Measuring ROI on Sponsored Search Ads

Lingyu Liu

Executive Summary

Business Overview

Bazaar. com is scrutinizing the effect of its Google sponsored search ads on web traffic and ROI. The core challenge is how to discerning the actual influence of these ads, seperating it from organic traffic to ensure accurate ROI calculation. What is wrong with Bob's calculation is that he inflat the revenue, for he treat all the revenue was earned only by the sponsored ads, ignoring the proportion of purchase via organic links. Thus, to get the accurate ROI, getting the true proportion of purchase via sponsored ads is the key question.

The Performed Analysis

To estimate the correct causal impact of the sponsored ads, Didderence-in-Difference method will be conducted through the following steps: 1) Calculate the first-difference of total traffic before and after the glitch, to understand the raw effect of sponsored ads of google.

2). To get the true incremental effect, compare the first level pre-post difference at Google with other search engines.

Results

Based on the experiment results, on average the true proportion of clicks via sponsored ads is about 81%, resulting a recaluated ROI of 241%.

Experiment

(a) What is Wrong with Bob's RoI Calculation?

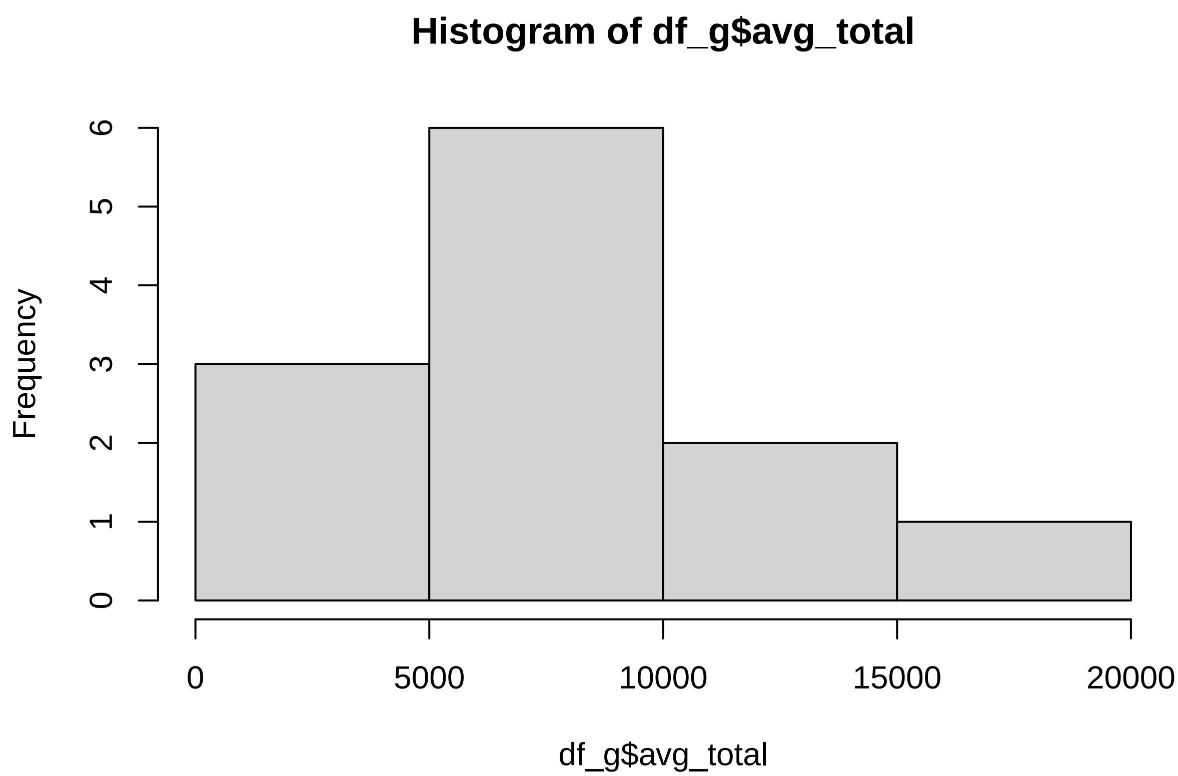
He overcalculated the ROI, for he inflat revenue. Among all customers who purchase, only the proportion of actually visited Bazaar's website via sponsored ads could be considered as valid. Other customers who do not see the advertised products in the search engine can also enter the website by organic links to purchase products. Thus, the current calculation is overestimating the revenue caused by ads.

