(0.033)
$I(LocalChain)$	-0.135***	-8.1%	-0.101*	-0.013	-0.322***
	(0.027)		(0.046)	(0.037)	(0.052)
$I(NationalChain)$	-0.421***	-25.2%	-0.472***	-0.258***	-0.769***
	(0.037)		(0.054)	(0.051)	(0.086)
$I(3.5star)$	0.094***	5.6%			
	(0.02)				
$I(4star)$	0.452***	27.0%			
	(0.01992)				
$I(\geq 4.5star)$	0.956***	57.2%			
	(0.027)				
$Ln(\#Reviews)$	0.034***	2.0%	-0.045**	0.004	0.057***
	(0.007)		(0.016)	(0.011)	(0.011)
Price Category, Subsample Dummies	x		x	x	x
N	208,38		3,087	7,624	710,127

Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

Note: **1** Column (1) reports the results of regressing an advertising business's CTR of paid links on predetermined (prior to the experiment) restaurant characteristics. The sample includes all treated restaurants during the experiment period, and each observation is at the business×month level. **2** Column (3)-(5) runs the same regression as in column (1) conditional on the sample of restaurants with different review ratings to examine the effect direction of the number of page views. **3** The outcome variable paid CTR is standardized by its standard deviation of all treated businesses during the treated period . **3** Column (2) is the created by dividing the effects by the mean paid CTR. **4** The dummy control variables exclude the lowest category within each characteristics dimension.

Table 5: Heterogeneous Effects on Call-to-action (CTA) Conversion Rates With Respect To Ratings and the Number of Reviews

Panel A. *Effect of Paid Search Ads on Overall CTA Conversion Rates*

[Outcomes Standardized]	Conversion Rate		Conversion Rate
ExprOn×Treated		ExprOn×Treated	
×I(<3.5 Stars)	-0.488***	×I(#Rev in Tier 1)	-0.527***
	(0.031)		(0.031)
×I(3.5 Stars)	-0.346***	×I(#Rev in Tier 2)	-0.361***
	(0.015)		(0.015)
×I(4 Star)	-0.214***	×I(#Rev in Tier 3)	-0.228***
	(0.012)		(0.012)
×I(>4 Star)	-0.224***	×I(#Rev in Tier 4)	-0.116***
	(0.029)		(0.009)
Other Controls	x		x
Fixed Effects	Business Month		Business Month
N	218,249		218,680
F-test	p-value		p-value
Coeff1=Coeff2	3.34×10^{-5}		1.39×10^{-6}
Coeff2=Coeff3	2.02×10^{-11}		1.07×10^{-11}
Coeff3=Coeff4	0.75		9.72×10^{-14}

a. Standard errors in parentheses, clustered at the business level. * p<0.05, ** p<0.01, *** p<0.001.
b. The regressions follow the specification in equation (5). Other controls include the full sets of period dummies, subsample dummies, treated dummy, and their interactions. Weights are applied to the regressors so that the above coefficient represents the treatment effect for restaurants with each characteristics in the fall sample.

Panel B. *Percentage Reduction in CTA Conversion Rate (Paid Page Views Vs. Organic Page Views)*

(% Conversion Rate Change)			
Rating		# of Reviews	
<3.5 Stars	-64.1%	Tier1 (in 0-25th percentile)	-48.9%
3.5 Stars	-51.0%	Tier2 (in 25-50th percentile)	-50.3%
4 Star	-33.4%	Tier3 (in 50-75th percentile)-	-42.4%
>4 Star	-38.3%	Tier4 (in 75-100th percentile)	-36.6%

Note: **1** Panel A reports regression results examining the differential reduction in overall conversion rate of the treated businesses due to paid search advertising with respect to restaurant ratings and number of reviews. Panel B reports the percentage reduction in CTA conversion rate comparing page views from paid clicks and those from organic clicks. **2** The regressions includes the full sample of businesses during the period seven months before and three months during the experiment. **3** The table shows that businesses with higher ratings, more reviews, and higher prices experience the smallest loss in CTA conversion of paid views.

Table 6: Heterogeneous Effects on Call-to-action (CTA) Conversion Rates With Respect To Restaurant Age and Chain Status

Panel A. *Effect of Paid Search Ads on Overall CTA Conversion Rates*

[Standardized Outcomes]	Conversion Rate		Conversion Rate
ExprOn×Treated		ExprOn×Treated	
×I(age<1yr)	-0.206***	×I(non-chain)	-0.265***
	(0.04)		(0.008)
×I(age∈[1,2]yr)	-0.216***	×I(local chain)	-0.468***
	(0.027)		(0.04)
×I(age∈[3,4]yr)	-0.279***	×I(national chain)	-0.854***
	(0.019)		(0.093)
×I(age∈[5,10]yr)	-0.293***		
	(0.013)		
×I(age>10yr)	-0.385***		
	(0.021)		
Other Controls	x		x
Fixed Effects	Business		Business
N	218,680		218,680
F-test	p-value		p-value
Coeff1=Coeff2	0.8324	*Coeff1=Coeff2*	4.62×10^{-7}
Coeff2=Coeff3	0.0572	*Coeff2=Coeff3*	1.32×10^{-4}
Coeff3=Coeff4	0.5532		
Coeff4=Coeff5	2.54×10^{-4}		

a. Standard errors in parentheses, clustered at the business level. * p<0.05, ** p<0.01, *** p<0.001.
b. The regressions follow the specification in equation (5). Other controls include the full sets of period dummies, subsample dummies, treated dummy, and their interactions. Weights are applied to the regressors so that the above coefficient represents the treatment effect for restaurants with each characteristics in the fall sample.

