Telemarketing Effectiveness in the Banking Industry

Team 3
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Background

Problem Context

Analysts and investors use a number of KPIs to evaluate firms in the banking industry. One of these metrics is Operating Expenses as a percentage of Assets Under Management[1]. The marketing function is an important driver of this metric through its relationship with both the numerator and denominator. Efficient marketing practices in any organization will naturally decrease operating expenses as less time is wasted on improbable leads. At the same time, increased effectiveness of targeted marketing campaigns leads to an increase in assets under management by successful soliciting deposits.

Causal Question

Do banks receive a significant increase in the number of deposits as a result of telemarketing campaigns?

To answer this question most effectively, we would ideally run an experiment randomly assigning customers into two groups. The treatment group would consist of those receiving a phone call solicitation as part of a marketing campaign aimed at convincing them to make a deposit. The control group would be those receiving a placebo phone call soliciting something unrelated to a bank. Unfortunately we do not have data on such experiments. The following section and analysis will dive into what data we do have and the inference that can be made from it.

Data & Objectives

The data set used documented various Portugese bank telemarketing campaigns conducted over a three year period spanning 2008-2010. Each row is representative of a phone call to a customer within a campaign. The outcome variable measured is a “yes” or “no” representing if the customer made a deposit following the phone call. This data set is a sample from a larger data set of

[1] https://opsdog.com/categories/kpis-and-metrics/banking

campaigns. From the larger data set, we assume the sample was randomly selected while noting it was stratified to provide balanced results in the dependent variable (deposit yes/no) across the data set. We don't assume however that the larger data set selected random customers for targeting within each campaign. We will therefore explore matching techniques in future analysis to manage endogeneity concerns.

Before conducting our analysis we merged the data into three distinct campaigns.

- Campaign 1: Treatment 1
- Campaign 2: Treatment 2
- Campaign 3: Baseline Campaign - constructed by combining campaigns 3 - 35

By merging campaigns 3-35 we hoped to achieve enough campaign feature/strategy diversity to capture a standard campaign by the firm. This is acknowledged to be a strong assumption and must be evaluated by the business for confirmation before implementing findings.

The data set contained various features:

- Demographic information - Age, Marital status, Education, Job,
- Loan information - House loan (Yes/No), credit default (Yes/No)
- Previous - Number of contacts performed before this campaign and for this client
- Poutcome - outcome of the previous marketing campaign (failure,nonexistent,success)
- Cons.price.idx - consumer price index (monthly indicator)
- Y - has the client subscribed to a term deposit? (yes/no)

We also collected external data in order to have the exact date of each campaign for each individual. The new table is merged based on the consumer price index.

Potential Threats to Causal Inference

While we are confident in the business insights discovered in the subsequent analysis, we acknowledge there are threats to causal inference present that may be affecting our results..

First, we lack some key information about customers such as location and income. This is likely related to the customer's decision to make a deposit and also with some of our independent variables (having a loan, education, job, etc.). Performing analysis without including this information may lead to an omitted variable bias of our estimates and thus affecting the integrity of our results.

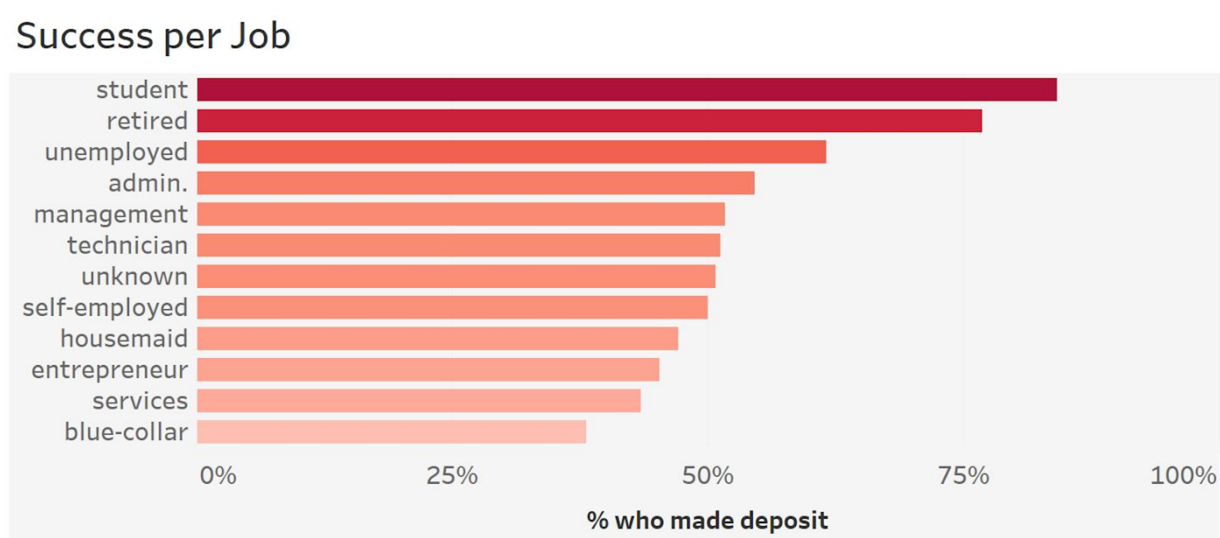
Secondly, we don't have a true control group to see the effectiveness of each campaign. While this is not a threat to inference itself, it limits the reach of our conclusions. Additionally, It is certainly possible that customers were targeted for phone calls because they had made more deposits in the past. This could introduce a simultaneity problem clouding the interpretation of our results. Finally, the targeted nature, and specificity of the data set (Portugal, during recession) make generalizing our findings very difficult.

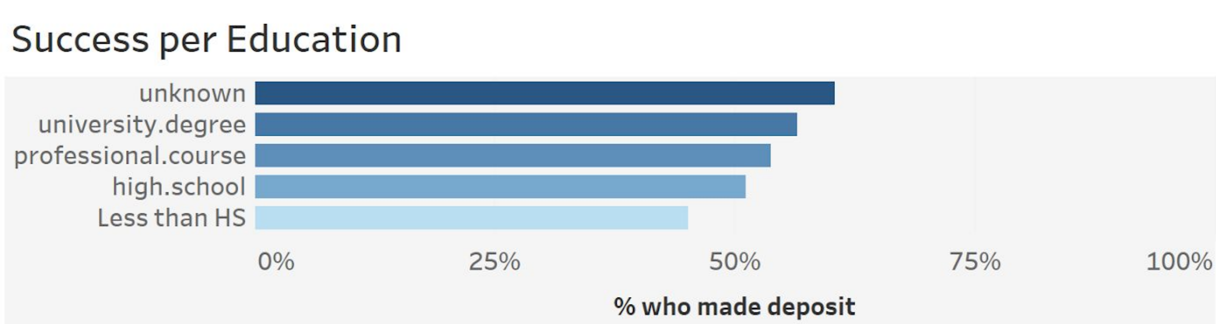
Analysis

Descriptive Analysis

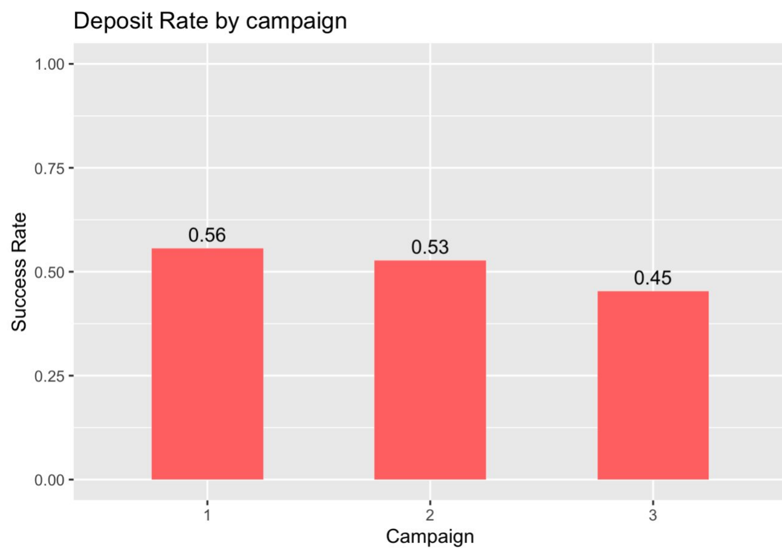
Before conducting our analysis we hoped to gain an understanding of the response rate across different groups of customers. A couple of interesting factors that we observed as significantly related to chance of deposit were Jobs and Education. The images illustrate the success rates of each group from all campaigns..

When looking only at Jobs, we see that calls to people who are not working (students, retired, and unemployed) appeared to be most successful across all calls.. Additionally, it turns out that calls to people whose education are unknown achieved the highest rate of success closely followed by those earning a university degree..





The below chart illustrates the success rates of the three identified campaigns. From a pure visual perspective we see that campaign 1 was the most successful before controlling for additional factors..



Simple Regression

Our preliminary analysis on the balance of data sets revealed that they were not overwhelmingly different with respect to independent variable balance. For these reasons we first applied simple regression as a means of first analyzing how Campaign 1 and Campaign 2 related to Campaign 3. This analysis was conducted in two separate stages comparing both 1 to 3 and 2 to 3 separately which allowed us to compare our results with the results of the same analysis after performing propensity score matching.

Campaign	Increase vs. Campaign 3	Std. Error	P-value
Campaign 1	+ 32.2%	5.8%	7.90e-07
Campaign 2	+ 19.4%	6.6%	0.0058

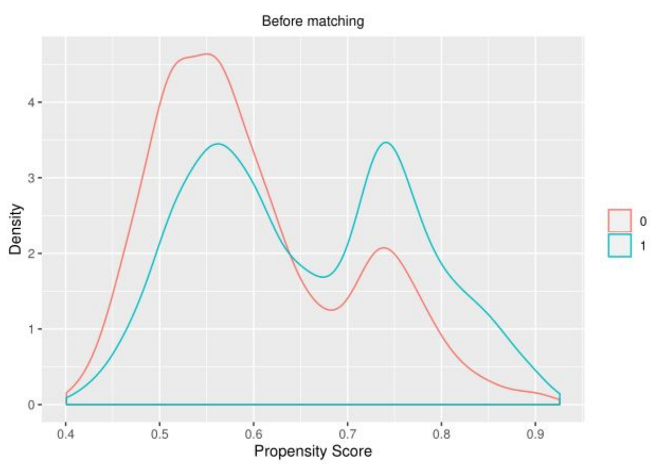
Appendix 2.5

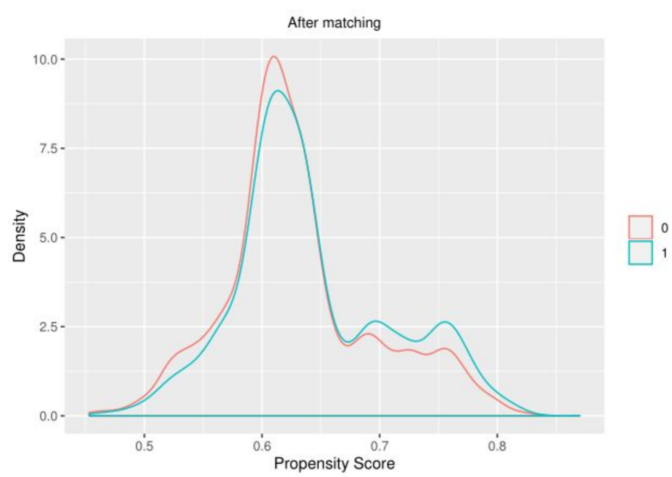
This simple regression output suggests that both campaigns 1 and 2 are significantly more effective in persuading customers to make deposits.