(b) Define the Treatment and Control.

In this case, treatment will be the glitch weeks, the stop of sponsored search ads on Google search at week10,week11,week12. Treatment group is Google, and Ask, BIng, Yahoo would be the control group.

(c) Consider a First Difference Estimate.

```
df_g = df %>% filter(platform == 'goog')
hist(df_g$avg_total)
```




```
#the dependent variable is skewed, and since there exists 0 traffic, we need to use lo
summary(lm(log(avg_total) ~ after, df_g))
```

```
##
## Call:
## lm(formula = log(avg_total) ~ after, data = df_g)
##
## 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
```

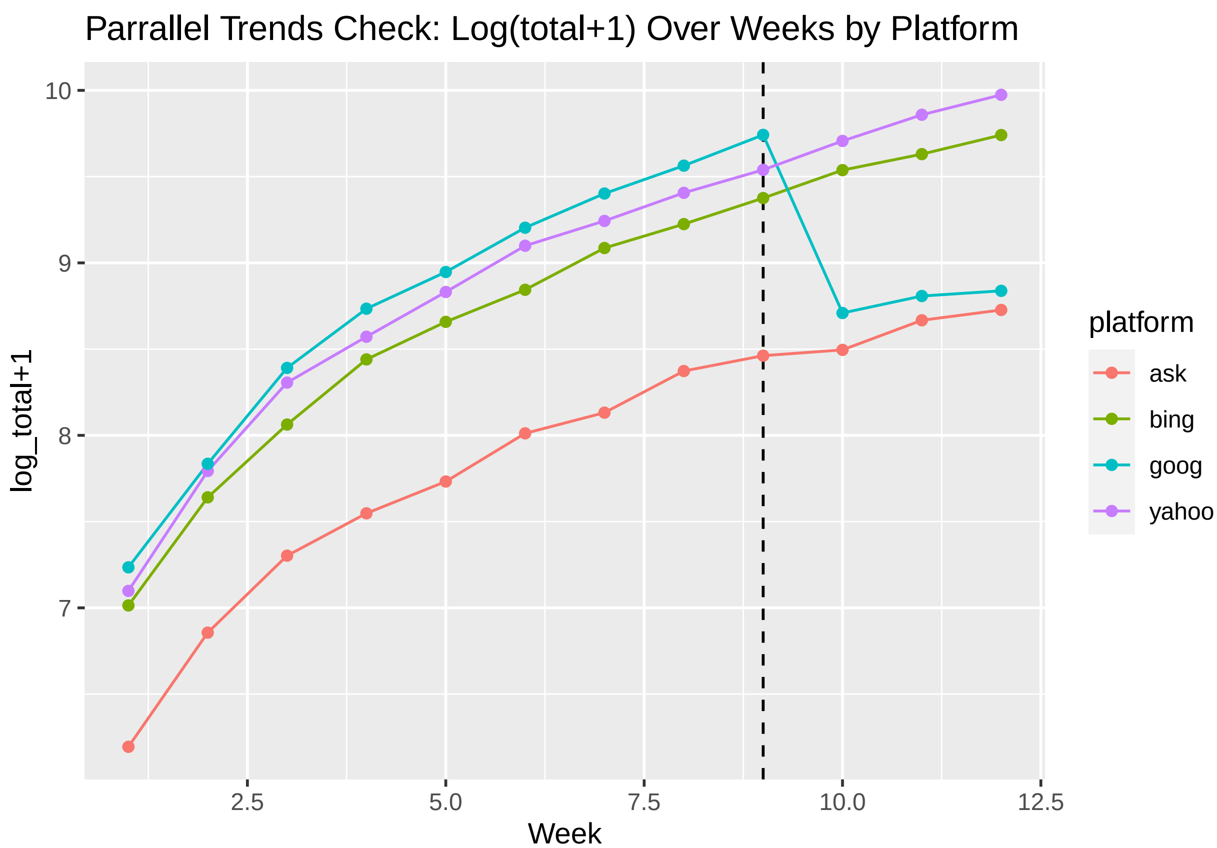
```
## [1] 0.001306853
```

With no sponsored ads at google, we observed a 0.13% change in traffic,however, based in the sample on average, the probability of getting the observed t-value if 0.998, which is extremely significant, thus, we can not conclude that there are differences with and without sponsored ads. This is because, when we are simply comparing the before and after results, we assume that the market remains constant and the online traffic will not be affected by the glitch. Thus, with this assumption, it is hard to draw causality from the ads. So we will conduct difference-in-difference method.

(d) Calculate the Difference-in-Differences.

Before we conduct DiD test, we should first checked the assumption of parallel trends: Before the glitch weeks, the treatment and control groups should have continued in parallel, and control group needs to behave differently with the treatment group.

```r
p = ggplot(df, aes(x = week, y = log(avg_total+1), group = platform, color = platform))
# visualize to see the trends of traffic across groups
p + geom_line() +
   geom_vline(xintercept = 9, linetype = "dashed", color = "black") +
   geom_point() +
   ggtitle("Parrallel Trends Check: Log(total+1) Over Weeks by Platform") +
   xlab("Week") +
   ylab("log_total+1")
```



As the plot shows, before the glitch, the clicks across these websites share a parallel trends before first-treatment.

consolidate the results statistically

```
summary(plm(log(avg_total)~treatment*factor(week),df,model='within',index=c('id')))