Panel B. *Percentage Reduction in CTA Conversion Rate (Paid Page Views Vs. Organic Page Views)*

(% Conversion Rate Reduction in Paid)			
Open in		Chain	
<1year	37.2%	non-chain	44.3%
1-2years	35.8%	local chain	57.4%
3-4years	46.5%	national chain	56.9%
5-10years	46.3%		
>10years	51.7%		

Note: **1** Panel A reports regression results examining the differential reduction in overall conversion rate of the treated businesses due to paid search advertising with respect to restaurant age and chain status. Panel B reports the percentage reduction in CTA conversion rate comparing page views from paid clicks and those from organic clicks. **2** The regressions includes the full sample of businesses during the period seven months before and three months during the experiment. **3** The table shows that businesses that are newer, none-chains, and have higher page traffic before the experiments had smallest loss in CTA conversion of paid views.

Table 7: Average Treatment Effect on Organic Impressions and Page Views

[Outcomes Standardized]

Weighted Regressors[a]	(1) Organic Impression	(2) Organic Page Views	(3) Organic CTR
Treated×ExprOn	0.001	-0.004	-0.091*
	(0.003)	(0.003)	(0.041)
Treated×PostExpr	-0.001	0.006	-0.157
	(0.005)	(0.004)	(0.085)
Other Controls & Business FE, Month FE	x	x	x
N	218,831	218,831	218,637

* $p<0.05$, ** $p<0.01$, *** $p<0.001$. Standard errors in parentheses, clustered at the business level.

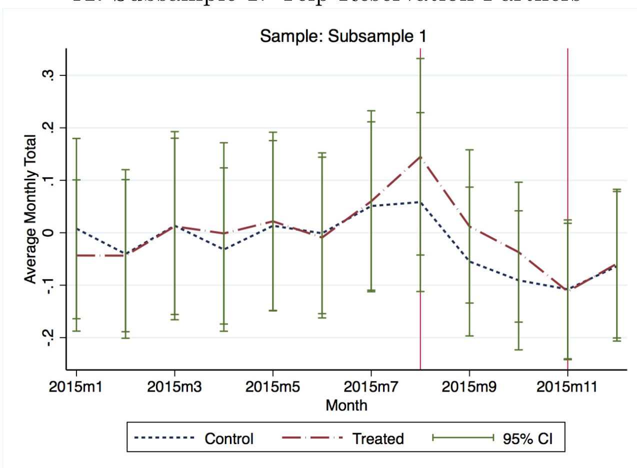
[a]Regressors are weighted according to regression equation (4) so coefficients of Treated×ExprOn and Treated×PostExpr reflect the overall sample treatment effects during and after the experiment.

Notes: The table shows the results of the regression specified by equation (4) that estimates the average treatment effects. The observation is at the business×month level, and the outcomes are standardized by the standard deviation of each subsample in the sample period before the experiment (Jan-Jul, 2015).

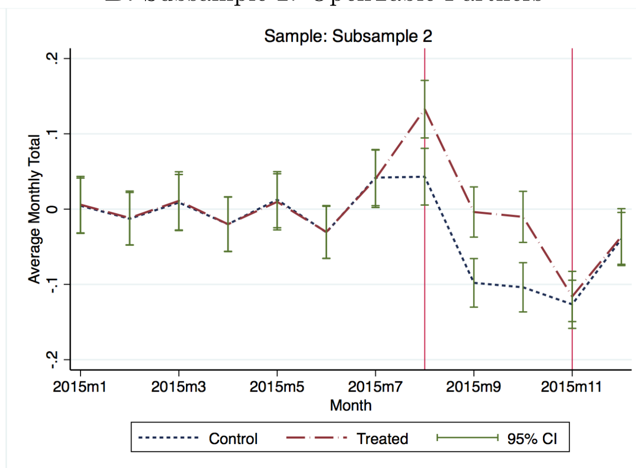
Appendix

Figure A1: Standardized Subsample Monthly Total Page Views by Treatment Status

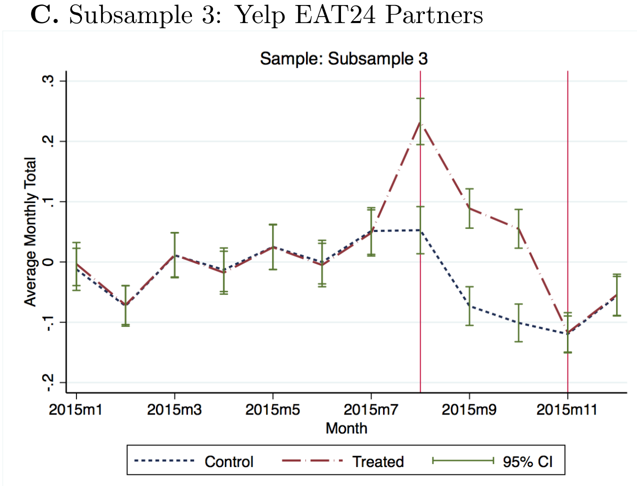
A. Subsample 1: Yelp Reservation Partners



