Weekend Effect in Internet Search Advertising

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This paper examines whether Internet search advertising exhibits a weekend effect, a substantial difference in the effectiveness of ad spending on weekends vs on weekdays. We employ a data set from a major hotel chain, consisting of daily spending on search ads for 13 months, across three search engines and two brands. We find that there is a strong weekend effect. Each dollar of ad spending on weekends delivers a lower sales return than the corresponding return on weekdays. The advertising elasticity (percentage change in sales for a percentage change in ad spending) is about 3.7% lower on weekends, which translates to a 10% reduction in sales return at the mean level of daily spending. The weekend effect is robust across the 6 combinations of search engines and brands. We show that the reduction in advertising elasticity is primarily attributable to an increase in the price of clicks on weekends rather than due to any differences in conversion rate of click-throughs to sales. Further, we find that the weekend effect is exacerbated for ad spending at the top-ranked paid search listings. Awareness of the weekend effect can help managers fine-tune the distribution of their advertising budget across time, and achieve greater sales returns from a given ad budget.

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1 Introduction

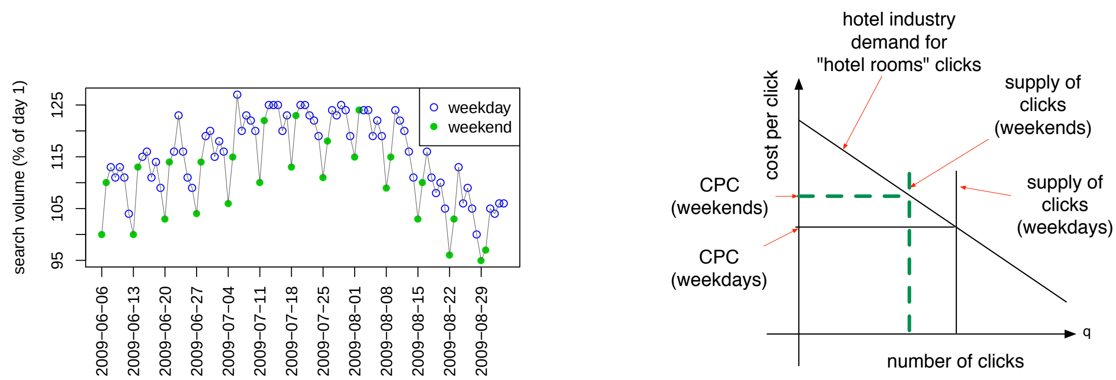
Information technologies and the Internet have transformed many industries and business practices. One example is marketing communications. Not only has Internet search advertising exhibited explosive growth, it has also transformed the way in which firms can measure the effectiveness of advertising. Traditionally, the link between advertising expenditures and advertising effectiveness was measurable only in the aggregate. For instance, one could estimate the effectiveness of ad expenditures over a few months across some broad geographical segment of the market, but it was not cost-effective to measure the impact of every single exposure to every single customer. The link between expenditures and sales could be inferred through sophisticated statistical modeling, but was generally not directly observable, leading to dubiety in attributing an outcome (such as a sale) to an advertising action. In contrast, for Internet and search advertising, it is possible to trace the path—from an ad impression to traffic at the firm's web site to page views or product sales—for every single ad exposure and every single customer. This transformation is an important qualitative shift in the conduct of advertising. It ought to raise new questions about advertising effectiveness and inspire development of new tools for allocating advertising resources more effectively.

This paper is concerned with one such question which has become viable to study because of how IT has enhanced the granularity and measurability of the effects of advertising. We examine whether there exists a weekend effect in search advertising—i.e., whether ad spending has systematically different payoff on weekends vs on weekdays—and whether the difference is substantial enough to justify alternate allocation rules for different days of the week. We investigate this effect empirically using a search advertising data set from a major hotel chain. The data set provides daily-level observations (impressions, clicks, room sales) for 395 days, accounting for about \$3.8 million in ad spending across 2 search engines and 3 brands. The data are distinctly suited to this day-level study because the information technologies associated with search advertising ensure that the sales levels for each day (attributed to clicks originating from search ads) are precisely linked with advertising impressions and expenditures for that day.

There have been several empirical studies of the payoff from online advertising which has become a substantial part of the economy.[1] Yang and Ghose (2010) study whether and how the effectiveness of paid search campaigns is influenced by the presence of organic listings, and uncover a complementary relationship between the two. Another key component of the advertising mechanism that determines outcomes is the position or rank of an ad. Position effects have received much recent interest (e.g., Ghose and Yang (2009); Rutz and Trusov (2011), among others). Narayanan and Kalyanam (2011) employ a regression discontinuity approach to tease out the causal connection between an ad's position and its likelihood of generating a sale or some other desirable outcome. Existing studies have also looked at the impacts of keyword characteristics (e.g., generic vs. branded) that capture consumer search goals and intentions (e.g., Ghose and Yang (2009); Hu and Sheng (2010); Rutz and Bucklin (2010); Yang and Ghose (2010)), and textual characteristics of the advertisement (Animesh et al., 2010; Rutz and Trusov, 2011).

To our knowledge, the present paper is the first to examine a weekend effect (or, more generally, day-of-week or calendar effect) in the payoff from advertising. In contrast, this kind of effect is widely studied in other domains, such as finance, medicine, public health, crime, etc. In medicine, several authors have claimed that medical outcomes are worse on weekends, presumably due to lower staffing levels or less aggressive diagnostic testing. Cram et al. (2004) found that mortality rates were higher for patients admitted to hospitals on weekends rather than weekdays. Kostis et al. (2007) demonstrated a similar effect in the case of cardiac patients. Jacob and Lefgren (2003) find a distinct shift in the pattern of juvenile crimes on weekend and non-school days. In the retail shopping sector, Warner and Barsky

[1] An eMarketer Report (June 2011, http://www.emarketer.com/PressRelease.aspx?R=1008432) estimates online ad spending at at $26 billion in 2010, and projects it at $50 billion by 2015



(a) Search volume in the “travel” sector.

(b) Effect of demand-supply on CPC.

Figure 1: Panel (a) is based on Google Trends data on search activity in the travel sector. A similar pattern is also observed for specific keywords in this sector, such as “hotel Chicago,” and search volumes are lower across the board on weekends.

(1995) found, counterintuitively, that retail stores tend to implement greater discounts on weekends (and holidays) despite the fact that shopping demand is exogenously high on these days. A weekend effect in offline metrics also can occur due to a weekend effect in online search. For instance, Mantin and Koo (2009) find a strong weekend effect in price dispersion for air travel, and attribute this to the lower Internet traffic during weekends which allows airlines to adopt distinctive pricing policies during weekends. The finance literature, since the seminal paper of French (1980), has ample discussion about a weekend or Monday effect in stock trading. Even in the relatively staid area of supply chain order fulfillment, researchers have found that operational performance metrics (order cycle time, complete orders fulfilled, and short shipment percentage) exhibit a day-of-week effect (Yao et al., 2010).

Why might advertising effectiveness be any different on weekends? There are several potential factors. First, there is general evidence that search activity is lower on weekends; specifically, this is true in the hotel/travel sector studied in this paper (see Fig. 1(a)). This reduces the supply of clicks available for grab by the entities (hotel reservation systems) who are competing for these clicks. That, in turn, should raise the price of clicks on weekends, thereby lowering the return per unit of advertising expenditure *ceteris paribus* (see Fig. 1(b)). Second, there is some evidence that consumers become more price-sensitive (or, equivalently, less time-sensitive) on weekends.[2] For online search, Narayanan and Kalyanam (2011) suggest that consumers dig deeper into search results; they may also be more likely to follow more links (i.e., click and cause the advertiser to incur an expenditure) for every purchase action. This suggests a lower conversion rate, hence lower ad effectiveness. Third, however, some factors can improve ad effectiveness. There is some evidence that consumers can be more decisive in making a shopping decision on weekends. Analysts in the insurance industry have posited that a weekend ad is more likely to be effective, because consumers are more available to connect with an insurance agent and more likely to reach a conclusion after consulting with family members. The weekend effect, then, depends on the interplay among these three factors. Establishing the existence and directionality of the weekend effect requires rigorous modeling to isolate each of these effects.