Propensity Score Matching (PSM)

Our data was balanced with regards to outcome variable. However, we use propensity score matching (PSM) to better balance the treatment and control data in regards to the independent variables like age, education, job etc. To proceed with this technique, we must make the assumption that the treatment assignment is fully determined by the observed variables. As mentioned previously, we believe there do exist important variables that are not included in the data. These factors like income or location may be directly related to any of the campaign targeting strategies and thus violate this assumption. We will proceed while acknowledging the possible violation,

The below plots provide a visual representation of the before and after effects of the matching technique on the balance of the data. In the leftmost plot is the density of treatment (1) vs control (0) before the matching (Campaign 1 (1) vs. Campaign 3 (0) pictured below). The rightward plot highlights the increased similarity in density of propensity scores between the two campaign groups.





In addition to the graphs, before and after t-tests were conducted across the set of independent variables. Comparing before and after p-values helped us confirm that PSM had provided us much more balanced data. (*Appendix 3.1*)

After performing matching, we re-ran our linear models with hopes of gaining better, unbiased estimates using the better matched data set.. Our analysis turned out to be drastically different when ran on the balanced data.

Campaign	Increase vs. Campaign 3	Std. Error	P-value
Campaign 1	20.5%	6.6%	0.00338 **
Campaign 2	12.3%	8.1%	0.13788

Appendix 3.1 & 3.2

As seen above, the coefficient varied greatly from that of the less balanced data used in our initial regression. With the more balanced data, we conclude that there is enough evidence to say that campaign 1 is significantly more effective in converting calls to deposits than campaign 3 and we believe that this 20.5% is a better estimate than 32.2% found before PSM. Furthermore, using the matched data we do not have enough evidence to conclude that campaign 2 is different from campaign 3 with respect to effectiveness acquiring deposits. This result is the opposite of what was observed before matching.

We also observed some interesting factors related to customer deposits. Customers who are retired are 184% more likely to make a deposit than blue collar customers keeping all other factors fixed (Appendix 3.1). Additionally, for every added contact by the bank before a given campaign, the chances of getting a deposit is 98% higher keeping other factors fixed (Appendix 3.1).Finally, we found that customers who are students are 245% more likely to make a deposit than blue collar customers keeping all other factors fixed. (Appendix 3.2)

We believe this is important information to the business from a campaign design perspective. By knowing this information, they may be able to design more custom campaigns catering to features that differentiate loan solicitation success.

Heterogeneity

In addition to exploring how Campaigns 1 and 2 compared to Campaign 3, we investigated if the different campaigns were more or less effective across various groups of customers. To do this, we used a full factorial model, hoping to understand the interaction effects between campaigns and different customer segments. The most significant interaction we found was between our treatment variable Campaign and independent variable Job.

Campaign vs. Campaign 3	Job vs. Baseline (blue-collar)	Estimate	Translated Percent
Campaign 1	Technician	0.397	48.7%
Campaign 2	Admin	0.436	54.6%

Appendix 3.3 & 3.4

The table above illustrates the difference in response to the various campaigns by different groups. More specifically, we see that Technician employees are 48.7% more likely than blue-collar workers to make a deposit in response to campaign 1 than campaign 3. Similarly we see that Admin employees are 54.6% more likely than blue-collar workers to make a deposit in response to campaign 2 than campaign 3.

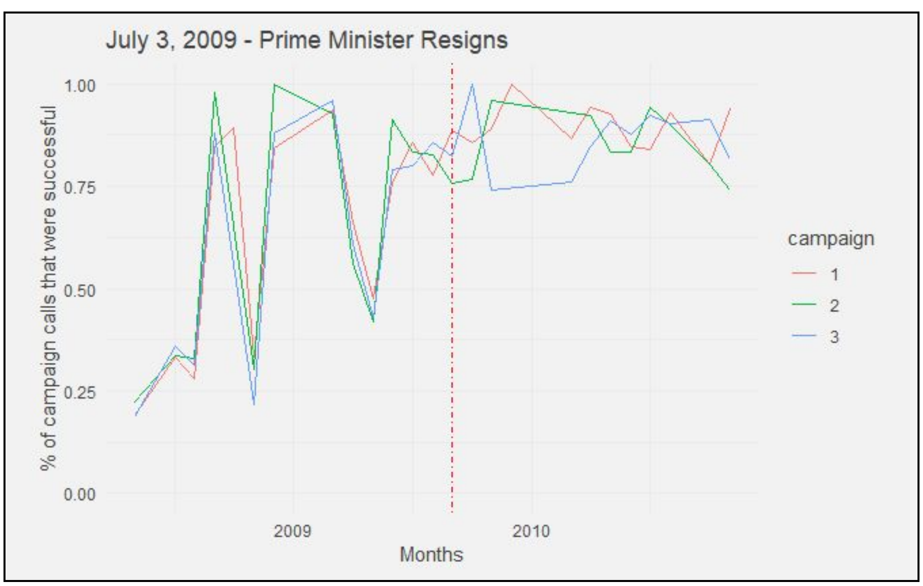
While this knowledge in itself is important and could possibly be useful to a subject matter expert, we believe that the true business value may be realized by digging into why blue-collar workers differ from these other groups across campaigns. It is very likely that upon further analysis, the bank may discover a valuable underlying driver of this difference..

Differences in Differences

On July 3, 2009, the Prime Minister of Portugal resigned after making an inappropriate gesture to a political opponent. We observed a decline in the consumer confidence index and assumed that due to the financial ramifications of such news it would have an effect on the banking industry. We wanted to see if this news also caused the campaigns to behave differently in terms of successful deposit solicitations. If so, such insights could be used by the bank with respect to which campaigns (or campaign “themes”) would be most effective to deploy in poor financial times. To explore this, we used a technique called “Difference in Differences” (DiD) to see if the news impacted our campaigns differently.

The data set we used only included “month”, and did not provide the associated year. We were able to match the Portuguese CPI values with monthly CPI data[2] that we found from the US Federal Reserve (Fred).

DiD is normally used when we have two different groups. There is a point in time when the first group gets the treatment, while the other group does not. This allows us to see the impact of the treatment on its own, because we can account for other factors that may have been impacting both groups. An important assumption for DiD results to hold is that the groups need to move parallel to each other before the news, because we are looking to isolate the impact of the treatment. The graph below provides strong evidence that from a visual perspective there are no issues with this assumption.



[2] https://fred.stlouisfed.org/series/PRTCPIALLMINMEI

For our DiD analysis, we again utilized “Campaign 3” as the control. As mentioned previously, this was the campaign that contains all others besides 1 and 2. For application of this technique we combined campaigns 1 and 2 as the “test” group and evaluated differences from Campaign 3; our “control” group.

Our analysis shows that there was in fact significant difference between campaign 3 and campaigns 1&2. The coefficient estimate in the below code output can be interpreted as follows: after the news, campaigns 1&2 saw a 26.8% decrease ($e^{-0.312}$) in the chances of making a deposit relative to campaign 3. Besides, robustness checks were conducted including the placebo test to help us confirm the significance of our findings. (Appendix 4.2)

```
## glm(formula = y ~ treat + after + treat * after, family = "binomial",
##     data = data_123)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9840  -1.0865   0.5486   1.2712   1.3965
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.50156    0.04667 -10.746  < 2e-16 ***
## treat1        0.28386    0.05513   5.149 2.62e-07 ***
## after         2.31912    0.15802  14.676  < 2e-16 ***
## treat1:after -0.31273    0.17659  -1.771   0.0766 .
```

Please note that since our outcome variable is 0/1 we used Logistic regression for Difference in Difference.

We were a bit limited in interpreting this in a way that would be helpful to the bank because we don’t know how the campaigns differed from one another in the way they were conducted. As it stands, this bank should be aware that campaigns 1&2 were impacted negatively compared to campaign 3 after the resignation of the Prime Minister and subsequent drop in consumer confidence. This may be useful in future campaign deployment strategy and times when there are expectations of negative financial news or drops in consumer confidence.

Robustness Check - Placebo Effect

We wanted to confirm that the resignation of the Prime Minister is the reason for the drop in performance of campaigns 1 and 2 compared to campaign 3 and not because of a parallel event happening at the same time. Hence, we moved the resignation date to 3 months prior and re-estimated the DiD regression. The treatment effect in this instance was insignificant suggesting our initial findings were robust (Appendix 4.2).

Conclusions

Business Implications

In summary, while our analysis was unable to directly answer the causal question of the effectiveness of telemarketing, we were able to find some interesting and valuable results. From our simple regression after matching we found that Campaign 1 is significantly more effective in soliciting deposits than Campaign 3 . The business can use these insights in tandem with internal information on campaign features for future campaign deployment and development. We also saw that different campaigns behave differently across groups of customers. This information can be useful in understanding customer segments and even developing sub-campaigns targeted at specific user groups. Additionally, we suggest the bank investigate why these differences exist for maximum value. Finally, our DiD techniques explored the performance of campaigns 1, 2, and 3 in the wake of news that the Prime Minister would be resigning. The divergence in performance of the three campaigns after this announcement could be a valuable insight for the bank in future campaign strategy and timing with respect to important financial news affecting consumer confidence.

Limitations

Our biggest limitation was the unknown nature of each of the campaigns. While this did not directly hamper our analysis, it made it very difficult to develop meaningful recommendations. Along with the lack of information about the campaigns, the specificity of the data itself (Portugal, unusual economic times) made it impossible to extrapolate our findings to the industry as a whole. Finally, the absence of key factors such as income and location were concerning and may have contributed to biased results in certain circumstances.

Future Analysis

In future analysis we would be interested in measuring the value of deposits in addition to the binary "yes" or "no" customer deposit. This would allow us to shed new light on campaign effectiveness. We also would like to perform the analysis controlling for factors such as income, location and family size to further eliminate the risk of endogeneity. Finally, our biggest hope in future analysis would be to evaluate the campaigns against a true control group and measure their subsequent behavior..

