Measuring ROI on Sponsered Search

Experiment Overview

Bazaar uses both display advertising and search engine advertising, running paid search ads on the two major search engines, Google and Bing.

Bazaar releases its ads in response to keywords used by online consumers; the marketing team classifies these keywords into two broad categories: branded and non branded.

Branded keywords include keywords such as "Bazaar," "Bazaar shoes," and "Bazaar guitar" that contain the Bazaar brand name.

Non branded keywords include keywords such as "shoes" and "guitar" that do not contain the Bazaar brand name.

The firm employs the same strategies for both Google and Bing for targeting ads, choosing keywords to advertise on, and ad copies used, and the mix of potential customers visiting the company's website from both search engines is virtually identical; the only difference is that their Bing campaign is much smaller than their Google campaign.

Experiment Setup

We used data from 12 weeks, which included average organic search results, sponsored branded terms, and data from various platforms (Google, Bing, Yahoo, and Ask).

The technical issue prevented sponsored adverts on the Google platform between weeks 10–12. The keyword advertising are aired continuously for 12 weeks on the other sites.

We wish to comprehend the causal impact of the advertisements given the circumstances. The week 10–12 Google sponsored ad interruptions are the treatment. Other search engines including Bing, Yahoo, and Ask serve as the control group while Google serves as the therapy group.

Threats to Causal Inference

1. Selection Bias

To prevent selection bias, it is ideal for experiment subjects to be substantially similar to one another and to the larger population from which they are selected. In our instance, it's safe to believe that this experimental design wouldn't result in selection bias because the ad techniques, keyword bids, and mix of potential buyers visiting a website are the same across Google and other search engines.

2. Omitted Variable Bias

We believe that some external factors that are not represented in the data set may also have an impact on this experiment. For instance, the Google search engine may experience additional technical difficulties that we were unaware of, or Bazaar's rivals may choose to use a specific search engine for a brief period of intense advertising.

3. Simultaneity Bias

Bidirectional effects between the independent and dependent variables are not taken into account in this experiment due to simultaneity bias. In other words, although website visits may occasionally also have an impact on ad clicks, only ad clicks are considered to influence website visits in the experiment. Because consumers may compare Bazaar items to those of their rivals while making their final purchasing choice, leading to an increase in ad clicks.

4. Measurement Error

Since we're unsure whether customers actually viewed the advertisement, there may be some problems with sponsored ad click-through measurement. It's very possible that customers accidentally clicked the advertisement and then quickly left the landing page.

Importing Packages

```
library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

library(plm)

## Warning: package 'plm' was built under R version 4.2.1

##
## Attaching package: 'plm'

## The following objects are masked from 'package:dplyr':
##
##     between, lag, lead

library(ggplot2)
```

Data Overview

The data set is weekly average traffic data through four platforms(Google, Bing, Yahoo, Ask) for 12 weeks. After importing the data, we created a "treatment" variable for test vs. control groups, an "after" variable that indicates 1 for treatment weeks and 0 for pre-treatment weeks and a "total_traffic" variable to aggregate the sponsored and organic traffic.

```
data = read.csv('did_sponsored_ads.csv')
treatment_week = c(10,11,12)
data <- data %>% mutate(treatment = ifelse(platform == 'goog',1,0),
                        after = ifelse(week %in% treatment_week,1,0),
                        total_traffic = avg_spons + avg_org)
```