We investigate the weekend effect on advertising effectiveness (degree of sales relative to ad expenditures) and also decompose this effect into two parts, sales as a function of clicks obtained from search advertising, and the purchase efficiency of clicks. We find that advertising effectiveness is significantly lower for each dollar of ad spending on weekends, and this effect holds in the aggregate as well as for each of the search engine-brand pairs in our study. Moreover, we are able to attribute this lower ad effectiveness to a higher purchase price for clicks rather than to lower conversion rates on weekends. Using daily trends in search activity obtained from Google Trends, we connect this higher price-per-click, and hence lower ad effectiveness, to a shift in the demand-supply curves for clicks on weekends. Further, we examine the effect of search advertising position on the weekend effect, and we find that this effect is more prominent at the top positions.

2 A Framework for Search Advertising Effectiveness

A few well-known characteristics of search advertising are worth repeating here because of their relevance to our analysis. First, while traditional advertising is broadcast or "pushed"

[2] Optimizing the Ecommerce Experience: Trends for 2011. e-Marketer Report, October 2010.

to users, search ads are delivered under a "pull" approach: they are displayed to a user only after the user has expressed an interest in the product, firm, or at least a related set of keywords. Due to this, search advertising is primarily oriented towards making sales (vs. building general awareness of the brand), hence it provides a good setting to study advertising effectiveness. Second, most search advertising is sold under a pay-for-performance paradigm, under which an ad impression results in an ad expenditure only if the ad is clicked. Third, the actions of the user subsequent to the display of the ad can be tracked, including whether they click the ad and visit the firm's web site, conduct any browsing activity, or make a purchase. This provides measurability of both costs and benefits (sales). Fourth, the infrastructure for search advertising allows for highly refined advertising strategies. It is possible today for advertisers to specify the ads that will be displayed to users searching for specific combinations of keywords, in essence allowing them to target ad spending to varying dimensions including location, depth of search query, and price-sensitivity, among others. However, little is known yet about the effectiveness of ad spending across different times, specifically, days of the week.

We employ the oft-used conversion funnel paradigm for search advertising. The advertising firm participates in a search advertising auction by creating several ad campaigns, each of which specifies bidding rules for a collection of keywords (there are about 200 such campaigns in our data set). Separate bidding rules may be specified for each search engine, and each brand has its own advertising budget, typically determined each 3-month period. A winning bid leads to an exposure, or an *impression.* With some probability an impression converts to a *click*, at which time the winning bid converts into an ad *expenditure* (all our data correspond to search advertising priced on a per-click rather than per-impression basis). A fraction of these clicks converts to a sale which, in our study, is the reservation of a hotel *room.*

Let $\text{Spend}_{i,t}$ represent the advertising expenditure corresponding to an index i (as specified later, the index is a triplet of ad campaign, search engine, and brand) on day t. Similarly, let $\text{Clicks}_{i,t}$ be the number of clicks, and $\text{Rooms}_{i,t}$ the number of room reservations for index i on day t. Then, $\frac{\text{Rooms}_{i,t}}{\text{Spend}_{i,t}}$ (room reservations per unit of ad spending) is an intuitive measure of the sales effectiveness of advertising expenditures. The ratio $\frac{\text{Clicks}_{i,t}}{\text{Spend}_{i,t}}$ can be interpreted as the *clicks-per-dollar* for index i on day t, the rate at which the firm buys traffic to its reservation site. Similarly, the ratio $\frac{\text{Rooms}_{i,t}}{\text{Clicks}_{i,t}}$ is the *conversion rate*. Intuitively, the effectiveness of ad spending (and, likewise, the clicks-per-dollar and the conversion rate) need not be a constant. One would expect clicks-per-dollar to exhibit diminishing marginal returns, with each click being increasingly more expensive than the previous one. Similarly, conversion rate might exhibit a nonlinear (and, specifically, diminishing returns) property. In order to account for these possible nonlinearities, we employ a constant-elasticity Cobb-Douglas specification which is commonly used to model advertising actions,

$$\text{Clicks}_{i,t} = \gamma_1 \text{Spend}_{i,t}^{\alpha_1} \tag{1}$$

$$\text{Rooms}_{i,t} = \gamma_2 \text{Clicks}_{i,t}^{\alpha_2} \tag{2}$$

$$\text{Rooms}_{i,t} = \gamma_1^{\alpha_2} \gamma_2 \text{Spend}_{i,t}^{\alpha_1 \alpha_2} \tag{3}$$

where α_1 and α_2 are response elasticities for the click purchase and conversion processes, respectively. The *advertising elasticity* $\alpha_1\alpha_2$ ($= \frac{\%\text{change in room sales}}{\%\text{change in ad spending}}$) then becomes the key metric for the sales effectiveness of advertising expenditures (an elasticity less than 1 represents diminishing marginal returns).

Our key objective is to examine whether this advertising elasticity varies by day of the week, and specifically over weekdays vs. weekends. We note that with the potential nonlinearities in the response functions, the ratios $\frac{\text{Clicks}}{\text{Spend}}$ and $\frac{\text{Rooms}}{\text{Clicks}}$ can no longer be interpreted in the usual way as rates, and cannot meaningfully be compared across different indices if the corresponding denominator variables differ in value. Rather, the respective elasticity—which is agnostic to the magnitude of the denominator—is a useful measure for comparing performance across different indices or day-of-week. We note that we define "weekend" more generally as inclusive of any NYSE designated holidays. For ease of exposition, we will refer to this combination of days interchangeably as holidays or weekends. The working week days will often be referred to as business days.

We refine Eq. 1–3 to account for potential differences in advertising effectiveness on weekdays vs weekends. Assume that each of the weekdays has identical effectiveness, as does each weekend day. Designate weekdays with B (for business days) and holidays or weekends as H. Then, the revised Eq. 3 is

$$\text{Rooms}_{i,t} = \begin{cases} \gamma_{1,B}^{\alpha_{2,B}} \cdot \gamma_{2,B} \cdot \text{Spend}_{i,t}^{\alpha_{1,B} \cdot \alpha_{2,B}} & \text{if t is a Business day} \\ \gamma_{1,H}^{\alpha_{2,H}} \cdot \gamma_{2,H} \cdot \text{Spend}_{i,t}^{\alpha_{1,H} \cdot \alpha_{2,H}} & \text{if t is a Holiday.} \end{cases} \tag{4}$$

To ease the notation, we rename and replace variables as follows. Let $\gamma = \gamma_{1,B}^{\alpha_{2,B}} \cdot \gamma_{2,B}$ with $\gamma_H = \frac{\gamma_{1,H}^{\alpha_{2,H}} \gamma_{2,H}}{\gamma_{1,B}^{\alpha_{2,B}} \gamma_{2,B}}$; and, let $\alpha = \alpha_{1,B} \cdot \alpha_{2,B}$ with $\alpha_H = \alpha_{1,H} \cdot \alpha_{2,H} - \alpha_{1,B} \cdot \alpha_{2,B}$. Then, Eq. 4 can be shortened to

$$\text{Rooms}_{i,t} = (\gamma \cdot \gamma_H^{H_t})\text{Spend}_{i,t}^{(\alpha + \alpha_H H_t)} \tag{5}$$

where the indicator variable $H_t = 1$ if day t is a holiday and 0 otherwise. With this notation, weekdays and weekends have indistinct ad effectiveness if $\alpha_H = 0$ and $\gamma_H = 1$.

3 Data and Estimation

dt	holiday	source	brand	campaignnm	clicks	spend	rooms
2009-03-29	1	YAHOO	Brand B	150	42	11.54	1
2009-04-06	0	YAHOO	Brand A	115	65	20.64	6
2009-04-25	1	GOOGLE	Brand G	35	411	1052.50	7
2009-04-13	0	YAHOO	Brand G	34	346	865.52	21

Table 1: Sample of daily data for search advertising expenditures and sales.