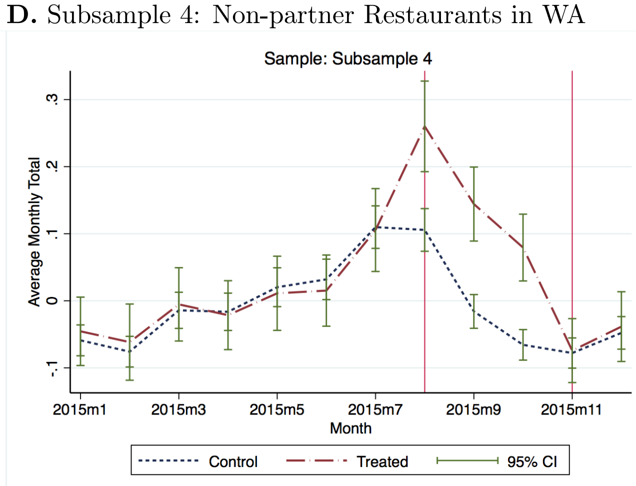
B. Subsample 2: OpenTable Partners



C. Subsample 3: Yelp EAT24 Partners

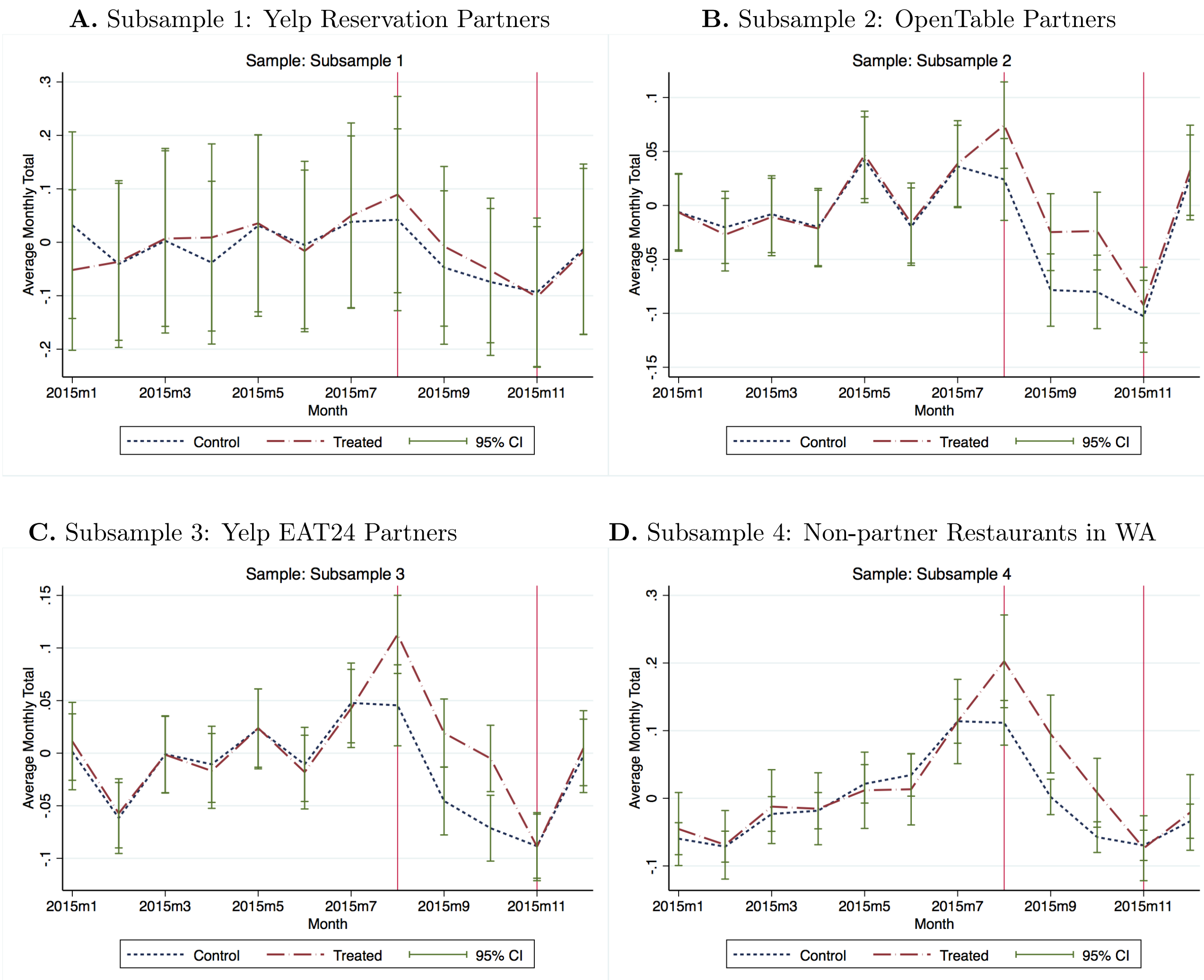


D. Subsample 4: Non-partner Restaurants in WA



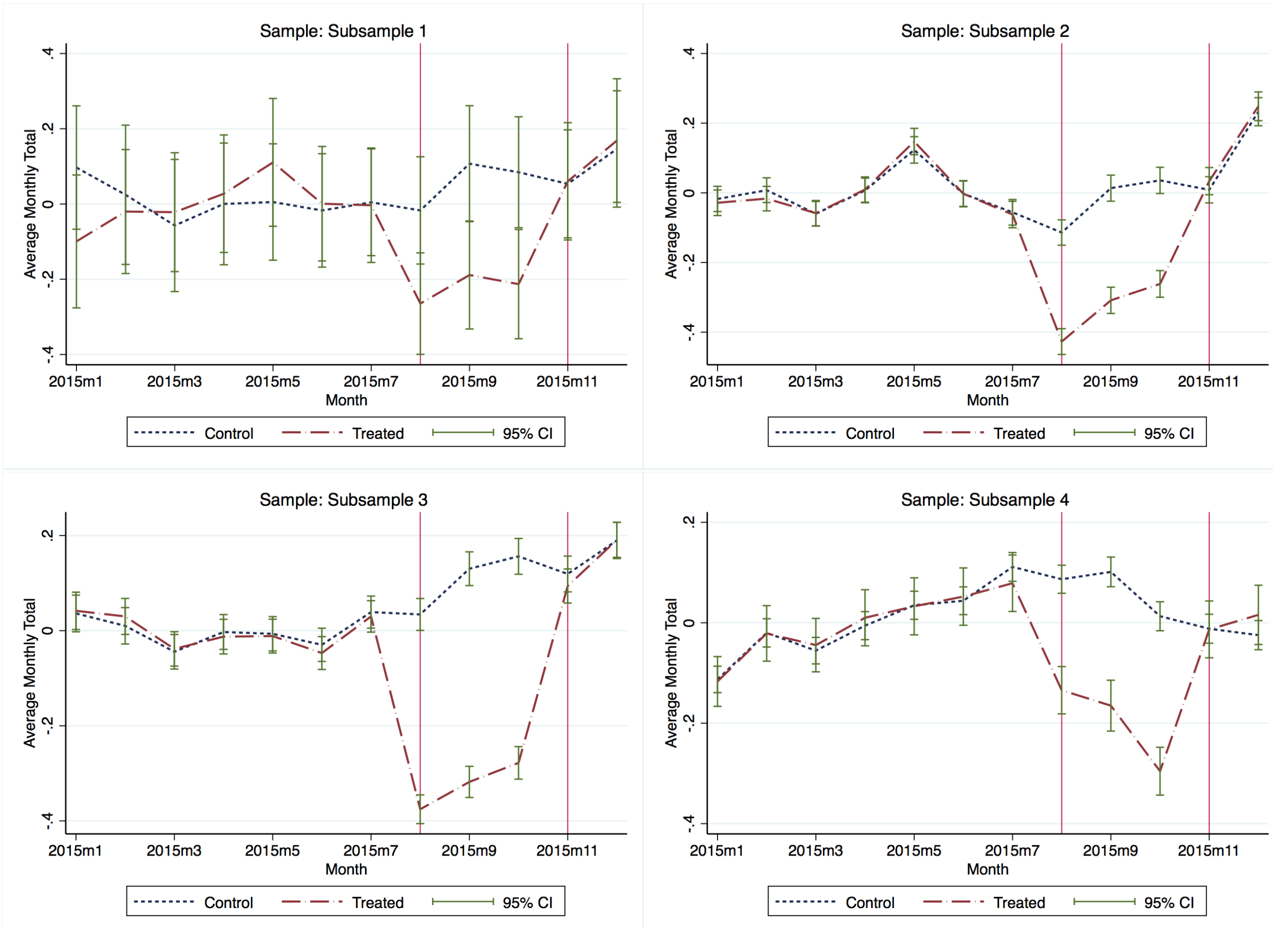
Notes: **1** The figures plot the monthly average Yelp page views at the business level. **2** The outcome is standardized by its subsample mean and standard deviation before the experiment to show the effect size relative to each subsample's SD. **3** The two solid vertical lines indicate the start and end of the experiment. **4** See Table 1 for information of each subsample.