Causal Inference Project - Appendix

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Contents

1 Data Quality Check

Load the data set

```
setwd("C:\\Users\\pardh\\Downloads\\Studies\\3-Spring\\CI\\Project")

data <-read.csv("FINAL_DATA.csv")
```

Missing Values

There are no missing values in our data.

```
sum(is.na(data))
```

```
## [1] 0
```

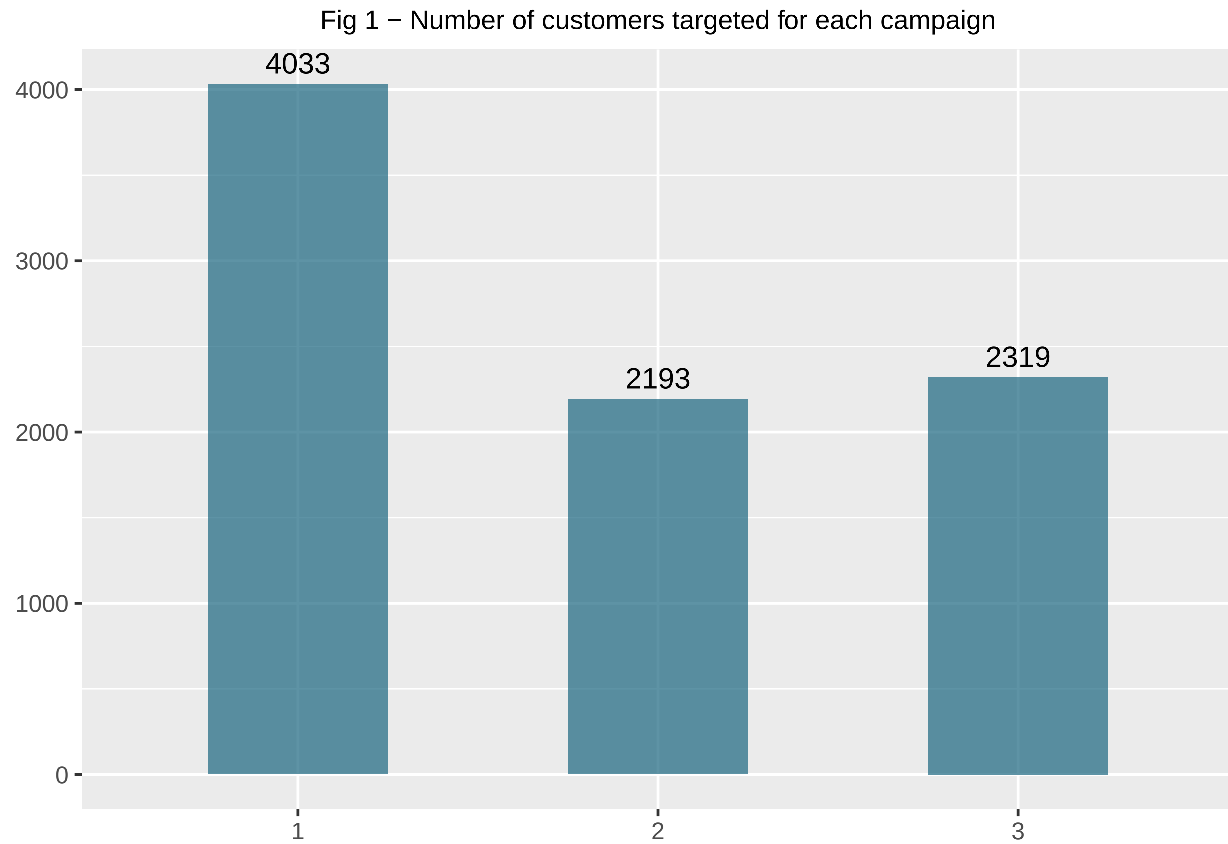
2 Exploratory Data Analysis

2.1 Customer distribution

The number of customers in each campaign are different. If these groups' attributes are different, we might need to consider using **Matching techniques** to make sure that independant variables are balanced across campaigns.

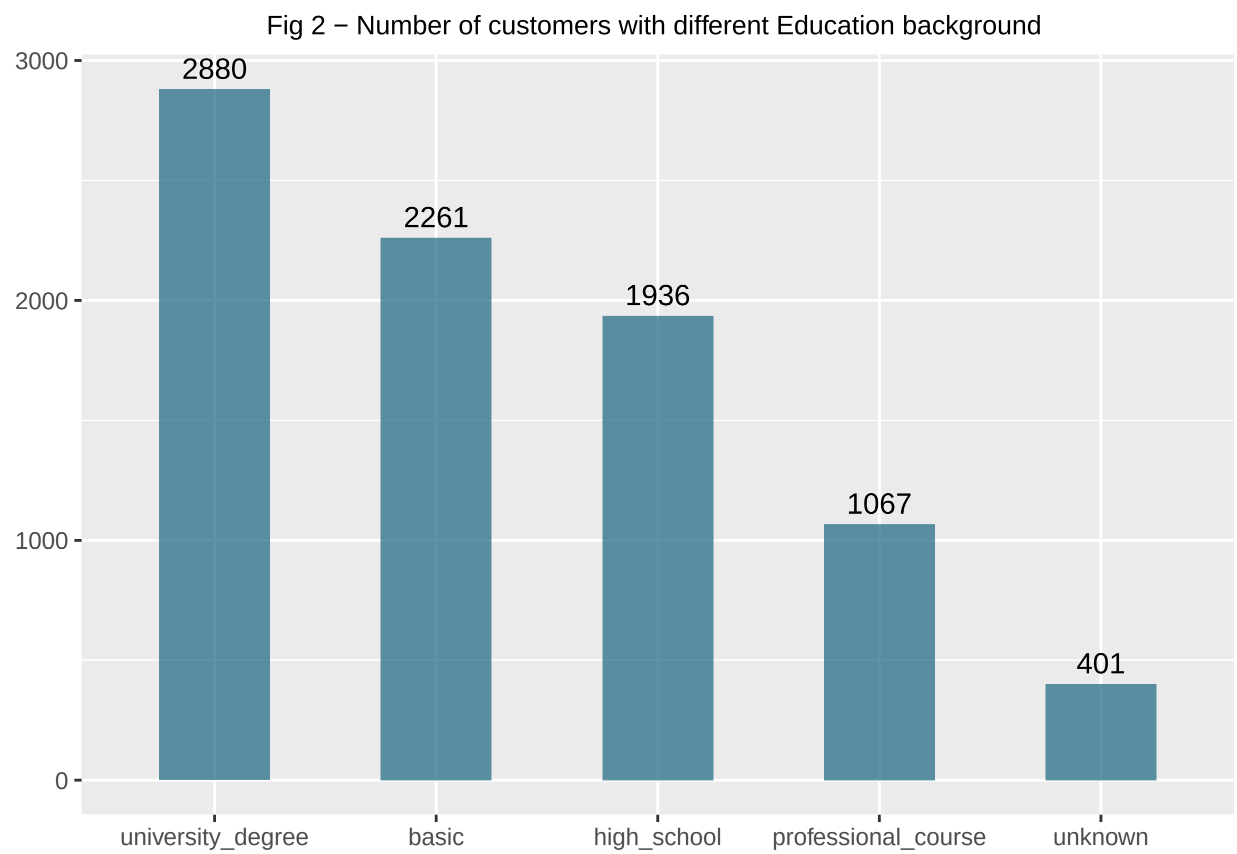
```
data_1 <- data %>% group_by(campaign) %>%
            summarise(num_customers = n()) %>%
            ungroup()

ggplot(data_1, aes(x = factor(campaign), y = num_customers)) +
        geom_bar(stat = "identity" , width=0.5, fill = rgb(0.1,0.4,0.5,0.7)) +
        ggtitle("Fig 1 - Number of customers targeted for each campaign") +
        geom_text(aes(label = num_customers,vjust = -0.5)) +
        theme(plot.title = element_text(color="black", size=10, hjust = 0.5)) +
        theme(axis.title.y = element_blank(), axis.title.x = element_blank() )
```



2.2 Distrbution of customers with different education background

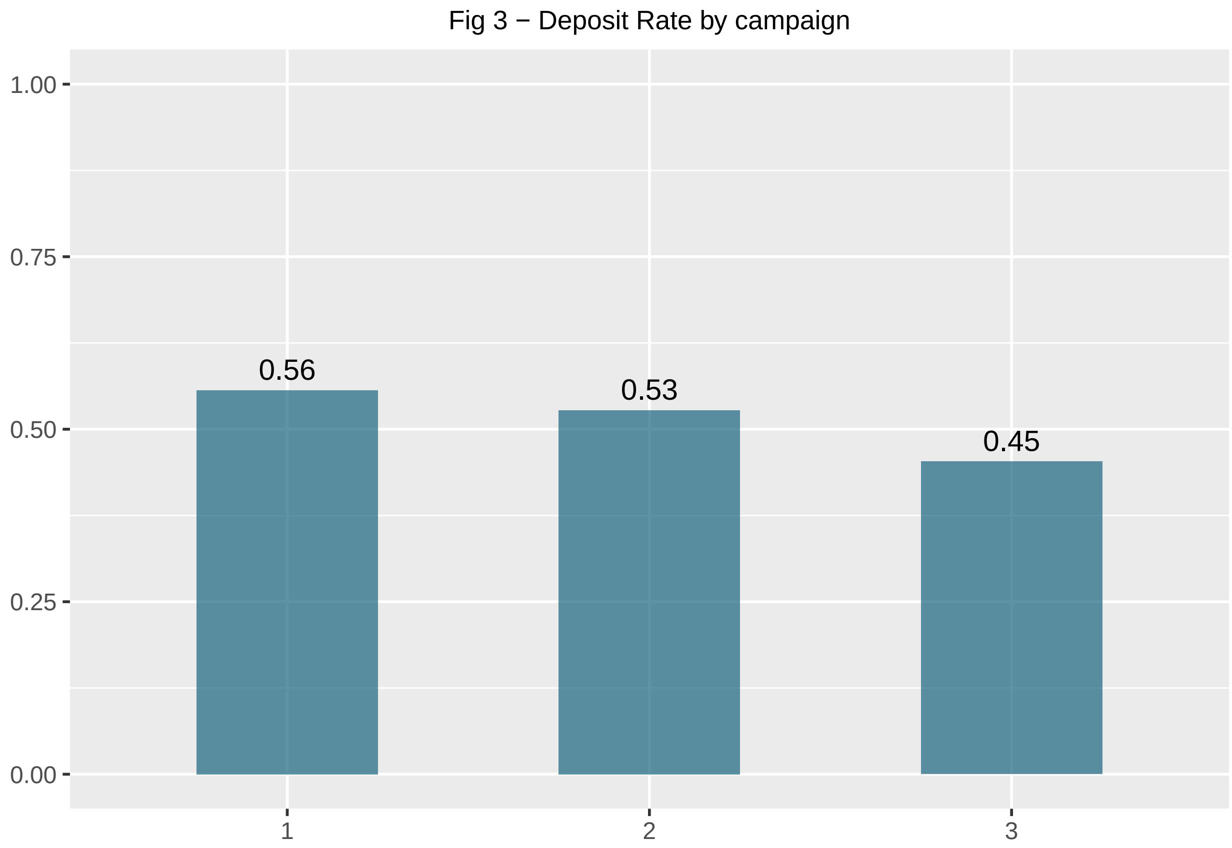
```
data %>% group_by(education) %>%
  summarise(fre = n()) %>%
  arrange(desc(fre)) %>%
  mutate(education=factor(education, levels=education)) %>%
  ggplot(aes(x = factor(education),width=0.5, y = fre)) +
  ggtitle("Fig 2 - Number of customers with different Education background ") +
  geom_bar( stat = "identity",  fill = rgb(0.1,0.4,0.5,0.7)) +
  theme(plot.title = element_text(color="black", size=10, hjust = 0.5)) +
  geom_text(aes(label = round(fre,2),vjust = -0.5)) +
   theme(axis.title.y = element_blank(), axis.title.x = element_blank() )
```