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = log(avg_total) ~ treatment * factor(week), data = df,
##     model = "within", index = c("id"))
##
## Balanced Panel: n = 4, T = 12, N = 48
##
## Residuals:
##        Min.     1st Qu.      Median     3rd Qu.        Max.
## -9.5844e-02 -1.4771e-02  1.7684e-15  1.8271e-02  8.3830e-02
##
## Coefficients:
##                             Estimate Std. Error  t-value  Pr(>|t|)
## factor(week)2               0.661926   0.048806  13.5623 3.662e-12 ***
```

```
## factor(week)3             1.122353   0.048806  22.9961 < 2.2e-16 ***
## factor(week)4             1.418721   0.048806  29.0685 < 2.2e-16 ***
## factor(week)5             1.639319   0.048806  33.5883 < 2.2e-16 ***
## factor(week)6             1.883716   0.048806  38.5958 < 2.2e-16 ***
## factor(week)7             2.052471   0.048806  42.0535 < 2.2e-16 ***
## factor(week)8             2.233356   0.048806  45.7597 < 2.2e-16 ***
## factor(week)9             2.357879   0.048806  48.3111 < 2.2e-16 ***
## factor(week)10            2.478929   0.048806  50.7913 < 2.2e-16 ***
## factor(week)11            2.617579   0.048806  53.6321 < 2.2e-16 ***
## factor(week)12            2.712997   0.048806  55.5871 < 2.2e-16 ***
## treatment:factor(week)2  -0.061315   0.097612  -0.6282    0.5364
## treatment:factor(week)3   0.034192   0.097612   0.3503    0.7295
## treatment:factor(week)4   0.081179   0.097612   0.8316    0.4145
## treatment:factor(week)5   0.073400   0.097612   0.7520    0.4600
## treatment:factor(week)6   0.085825   0.097612   0.8792    0.3888
## treatment:factor(week)7   0.115221   0.097612   1.1804    0.2505
## treatment:factor(week)8   0.095926   0.097612   0.9827    0.3364
## treatment:factor(week)9   0.149794   0.097612   1.5346    0.1391
## treatment:factor(week)10 -1.003972   0.097612 -10.2853 7.218e-10 ***
## treatment:factor(week)11 -1.044135   0.097612 -10.6967 3.496e-10 ***
## treatment:factor(week)12 -1.109493   0.097612 -11.3663 1.119e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    28.708
## Residual Sum of Squares: 0.078607
## R-Squared:      0.99726
## Adj. R-Squared: 0.99415
## F-statistic: 364.207 on 22 and 22 DF, p-value: < 2.22e-16
```