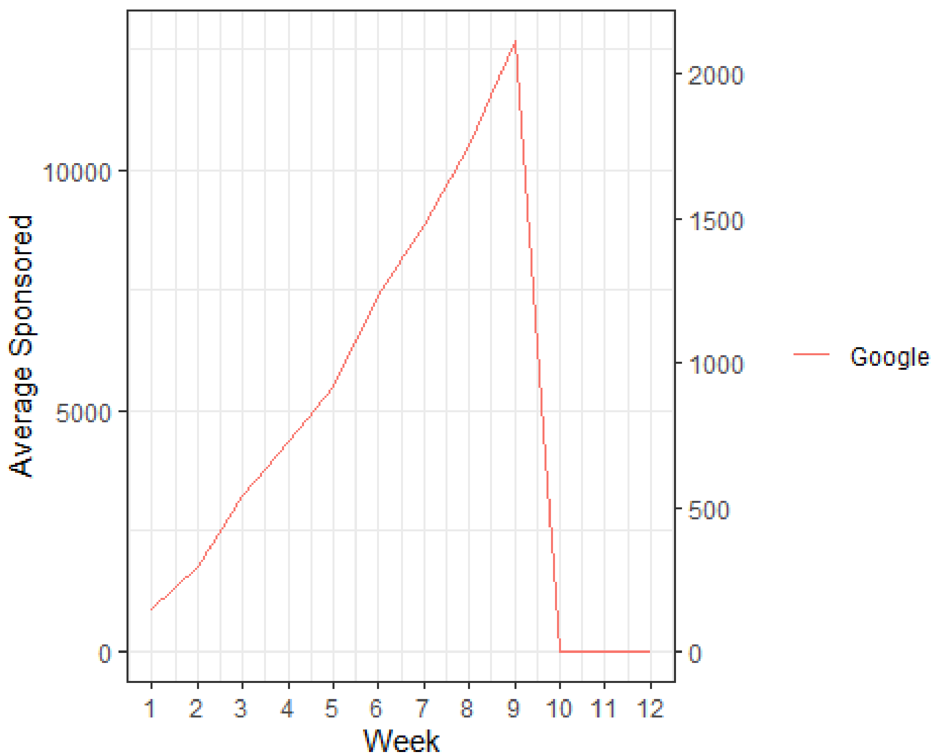
Data description:

```
summary(data)

##        id          platform              week         avg_spons
##  Min.   :1.00   Length:48          Min.   : 1.00   Min.   :    0
##  1st Qu.:1.75   Class :character   1st Qu.: 3.75   1st Qu.: 1665
##  Median :2.50   Mode  :character   Median : 6.50   Median : 3816
##  Mean   :2.50                      Mean   : 6.50   Mean   : 5120
##  3rd Qu.:3.25                      3rd Qu.: 9.25   3rd Qu.: 7834
##  Max.   :4.00                      Max.   :12.00   Max.   :16211
##     avg_org       treatment        after       total_traffic
##  Min.   : 128   Min.   :0.00   Min.   :0.00   Min.   :  489
##  1st Qu.:1027   1st Qu.:0.00   1st Qu.:0.00   1st Qu.: 3134
##  Median :1904   Median :0.00   Median :0.00   Median : 6112
##  Mean   :2323   Mean   :0.25   Mean   :0.25   Mean   : 7443
##  3rd Qu.:3448   3rd Qu.:0.25   3rd Qu.:0.25   3rd Qu.:10700
##  Max.   :6889   Max.   :1.00   Max.   :1.00   Max.   :21463
```

Natural Experiment Visualization:

```
ggplot(data %>% filter(platform == 'goog'), aes(x=week, y= avg_spons, color =
'Google')) +
  geom_line() +
  scale_y_continuous(sec.axis = sec_axis(~./6)) +
  scale_x_continuous(breaks = seq(1, 12, by = 1)) +
  labs(y = "Average Sponsored", x = "Week") +
  theme_bw() +
  theme(legend.title = element_blank())
```



As observed from the graph above, at week 9 there was a glitch with Google Ad campaign.For the week 10, 11 and 12 there was no sponsored Ad on Google, which explains the sudden drop and Zero values for those three weeks.

Question1: What is Wrong with Bob's RoI Calculation?

Sponsored advertisements play a crucial role in the survival and growth of businesses, and they also make up a sizable portion of overall operating costs. But evaluating the ROI of advertising spend has never been easy.

We discovered that revenue inflation was the primary cause of Bob's incorrect ROI calculation.That is to say, Bob failed to take into account one of the behaviors of those who use sponsored advertisements to find the website and make a purchase.

Only a small portion of users who click on sponsored adverts actually visit Bazaar's website as a result. Others will still access the website via organic links to make purchases even if they don't see the product promoted in a search engine.

As a result, these individuals' income is not derived from sponsored advertisements. The marketing analytics team may overestimate revenue and ROI if they treat all user clicks on sponsored advertising as real.

The error suggests that a portion of people who searched for branded keywords already had the intention to visit Bazaar.com, logically this portion of people is not driven by the sponsored ads.

The current ROI calculation assumes that everyone who clicked on the sponsored ads was casually driven by the sponsored ads. Instead, regardless of whether sponsored ads were present or not, people would still access the website via an organic link, hence their inclusion in the ROI calculation is unnecessary.)

Question 2: Define the Treatment and Control.

In this case, treatment consists of disabling sponsored search advertising on Google for the 10th, 11th, and 12th weeks. Bing, Yahoo, and Ask served as the control groups, with Google serving as the treatment group.