2.3 Deposit rate across campaigns

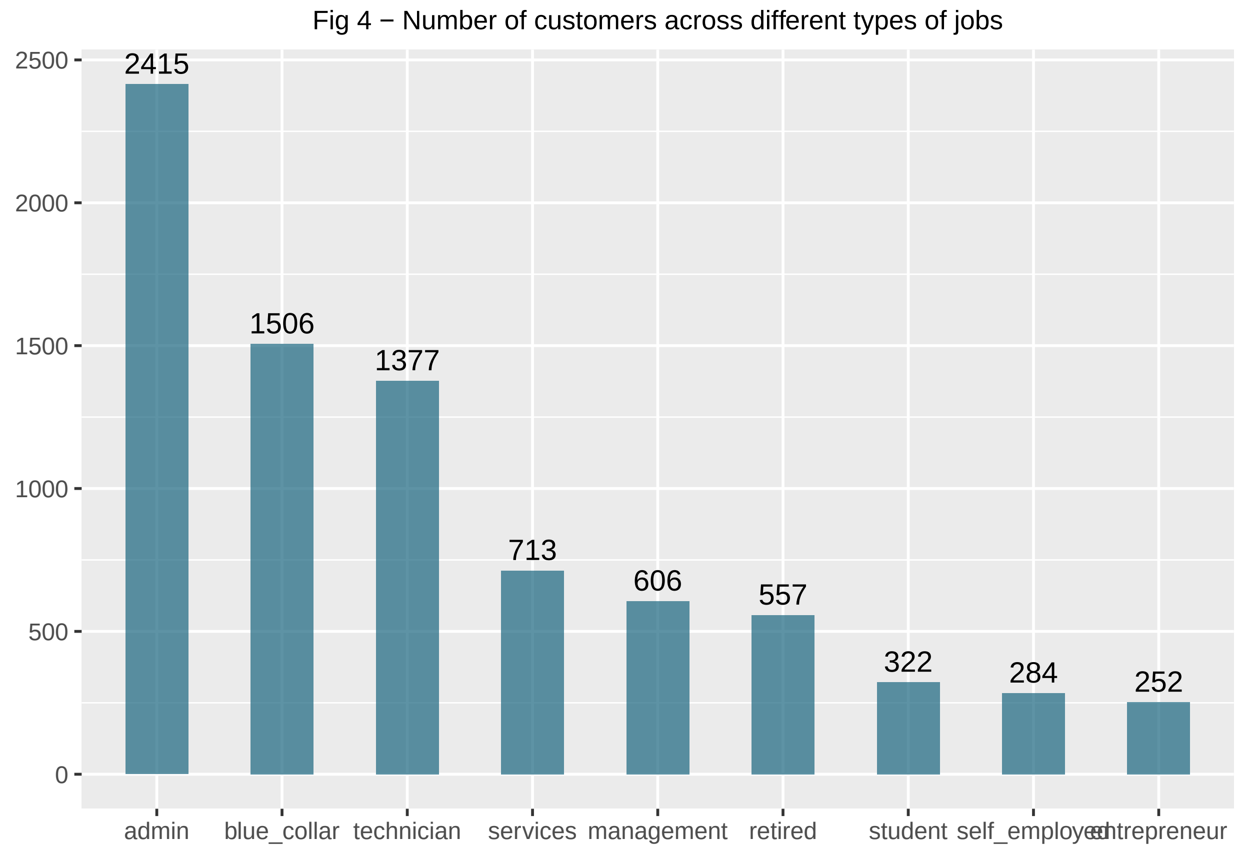
```
# generate data for the plot
group <- data %>% group_by(campaign) %>%
  summarise(succ = sum(y),
            ttl = n(),
            ratio = succ / ttl) %>%
  select(-succ,-ttl)
```

```
ggplot(group, aes(x = factor(campaign), y = ratio)) +
  geom_bar(stat = "identity", width = 0.5, position = "dodge",
           fill = rgb(0.1,0.4,0.5,0.7)) +
  ggtitle('Fig 3 - Deposit Rate by campaign') +
  xlab("Campaign") +
  ylab('Success Rate') +
  theme(plot.title = element_text(color="black", size=10, hjust = 0.5)) +
  ylim(0,1) +
  geom_text(aes(label = round(ratio,2),vjust = -0.5)) +
  theme(axis.title.y = element_blank(), axis.title.x = element_blank())
```



2.4 Distrbution of customers across different types of Jobs

```
data %>% group_by(job) %>%
  summarise(fre = n()) %>%
  filter(fre > 250) %>%
  arrange(desc(fre)) %>%
  mutate(job=factor(job, levels=job)) %>%
  ggplot(aes(x = factor(job),width=0.5, y = fre)) +
  geom_bar( stat = "identity",  fill = rgb(0.1,0.4,0.5,0.7)) +
  ggtitle('Fig 4 - Number of customers across different types of jobs') +
  theme(plot.title = element_text(color="black", size=10, hjust = 0.5)) +
  geom_text(aes(label = round(fre,2),vjust = -0.5)) +
  theme(axis.title.y = element_blank(), axis.title.x = element_blank())
```



2.5 Regression before matching

We are running a simple regression to check if different groups of customers behave differently across groups.

```
# set campaing 3 as base level

data_1 = data %>% select(-cons.conf.idx, -DATE)
data_1$campaign = as.factor(data_1$campaign)

# filter data for specific campaigns
data_c1 = data_1 %>% filter(campaign != 2)
data_c2= data_1 %>% filter(campaign != 1)

# Simple regression: C1 vs C3
data_c1 <- within(data_c1, campaign <- relevel(campaign, ref = 3))
mod1 = glm(y ~ campaign +                                  # Treatment vs. Control
             age + marital + housing + job + education +   # Demographic Factors
             previous + poutcome + default,                # Financial Factors
             data = data_c1, family = 'binomial')
summary(mod1)
```

```
##
## Call:
## glm(formula = y ~ campaign + age + marital + housing + job +
##     education + previous + poutcome + default, family = "binomial",
```

```
##     data = data_c1)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.6648  -1.0735   0.1945   1.1625   1.8184
##
## Coefficients:
##                              Estimate Std. Error z value Pr(>|z|)
## (Intercept)                 -1.215286   0.267799  -4.538 5.68e-06 ***
## campaign1                    0.279360   0.056576   4.938 7.90e-07 ***
## age                          0.004490   0.003228   1.391  0.16429
## maritalmarried               0.062016   0.091081   0.681  0.49594
## maritalsingle                0.320914   0.102916   3.118  0.00182 **
## maritalunknown               0.504068   0.546262   0.923  0.35613
## housingunknown               0.014061   0.188466   0.075  0.94053
## housingyes                  -0.019629   0.055516  -0.354  0.72366
## jobblue_collar              -0.213283   0.104687  -2.037  0.04162 *
## jobentrepreneur              0.046326   0.164483   0.282  0.77821
## jobhousemaid                -0.013751   0.189199  -0.073  0.94206
## jobmanagement               -0.027048   0.116562  -0.232  0.81650
## jobretired                   1.048225   0.158654   6.607 3.92e-11 ***
## jobself_employed            -0.039164   0.151746  -0.258  0.79634
## jobservices                 -0.133284   0.112445  -1.185  0.23589
## jobstudent                   1.266364   0.200325   6.322 2.59e-10 ***
## jobtechnician               -0.072949   0.092510  -0.789  0.43038
## jobunemployed                0.247568   0.183407   1.350  0.17707
## jobunknown                   0.171060   0.318346   0.537  0.59103
## educationhigh_school         0.027687   0.094006   0.295  0.76836
## educationprofessional_course 0.116760   0.112839   1.035  0.30079
## educationuniversity_degree   0.192558   0.095407   2.018  0.04356 *
## educationunknown             0.234774   0.147673   1.590  0.11187
## previous                     0.687367   0.143889   4.777 1.78e-06 ***
## poutcomenonexistent          0.540628   0.186811   2.894  0.00380 **
## poutcomesuccess              2.385267   0.191592  12.450  < 2e-16 ***
## defaultunknown              -0.701135   0.081746  -8.577  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 8796.8  on 6351  degrees of freedom
## Residual deviance: 7707.9  on 6325  degrees of freedom
## AIC: 7761.9
##
## Number of Fisher Scoring iterations: 5
```

```r
# Simple regression: C2 vs C3
data_c2 <- within(data_c2, campaign <- relevel(campaign, ref = 3))
mod2 = glm(y ~ campaign +                                 # Treatment vs. Control
             age + marital + housing + job + education +  # Demographic Factors
             previous + poutcome + default,               # Financial Factors
             data = data_c2, family = 'binomial')
summary(mod2)
```

```
##
## Call:
## glm(formula = y ~ campaign + age + marital + housing + job +
##     education + previous + poutcome + default, family = "binomial",
##     data = data_c2)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.8558  -1.0633  -0.6729   1.1977   1.8818
##
## Coefficients:
##                               Estimate Std. Error z value Pr(>|z|)
## (Intercept)                  -0.741696   0.291765  -2.542   0.0110 *
## campaign2                     0.178316   0.064634   2.759   0.0058 **
## age                           0.005475   0.003795   1.443   0.1491
## maritalmarried               -0.054243   0.108973  -0.498   0.6187
## maritalsingle                 0.066529   0.122214   0.544   0.5862
## maritalunknown               -0.221241   0.907187  -0.244   0.8073
## housingunknown               -0.182798   0.219638  -0.832   0.4053
## housingyes                    0.095318   0.065489   1.455   0.1455
## jobblue_collar               -0.210969   0.123199  -1.712   0.0868 .
## jobentrepreneur              -0.299437   0.193985  -1.544   0.1227
## jobhousemaid                 -0.310321   0.218895  -1.418   0.1563
## jobmanagement                -0.229816   0.136718  -1.681   0.0928 .
## jobretired                    0.937602   0.186716   5.022 5.13e-07 ***
## jobself_employed              0.105011   0.181548   0.578   0.5630
## jobservices                  -0.034963   0.127987  -0.273   0.7847
## jobstudent                    1.364817   0.230589   5.919 3.24e-09 ***
## jobtechnician                -0.062297   0.111365  -0.559   0.5759
## jobunemployed                 0.324431   0.215110   1.508   0.1315
## jobunknown                   -0.671852   0.449423  -1.495   0.1349
## educationhigh_school         -0.017892   0.110775  -0.162   0.8717
## educationprofessional_course  0.043602   0.133046   0.328   0.7431
## educationuniversity_degree    0.177769   0.110961   1.602   0.1091
## educationunknown              0.115629   0.178156   0.649   0.5163
## previous                      0.352270   0.137993   2.553   0.0107 *
## poutcomenonexistent           0.197921   0.192266   1.029   0.3033
## poutcomesuccess               2.096314   0.197849  10.596  < 2e-16 ***
## defaultunknown               -0.793109   0.094526  -8.390  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6252.9  on 4511  degrees of freedom
## Residual deviance: 5557.4  on 4485  degrees of freedom
## AIC: 5611.4
##
## Number of Fisher Scoring iterations: 5
```

3 Matching

Below we are performing some data transformations for doing regression and matching.

```r
# create dummy columns for categorical variables
bank_dummy_p <- dummy_cols(data %>% select(-c("DATE", "cons.conf.idx")) )

# deselect the unnecessary columns
bank_dummy_req_cols <- bank_dummy_p %>%
                           select(-c('job',    'marital',  'education',
                                     'default',    'housing',  'loan',
                                     'month',  'poutcome',
                                     'job_self_employed','marital_unknown',
                                     "default_unknown",
                                     "loan_unknown", "loan_yes", "month_sep",
                                     "poutcome_success"))


# create a data frame for campaings 1 and 3
data_13 <- bank_dummy_req_cols %>%
                     filter(campaign %in% c(1,3)) %>%
                     mutate(campaign = ifelse(campaign == 3, 0, 1))

# create a data frame for campaings 2 and 3
data_23 <- bank_dummy_req_cols %>%
                     filter(campaign %in% c(2,3)) %>%
                     mutate(campaign = ifelse(campaign == 3, 0, 1))
```

3.1 Campaigns 1 vs 3

Below we are trying Propensity Score matching for camapings 1 and 3

```r
match_13 <- matchit(campaign ~ age +  previous +  job_admin +
                     job_technician +  job_management +
                     job_blue_collar +  job_retired +  job_services +
                     job_student + job_unknown +  job_housemaid +
                     job_unemployed +  job_entrepreneur +
                     marital_divorced +  marital_married +  marital_single +
                     education_university_degree +
                     education_professional_course +  education_high_school +
                     education_unknown +  education_basic +  default_no +
                     housing_no +  housing_unknown +  housing_yes +
                     poutcome_failure +
                     poutcome_nonexistent,
                     data = data_13, ratio = 1, method = "nearest",
                     replace = TRUE ,distance = "logit", calliper = 0.001)

# Extract the matched data from matching output (m.out_2)
matched_data_13 <- match.data(match_13)
```