Our data set represents 13 months of search advertising activity for a major multi-brand international lodging chain. As noted earlier, the firm spent $3,844,589 on search

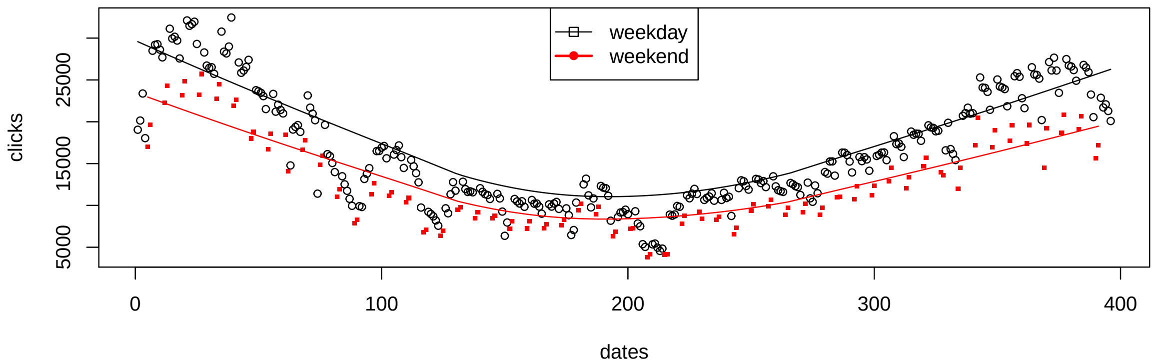


Figure 2: Variation in clicks over time and across weekends vs. weekdays.

advertising in this period. This spending reflects 6,158,157 clicks, of which 550,063 led to room reservations, a conversion rate of a little less than 1%. Table 1 provides a sample of the data. As noted earlier, we designated weekends and other bank holidays using the NYSE holiday calendar. Our data are generated by 212 advertising campaigns, each of which is a collection of relevant keywords purchased on a single search engine (Yahoo or Google) and used to promote a single hotel brand.

Our research was motivated by the observation that the firm's advertising levels on weekends were substantially, and consistently, lower on weekends than on weekdays. Figure 2 displays the variation in daily *clicks* (from search advertising) received by the firm during the study period, it demonstrates both seasonal variation and a reduction in clicks every weekend. The latter is demonstrated more vividly by examining a shorter period more closely as in Figure 3 which also demonstrates this pattern for other metrics, such as number of impressions, advertising expenditures, and sales attributed to search advertising. This initial observation led us to inquire whether the reduced spending on weekends was a result of lower anticipated effectiveness of ad spending, or whether it represented a lost opportunity for increasing sales through additional ad spending on weekends.

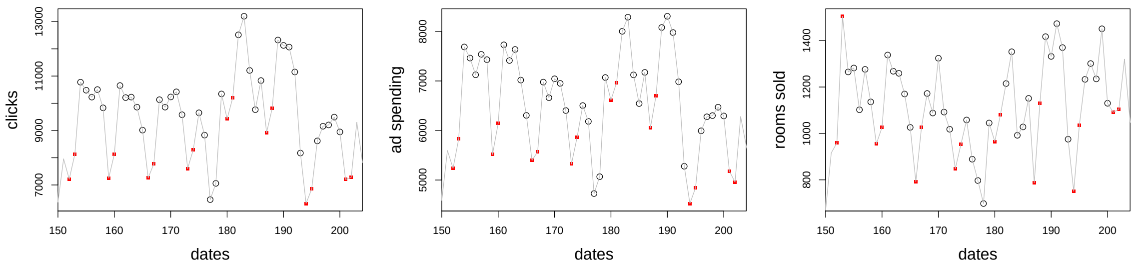
Table 2 lists the variables used in our empirical model. The three key metrics of interest are $\text{Spend}_{i,t}$, $\text{Clicks}_{i,t}$ and $\text{Rooms}_{i,t}$, representing ad spending, clicks, and room sales for

Table 2: Description of Variables

Variable	Description
$\text{Spend}_{i,t}$	Amount of ad spending on campaign i on day t.
$\text{Clicks}_{i,t}$	Number of clicks (web traffic) due to ad spending for campaign i on day t.
$\text{Rooms}_{i,t}$	Count of room reservations owing to campaign i on day t. Measure of sales.
H_t	Equals 1 if t is a holiday, 0 otherwise.
$\mathbf{B}_i$	A set of indicators for three brands, Brand A, Brand B, and Brand G.
$\mathbf{S}_i$	Equals 1 if campaign i ran on search engine Yahoo!, 0 if Google.
J_i	Equals 1 if campaign i was the Jumbo campaign, 0 otherwise.
M_t	A set of indicators for 12 months.
C_i	A set of indicators for 212 campaigns with (positive) clicks.

Table 3: Summary of variables for estimation sample, split by brand and search engine.

Source	GOOGLE			YAHOO			Pooled
Brand	Brand A	Brand B	Brand G	Brand A	Brand B	Brand G	
N	5893	6033	18892	5192	5326	13423	47070
Rooms	197484	163173	75766	50054	43383	20203	550063
Spend	828757.6	890315.2	1035662	398103.5	394464	297286.8	3844589
Clicks	1591231	1695621	1301910	563067	607427	398901	6158157
H	1650	1696	5261	1463	1485	3735	15290



(a) (b) (c)

Figure 3: Weekend volume (clicks, spending, room sales) is consistently lower than weekday volume. The empty circles are weekdays, while the filled red boxes are weekends.

campaign i on day t. Table 3 provides summaries of the main variables split by the brand corresponding to the campaign and the search engine on which it was run. Fortunately, the six groups are nearly identical in the proportion of holidays vs. weekdays in their use of advertising (for each group, about 28% of days in which advertising occurred were holidays), suggesting that there were no selection effects in assigning advertising campaigns across days of the week. However, as illustrated in Figure 3, both advertising activity and consumer responses were lower on holidays. The advertising campaigns sold on average 12.36 rooms, spent \$81.17 and attracted 135.16 clicks per weekday as compared to holidays and weekends where on average they sold 9.94 rooms, spent \$67.02 and attracted 107.07 clicks.

As a starting point to understand whether the effectiveness of advertising varies across holidays and weekdays, we compare average ratios pooled across brands and sources. These simple average comparisons indicate that clicks cost more on holidays (\$0.63) than weekdays (\$0.60), and the amount of ad spend required to sell a unit room is also higher on holidays (\$6.74) than weekdays (\$6.56), whereas the number of clicks it takes to sell a room (the ratio of clicks to rooms) is slightly lower for holidays (10.77) than weekends (10.94). However, these comparisons are naïve and do not take into account the differences in the size of the campaigns, and campaign-specific unobservables (factors such as competitiveness, nature of keywords, broad vs. exact match, among others) that may determine the differences in the levels of spending across campaigns. In order to examine the issue rigorously, we build regression models to examine whether there exist differences in the effectiveness of ad spending on sales across holidays and weekdays, after controlling for a variety of confounding factors.

4 Ad Spending Effectiveness (Rooms on Spend)

In this section, we develop and implement an estimation strategy to measure the relationship between advertising expenditures and room sales and to investigate whether the sales returns from search advertising display a weekend effect. After establishing that such an effect exists, we then examine (in §5) whether the differential returns are caused by differences in conversion rates or by differences in the cost of purchasing clicks. §6 demonstrates that the weekend effect is moderated by search rank, and that higher ranks (the top positions in the search results) exhibit a greater intensity of weekend effect.

4.1 Estimation Strategy

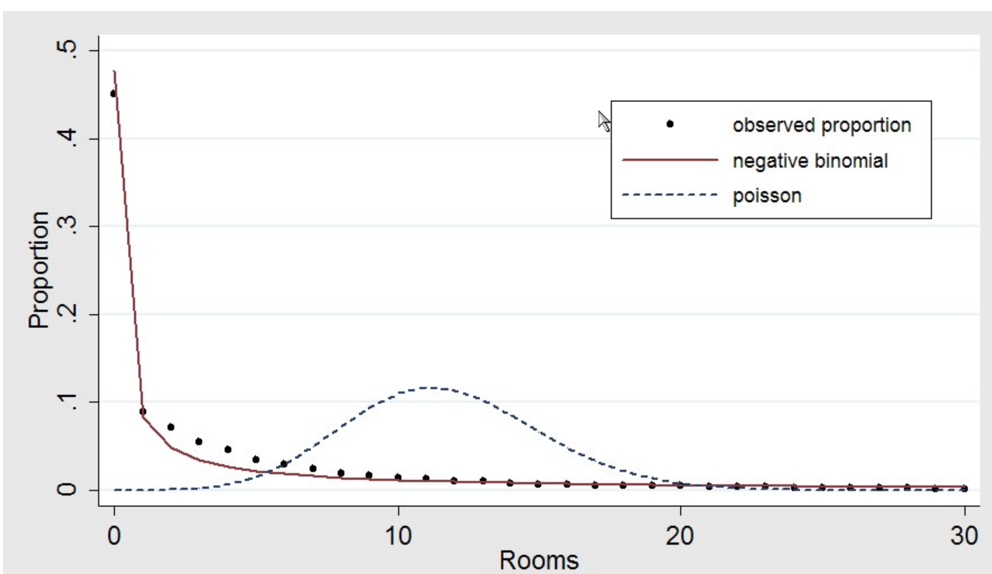


Figure 4: Comparison of densities in empirical data with a Poisson distribution and a negative binomial distribution.