Figure A2: Standardized Subsample Monthly Total Leads by Treatment Status



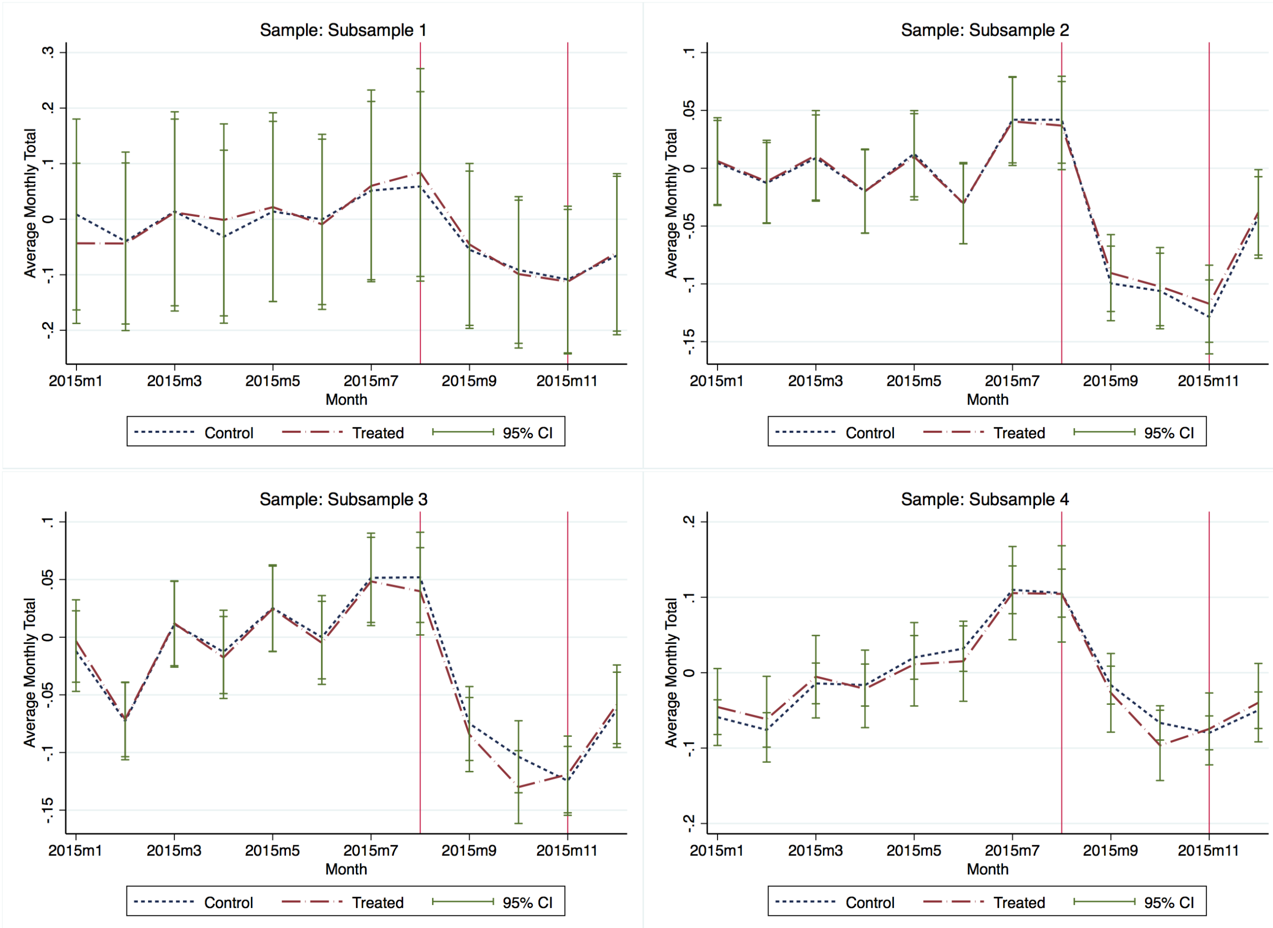
Notes: **1** The figures plot the monthly leads (requests for direction, calls to restaurants, and clicks of the restaurant's external URL) at the business level. **2** The outcome is standardized by the its subsample mean and standard deviation before the treatment. **3** The two solid vertical lines indicate the start and end of the experiment. **4** See Table 1 for information of each subsample.

Figure A3: Standardized Subsample Monthly Call-to-action Conversion Rate by Treatment Status



Notes: **1** The figures plot the monthly average CTA conversion rates at the business level. The CTA conversion rate is calculated by $Leads/PageViews$, measuring the probability consumers clicking on the call-to-action buttons (that result to leads) after visiting the restaurant's page. **2** The outcome is standardized by its mean and standard deviation before the treatment. **3** The two solid vertical lines indicates the start and end of the treatment. **4** See Table 1 for information of each subsample.

Figure A4: Standardized Subsample Monthly Organic Views by Treatment Status



Notes: **1** The figures plot the monthly average Yelp organic page views at the business level. **2** The outcome is standardized by its subsample mean and standard deviation before the experiment to show the effect size relative to each subsample's SD. **3** The two solid vertical lines indicate the start and end of the experiment. **4** See Table 1 for information of each subsample.