Below output shows how much balance we achieved through PSM

```r
# number of records matched
summary(match_13)[["nn"]]
```

```
##          Control Treated
```

```
## All           2319    4033
## Matched       1599    4033
## Unmatched      720       0
## Discarded        0       0
```

```r
# select list of Covariates to perform T test on data_23 before matching
list_of_covariates <- c('age', 'previous', 'job_admin', 'job_technician',
                        'job_management', 'job_blue_collar', 'job_retired',
                        'job_services', 'job_student', 'job_unknown',
                        'job_housemaid', 'job_unemployed', 'job_entrepreneur',
                        'marital_divorced', 'marital_married', 'marital_single',
                        'education_university_degree',
                        'education_professional_course', 'education_high_school',
                        'education_unknown', 'education_basic', 'default_no',
                        'housing_no', 'housing_unknown', 'housing_yes', 'loan_no',
                        'month_apr', 'month_aug',
                        'month_dec', 'month_jul', 'month_jun', 'month_mar',
                        'month_may', 'month_nov', 'month_oct', 'poutcome_failure',
                        'poutcome_nonexistent')

# Create a dummy DataFrame to store the results of T test of data_13 before matching
t_test_13_before <- data.frame(matrix(ncol = 2, nrow = 0))
colnames(t_test_13_before) <- c('Covariate', 'p_value_before')

# Run T test for each selected covariate
for (covariate in list_of_covariates){
  t <- t.test(data_13[,covariate] ~ campaign, data = data_13 )
  t_test_13_before[nrow(t_test_13_before) + 1,] = c(covariate,round(t[["p.value"]],2))
}


# Create a dummy DataFrame to store the results of T test of data_13 after matching
t_test_13_after <- data.frame(matrix(ncol = 2, nrow = 0))
colnames(t_test_13_after) <- c('Covariate', 'p_value_after')

# Run T test for each selected covariate
for (covariate in list_of_covariates){
  t <- t.test(matched_data_13[,covariate] ~ campaign, data = matched_data_13 )
  t_test_13_after[nrow(t_test_13_after) + 1,] = c(covariate,round(t[["p.value"]],2))
}

merge_data_13 <- t_test_13_before %>%
              inner_join(t_test_13_after, c("Covariate" = "Covariate")) %>%
              filter( (p_value_before <= 0.2) & (p_value_after != 0) )

print(merge_data_13)
```

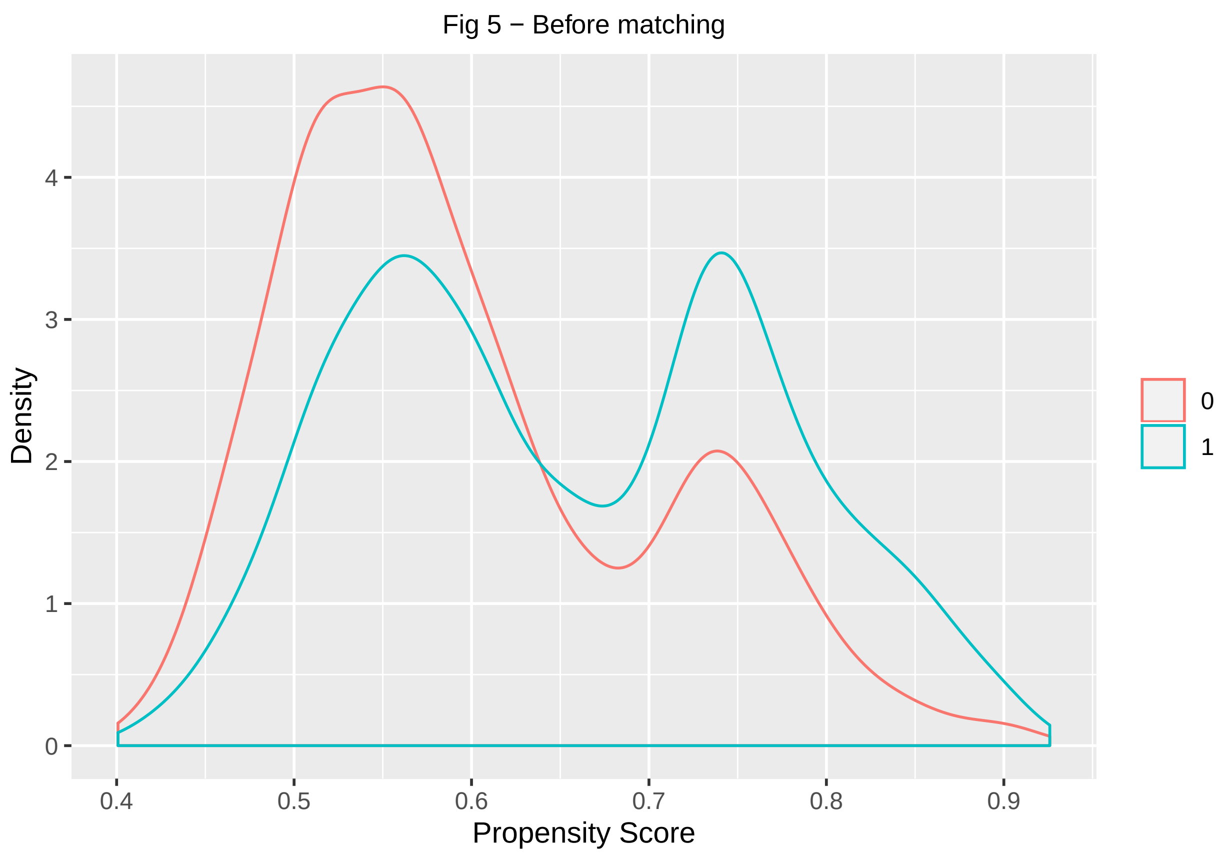
```
##          Covariate p_value_before p_value_after
## 1      job_retired           0.01          0.16
## 2     job_services           0.01          0.12
## 3      job_student           0.15          0.32
## 4  education_basic           0.13          0.11
## 5       default_no              0          0.03
## 6        month_mar           0.07          0.43
```

```
## 7 poutcome_failure               0          0.03
```

Plot densities of propensity scores for camapaigns 1 and 3 before matching

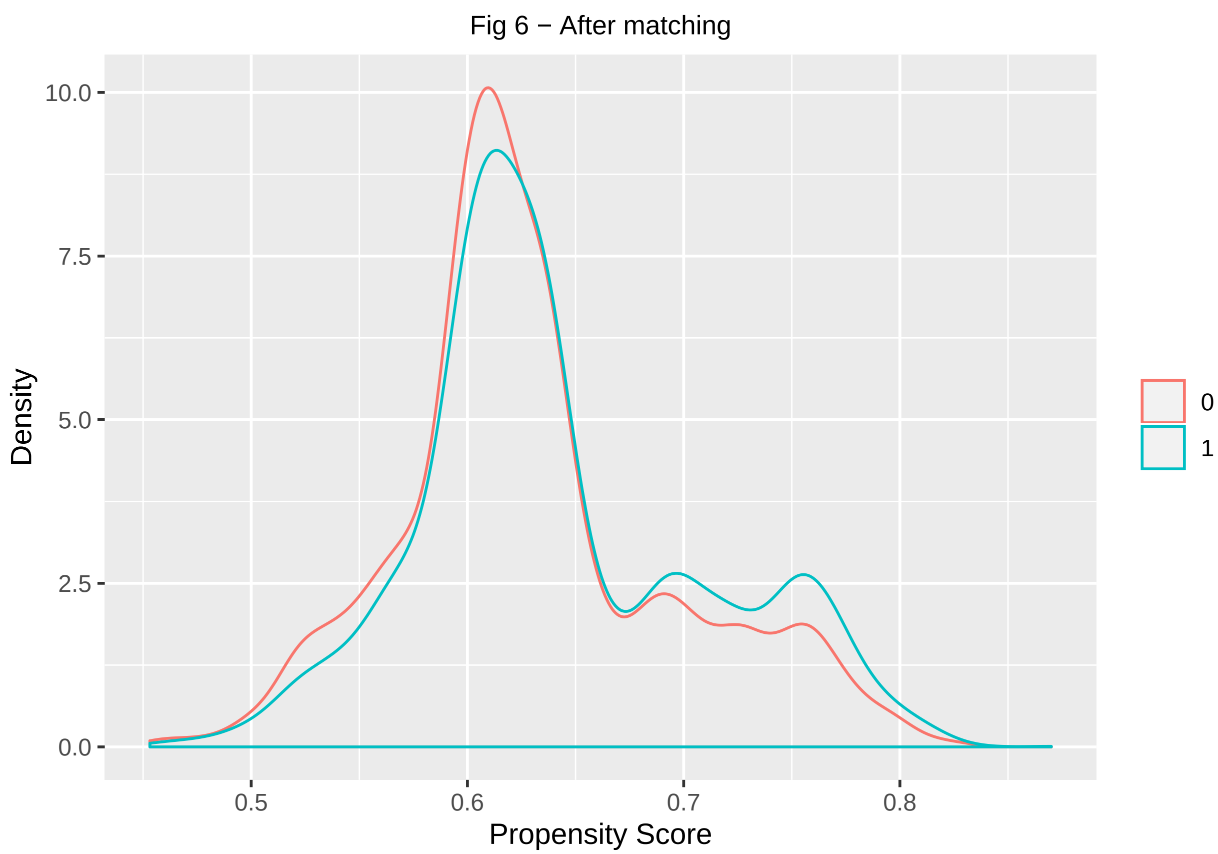
```
# plot before matching
pscore_before_13 = glm(campaign ~ ., data = data_13, family = "binomial" )$fitted.values
data_13$pscore <- pscore_before_13

ggplot(data_13, aes(x = pscore, col = factor(campaign))) +
  geom_density() +
  xlab("Propensity Score") + ylab("Density") +
  ggtitle("Fig 5 - Before matching") +
  theme(legend.title = element_blank()) +
  theme(plot.title = element_text(color="black", size=10, hjust = 0.5))
```



Plot densities of propensity scores for camapaigns 1 and 3 after matching

```
# plot after matching
ggplot(matched_data_13, aes(x = distance, col = factor(campaign))) +
  geom_density() +
  xlab("Propensity Score") + ylab("Density") +
  ggtitle("Fig 6 - After matching") +
  theme(legend.title = element_blank()) +
  theme(plot.title = element_text(color="black", size=10, hjust = 0.5))
```