Several characteristics of our data pose challenges in estimation. First, our primary outcome variable of interest, Rooms, is a count variable, calling for Poisson regression methods. The average daily clicks-to-conversion rate, while low (a little less than 1%), is comparable to rates typical for online advertising campaigns.[3] However, this count variable displays over-dispersion (mean daily reservations = 11.69, s.d. = 50.14) and positive skew (55% of days have zero room sales) as depicted in Figure 4.

Second, the data are obtained from multiple campaigns, where each campaign consists of a specific set of keywords advertising a single brand on a specific search engine. This campaign structure naturally produces structural heterogeneity in the population that would best be modeled using a mixture of Poisson processes, such as a negative binomial model that provides a continuous mixture of Poisson distributions where the Poisson rates (heterogeneity) are modeled as a gamma distribution. Figure 4 confirms that the negative binomial model provides a good fit to the observed sample data. We plot the observed distribution of Rooms with Poisson and Negative Binomial distributions with the same mean and an estimated variance. The estimated mean is 11.69 and the over-dispersion parameter is 5.713.

Third, each campaign is observed for several days (mean = 290.02, s.d.= 102.27), rendering the multi-day observations from a given campaign unlikely to be independent of each other. For example, it could be the case that some campaigns or collections of keyword are advertised with a primary goal of brand building rather than selling rooms, and may thus fetch lower clicks and conversion per dollar of ad-spending compared to other campaigns that are designed to sell. Further, if certain types of campaigns were more likely to be activated or run on holidays and weekends (as compared to weekdays), treating multi-day observations from the same campaign as independent would produce coefficients (of the weekend effect, for instance) that are inconsistent.

Given these considerations, we employ negative binomial regression models that also take into account the panel structure of the data for estimating the parameters of interest.

[3] http://www.comscore.com/Press_Events/Press_Releases/2011/1/TOMORROW_FOCUS_and_comScore_Announce_Results_of_Brand_Advertising_Online_in_Germany_Study_at_DLD_Conference

Accounting for the campaign structure allows us to control for campaign-specific invariant unobservables (and observables) that may affect the daily relationships between spending, rooms, and clicks, while the heterogeneity across campaigns is modeled using a negative binomial distribution. As we show in more detail later, these models provide better fit than alternate assumptions about the distribution of errors for our data.

The negative binomial regression model estimates the probability of an observed count, conditional on an expected mean $\mu_{i,t}$, which is parameterized as an exponential function of the independent variables that affect the outcome in order to avoid negative estimates of the expected value of the count outcome (Cameron and Trivedi, 2005). In a panel model, the mixing over the gamma distribution is applied to all observations produced by a given panel. In other words, the individual campaign fixed effect $\delta_i = e^{\alpha_i}$ is modeled as separable and multiplicative, and applied commonly to all daily observations belonging to a particular campaign i rather than separately to individual observations. This model was originally proposed by Hausman et al. (1984).

We implement the above estimation strategy by regressing room sales on advertising expenditures (Eq. 5) along with appropriate controls as shown below.

$$
\begin{aligned}
E[\text{Rooms}_{i,t} \mid \text{Spend}_{i,t}, \epsilon_{i,t}] = \exp((\beta_0 + \beta_1 \log(\text{Spend}_{i,t})) + (\beta_2 + \beta_3 \log(\text{Spend}_{i,t}))\text{H}_t \\
+ (\beta_4 + \beta_5 \log(\text{Spend}_{i,t}))\text{J}_i + (\boldsymbol{\beta}_6 + \boldsymbol{\beta}_7 \log(\text{Spend}_{i,t}))\mathbf{B}_i \\
+ (\boldsymbol{\beta}_8 + \boldsymbol{\beta}_9 \log(\text{Spend}_{i,t}))\mathbf{S}_i + \boldsymbol{\beta}_{10}\mathbf{M}_t + \boldsymbol{\beta}_{11}\mathbf{C}_i + \epsilon_{i,t})
\end{aligned} \tag{6}
$$

where i represents campaigns and t represents month. Dummies $\mathbf{B}$ and $\mathbf{S}$ allow the effect on spending to vary across brands and search engines, respectively. We also includes dummies ($\mathbf{C}$) for the individual campaigns in order to allow for the intercepts (the effect of log(Spend)) to differ. Additionally, we include the interactions $\mathbf{B}*\log(\text{Spend})$ and $\mathbf{S}*\log(\text{Spend})$ to allow for the effect of ad spending to vary across brands and search engines. Finally, we include two additional controls, (i) a vector of dummy variables (for 12 months $\mathbf{M}$) that help account for seasonality effects in search advertising activities, and (ii) a dummy J to control for the effects of one jumbo master campaign (which included observations across all six combinations of brand and search engine), which accounted for nearly 50% of the observed clicks in our data, and may have experienced different levels of effectiveness for its ad spending as compared to the rest of the smaller campaigns. Each of the bold face terms $\boldsymbol{\beta}_6 \ldots \boldsymbol{\beta}_{11}$ represents a vector of parameters corresponding to the respective vectors of dummy variables (**B** is brand, **S** is search engine, **M** is month, and **C** is campaign).

With the negative binomial regression model, the expected value of the outcome variable y, given the dependent variable x, is $E[y_{i,t} \mid \ x_{i,t}\delta_i] = \exp(x_{i,t}\beta + \alpha_i) = \mu_{i,t}\delta_i$. Eq. 6 provides a "conditional" fixed effects estimator, where the campaign level fixed effects are conditioned on the sum of the sales counts within the panel and then concentrated out of the likelihood so that the fixed effects can take on any population distribution that need not be specified. This remedies the need to include a host of dummy intercepts especially when the number of panels is large. Further, a fixed effect estimator allows the panel-specific fixed effects to be correlated with explanatory variables $x_{i,t}$. Our main dependent variable of interest - H (Holiday) - however appears to be uniformly distributed across sources and brands, suggesting that campaigns nested within these groups (when aggregated) are not correlated with H. If this was the case, fixed effect models would still produce consistent estimates. However, due to the conditioning, campaigns whose total counts of rooms sold (across all days) are zero are dropped from the estimation sample since there is no variation over time. This model further assumes that observations across panels are independent which is a reasonable assumption for our daily sales data across campaigns.

To address the concerns related to a conditional fixed effects estimator (i.e., that it may not truly control for all time invariant panel effects unlike an unconditional estimator, see Allison and Waterman (2002)), we also present random effects estimates for the negative binomial regression models. In this model too, the heterogeneity parameter is commonly allocated to all observations belonging to a campaign, but is assumed to be i.i.d randomly distributed according to a beta distribution. Specifically, the dispersion parameter defined as the variance divided by the mean follows a beta distribution. A limitation of random effects models is the assumption that panel-specific effects are uncorrelated with other predictors. However, as described above, this may not be a concern for the weekend effect.

4.2 Results

The parameters β_2 and β_3 measure whether there is a difference in advertising effectiveness between weekdays and weekends (note that $e^{\beta_2} = \gamma_H$ and $\beta_3 = \alpha_H$, in Eq. 5). $\beta_2 > 0$ (< 0), and similarly $\beta_3 > 0$ (< 0), indicates a higher (lower) level of return on weekends. However, β_2 impacts only the absolute return on advertising for a given level of spending, but cancels out when we compute the percentage change in sales as advertising expenditure changes. This latter effect is better captured by the parameter β_3, which represents the difference in advertising elasticity on weekends. Hence the discussion below primarily centers on β_3.

