

PS532 Final Paper: Exploring the Relationship Between Perceived Discrimination and Political Participation: Evidence from Asian Americans

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```
#load dataset
setwd("/Users/qiaoyinie/Desktop/PS532Quant III/PS532-Final-Project")
getwd()

## [1] "/Users/qiaoyinie/Desktop/PS532Quant III/PS532-Final-Project"
data <- read.csv("Asian Americans' Experiences of Discrimination and Political Participation Survey_Aug2019.csv")
View(data)

###data cleaning
fdata <- data[-c(1,2,3,4,12,27,28,50,59,178,205,250,267,268,269,270,271,276,278,279,281,286,288,289,293)]
View(fdata)

install.packages('tidyverse')

##
## The downloaded binary packages are in
## /var/folders/9m/8_zrd0b55yvt7g8szv9rr5c0000gn/T//Rtmp0E81D1/downloaded_packages
library(tidyverse)

## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr      1.1.4      v readr      2.1.4
## v forcats    1.0.0      v stringr    1.5.0
## v ggplot2     3.4.4      v tibble     3.2.1
## v lubridate  1.9.2      v tidyr      1.3.0
## v purrr       1.0.1
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors

#mutate new variables
fdata$X1<- as.numeric(fdata$X1)
fdata$X2<- as.numeric(fdata$X2)
fdata$X3<- as.numeric(fdata$X3)
fdata$X4<- as.numeric(fdata$X4)
fdata$X5<- as.numeric(fdata$X5)

fdata1 <- fdata %>%
  mutate(MPP = rowMeans(select(fdata, c(25:29)), na.rm = TRUE))
```

```

fdata1 <- fdata1 %>%
  mutate_at(vars(c(30:129)), as.numeric)

fdata1 <- fdata1 %>%
  mutate(APP = rowMeans(select(fdata1, c(30:129))), na.rm = TRUE))

###subset treatment
fdata1 <- fdata1 %>%
  mutate_at(vars(c(15:24)), as.numeric)

fdata1 <- fdata1 %>%
  mutate(Treatment = case_when(
    PD1 >= 1 ~ "1",
    SD1 >= 1 ~ "2",
    P1 >= 1 ~ "3",
    PD1.1 >= 1 ~ "4",
    TRUE ~ "F" # Default case if none of the conditions match
  ))

fulldata <- fdata1 %>%
  select(c(1:24,130,132,133,134))

###preps for analysis

#assign meaning
install.packages("Hmisc")

##
## The downloaded binary packages are in
## /var/folders/9m/8_zrd0b55yvb7g8szv9rr5c0000gn/T//Rtmp0E81D1/downloaded_packages
library(Hmisc)

##
## Attaching package: 'Hmisc'
##
## The following objects are masked from 'package:dplyr':
##
##   src, summarize
##
## The following objects are masked from 'package:base':
##
##   format.pval, units
label(fulldata$Race.and.Ethnicity) <- "Ethnicity"
label(fulldata$Q19) <- "Frequency of Dis"

###descriptive analysis
#ethnicity
unique(fulldata$Asian)

## [1] "1" "6" "20" "7" "11" "2" "8" "10" "19" "5" "17" "3" "12" "15" "9"
## [16] "18" "13" "14"

```

```

fulldata <- fulldata[order(fulldata$Asian, decreasing = TRUE), ]

fulldata <- fulldata %>%
  mutate(Ethcinity = case_when(
    Asian== 1 ~ "Asian Indian",
    Asian== 2 ~ "Bangladeshi",
    Asian== 3 ~ "Bhutanese",
    Asian== 4 ~ "Burmese",
    Asian== 5 ~ "Cambodian",
    Asian== 6 ~ "Chinese",
    Asian== 7 ~ "Philippino",
    Asian== 8 ~ "Hmong",
    Asian== 9 ~ "Indonesian",
    Asian== 10 ~ "Japanese",
    Asian== 11 ~ "Korean",
    Asian== 12 ~ "Laotian",
    Asian== 13 ~ "Mongolian",
    Asian== 14 ~ "Malaysian",
    Asian== 15 ~ "Nepalese",
    Asian== 16 ~ "Okinawan",
    Asian== 17 ~ "Pakistani",
    Asian== 18 ~ "Sri Lankan",
    Asian== 19 ~ "Thai",
    Asian== 20 ~ "Vietnamese",
    TRUE ~ "F" # Default case if none of the conditions match
  ))

```