Regression after matching

```
model_13_after <- glm( y ~ ., data = matched_data_13 %>%
                                select(-c( "distance", "month_apr", "month_aug",
                                           "month_dec",
                                           "month_jul", "month_jun",
                                           "month_mar","month_may",
                                           "month_nov", "month_oct", "loan_no"))
                              , family = 'binomial')

summary(model_13_after)
```

```
##
## Call:
## glm(formula = y ~ ., family = "binomial", data = matched_data_13 %>%
##     select(-c("distance", "month_apr", "month_aug", "month_dec",
##         "month_jul", "month_jun", "month_mar", "month_may", "month_nov",
##         "month_oct", "loan_no")))
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.6638  -1.1006   0.2468   1.1462   1.8176
##
## Coefficients: (2 not defined because of singularities)
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                      1.499602   0.731951   2.049  0.04048 *
```

```
## age                            0.004947   0.003470   1.425  0.15405
## campaign                       0.187980   0.064146   2.931  0.00338 **
## previous                       0.684004   0.145403   4.704 2.55e-06 ***
## job_admin                      0.025824   0.163836   0.158  0.87476
## job_blue_collar               -0.254157   0.177252  -1.434  0.15161
## job_entrepreneur               0.017732   0.225772   0.079  0.93740
## job_housemaid                  0.017008   0.253068   0.067  0.94642
## job_management                -0.014791   0.189545  -0.078  0.93780
## job_retired                    1.043531   0.221180   4.718 2.38e-06 ***
## job_services                  -0.123481   0.189538  -0.651  0.51473
## job_student                    1.281649   0.260412   4.922 8.58e-07 ***
## job_technician                -0.094623   0.172649  -0.548  0.58364
## job_unemployed                 0.237145   0.243662   0.973  0.33043
## job_unknown                    0.172670   0.380526   0.454  0.65000
## marital_divorced              -0.849989   0.623200  -1.364  0.17260
## marital_married               -0.785851   0.617552  -1.273  0.20319
## marital_single                -0.535781   0.618842  -0.866  0.38661
## education_basic               -0.277957   0.159674  -1.741  0.08172 .
## education_high_school         -0.254428   0.159555  -1.595  0.11080
## education_professional_course -0.167603   0.174744  -0.959  0.33749
## education_university_degree   -0.114689   0.159332  -0.720  0.47164
## education_unknown                    NA         NA      NA       NA
## default_no                     0.700554   0.089389   7.837 4.61e-15 ***
## housing_no                     0.042737   0.059072   0.723  0.46939
## housing_unknown                0.143992   0.205812   0.700  0.48416
## housing_yes                          NA         NA      NA       NA
## poutcome_failure              -2.411223   0.197049 -12.237  < 2e-16 ***
## poutcome_nonexistent          -1.813432   0.262171  -6.917 4.61e-12 ***
## weights                        0.128601   0.075197   1.710  0.08723 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 7777.1  on 5631  degrees of freedom
## Residual deviance: 6800.6  on 5604  degrees of freedom
## AIC: 6856.6
##
## Number of Fisher Scoring iterations: 5
```

3.2 Campaigns 2 vs 3

Below we are trying Propensity Score matching for camapings 2 and 3

```
match_23 <- matchit(campaign ~ age +  previous +  job_admin +
                      job_technician +  job_management +
                      job_blue_collar +  job_retired +  job_services +
                      job_student + job_unknown +  job_housemaid +
                      job_unemployed +  job_entrepreneur +
                      marital_divorced +  marital_married +
                      marital_single +  education_university_degree +
                      education_professional_course +  education_high_school +
                      education_unknown +  education_basic +  default_no +
```

```r
                        housing_no +  housing_unknown +  housing_yes +
                        poutcome_failure +  poutcome_nonexistent,
                        data = data_23, ratio = 1, method = "nearest",
                        replace = TRUE ,distance = "logit", calliper = 0.02)

# Extract the matched data from matching output (m.out_2)
matched_data_23 <- match.data(match_23)
```

Below output shows how much balance we achieved through PSM

```r
# number of records matched
summary(match_23)[["nn"]]
```

```
##           Control Treated
## All          2319    2193
## Matched      1180    2193
## Unmatched    1139       0
## Discarded       0       0
```

```r
# Create a dummy DataFrame to store the results of T test of data_13 before matching
t_test_23_before <- data.frame(matrix(ncol = 2, nrow = 0))
colnames(t_test_23_before) <- c('Covariate', 'p_value_before')

# Run T test for each selected covariate
for (covariate in list_of_covariates){
  t <- t.test(data_23[,covariate] ~ campaign, data = data_23 )
  t_test_23_before[nrow(t_test_23_before) + 1,] = c(covariate,round(t[["p.value"]],2))
}


# Create a dummy DataFrame to store the results of T test of data_13 after matching
t_test_23_after <- data.frame(matrix(ncol = 2, nrow = 0))
colnames(t_test_23_after) <- c('Covariate', 'p_value_after')

# Run T test for each selected covariate
for (covariate in list_of_covariates){
  t <- t.test(matched_data_23[,covariate] ~ campaign, data = matched_data_23 )
  t_test_23_after[nrow(t_test_23_after) + 1,] = c(covariate,round(t[["p.value"]],2))
}

merge_data_23 <- t_test_23_before %>%
              inner_join(t_test_23_after, c("Covariate" = "Covariate")) %>%
              filter( (p_value_before <= 0.2) & (p_value_after != 0) )

print(merge_data_23)
```

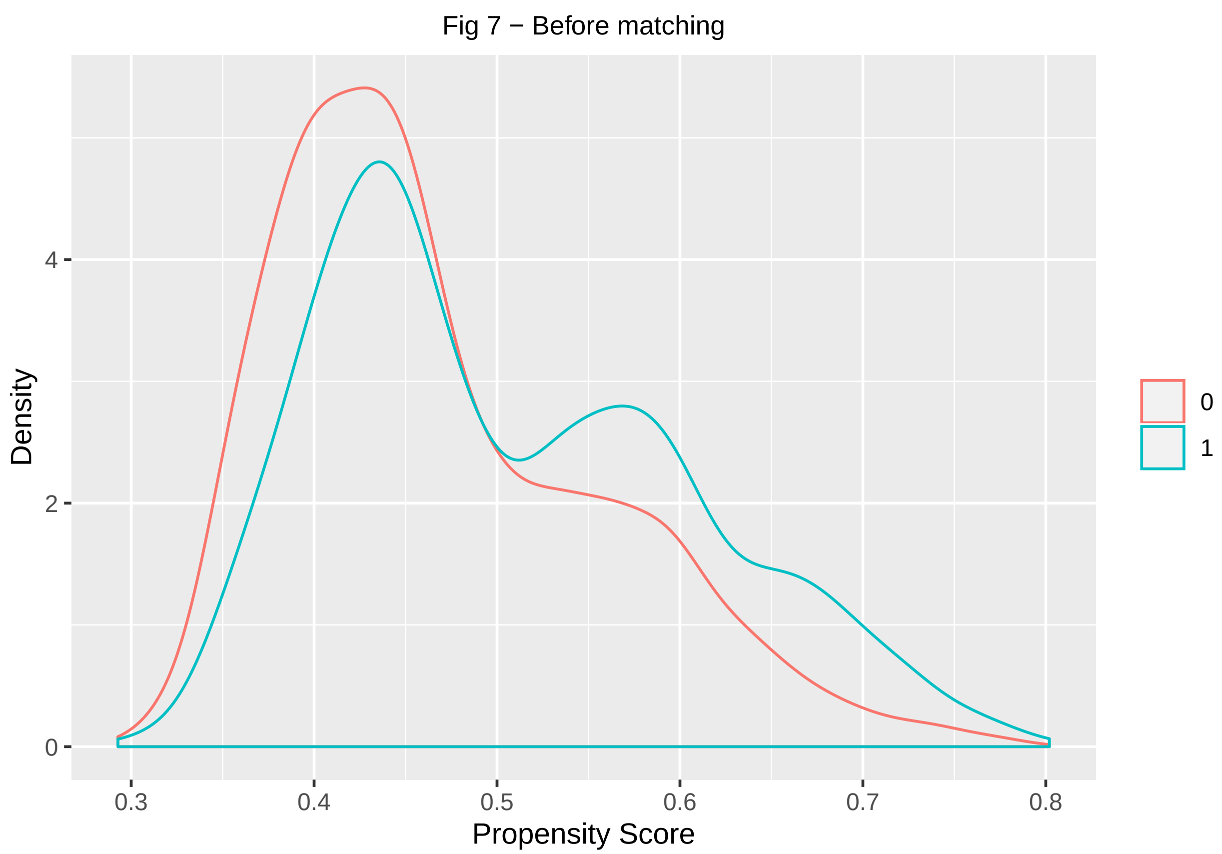
```
##                    Covariate p_value_before p_value_after
## 1                  job_admin            0.1          0.29
## 2             job_management           0.09          0.42
## 3                job_retired            0.1          0.01
## 4                job_student           0.14          0.73
## 5           marital_divorced           0.15          0.13
```

```
## 6  education_university_degree            0.2          0.98
## 7        education_high_school            0.12          0.63
## 8                   default_no               0          0.94
## 9                    month_aug               0          0.02
## 10                   month_jun               0          0.12
## 11                   month_mar            0.18          0.79
## 12                   month_may            0.01          0.04
## 13            poutcome_failure               0          0.06
```

Plot densities of propensity scores for camapaigns 1 and 3 before matching

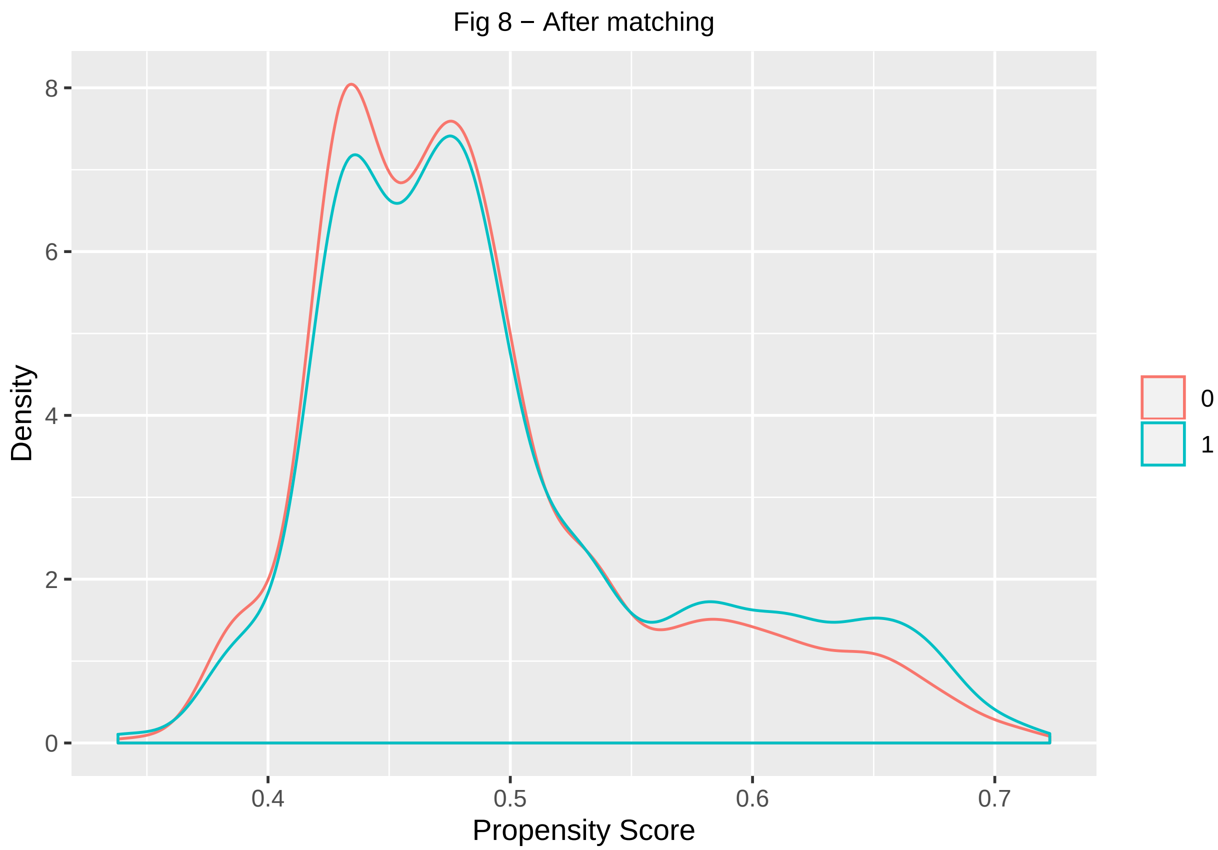
```r
# plot before matching
pscore_before_23 = glm(campaign ~ ., data = data_23,
                       family = "binomial" )$fitted.values
data_23$pscore <- pscore_before_23

ggplot(data_23, aes(x = pscore, col = factor(campaign))) +
  geom_density() +
  xlab("Propensity Score") + ylab("Density") +
  ggtitle("Fig 7 - Before matching") +
  theme(legend.title = element_blank()) +
  theme(plot.title = element_text(color="black", size=10, hjust = 0.5))
```