The results for the regression of Rooms on Spend are presented in Table 4. Columns (1) and (2), corresponding to fixed and random dispersion across campaigns, represent regression of Rooms on log(Spend) and its interactions with Holiday (H), Brand (**B**), Search engine (**S**). In Columns (3) and (4) we add a dummy variable to control for the jumbo master campaign, and we add month dummies in Columns (5) and (6). Results in columns (1), (3), (5) are estimates from fixed effect models, while the results in columns (2), (4), (6) are estimates from random effect models. The model with the best fit (in terms of BIC score for non-nested models) in Table 4 is in Column (5) which is a conditional fixed effect model where we control for both month effects and the jumbo campaign. In all of the models, the coefficient of the log(Spend) term confirms the suitability of employing a diminishing returns specification (this coefficient would have been close to 1 under a linear relationship).

The coefficient for H$*$log(Spend) is -0.019, negative and significant in Column (5) (as also in other models). Given the negative binomial distribution of the outcome, the coefficient can be interpreted as an elasticity value since the independent variable is also logged. Therefore,

Table 4: Negative Binomial Regression of Rooms on log(Spend).

	(1) FE1	(2) RE1	(3) FE2	(4) RE2	(5) FE3	(6) RE3
H	-0.027	-0.026	0.025	0.026	0.009	0.010
	(0.025)	(0.025)	(0.026)	(0.026)	(0.025)	(0.025)
log(Spend)	0.464***	0.467***	0.580***	0.583***	0.509***	0.512***
	(0.010)	(0.010)	(0.012)	(0.012)	(0.013)	(0.013)
H X log(Spend)	-0.012*	-0.012*	-0.022***	-0.022***	-0.019***	-0.019***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Brand B	-0.893***	-0.881***	-0.765***	-0.753***	-0.737***	-0.728***
	(0.051)	(0.050)	(0.054)	(0.054)	(0.054)	(0.054)
Brand B X log(Spend)	0.038***	0.036**	0.009	0.008	0.099***	0.097***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.013)	(0.013)
Brand G	-1.879***	-1.888***	-1.666***	-1.672***	-1.815***	-1.820***
	(0.053)	(0.052)	(0.057)	(0.056)	(0.057)	(0.056)
Brand G X log(Spend)	0.120***	0.121***	0.051***	0.052***	0.166***	0.165***
	(0.014)	(0.013)	(0.015)	(0.015)	(0.016)	(0.016)
YAHOO	0.029	0.034	0.038	0.044	0.023	0.029
	(0.041)	(0.041)	(0.043)	(0.043)	(0.043)	(0.043)
YAHOO X log(Spend)	-0.102***	-0.103***	-0.101***	-0.102***	-0.112***	-0.113***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
J			1.098***	1.111***	0.855***	0.866***
			(0.099)	(0.098)	(0.099)	(0.098)
J X log(Spend)			-0.245***	-0.247***	-0.178***	-0.180***
			(0.016)	(0.016)	(0.016)	(0.016)
Intercept	-0.498***	-0.508***	-0.839***	-0.849***	-0.732***	-0.741***
	(0.043)	(0.043)	(0.049)	(0.049)	(0.054)	(0.053)
BIC	184731.25	187746.24	184461.81	18747.13	182524.24	185531.96

Notes: ($^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$). N = 47070 and campaign groups = 212 across all models. Models (1), (3), (5) are panel negative binomial regression models where the dispersion across campaigns is conditioned out of the likelihood providing a conditional fixed effects model. Models (2), (4), (6) are panel negative binomial regression models where the dispersion is modeled using a beta distribution and varies randomly across campaigns. Models (3)-(6) control for a Jumbo campaign, and Models (5)-(6) also contain 12 Month dummies.

we see that the advertising elasticity for weekend ad spending is lower by an amount 0.019 relative to its weekday value of 0.509, a reduction in elasticity of 3.73% (averaged across all brand and search engine pairs). With these elasticities, Eq. 5 can be used to compute the difference between room sales on a weekday or weekend, for a given level of ad spending. For instance, at the mean daily spending level ($\approx$ \$127), the firm will generate about 8.79% lower returns on a weekend compared with a weekday. Similar findings are obtained in the alternate fixed and random model specifications presented in Table 4. Hence we can conclude that the effectiveness of ad spending is significantly reduced on holidays and weekends as compared to weekdays.

We assessed the robustness of the holiday or weekend effect using a number of alternate model specifications for the regression of Rooms on Spend (see Table 5). For comparison purposes, Column (1) presents the results from the best panel model in Column (5) of Table 4. Column (2) is a NB-2 model proposed by Cameron and Trivedi (2005), and assumes additive separable log-gamma distributed heterogeneity in the Poisson process. Let θ denote the dispersion parameter (variance of the one-parameter Gamma distribution used to model heterogeneity with the mean fixed at unity), then the variance of the NB-2 distribution is given as $var(\mathrm{Rooms}_{i,t}; \mu_{i,t}) = \mu_{i,t} + \theta\mu_{i,t}^2$. Column (3) is a generalized negative binomial model where the heterogeneity parameter (shape of the gamma distribution) itself is parameterized to allow model predictors to influence over-dispersion. We specify a function $\ln(\theta) = \rho_0 + \boldsymbol{\rho}_1\mathbf{B}(i) + \boldsymbol{\rho}_2\mathbf{S}(i) + \rho_3\mathrm{H}_t + \rho_4 J_i + \xi_{i,t}$. Both models (2) and (3) include a full set of campaign dummies, $\mathbf{C}$, to control for fixed effects. The standard errors are corrected by scaling by the dispersion parameter, as suggested by Allison and Waterman (2002). Finally Column (4) presents results from a fixed effects Poisson regression model. Hausman et al. (1984) showed that a fixed effect Poisson would yield unbiased (albeit inefficient) estimates, and can be a useful robustness check.

Both the negative binomial models with campaign dummies provide comparable, though lower, fits to the model in Column (1). The Poisson panel model however is a poor fit. In

Table 5: Robustness Checks for the weekend effect (Rooms on log(Spend)).

	(1) NB-FE	(2) NB2	(3) GenNB	(4) Pois-FE
H	0.009	0.046	0.041	0.019
	(0.025)	(0.038)	(0.032)	(0.040)
log(Spend)	0.509***	0.810***	0.765***	0.749***
	(0.013)	(0.050)	(0.056)	(0.035)
H X log(Spend)	-0.019***	-0.017*	-0.023**	-0.025**
	(0.005)	(0.008)	(0.008)	(0.008)
Brand B X log(Spend)	0.099***	-0.174***	-0.156***	-0.142***
	(0.013)	(0.038)	(0.043)	(0.035)
Brand G X log(Spend)	0.166***	-0.303***	-0.281***	-0.306***
	(0.016)	(0.076)	(0.070)	(0.046)
YAHOO X log(Spend)	-0.112***	-0.020	-0.042	-0.176***
	(0.011)	(0.054)	(0.067)	(0.049)
J X log(Spend)	-0.178***	-0.025	0.006	-0.078*
	(0.016)	(0.051)	(0.053)	(0.035)
Brand B	-0.737***			
	(0.054)			
Brand G	-1.815***			
	(0.057)			
YAHOO	0.023			
	(0.043)			
J	0.855***			
	(0.099)			
Intercept	-0.732***	-3.311***	-5.290***	
	(0.054)	(0.193)	(0.135)	
BIC	182524.24	189847.876	185263.770	269011.11

Notes: $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$. N = 47070 and campaign groups = 212 across all models. The dependent variable is Rooms. Model (1) is a negative binomial regression model with conditional fixed effects. Models (2)-(3) are negative binomial regression models. The dispersion is a function of the mean of the covariates in model (2), while model (3) specifies a generalized parameterization of dispersion such that ln(dispersion) = f(Brand B, Brand G, Yahoo, Holiday, Jumbo). Both (3) and (4) include dummy variables for 212 campaigns and standard error correction for the campaign clusters. Model (4) is a panel Poisson fixed effects regression model. All models contain 12 Month dummies and control for a Jumbo campaign.

particular, the standard errors are downward biased and the ratio of deviance to the degrees of freedom is not close to 1, indicating the presence of significant over-dispersion remaining within panels that is not accounted for in the model. In all these models, we still continue to obtain a negative and significant weekend effect, with a reduction in advertising elasticity of .017-.025 on weekends as compared to weekdays. We conducted three additional robustness checks: (i) added day controls using calendar days, (ii) included a lagged effect of sales from the previous day, and (iii) included a lagged effect of the previous day's ad spending. All these variations produced similar findings on the weekend effect, hence we do not present these results here. We also tested a zero-inflated negative binomial model, but it produced poorer fit than the negative binomial models discussed above.