```

##linear regression without matching
##subset
fulldata <- fulldata %>%
  mutate(Treat = case_when(
    Treatment== 3 ~ "1",
    Treatment== 1 ~ "2",
    Treatment== 2 ~ "3",
    Treatment== 4 ~ "4",
  ))

PD <- fulldata[fulldata$Treat ==2, ]
SD <- fulldata[fulldata$Treat ==3, ]
Placebo <- fulldata[fulldata$Treat ==1, ]

## combine the treated and control/placebo group
PD <- subset(fulldata, Treat < 3)
SD <- subset(fulldata, Treat ==1 | Treat == 3)

PD <- PD %>%
  mutate(Treat = case_when(
    Treatment== 1 ~ "1",
    Treatment== 3 ~ "0",
  ))

SD <- SD %>%
  mutate(Treat = case_when(
    Treatment== 2 ~ "1",

```

```

    Treatment== 3 ~ "0",
  ))

#remove NAs columns and rows
PD <- subset(PD, select = c(Age,Gender,Race.and.Ethnicity,Birthplace,Education,Residence.area.1,HouseholdIncome))
PD <- PD[-4,]
PD <- PD[-40,]
PD <- PD[-75,]

SD <- subset(SD, select = c(Age,Gender,Race.and.Ethnicity,Birthplace,Education,Residence.area.1,HouseholdIncome))
SD <- SD[-5,]
SD <- SD[-77,]

#Check the observations
table(PD$Treat) #control: 79 Treated:77

##
## 0 1
## 79 77

table(SD$Treat) #control: 79 Treated:81

##
## 0 1
## 79 81

#regression analysis
install.packages("estimatr")