Question 3: Consider a First Difference Estimate.

One approach we might take(if we could only observe the treated unit) would be to calculate the first difference (that is, the % change in web traffic arriving from Google; (after – before) / before). This estimate is the pre-post difference in the treated cohort.

```
google<- data %>% filter(platform == "goog")

model1 <- lm(log(total_traffic) ~ after, data = google)

summary(model1)

##
## Call:
## lm(formula = log(total_traffic) ~ after, data = google)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.54933 -0.15495  0.03784  0.46975  0.95834
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 8.783506   0.248968  35.280 7.94e-12 ***
## after       0.001306   0.497936   0.003    0.998
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7469 on 10 degrees of freedom
## Multiple R-squared:  6.88e-07,   Adjusted R-squared:   -0.1
## F-statistic: 6.88e-06 on 1 and 10 DF,  p-value: 0.998

exp(coef(summary(model1))[2])-1

## [1] 0.001306972
```

We noticed a weekly reduction in total visits to the website of 0.13% when there were no sponsored search advertising on Google.

Due to the p-value of 0.998(which is > 0.05), we were unable to draw any conclusions about whether there are differences between conditions involving and without sponsored advertisements.

This is not the right technique to calculate the impact of sponsored advertisements. By using the pre-post estimate, we presupposed that the market would remain stable and that traffic wouldn't alter as a result of external factors.

Therefore, we only contrasted the therapy group's before- and after-treatment data. To be more precise, week 1 through week 9 and week 10 through week 12 share the same search nature. There are no weekly seasonal differences.

Establishing the causality of sponsored advertisements would be challenging given all these presumptions. As a result, we used Difference in Difference (DiD).

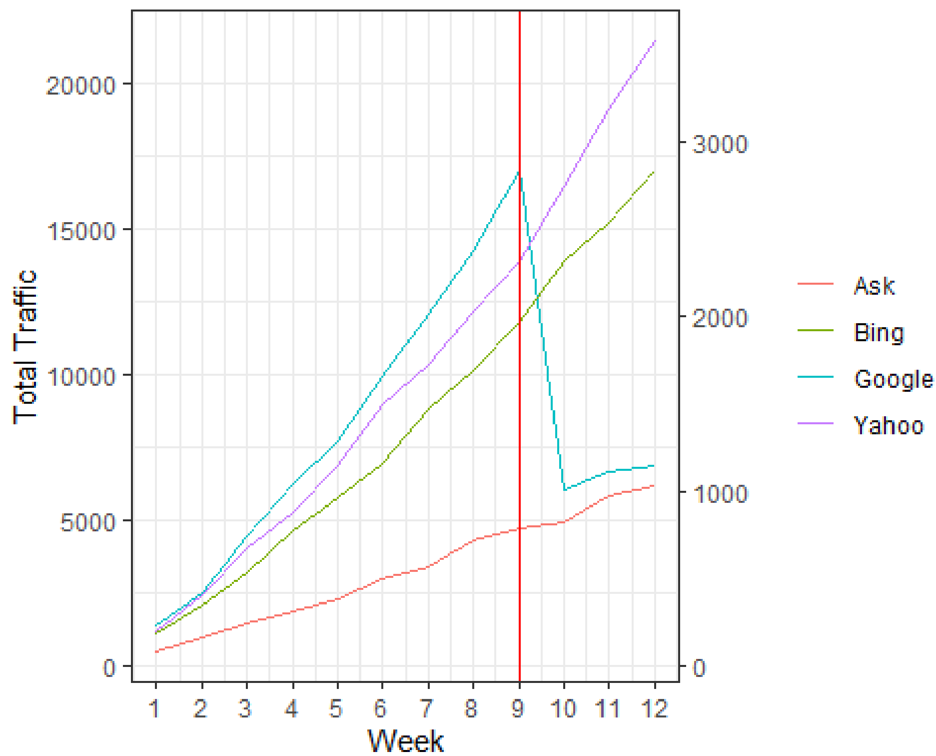
Question 4: Calculate the Difference-in-Difference

We first verified the presumption of parallel trends before calculating the difference in differences estimate of the treatment impact. The pre-treatment weeks should show behavioral similarities between the treatment and control groups. Additionally, a strong counter factual for the treatment group must exist.