Table A1: Randomization Check

	p-value of T-test ($H_0 : \mu_{treated} = \mu_{control}$)	
	Partner Sample (Subsample 1-3)	WA non-partner Sample (Subsample 4)
Outcome Variables		
Page Views on Web	0.709	0.427
Page Views on Mobile	0.571	0.652
Total Page Views	0.654	0.726
Map Views on Web	0.818	0.925
Map Views on Mobile	0.276	0.312
Total Map Views	0.564	0.627
External URL Clicks	0.514	0.175
Call from Mobile	0.707	0.203
Check-Ins	0.198	0.561
# of Trusted Reviews	0.526	0.566
% of Trusted Reviews	0.498	0.728
Average Review Ratings	0.130	0.452
Review Length	0.432	0.415

Notes: **1** The table reports the the p-values of tests of the null hypothesis that the mean of the treated and control samples are equal. **2** The test is done separately for strata1-3 and strata 4 because the treated ratio is different for subsample 4. The result remains the same testing the randomization within each subsample. **3** The tests are conducted on the sample in July 2015, the month before the start of the experiment.

Table A2: Overall Average Treatment Effect

[Outcomes Standardized]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Weighted Regressors[a]	Organic Impression	Organic Page Views	Organic CTR	Total Page Views	Map Views	Calls from Mobile	External URL Clicks	Reviews	Orders
Treated×ExprOn	0.001	-0.004	-0.091*	0.092***	0.064***	0.031***	0.032***	0.027***	0.017
	(0.003)	(0.003)	(0.041)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.018)
Treated×ExprOn×SS2	0.004	0.001	-0.035	0.125***	0.082***	0.033***	0.07***	0.045***	
	(0.006)	(0.006)	(0.043)	(0.006)	(0.007)	(0.007)	(0.009)	(0.011)	
Treated×ExprOn×SS3	0.005	-0.008*	-0.112	0.103***	0.072***	0.042***	0.014**	0.022**	
	(0.005)	(0.004)	(0.091)	(0.004)	(0.006)	(0.006)	(0.006)	(0.008)	
Treated×ExprOn×SS4	-0.002	-0.006**	-0.135	0.051***	0.041***	0.017***	0.011**	0.017**	
	(0.002)	(0.002)	(0.075)	(0.003)	(0.004)	(0.003)	(0.004)	(0.006)	
Treated×PostExpr	-0.001	0.006	-0.157	0.004	0.008*	0.004	0.003	0.002	0.023
	(0.005)	(0.004)	(0.085)	(0.004)	(0.00415)	(0.0054)	(0.00482)	(0.00627)	(0.024)
Treated×PostExpr×SS2	-0.001	0.007	0.024	0.006	0.011	0.002	0.012	0.001	
	(0.011)	(0.009)	(0.161)	(0.009)	(0.009)	(0.012)	(0.012)	(0.013)	
Treated×PostExpr×SS3	0.007	0.007	-0.099	0.005	0.012	0.002	-0.002	-0.005	
	(0.007)	(0.006)	(0.12)	(0.006)	(0.008)	(0.01)	(0.007)	(0.01)	
Treated×PostExpr×SS4	-0.004	0.003	-0.377**	0.003	0.004	0.006	0.000	0.008	
	(0.003)	(0.003)	(0.164)	(0.003)	(0.004)	(0.004)	(0.004)	(0.006)	
Other Controls & Business FE, Month FE	x	x	x	x	x	x	x	x	x
N	218,831	218,831	218,637	218,831	218,831	218,831	218,831	218,831	70,294

* p<0.05, ** p<0.01, *** p<0.001. Standard errors in parentheses, clustered at the business level.

[a]Regressors are weighted according to regression equation (4) so coefficients of Treated×ExprOn and Treated×PostExpr reflect the overall sample treatment effects during and after the experiment. The coefficients interacted with the subsample dummies SS2 - SS4 represent the treatment effects in subsample 2-4.

Notes: The table shows the results of the regression specified by equation (4) that estimates the average treatment effects. The observation is at the business×month level, and the outcomes are standardized by the standard deviation of each subsample in the sample period before the experiment (Jan-Jul, 2015).

Table A3: Heterogeneous Click-through Rate (CTR) of Paid Links

[Outcome Standardized]	(1) Paid CTR (Web)	(2) Paid CTR (MobSite)	(3) Paid CTR (MobApp)	(4) Paid CTR (Overall)	(5) Overall % Effects
$Age(Year)\|Age < 10$	-0.001	-0.009**	0.002	-0.002	-0.1%
	(0.003)	(0.003)	(0.003)	(0.003)	
$I(Age \geq 10Yrs)$	-0.022	-0.083**	0.001	-0.027	-1.6%
	(0.02)	(0.021)	(0.019)	(0.02)	
$I(LocalChain)$	-0.137***	-0.146***	-0.057**	-0.122***	-7.3%
	(0.027)	(0.028)	(0.027)	(0.027)	
$I(NationalChain)$	-0.472***	-0.616***	-0.318***	-0.442***	-26.4%
	(0.037)	(0.038)	(0.036)	(0.036)	
$I(3.5star)$	0.076***	-0.056**	0.131***	0.101***	6.0%
	(0.02)	(0.021)	(0.019)	(0.019)	
$I(4star)$	0.359***	0.186***	0.494***	0.435***	26.1%
	(0.02066)	(0.0213)	(0.02005)	(0.02017)	
$I(\geq 4.5star)$	0.755***	0.534***	0.982***	0.92***	55.1%
	(0.028)	(0.028)	(0.027)	(0.027)	
$TrafficTier2$	-0.146***	-0.05**	0.075***	-0.03	-1.8%
	(0.017)	(0.018)	(0.017)	(0.017)	
$TrafficTier3$	-0.198***	-0.052**	0.181***	0.004	0.2%
	(0.02)	(0.021)	(0.02)	(0.02)	
$TrafficTier4$	-0.075***	0.009	0.434***	0.191***	11.4%
	(0.025)	(0.025)	(0.024)	(0.024)	
$TrafficTier5$	0.437***	0.255***	1.28***	0.902***	54.0%
	(0.061)	(0.063)	(0.059)	(0.059)	
$I(\$\$)$	0.213***	0.147***	0.178***	0.2***	12.0%
	(0.017)	(0.018)	(0.017)	(0.017)	
$I(\$\$\$)$	0.27***	0.027	-0.064**	0.059*	3.6%
	(0.027)	(0.027)	(0.026)	(0.026)	
$I(\$\$\$\$)$	0.167***	-0.14**	-0.156**	-0.048	-2.9%
	(0.051)	(0.052)	(0.049)	(0.049)	
$I(\$missing)$	-0.014	-0.331***	-0.07	-0.031	-1.9%
	(0.086)	(0.089)	(0.083)	(0.084)	
Subsample Dummies	x	x	x	x	
N	208,38	208,38	208,38	208,38	

Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

Note: **1** This table reports the results from OLS regressions of an advertising business's click-through rate (CTR) of paid links on predetermined restaurant characteristics before the experiment. The sample includes all treated restaurants during the experiment period. The observation is at the business-month level. **2** The dependent variables in column (1)-(4) are click-through rate of paid links of the treated businesses standardized by the standard deviation of the outcomes of the treated businesses during the treated period . **3** Column (5) is the created by dividing the estimates in column (4) by the mean CTR. **4** The dummy control variables exclude the lowest within each characteristics category. We define Tier2 to Tier 5 websites in terms of website traffic if the website's total page views before the experiment is in the 0-50th, 50-75th, 75-90th, 90–99th or above 99th percentile.

Table A4: Heterogeneous Effects on Call-to-action (CTA) Conversion Rates With Respect To Ratings, Number of Reviews and Price

Panel A. *Effect of Paid Search Ads on Overall CTA Conversion Rates*

[Outcomes Standardized]	Conversion Rate		Conversion Rate
ExprOn×Treated		ExprOn×Treated	
×I($)	-0.413***	×I(Traffic in Tier 1)	-0.468***
	(0.022)		(0.017)
×I($$)	-0.273***	×I(Traffic in Tier 2)	-0.22***
	(0.011)		(0.011)
×I($$$)	-0.194***	×I(Traffic in Tier 3)	-0.087***
	(0.013)		(0.013)
×I($$$$)	-0.156***	×I(Traffic in Tier 4)	-0.055***
	(0.035)		(0.012)
		×I(Traffic in Tier 5)	0.035
			(0.025)
	x		x
Fixed Effects	Business		Business
	Month		218,680
N	218,680		p-value
F-test	p-value	*Coeff1=Coeff2*	2.83×10^{-33}
Coeff1=Coeff2	1.25×10^{-8}	*Coeff2=Coeff3*	1.58×10^{-14}
Coeff2=Coeff3	3.66×10^{-6}	*Coeff3=Coeff4*	0.072
Coeff3=Coeff4	0.37	*Coeff4=Coeff5*	1.41×10^{-3}

a. Standard errors in parentheses, clustered at the business level. * p<0.05, ** p<0.01, *** p<0.001.
b. The regressions follow the specification in equation (5). Other controls include the full sets of period dummies, subsample dummies, treated dummy, and their interactions. Weights are applied to the regressors so that the above coefficient represents the treatment effect for restaurants with each characteristics in the fall sample.

Panel B. *Percentage Reduction in CTA Conversion Rate (Paid Page Views Vs. Organic Page Views)*

(% Conversion Rate Change)			
Price		pre-experiment Traffic	
$	-49.9%	Tier1 (in 0-50th percentile)	46.9%
$$	-45.6%	Tier2 (in 50-75th percentile)	42.7%
$$$	-44.9%	Tier3 (in 75-90th percentile)-	19.5%
$$$$	-43.2%	Tier4 (in 90-99th percentile)	32.2%

Note: **1** Panel A reports regression results examining the differential reduction in overall conversion rate of the treated businesses due to paid search advertising with respect to restaurant price and pre-experiment traffic on Yelp. Panel B reports the percentage reduction in CTA conversion rate comparing page views from paid clicks and those from organic clicks. **2** The regressions includes the full sample of businesses during the period seven months before and three months during the experiment. **3** The table shows that businesses with higher ratings, more reviews, and higher prices experience the smallest loss in CTA conversion of paid views.