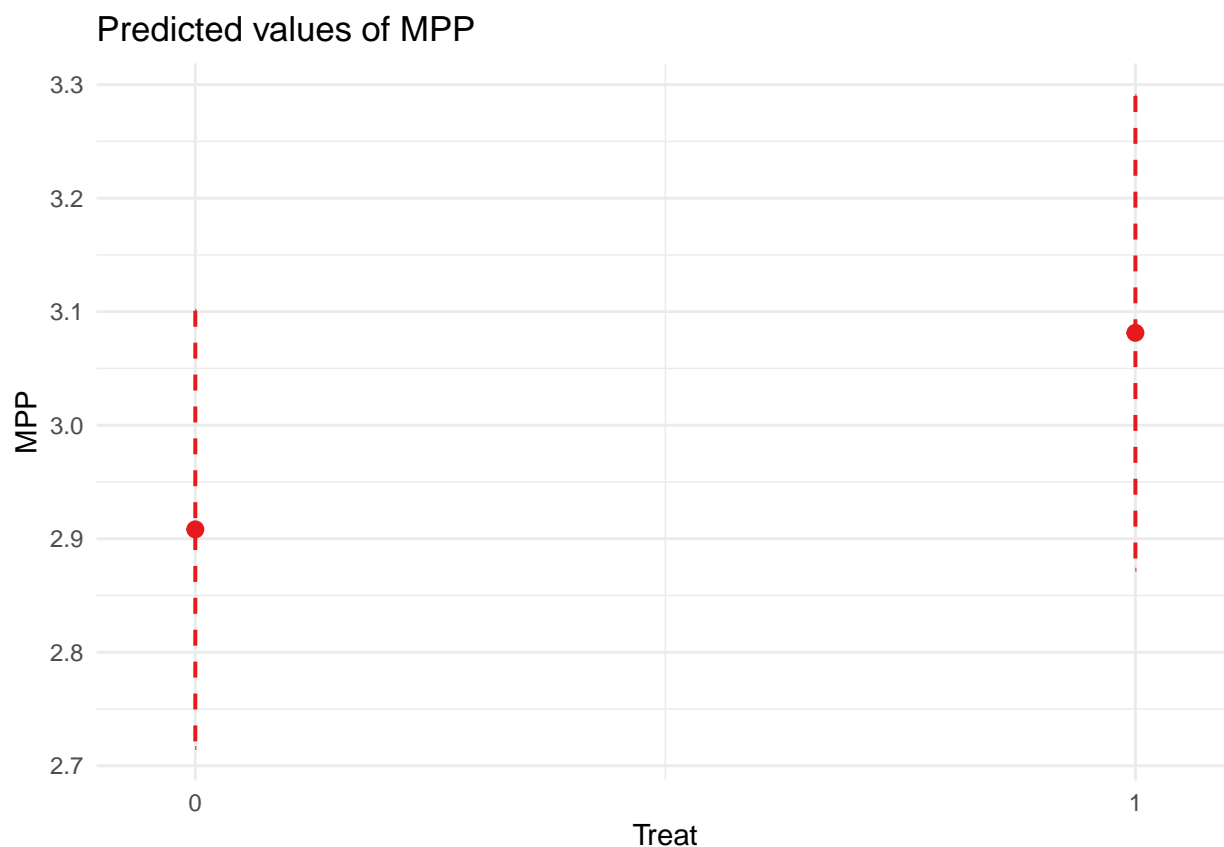
##
## The downloaded binary packages are in
## /var/folders/9m/8_zrd0b55yvb7g8szv9rr5c0000gn/T//Rtmp0E81D1/downloaded_packages

library(estimatr)
lm1 <- lm_robust(MPP ~ Treat, data=PD)
summary(lm1)

##
## Call:
## lm_robust(formula = MPP ~ Treat, data = PD)
##
## Standard error type: HC2
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF
## (Intercept)   2.9082    0.09747  29.838 6.768e-66  2.7157    3.101 154
## Treat1        0.1732    0.14369   1.205 2.300e-01 -0.1107    0.457 154
##
## Multiple R-squared:  0.009357 , Adjusted R-squared:  0.002925
## F-statistic: 1.452 on 1 and 154 DF, p-value: 0.23