Visualization Showcasing Parallel Trends

```
bing = data %>%  filter(platform %in%  c('bing')) %>% select(week,
total_traffic)
yahoo = data %>%  filter(platform %in%  c('yahoo')) %>% select(week,
total_traffic)
ask = data %>%  filter(platform %in%  c('ask')) %>% select(week,
total_traffic)

ggplot(data %>% filter(platform == 'goog'), aes(x=week, y= total_traffic,
color = 'Google')) +
  geom_line() +
  geom_line(aes(x=week, y= total_traffic, color = 'Bing'), data = bing) +
  geom_line(aes(x=week, y= total_traffic, color = 'Yahoo'), data = yahoo) +
  geom_line(aes(x=week, y= total_traffic, color = 'Ask'), data = ask) +
  geom_vline(xintercept = 9,color='red') +
  scale_y_continuous(sec.axis = sec_axis(~./6)) +
  scale_x_continuous(breaks = seq(1, 12, by = 1)) +
  labs(y = "Total Traffic", x = "Week") +
  theme_bw() +
  theme(legend.title = element_blank())
```



Pre-treatment parallel trends were not visible in the aforementioned visualization. However, to determine whether the post-treatment weeks are relevant whereas the pre-treatment weeks are not, we employed the dynamic DiD.

```
did_dynamic <- lm(total_traffic ~ treatment + factor(week) + treatment *
factor(week),data=data)
summary(did_dynamic)

##
## Call:
## lm(formula = total_traffic ~ treatment + factor(week) + treatment *
##     factor(week), data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8710.7  -111.8    87.3  1422.3  6586.3
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 936.3     2465.2   0.380 0.707414
## treatment                   449.7     4930.3   0.091 0.928087
## factor(week)2               881.3     3486.3   0.253 0.802574
## factor(week)3              1964.7     3486.3   0.564 0.578291
## factor(week)4              2998.3     3486.3   0.860 0.398274
## factor(week)5              4023.3     3486.3   1.154 0.259840
## factor(week)6              5361.0     3486.3   1.538 0.137190
## factor(week)7              6584.7     3486.3   1.889 0.071069 .
```

```
## factor(week)8              7940.0     3486.3   2.278 0.031955 *
## factor(week)9              9204.3     3486.3   2.640 0.014337 *
## factor(week)10            10794.3     3486.3   3.096 0.004932 **
## factor(week)11            12445.3     3486.3   3.570 0.001550 **
## factor(week)12            13940.3     3486.3   3.999 0.000529 ***
## treatment:factor(week)2     259.7     6972.5   0.037 0.970600
## treatment:factor(week)3    1055.3     6972.5   0.151 0.880960
## treatment:factor(week)4    1826.7     6972.5   0.262 0.795571
## treatment:factor(week)5    2274.7     6972.5   0.326 0.747075
## treatment:factor(week)6    3187.0     6972.5   0.457 0.651723
## treatment:factor(week)7    4140.3     6972.5   0.594 0.558196
## treatment:factor(week)8    4909.0     6972.5   0.704 0.488177
## treatment:factor(week)9    6424.7     6972.5   0.921 0.365997
## treatment:factor(week)10  -6122.3     6972.5  -0.878 0.388613
## treatment:factor(week)11  -7146.3     6972.5  -1.025 0.315616
## treatment:factor(week)12  -8437.3     6972.5  -1.210 0.238030
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4270 on 24 degrees of freedom
## Multiple R-squared:  0.6819, Adjusted R-squared:  0.3771
## F-statistic: 2.237 on 23 and 24 DF,  p-value: 0.0278
```

The aforementioned finding showed that the assumption was false. We nonetheless conducted a Difference in Difference regression comparing the treatment and control groups despite the fact that the assumption wasn't supported in order to determine the actual causality of the sponsored advertisements. Treatment, After, and the interaction between Treatment and After would all be independent variables for the DiD regression.

```
did <- lm(total_traffic ~ treatment + after + treatment * after, data=data)
summary(did)
```

```
##
## Call:
## lm(formula = total_traffic ~ treatment + after + treatment *
##     after, data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8437.7 -3231.0  -510.5  3591.6  8630.0
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)       5265.0      882.5   5.966 3.79e-07 ***
## treatment         3124.9     1765.0   1.770  0.08357 .
## after             8064.7     1765.0   4.569 3.94e-05 ***
## treatment:after  -9910.6     3530.0  -2.808  0.00741 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 4586 on 44 degrees of freedom
## Multiple R-squared:  0.3274, Adjusted R-squared:  0.2816
## F-statistic: 7.141 on 3 and 44 DF,  p-value: 0.0005211
```

Bazaar.com loses, on average, 9910 clicks per week without sponsored advertisements on the Google network. The true causality for the sponsored commercials is captured by the new treatment effect assessed above and above the behavior of the control group. As a result of our knowledge of the behavior of the control and treatment groups,this method is more accurate than the pre-post estimate.