5 Decomposing the Weekend Effect

Having established the presence of a statistically significant and economically relevant weekend effect in online search advertising, we now seek to understand the source of this effect. The typical conversion funnel described earlier suggests that the translation of advertising spend into room sale occurs through two intermediate steps. The first is the cost of purchasing clicks, or the clicks obtained by the firm for every dollar spent. The second is the effectiveness of clicks, or the rate at which clicks convert to room reservations. We examine whether the weekend effect is driven by the reduced acquisition of clicks for each dollar of spending or the reduced conversion effectiveness of the obtained clicks. More importantly, disparate factors are likely to determine the number of clicks an advertisement attracts on a search engine and the number of sales the advertisement produces once the ad has been clicked on, and additionally the impact of these factors may vary across weekdays and holidays. Examining these two processes separately can better help understand the source of the weekend effect. These two models are described next.

First we estimate the effect of the number of clicks on the amount of room sales. The regression of Rooms on Clicks is best modeled using a negative binomial distribution for the outcome since Rooms is a count, as discussed earlier. As before, we log the main independent variable, Clicks, to specify a model of diminishing returns in the conversion of clicks to room sales. This allows us to interpret the coefficient of interest - γ_3 - as an elasticity coefficient.

$$
\begin{aligned}
E[\text{Rooms}_{i,t} \mid \text{Clicks}_{i,t}, \epsilon_{i,t}] = \exp((\gamma_0 + \gamma_1 \log(\text{Clicks}_{i,t})) &+ (\gamma_2 + \gamma_3 \log(\text{Clicks}_{i,t}))\text{H}_t \\
&+ (\gamma_4 + \gamma_5 \log(\text{Clicks}_{i,t}))\text{J}_i + (\boldsymbol{\gamma}_6 + \boldsymbol{\gamma}_7 \log(\text{Clicks}_{i,t}))\mathbf{B}_i \\
&+ (\boldsymbol{\gamma}_8 + \boldsymbol{\gamma}_9 \log(\text{Clicks}_{i,t}))\mathbf{S}_i + \boldsymbol{\gamma}_{10}\mathbf{M}_t + \boldsymbol{\gamma}_{11}\mathbf{C}_i + \epsilon_{i,t})
\end{aligned} \tag{7}
$$

Table 6 presents the results for the regression of Rooms on Clicks corresponding to the models shown in Table 5. We estimated a variety of panel negative binomial models, and the best fit was provided by the fixed effects model. This model is presented in Column (1) in Table 6. In Columns (2) and (3) are a NB-2 and a generalized negative binomial model, and in Column (4), we have a fixed effect panel Poisson model. As before, Column (4) has the lowest fit due to the presence of remaining over-dispersion, whereas the models (2) and (3) have comparatively better fit, with the negative binomial fixed effects model in column (1) providing the lowest BIC score. After taking into account the effects of other covariates, we find that the coefficient of the interaction $\text{H} * \log(\text{Clicks})$ is statistically insignificant (see Column (1) of Table 6). This result is also observed in columns (2) (3), and (4), and suggests that the rate of conversion of clicks to room sales is not significantly different across weekdays and holidays.

Next we regress Clicks on Spend in order to examine the rate at which advertising expenditure (bids, to buy clicks) generates clicks. The Clicks variable, unlike Rooms, does not suffer from the presence of excess zeros, and log(Clicks) has an approximately normal distribution. We therefore estimate a model of log(Clicks) on log(Spend). The coefficient of

Table 6: Regression of Rooms on Clicks ($^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$). N = 47070 and campaign groups = 212 across all models. The dependent variable is Rooms.

	(1) NB-FE	(2) NB2-3	(3) GenNB-3	(4) Pois-FE2
H	0.051	0.033	0.015	-0.039
	(0.043)	(0.063)	(0.056)	(0.082)
log(Clicks)	0.762***	0.886***	0.921***	1.079***
	(0.015)	(0.046)	(0.065)	(0.072)
H X log(Clicks)	-0.011	0.000	0.001	0.013
	(0.009)	(0.014)	(0.013)	(0.018)
Brand B X log(Clicks)	-0.004	0.069	-0.074	-0.394***
	(0.016)	(0.057)	(0.094)	(0.103)
Brand G X log(Clicks)	0.107***	0.027	-0.011	-0.241***
	(0.018)	(0.054)	(0.063)	(0.054)
YAHOO X log(Clicks)	0.006	-0.049	-0.033	-0.095
	(0.013)	(0.041)	(0.079)	(0.069)
J X log(Clicks)	-0.192***	-0.169	-0.180	-0.269***
	(0.017)	(0.109)	(0.098)	(0.061)
Brand B	-0.244**			
	(0.077)			
Brand G	-1.210***			
	(0.078)			
YAHOO	-0.239***			
	(0.059)			
J	0.801***			
	(0.116)			
Intercept	-2.345***	-6.371***	-6.045***	
	(0.075)	(0.159)	(0.210)	
BIC	179897.72	189459.276	184335.293	255244.7

Notes: Model (1) is a negative binomial regression models with unconditional fixed effects. Models (2)-(3) are negative binomial regression models. The dispersion is a function of the mean of the covariates in model (2), while model (3) specifies a generalized parameterization of dispersion such that ln(dispersion) = f(Brand B, Brand G, Yahoo, Holiday, Jumbo). Both (3) and (4) include dummy variables for 212 campaigns and standard error correction for the campaign clusters. Model (4) is a panel Poisson fixed effects regression model. All models contain 12 Month dummies and control for a Jumbo campaign.

interest, ω_3, can again be interpreted as an elasticity coefficient.

$$\begin{aligned}\log(\text{Clicks}) = &(\omega_0 + \omega_1 \log(\text{Spend}_{i,t})) + (\omega_2 + \omega_3 \log(\text{Spend}_{i,t}))\text{H}_t \\ &+ (\omega_4 + \omega_5 \log(\text{Spend}_{i,t}))\text{J}_i + (\boldsymbol{\omega}_6 + \boldsymbol{\omega}_7 \log(\text{Spend}_{i,t}))\mathbf{B}_i \\ &+ (\boldsymbol{\omega}_8 + \boldsymbol{\omega}_9 \log(\text{Spend}_{i,t}))\mathbf{S}_i + \boldsymbol{\omega}_{10}\mathbf{M}_t + \boldsymbol{\omega}_{11}\mathbf{C}_i + \epsilon_{i,t}\end{aligned} \tag{8}$$

Table 7 states the results regarding the relationship between Clicks and Spend using linear panel regression. In Column (1), we present a fixed effect model followed by a random effect model in Column (2). The coefficient of $\text{H} * \log(\text{Spend})$ is negative and statistically significant. The results suggest that every dollar of ad spending produces lower returns in terms of clicks received on holidays when compared to weekdays. The estimated elasticity of returns is 0.013 lower on holidays, indicating that for every \$127 dollars of ad spending, the number of clicks acquired would be about 6.5% lower on holidays as compared to weekdays. Hence the results suggest that clicks cost more to purchase on holidays than on weekdays.

Taken together, our set of results in Tables 6 and 7 support the presence of a significant weekend effect - a reduced effectiveness of advertising dollars on room sales. Further the results indicate that this weekend effect is attributable to the higher cost of (acquiring) clicks on holidays, rather than due to differences in the conversion of clicks to sales on weekdays vs. holidays. The results are robust across the three brands and two search engines in our study, as vividly illustrated in Figure 5. Panel A shows that each of our 6 combinations of search engine and brand exhibits a reduction in advertising elasticity on weekends. Panel B indicates that there is no difference in conversion rates, while Panel C shows that the purchase price for clicks is higher on weekends for each combination.

6 Effect of Position and Consumer Search Behavior

§4.2 demonstrated that the sales effectiveness of paid search advertising is significantly reduced on weekends (Table 4), plausibly because of the higher cost of acquiring clicks (Ta-

Table 7: Regression of Clicks on Spend ($^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$). N = 47070 and campaign groups = 212 across all models. The dependent variable is log(Clicks).