Plot densities of propensity scores for camapaigns 1 and 3 after matching

```r
# plot after matching
ggplot(matched_data_23, aes(x = distance, col = factor(campaign))) +
  geom_density() +
  xlab("Propensity Score") + ylab("Density") +
  ggtitle("Fig 8 - After matching") +
  theme(legend.title = element_blank()) +
  theme(plot.title = element_text(color="black", size=10, hjust = 0.5))
```



Regression after matching

```r
model_23_after <- glm( y ~ ., data = matched_data_23 %>%
                              select(-c( "distance", "month_apr", "month_aug",
                                         "month_dec",
                                         "month_jul", "month_jun",
                                         "month_mar","month_may",
                                         "month_nov", "month_oct", "loan_no"))
                            , family = 'binomial')

summary(model_23_after)
```

```
##
## Call:
## glm(formula = y ~ ., family = "binomial", data = matched_data_23 %>%
##     select(-c("distance", "month_apr", "month_aug", "month_dec",
##         "month_jul", "month_jun", "month_mar", "month_may", "month_nov",
```

```
##        "month_oct", "loan_no")))
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.7778  -1.0716   0.2439   1.1566   1.8760
##
## Coefficients: (2 not defined because of singularities)
##                               Estimate Std. Error z value Pr(>|z|)
## (Intercept)                  -0.647532   1.246636  -0.519  0.60347
## age                           0.004817   0.004441   1.085  0.27803
## campaign                      0.116517   0.078529   1.484  0.13788
## previous                      0.322437   0.150177   2.147  0.03179 *
## job_admin                    -0.229757   0.225775  -1.018  0.30885
## job_blue_collar              -0.469645   0.243971  -1.925  0.05423 .
## job_entrepreneur             -0.534093   0.295586  -1.807  0.07078 .
## job_housemaid                -0.524030   0.317209  -1.652  0.09853 .
## job_management               -0.523886   0.253552  -2.066  0.03881 *
## job_retired                   0.638157   0.296907   2.149  0.03161 *
## job_services                 -0.301506   0.255954  -1.178  0.23881
## job_student                   1.244034   0.335625   3.707  0.00021 ***
## job_technician               -0.261865   0.237444  -1.103  0.27009
## job_unemployed                0.217006   0.312703   0.694  0.48770
## job_unknown                  -1.396095   0.602939  -2.315  0.02059 *
## marital_divorced              1.530368   1.166589   1.312  0.18958
## marital_married               1.403504   1.160559   1.209  0.22653
## marital_single                1.450633   1.160731   1.250  0.21139
## education_basic              -0.252035   0.216878  -1.162  0.24519
## education_high_school        -0.304499   0.218140  -1.396  0.16275
## education_professional_course -0.175770   0.234957  -0.748  0.45440
## education_university_degree   -0.016306   0.216028  -0.075  0.93983
## education_unknown                    NA         NA      NA       NA
## default_no                    0.866064   0.115189   7.519 5.53e-14 ***
## housing_no                   -0.061185   0.076407  -0.801  0.42326
## housing_unknown              -0.157658   0.255416  -0.617  0.53706
## housing_yes                          NA         NA      NA       NA
## poutcome_failure             -2.039849   0.209097  -9.756  < 2e-16 ***
## poutcome_nonexistent         -1.821476   0.281329  -6.475 9.51e-11 ***
## weights                       0.274295   0.100513   2.729  0.00635 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 4674.3  on 3372  degrees of freedom
## Residual deviance: 4104.0  on 3345  degrees of freedom
## AIC: 4160
##
## Number of Fisher Scoring iterations: 5
```

3.3 Heterogeneity between campaigns 1 and 3 after matching the data

```r
# create a row number
matched_data_13_r <- matched_data_13 %>% mutate(id = row_number())

# converting education dummy columns in to a single column
edu_list <- c("id","education_basic", "education_high_school",
              "education_professional_course",
              "education_university_degree", "education_unknown")


matched_data_13_edu <- matched_data_13_r %>% select(edu_list) %>%
                        gather("education", "value", -id ) %>%
                        filter(value == 1) %>%
                        select(-value) %>%
                        mutate(education = str_replace(education,"education_",""))

# converting Job dummy columns in to a single column
job_list <- c("id","job_admin", "job_blue_collar", "job_entrepreneur",
              "job_housemaid", "job_management", "job_retired",
              "job_services", "job_student", "job_technician",
              "job_unemployed", "job_unknown")

matched_data_13_job <- matched_data_13_r %>% select(job_list) %>%
                        gather("job", "value", -id ) %>%
                        filter(value == 1) %>%
                        select(-value) %>%
                        mutate(job = str_replace(job,"job_",""))

# converting marital status dummy columns in to a single column
mar_status <- c("id","marital_divorced", "marital_married", "marital_single")

matched_data_13_mar <- matched_data_13_r %>% select(mar_status) %>%
                        gather("marital_status", "value", -id ) %>%
                        filter(value == 1) %>%
                        select(-value) %>%
                        mutate(marital_status = str_replace(marital_status,"marital_",""))

# converting Housing  dummy columns in to a single column
hous_list <- c("id","housing_no", "housing_yes", "housing_unknown")

matched_data_13_hous <- matched_data_13_r %>% select(hous_list) %>%
                        gather("housing", "value", -id ) %>%
                        filter(value == 1) %>%
                        select(-value) %>%
                        mutate(housing = str_replace(housing,"housing_",""))

# converting poutcome  dummy columns in to a single column
pout_list <- c("id","poutcome_failure", "poutcome_nonexistent")

matched_data_13_pout <- matched_data_13_r %>% select(pout_list) %>%
                        gather("poutcome", "value", -id ) %>%
                        filter(value == 1) %>%
                        select(-value) %>%
                        mutate(poutcome = str_replace(poutcome,"poutcome_",""))
```

```r
# Merge all data frames into a single data frame
merged_het_13_after <- matched_data_13_r %>%
                    select("id","y" ,"age", "campaign", "previous",
                           "default_no", "weights") %>%
                    left_join(matched_data_13_edu, c("id" = "id")) %>%
                    left_join(matched_data_13_job, c("id" = "id")) %>%
                    left_join(matched_data_13_mar, c("id" = "id")) %>%
                    left_join(matched_data_13_hous, c("id" = "id")) %>%
                    left_join(matched_data_13_pout, c("id" = "id"))

# C1 vs C3 heterogeneity

merged_het_13_after$job <- as.factor(merged_het_13_after$job)
merged_het_13_after <- within(merged_het_13_after, job <- relevel(job, ref = 2))

# check if any ionteraction terms are significant
mod_het_13_after = glm(y ~ campaign +
                           age + marital_status + housing + job + education +
                           previous + poutcome + default_no + job*campaign,
                           data = merged_het_13_after, family = 'binomial')

summary(mod_het_13_after)
```

```
##
## Call:
## glm(formula = y ~ campaign + age + marital_status + housing +
##     job + education + previous + poutcome + default_no + job *
##     campaign, family = "binomial", data = merged_het_13_after)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4452  -1.1107  -0.7399   1.1652   1.7849
##
## Coefficients:
##                              Estimate Std. Error z value Pr(>|z|)
## (Intercept)                 -1.916738   0.316750  -6.051 1.44e-09 ***
## campaign                    -0.003773   0.146672  -0.026 0.979476
## age                          0.005352   0.003603   1.485 0.137416
## marital_statusmarried        0.078348   0.101301   0.773 0.439278
## marital_statussingle         0.316556   0.114757   2.758 0.005807 **
## housingunknown               0.102736   0.213475   0.481 0.630334
## housingyes                  -0.039276   0.061101  -0.643 0.520351
## jobadmin                     0.144313   0.175187   0.824 0.410073
## jobentrepreneur             -0.116174   0.352942  -0.329 0.742036
## jobhousemaid                -0.036016   0.427500  -0.084 0.932859
## jobmanagement                0.068362   0.259915   0.263 0.792537
## jobretired                   1.225948   0.284617   4.307 1.65e-05 ***
## jobservices                  0.229228   0.223875   1.024 0.305877
## jobstudent                   1.213973   0.396820   3.059 0.002219 **
## jobtechnician               -0.111864   0.195731  -0.572 0.567647
## jobunemployed                0.307040   0.446321   0.688 0.491493
## jobunknown                  -0.216943   0.892593  -0.243 0.807968
## educationhigh_school         0.031567   0.103473   0.305 0.760310
```

```
## educationprofessional_course  0.112266   0.126702   0.886 0.375586
## educationuniversity_degree    0.160118   0.107604   1.488 0.136745
## educationunknown              0.262894   0.163207   1.611 0.107223
## previous                      0.593811   0.162760   3.648 0.000264 ***
## poutcomenonexistent           0.484834   0.211056   2.297 0.021609 *
## default_no                    0.702380   0.091447   7.681 1.58e-14 ***
## campaign:jobadmin             0.222389   0.188214   1.182 0.237374
## campaign:jobentrepreneur      0.555713   0.407197   1.365 0.172339
## campaign:jobhousemaid         0.426708   0.489249   0.872 0.383116
## campaign:jobmanagement        0.270310   0.291108   0.929 0.353118
## campaign:jobretired           0.089643   0.322541   0.278 0.781069
## campaign:jobservices         -0.186330   0.261196  -0.713 0.475616
## campaign:jobstudent           0.436694   0.462895   0.943 0.345478
## campaign:jobtechnician        0.397403   0.214798   1.850 0.064296 .
## campaign:jobunemployed        0.352372   0.502101   0.702 0.482807
## campaign:jobunknown           1.246874   0.986308   1.264 0.206164
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6647.2  on 4798  degrees of freedom
## Residual deviance: 6302.5  on 4765  degrees of freedom
##   (833 observations deleted due to missingness)
## AIC: 6370.5
##
## Number of Fisher Scoring iterations: 4
```