As the results show, the p-values of the treatment group from Week2 to Wee9 are not significant, but the p-values of the treatment group from Week10 to Week12 are significant. Thus, we also have enough evidence to conclude that the parallel trends of the treatment group before glitch is valid.

Thus, we will conduct DiD test to check the effect of the glitch. First, let's see how much the ads will affect the total traffic volume.

```
summary(plm(log(avg_total)~after * platform,df,index = c('id','week'),effect="twoways"))
```

```
## Twoways effects Within Model
##
## Call:
## plm(formula = log(avg_total) ~ after * platform, data = df, effect = "twoways",
##     index = c("id", "week"))
```

```
##
## Balanced Panel: n = 4, T = 12, N = 48
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -0.093838 -0.022221  0.003899  0.021242  0.087408
##
## Coefficients:
##                      Estimate Std. Error  t-value  Pr(>|t|)
## after:platformbing   0.146846   0.043598   3.3682  0.002091 **
## after:platformgoog  -1.005531   0.043598 -23.0636 < 2.2e-16 ***
## after:platformyahoo  0.185568   0.043598   4.2563  0.000188 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    2.2102
## Residual Sum of Squares: 0.064152
## R-Squared:      0.97098
## Adj. R-Squared: 0.95453
## F-statistic: 334.533 on 3 and 30 DF, p-value: < 2.22e-16
```

```r
exp(-1.005531)-1
```

```
## [1] -0.6341497
```

```r
improvement = abs(exp(-1.005531)-1)
improvement
```

```
## [1] 0.6341497
```

As the result shows, the odds of traffic of without sponsored ads at Google platform after glitch is -0.63, which means without the sponsored ads, the total traffic will decrease 63% per week.

Then estimate the true causality of sponsored ads

```r
did_total = lm(avg_total ~ treatment + after + treatment * after, data=df)
summary(did_total)
```

```
##
## Call:
## lm(formula = avg_total ~ treatment + after + treatment * after,
##     data = df)
```

```
##
## 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
```

As the results show, the probability of getting a result that is as or more extreme than the observed t-value is 0.00741, which is extremely small, thus, we have enough evidence to conclude that without sponsored ads at Google platform, on average Bazarr loses 9910.6 clicks per week.

(e) Given Your Treatment Effect Estimate, Fix Bob's RoI Calculation.

To get the accurate calculation of ROI, We need to capture the true proportion of clicks via sponsored ads.

```
did_org = lm(avg_org ~ treatment + after + treatment * after, data=df)
summary(did_org)
```

```
##
## Call:
## lm(formula = avg_org ~ treatment + after + treatment * after,
##     data = df)
##
## 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
```

As the new treatment effect result shows, in the absense of running sponsored ads, the average amount of clicks via organic link to visit Bazarr is 2293.2.

Thus, the new ROI equals to (Margin per conversion * probability of click * true proportion of click via ads - cost per click) / cost per click

```r
proportion_of_true_traffic = 9910.6/(2293.2+9910.6)
New_ROI = ((21 * 0.12 * proportion_of_true_traffic - 0.6)/0.6) * 100
New_ROI
```

```
## [1] 241.0784
```

Based on the new estimated treatment effect, the accurate ROI of sponsored ads is 241%.