Table A5: Heterogeneous Effects on Click-through Rates (CTR) of Organic Links With Respect To Ratings, Number of Reviews and Price

[Outcomes Standardized]	Organic CTR	Total Page Views		Organic CTR	Total Page Views		Organic CTR	Total Page Views
ExprOn×Treated			ExprOn×Treated			ExprOn×Treated		
×I(<3.5 Stars)	-0.026	0.071***	×I(#Rev in Tier 1)	-0.061	0.06***	×I($)	-0.07	0.078***
	(0.102)	(0.004)		(0.089)	(0.002)		(0.059)	(0.003)
×I(3.5 Stars)	-0.191*	0.092***	×I(#Rev in Tier 2)	-0.088	0.088***	×I($$)	-0.129	0.094***
	(0.086)	(0.004)		(0.072)	(0.004)		(0.069)	(0.004)
×I(4 Star)	-0.04	0.101***	×I(#Rev in Tier 3)	-0.081	0.103***	×I($$$)	-0.009	0.12***
	(0.052)	(0.005)		(0.061)	(0.005)		(0.061)	(0.011)
×I(>4 Star)	-0.038	0.098***	×I(#Rev in Tier 4)	-0.133	0.116***	×I($$$$)	-0.028	0.092***
	(0.104)	(0.01)		(0.1)	(0.008)		(0.198)	(0.028)
Other Controls					X			
Fixed Effects				Business, Month				
N	218,249	218,249		218,680	218,680		218,680	218,680
F-test	p-value	p-value		p-value	p-value		p-value	p-value
Coeff1=Coeff2	0.22	8.8×10^{-5}		0.80	6.4×10^{-11}		0.51	5.1×10^{-4}
Coeff2=Coeff3	0.14	0.15		0.94	0.022		0.19	0.03
Coeff3=Coeff4	0.99	0.75		0.66	0.18		0.88	0.13

a. Standard errors in parentheses, clustered at the business level. * p<0.05, ** p<0.01, *** p<0.001.

b. The regressions follow the specification in equation (5). Other controls include the full sets of period dummies, subsample dummies, treated dummy, and their interactions. Weights are applied to the regressors so that the above coefficient represents the treatment effect for restaurants with each characteristics in the fall sample.

Note: **1** The table reports regression results examining the heterogeneous treatment effect of paid search advertising on organic CTR and total page views with respect to restaurant ratings, number of reviews, and price. **2** The regressions includes the full sample of businesses during the period seven months before and three months during the experiment.

Table A6: Heterogeneous Effects on Click-through Rates (CTR) of Organic Links With Respect To Restaurant Age, Chain Status and Pre-Experiment Page Traffic

Panel A. *Effect of Paid Search Ads on Overall CTA Conversion Rates*

[Standardized Outcomes]	Organic CTR	Total Page Views		Organic CTR	Total Page Views		Organic CTR	Total Page Views
ExprOn×Treated			ExprOn×Treated			ExprOn×Treated		
×I(age<1yr)	-0.079	0.119***	×I(non-chain)	-0.095	0.095***	×I(Traffic in Tier 1)	-0.095	0.071***
	(0.192)	(0.023)		(0.046)	(0.003)		(0.056)	(0.001)
×I(age∈[1,2]yr)	-0.042	0.103***	×I(local chain)	-0.039	0.095***	×I(Traffic in Tier 2)	-0.024	0.106***
	(0.134)	(0.013)		(0.063)	(0.007)		(0.057)	(0.004)
×I(age∈[3,4]yr)	-0.036	0.09***	×I(national chain)	0.003	0.045***	×I(Traffic in Tier 3)	-0.083	0.107***
	(0.088)	(0.007)		(0.011)	(0.004)		(0.062)	(0.007)
×I(age∈[5,10]yr)	-0.066	0.097***				×I(Traffic in Tier 4)	-0.277	0.125***
	(0.048)	(0.004)					(0.267)	(0.018)
×I(age>10yr)	-0.18	0.08***				×I(Traffic in Tier 5)	-0.039	0.203
	(0.103)	(0.003)					(0.024)	(0.131)
Other Controls					X			
Fixed Effects					Business			
N	218,680	218,680		218,680	218,680		218,680	218,680
F-test	p-value	p-value		p-value	p-value		p-value	p-value
Coeff1=Coeff2	0.88	0.53	*Coeff1=Coeff2*	0.47	0.98	*Coeff1=Coeff2*	0.38	3.9×10^{-21}
Coeff2=Coeff3	0.97	0.38	*Coeff2=Coeff3*	0.51	2.0×10^{-9}	*Coeff2=Coeff3*	0.49	0.93
Coeff3=Coeff4	0.77	0.39				*Coeff3=Coeff4*	0.48	0.35
Coeff4=Coeff5	0.31	8.3×10^{-4}				*Coeff4=Coeff5*	0.38	0.56

a. Standard errors in parentheses, clustered at the business level. * p<0.05, ** p<0.01, *** p<0.001.

b. The regressions follow the specification in equation (5). Other controls include the full sets of period dummies, subsample dummies, treated dummy, and their interactions. Weights are applied to the regressors so that the above coefficient represents the treatment effect for restaurants with each characteristics in the fall sample.

Note: **1** The table reports regression results examining the heterogeneous treatment effect of paid search advertising on organic CTR and total page views with respect to restaurant age, chain status, the page traffic of the business's Yelp page. **2** The regressions includes the full sample of businesses during the period seven months before and three months during the experiment.