Question 5: Given Your Treatment Effect Estimate, Fix Bob's ROI Calculation

Average probability of purchasing from Bazaar.com is 12% given they clicked onto the website and average margin per conversion is $21.

Hence average revenue per click is 0.12 x $21 = $2.52.

Average cost per click for a sponsored ad is $0.6.

Bob's ROI calculation is (Margin per conversion * probability of click - cost per click / cost per click) - ($2.52 - $0.60) / ($0.60) = 320%.

We needed a more precise estimate of the percentage of people who were causally influenced by the sponsored ads in order to calculate the correct ROI.

Given that sponsored advertising were no longer running, we needed to compute the traffic that would have used organic search results in order to calculate the percentage of traffic that was causally driven by ads. This was done in the preceding section.

```
did_organic <- lm(avg_org ~ treatment + after + treatment * after, data=data)
summary(did_organic)

##
## Call:
## lm(formula = avg_org ~ treatment + after + treatment * after,
##     data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1928.78  -847.92   -52.67   825.00  2067.33
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)       1489.7      215.4   6.917 1.51e-08 ***
## treatment          777.0      430.7   1.804   0.0781 .
## after             1984.1      430.7   4.607 3.49e-05 ***
## treatment:after   2293.2      861.4   2.662   0.0108 *
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1119 on 44 degrees of freedom
## Multiple R-squared:  0.6043, Adjusted R-squared:  0.5773
## F-statistic:  22.4 on 3 and 44 DF,  p-value: 5.881e-09
```

In the absence of running sponsored ads on Google, 2293 would have used organic search results to visit Bazaar.com.

C = A + B

C = Total clicks from sponsored ads A = clicks truly motivated by sponsored ads B = clicks by customers who would still visit Bazaar.com in the absence of sponsored ads (B)

A = 9,910 (new treatment effect in did) B = 2,293 (new treatment effect in did_organic)

Proportion of true traffic = A / (A+B) = 9,910 / (9,910+2,293) = 0.8120954 (81%)

The new ROI should be (Margin per conversion * probability of click * proportion - cost per click) / cost per click

New_ROI = ($21 * 0.12 * 0.8120954- 0.6)/0.6 New_ROI = 241.080%

```
New_ROI = (21 * 0.12 * 0.8120954 - 0.6)/0.6
New_ROI

## [1] 2.410801
```

Based on the updated projected treatment effect, our revised ROI from sponsored branded advertisements is 241%. The preceding figure of ROI 320% is reduced to 241% without the fictitious augmentation of sponsored ads revenue, which is still a respectable return on investment in sponsored ads advertising.

Conclusion

sponsored advertisements actually drive 81% of all visits. For the remaining 19% of branded keyword search visitors who still access the website through organic links in the absence of sponsored adverts, Bazaar.com continues to pay a cost per click of $0.6. Given that the corporation might have used this advertising budget to fund alternative marketing initiatives, it represents an opportunity.

We employed Difference-in-Difference through the following procedures to determine the correct causal impact of sponsored adverts on Bazaar.com's traffic:

1) Determine the initial difference between the weekly average traffic (Ads + Organic) before and after the technical issue. Instead of the overall treatment effect, this provides us with the raw effect of the Google search sponsored advertising.

2) Contrast Google's first level pre-post difference with that of other search engines' first level pre-post differences. Since this step accounts for potential con-founders

like seasonal differences among weeks and market conditions, it establishes the actual incremental effect.

We concluded that the remaining 19% of traffic was visiting Bazaar.com via organic links as opposed to sponsored ads and that this 19% should be disregarded when calculating the original ROI because, as shown from the new treatment effects of the experiments, an average of 9.9K clicks per week are lost in the absence of sponsored ads, which is roughly 81% of the weekly traffic.

We recalculated a revised ROI from sponsored branded advertisements based on the two parameters mentioned above with the additional treatment effects.

The prior calculation of ROI 320% is down to the current adjusted ROI 241% after weeding out the erroneous overvaluation of sponsored ads revenue and adjusted opportunity cost, which is still a respectable return on investment in sponsored ads advertising.