	(1) Reg-FE	(2) Reg-RE
H	-0.009	-0.009
	(0.008)	(0.008)
log(Spend)	0.870***	0.870***
	(0.020)	(0.020)
H X log(Spend)	-0.013***	-0.013***
	(0.002)	(0.002)
Brand B X log(Spend)	-0.088***	-0.088***
	(0.025)	(0.024)
Brand G X log(Spend)	-0.110***	-0.110***
	(0.023)	(0.023)
YAHOO X log(Spend)	-0.114***	-0.113***
	(0.024)	(0.023)
J X log(Spend)	-0.132**	-0.133**
	(0.045)	(0.045)
Brand B		0.209
		(0.114)
Brand G		-0.341***
		(0.098)
YAHOO		0.291***
		(0.083)
J		1.578***
		(0.213)
Intercept	1.440***	1.246***
	(0.033)	(0.099)
R2	0.843	0.913

Notes: Model (1) is a linear panel regression model with fixed effects, while model (2) is a linear panel regression model with random effects. Both models contain 12 Month dummies and control for a Jumbo campaign. Standard errors are corrected for clustering of observations within campaigns.

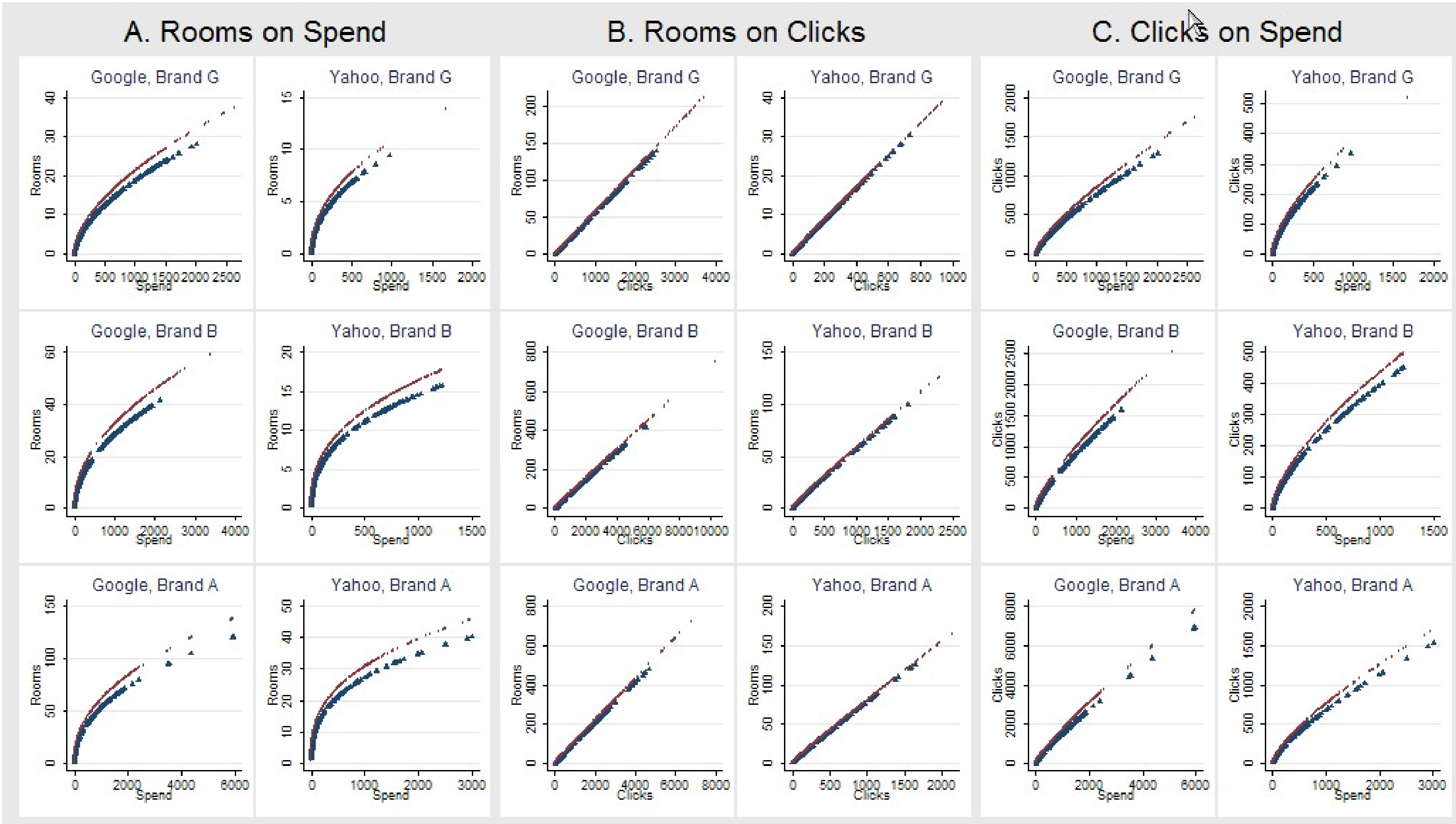


Figure 5: Illustration that ad spending is less effective on weekends, for each of the brand-search engine pairs in our study (left panel). The result occurs not because of differences in conversion rate of clicks to room sales (middle panel) but because of higher cost of clicks (right panel).

bles 6–7 in §5). Our analysis employed an aggregate of spending and sales (and clicks) metrics over all search ranks or positions. In this section, we take the analyses a step further to examine whether the observed weekend effect applies uniformly to all positions in the paid search listings, or if the effect is more pronounced in the top (or bottom) ranks of the listings.

To understand why search advertising position might moderate or alter the weekend effect, consider the search behaviors or patterns of consumers apropos paid search listings. For simplicity, suppose that we can partition the space of ranks into "top" ranks and "low" ranks. There is some evidence that conversion rates (the fraction of clicks that lead to sales) are lower at the top ranks than at low ranks (Agarwal et al., forthcoming), and we also observe this property in our data set. Even if the rates were the same, spending on the low-ranked positions would generate higher normalized returns (i.e., in terms of advertising elasticity) because those positions have a lower cost per click. Hence the low-ranked positions have a more favorable payoff ratio than the top-ranked positions. Now, while the firm received far fewer total clicks on weekends (see Figure 1), the drop in clicks primarily occurred at the top ranks and was negligible for the low ranks (see Figure 6). In other words, on weekends the firm spent a greater fraction of its ad spending on positions that have a more favorable payoff ratio (than the corresponding fraction on weekdays). Therefore, the observed reduction in advertising effectiveness on weekends (discussed in §4.2) must primarily be driven by the top positions, and be even more pronounced for top positions than the aggregate effect described in §4.2.

Estimating the effect of position on sales is usually complicated due to the endogeneity between the firms' bidding strategies and payoffs from advertising. Recently, researchers have proposed various techniques to examine and isolate the causal effect of position (see e.g., Narayanan and Kalyanam (2011)). However, we are interested only in the weekend effect across different positions—i.e., whether the variation in advertising elasticity across weekdays and weekends itself differs across top and bottom positions in the paid search listings—rather than the causal effect of position on outcomes. Therefore, we can address our objective by regressing sales on expenditures while controlling for position.

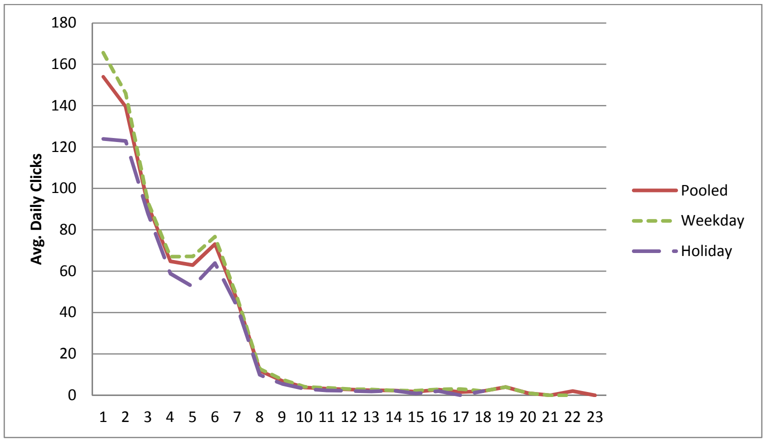


Figure 6: Average Daily Clicks across Position for Weekdays and Holidays

We examine this intuition about the impact of position on the weekend effect. We denote top ranks as those above the mean average daily position or rank obtained by all the advertisements (2.95, in our sample). We define a new binary variable LOW to indicate low ranks (LOW=1) vs. top ranks (LOW=0). We use the interactions LOW*H, LOW*log(Spend), and LOW*H*log(Spend) to calculate the impact of position on the weekend effect. Table 8 presents the results of three models for the regression of Rooms on Spend after incorporating a dummy variable for low vs. top ranks. The first is a pooled model. We start with the negative binomial model presented in Table 4, and include a set of position effects. We also present an alternative specification—two split-sample models focusing on just the top ranks (Column (2)) and low ranks (Column (3))—which facilitates interpretation of the effect.