3.4 Heterogeneity between campaigns 2 and 3 after matching the data

```r
# create a row number
matched_data_23_r <- matched_data_23 %>% mutate(id = row_number())

# converting education dummy columns in to a single column
matched_data_23_edu <- matched_data_23_r %>% select(edu_list) %>%
                        gather("education", "value", -id ) %>%
                        filter(value == 1) %>%
                        select(-value) %>%
                        mutate(education = str_replace(education,"education_",""))

# converting Job dummy columns in to a single column
matched_data_23_job <- matched_data_23_r %>% select(job_list) %>%
                        gather("job", "value", -id ) %>%
                        filter(value == 1) %>%
                        select(-value) %>%
                        mutate(job = str_replace(job,"job_",""))

# converting marital status dummy columns in to a single column
matched_data_23_mar <- matched_data_23_r %>% select(mar_status) %>%
                        gather("marital_status", "value", -id ) %>%
                        filter(value == 1) %>%
                        select(-value) %>%
```

```r
                        mutate(marital_status = str_replace(marital_status,"marital_",""))

# converting Housing dummy columns in to a single column
matched_data_23_hous <- matched_data_23_r %>% select(hous_list) %>%
                        gather("housing", "value", -id ) %>%
                        filter(value == 1) %>%
                        select(-value) %>%
                        mutate(housing = str_replace(housing,"housing_",""))

# converting poutcome dummy columns in to a single column
matched_data_23_pout <- matched_data_23_r %>% select(pout_list) %>%
                        gather("poutcome", "value", -id ) %>%
                        filter(value == 1) %>%
                        select(-value) %>%
                        mutate(poutcome = str_replace(poutcome,"poutcome_",""))

# merging all dataframes into a single data frame
merged_het_23_after <- matched_data_23_r %>%
                    select("id","y" ,"age", "campaign", "previous", "default_no", "weights") %>%
                    left_join(matched_data_23_edu, c("id" = "id")) %>%
                    left_join(matched_data_23_job, c("id" = "id")) %>%
                    left_join(matched_data_23_mar, c("id" = "id")) %>%
                    left_join(matched_data_23_hous, c("id" = "id")) %>%
                    left_join(matched_data_23_pout, c("id" = "id"))

# C2 vs C3 heterogeneity
merged_het_23_after$job <- as.factor(merged_het_23_after$job)
merged_het_23_after <- within(merged_het_23_after, job <- relevel(job, ref = 2))

# check if any ionteraction terms are significant
mod_het_23_after = glm(y ~ campaign +
                           age + marital_status + housing + job + education +
                           previous + poutcome + default_no + job*campaign,
                           data = merged_het_23_after, family = 'binomial')

summary(mod_het_23_after)
```

```
##
## Call:
## glm(formula = y ~ campaign + age + marital_status + housing +
##     job + education + previous + poutcome + default_no + job *
##     campaign, family = "binomial", data = merged_het_23_after)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0122  -1.0828  -0.7178   1.2059   1.9327
##
## Coefficients:
##                               Estimate Std. Error z value Pr(>|z|)
## (Intercept)                  -1.752804   0.394802  -4.440 9.01e-06 ***
## campaign                     -0.092442   0.181348  -0.510  0.61023
## age                           0.005418   0.004680   1.158  0.24699
## marital_statusmarried        -0.116058   0.139762  -0.830  0.40631
```

```
## marital_statussingle         -0.036248   0.155161  -0.234  0.81529
## housingunknown               -0.124463   0.264651  -0.470  0.63815
## housingyes                    0.078555   0.079580   0.987  0.32358
## jobadmin                     -0.069298   0.209615  -0.331  0.74095
## jobentrepreneur               0.070862   0.379004   0.187  0.85168
## jobhousemaid                  0.049378   0.407865   0.121  0.90364
## jobmanagement                -0.024203   0.297874  -0.081  0.93524
## jobretired                    0.931199   0.363065   2.565  0.01032 *
## jobservices                  -0.046779   0.274208  -0.171  0.86454
## jobstudent                    1.398495   0.443630   3.152  0.00162 **
## jobtechnician                -0.013263   0.237205  -0.056  0.95541
## jobunemployed                 0.609971   0.422093   1.445  0.14843
## jobunknown                   -0.305211   0.758879  -0.402  0.68755
## educationhigh_school         -0.019376   0.133115  -0.146  0.88427
## educationprofessional_course  0.142917   0.165894   0.861  0.38897
## educationuniversity_degree    0.281031   0.137479   2.044  0.04094 *
## educationunknown              0.196433   0.226998   0.865  0.38685
## previous                      0.476837   0.203288   2.346  0.01900 *
## poutcomenonexistent           0.384585   0.264629   1.453  0.14614
## default_no                    0.846063   0.118582   7.135 9.69e-13 ***
## campaign:jobadmin             0.436325   0.234221   1.863  0.06248 .
## campaign:jobentrepreneur     -0.268122   0.464753  -0.577  0.56400
## campaign:jobhousemaid        -0.118391   0.515256  -0.230  0.81827
## campaign:jobmanagement        0.039944   0.347356   0.115  0.90845
## campaign:jobretired           0.278940   0.427833   0.652  0.51441
## campaign:jobservices          0.315386   0.323423   0.975  0.32948
## campaign:jobstudent           0.366828   0.544873   0.673  0.50080
## campaign:jobtechnician        0.257787   0.267993   0.962  0.33609
## campaign:jobunemployed        0.250819   0.521974   0.481  0.63086
## campaign:jobunknown          -1.238950   1.300333  -0.953  0.34069
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 3970.6  on 2880  degrees of freedom
## Residual deviance: 3751.5  on 2847  degrees of freedom
##   (492 observations deleted due to missingness)
## AIC: 3819.5
##
## Number of Fisher Scoring iterations: 4
```

4 Difference in Difference

Data preparation

```r
# Make sure date is in correct form
data <- data %>% mutate(DATE = mdy(DATE))


# Implement resignation date
resignation_date <- mdy('07-03-2009')
```

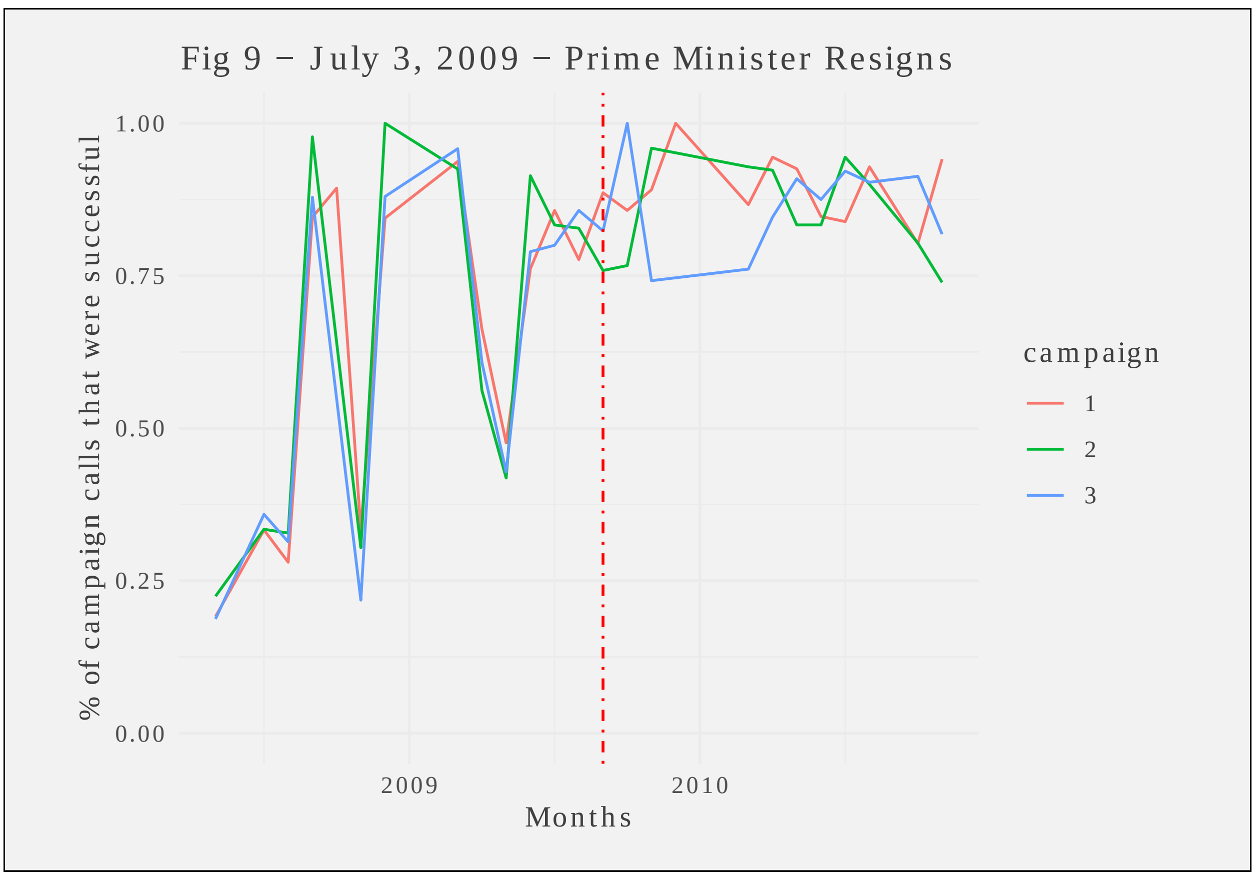
```r
data <- data %>% mutate(after = ifelse(DATE > resignation_date, 1, 0))


# Month-by-month success of each campaign
df <- data %>% group_by(per_year = year(DATE),
                        per_month = month(DATE),
                        campaign = factor(campaign)) %>%
  summarize(averaging = mean(y),
            counting = n())


# Make easier to plot
df$Date <- as.yearmon(paste(df$per_year, df$per_month), "%Y %m")
```

Analyse call success rate across time before and after the news

```r
ggplot(data=df, aes(x=Date, y = averaging, color = campaign)) +
  geom_line() + ylim(0,1) +
  xlab("Months") + ylab("% of campaign calls that were successful") +
  ggtitle('Fig 9 - July 3, 2009 - Prime Minister Resigns') +
  geom_vline(xintercept = as.numeric(df$Date[38]), linetype=4, colour="red") +
  theme_ilo()
```



4.1 Regression for Difference in Difference

```r
# setting campaign 3 as reference
data$campaign <- factor(data$campaign)
data <- within(data, campaign <- relevel(campaign, ref = 3))

# Set camapign 3 as 0 and rest of the campaigns as 1
data_123 <- data %>%
  mutate(treat = ifelse(campaign == 3, 0, 1))

# setting campaign 3 as reference
data_123 <- within(data_123, campaign <- relevel(campaign, ref = 3))
data_123$treat <- factor(data_123$treat)

# DiD regresion to chech the impact on campaings after the news
did_one <- glm(y ~ treat + after + treat * after,
               data = data_123, family = "binomial")

summary(did_one)
```

```
##
## Call:
## glm(formula = y ~ treat + after + treat * after, family = "binomial",
##     data = data_123)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9840  -1.0865   0.5486   1.2712   1.3965
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.50156    0.04667 -10.746  < 2e-16 ***
## treat1       0.28386    0.05513   5.149 2.62e-07 ***
## after        2.31912    0.15802  14.676  < 2e-16 ***
## treat1:after -0.31273    0.17659  -1.771   0.0766 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 11831  on 8544  degrees of freedom
## Residual deviance: 10601  on 8541  degrees of freedom
## AIC: 10609
##
## Number of Fisher Scoring iterations: 4
```

4.2 Placebo effect

We wanted to move the resignation date of president few months back artificially and check the treatment effect

```r
# moving the prime minister resigantion data 3 months prior
resignation_plc_date <- mdy('04-03-2009')

data_placebo = data_123 %>%
               mutate(after_placebo = ifelse(DATE > resignation_plc_date, 1, 0))

# DiD with placebo data
did_basic_placebo_one = glm(y ~ treat + after_placebo + treat * after_placebo,
                            data = data_placebo,
                            family = "binomial")

summary(did_basic_placebo_one)
```

```
##
## Call:
## glm(formula = y ~ treat + after_placebo + treat * after_placebo,
##     family = "binomial", data = data_placebo)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6160  -1.0253   0.7950   0.9061   1.4596
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -0.64255    0.05381 -11.941  < 2e-16 ***
## treat1               0.27377    0.06372   4.297 1.73e-05 ***
## after_placebo        1.32055    0.09254  14.270  < 2e-16 ***
## treat1:after_placebo  0.03800    0.10781   0.353    0.724
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 11831  on 8544  degrees of freedom
## Residual deviance: 10909  on 8541  degrees of freedom
## AIC: 10917
##
## Number of Fisher Scoring iterations: 4
```