The results in Table 8 provide evidence of a difference in the weekend effect for top vs. low ranks. Consider Column (2), where the coefficient of H$*$log(Spend) is -0.024, relative to -0.019 for the aggregate analysis presented in §4.2. Recall that, aggregated across all positions, the firm's return from advertising on weekends was 8.79% lower on weekends, at the mean daily spending level of $\approx$ \$127. Computing the corresponding numbers for ad spending on the top ranks, we see that the return from ad spending on weekends is lower by 10.98%.

Table 8: Estimation Results with Position Effects ($^{*}p < 0.05,^{**} p < 0.01,^{***} p < 0.001$). N = 47070 and campaign groups = 212 across all models. The dependent variable is Rooms.

	(1) NB-FE Pooled	(2) NB-FE top rank	(3) NB-FE low rank	(4) Gen NB Pooled	(5) Gen NB top rank	(6) Gen NB low rank	(7) Gen NB top rank	(8) Gen NB low rank
H	-0.005	0.028	0.070	0.01	-0.012	0.037	-0.013	-0.480
	(0.027)	(0.027)	(0.071)	.(0.028)	(0.030)	(0.092)	(0.030)	(0.425)
log(Spend)	0.494***	0.548***	0.657***	0.715***	0.687***	0.823***	0.684***	0.788***
	(0.013)	(0.014)	(0.034)	(0.017)	(0.019)	(0.040)	(0.021)	(0.130)
H X log(Spend)	-0.019***	-0.024***	-0.015	-0.022***	-0.016*	0.003	-0.017**	0.112
	(0.006)	(0.006)	(0.015)	(0.006)	(0.008)	(0.022)	(0.006)	(0.105)
B X log(Spend)	0.115***	0.076***	0.386***	-0.027	-0.015	0.258***	-0.061**	0.131
	(0.013)	(0.014)	(0.039)	(0.018)	(0.021)	(0.045)	(0.022)	(0.213)
G X log(Spend)	0.191***	0.249***	0.166***	-0.009	-0.027	0.161**	-0.020	-0.058
	(0.016)	(0.017)	(0.037)	(0.024)	(0.028)	(0.051)	(0.029)	(0.195)
S X log(Spend)	-0.119***	-0.113***	-0.176***	-0.163***	-0.166***	-0.135**	-0.181***	-0.139
	(0.011)	(0.012)	(0.032)	(0.016)	(0.019)	(0.042)	(0.021)	(0.345)
J X log(Spend)	-0.179***	-0.225***	-0.347	-0.234***	-0.196***	-0.415	-0.216***	
	(0.016)	(0.017)	(0.233)	(0.020)	(0.028)	(0.213)	(0.023)	
Brand B	-0.760***	-0.543***	-2.244***	-2.000**	-19.131	-2.636***	14.016	-2.023*
	(0.054)	(0.060)	(0.171)	(0.659)	(4073.555)	(0.747)	(402.143)	(0.959)
Brand G	-1.861***	-1.862***	-2.357***	-0.059	-0.433	-0.675	13.021	-2.876***
	(0.057)	(0.063)	(0.146)	(0.411)	(1.095)	(0.527)	(402.143)	(0.615)
YAHOO	0.091*	0.021	0.707***	0.406	-0.762	0.391	0.128	0.516
	(0.043)	(0.047)	(0.133)	(0.461)	(1.134)	(0.586)	(0.131)	(0.659)
J	0.737***	0.773***	1.273	4.439***	5.139***	6.574***	2.928***	
	(0.099)	(0.101)	(1.452)	(0.387)	(1.025)	(1.537)	(0.178)	
LOW	-1.303***			-0.568***				
	(0.060)			-0.067				
LOW X log(Spend)	0.152***			0.162***				
	(0.013)			(0.016)				
LOW X H	0.040			0.036				
	(0.077)			(0.088)				
LOW X log(Sp)X H	0.011			0.017				
	(0.016)			(0.021)				
Intercept	-0.564***	-0.676***	-1.791***	-3.099***	-2.124	-3.308***	-14.114	0.194
	(0.054)	(0.058)	(0.158)	(0.483)	(1.202)	(0.604)	(402.143)	(1.150)
BIC	181594.123	134630.443	45381.996	187442.557	139775.437	48670.024	113479.748	2772.937
N	47070	30018	16907	47070	30081	16989	24923	2398

Notes: Models (1)-(3) are panel negative binomial models with fixed effects, and models (4)-(6) are generalized negative binomial models where dispersion is parameterized as ln(dispersion) = f(B, S, H, J). In models (1)-(6) the top and bottom ranks are distinguished at the mean rank value. The generalized negative binomial models models in the last two columns (7)-(8) use an alternate (more extreme) measures of top and bottom ranks. Standard errors are corrected for the campaign clusters.

Hence we find that the weekend effect is stronger for the top ranks, and is not statistically significant at the low ranks (Column (3)). The same finding can be derived by combining multiple coefficients from Column (1). The finding is robust to alternative specifications (Columns (4-6) are generalized negative binomial models) and alternative thresholds for low vs. top ranks (see Columns (7)-(8), which are the split-sample models using a more extreme definition of top (< 2) and low ranks (> 7)). This finding sharpens our insights regarding the weekend effect. Moreover, since a significant share of the paid search advertising spending occurs in the top positions, the presence of a significant reduction in advertising effectiveness there underscores the importance of the weekend effect.

7 Conclusion

One of the essential characteristics of the Internet and Internet-based commerce is that it is an always open 24/7/365 system, agnostic to time of day, day of week, or other such temporal characteristics. Yet, societal and cultural factors dictate that user activity on the Internet will vary along these temporal dimensions. This variation suggests that, with respect to Internet commerce, business decisions and resource allocation policies ought to be sensitive to these temporal dimensions. For instance, in search advertising, the price (of each keyword) and spending level is determined through real-time auctions where multiple firms compete to display their ads alongside search results, typically employing an automated system that governs its bids and other parameters of participation in these real-time auctions. Should an advertiser's bidding strategies involve a temporal component? Should they employ the same, or different, allocation rules at different periods within a day, week, or month?

Our findings about the weekend effect are relevant to managers and firms because paid search is a highly data-driven and measurable form of advertising. To our knowledge, media managers do not presently configure their bidding strategies by day-of-week, primarily due to lack of awareness of a weekend effect. Therefore our work introduces an additional metric or lever with which managers can fine-tune and optimize their advertising expenditures on paid search. This recommendation is immediately actionable because all leading search engines already offer "day-parting" rules which allow bidding strategies to be customized by day of week (or time of day). Moreover, while we demonstrated the weekend effect in the specific context of the hotel and travel sector, it is plausible that it holds more generally because it is caused by a reduction in search activity on weekends, a phenomenon that is widespread across many industries and products. It would also be useful for managers to examine whether the weekend effect can be refined into a day-of-week effect, which would then motivate further tuning of bidding and budget allocation strategies.

We are pursuing certain additional directions on this topic. While this draft describes a weekend effect, a natural follow-on question is whether media managers are already taking this into account in making their spending decisions. We can address this question by comparing the marginal performance of advertising expenditures across weekdays and weekends. Additionally, it would also be of interest to examine whether the weekend effect is moderated by the nature of the advertising campaign. For instance, paid search advertisements that allow retailers to target particular brands to specific geographic (local vs. national) markets may differ in the advertising elasticity across weekdays and holidays. Finally, while we control for the multitude of campaigns, useful insights could emerge from studying whether there exist interdependencies or synergies in sales generated from spending across campaigns, and whether they varied across weekdays and holidays. These refinements can lead to a better understanding of advertising effectiveness and the weekend effect.

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