sjPlot::plot_model(lm1, type = "pred")+
  theme(plot.background = element_rect(fill = "white"))+
  theme_minimal()

```

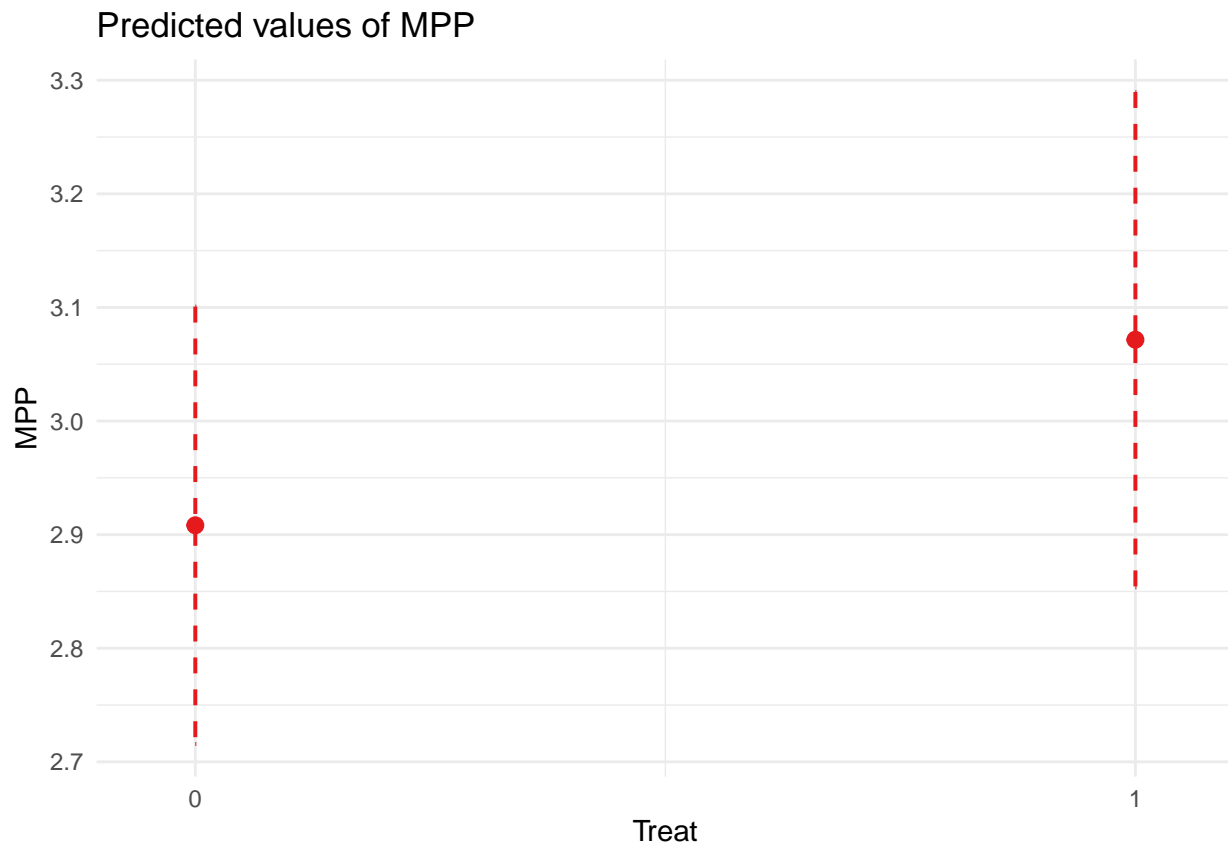


```
lm2 <- lm_robust(MPP ~ Treat, data=SD)
```

```
summary(lm2)
```

```
##
## Call:
## lm_robust(formula = MPP ~ Treat, data = SD)
##
## Standard error type: HC2
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF
## (Intercept)   2.9082    0.09747  29.838 8.161e-67  2.7157  3.1007 158
## Treat1        0.1634    0.14726   1.109 2.689e-01 -0.1275  0.4542 158
##
## Multiple R-squared:  0.007704 , Adjusted R-squared:  0.001423
## F-statistic: 1.231 on 1 and 158 DF, p-value: 0.2689
```

```
sjPlot::plot_model(lm2, type = "pred", )+
  theme_minimal()
```



```
##matching
```

```
# Display the result
#print(PD)
#print(SD)
```

```
### Propensity Score Matching
install.packages("Matching")
```

```
##
## The downloaded binary packages are in
## /var/folders/9m/8_zrd0b55yvt7g8szv9rr5c0000gn/T//Rtmp0E81D1/downloaded_packages
library(Matching)
```

```
## Loading required package: MASS
```

```
##
```

```
## Attaching package: 'MASS'
```

```
## The following object is masked from 'package:dplyr':
```

```
##
```

```
## select
```

```
## ##
```

```
## ## Matching (Version 4.10-14, Build Date: 2023-09-13)
```

```
## ## See https://www.jsekhon.com for additional documentation.
```

```
## ## Please cite software as:
```

```
## ## Jasjeet S. Sekhon. 2011. ``Multivariate and Propensity Score Matching
```

```
## ## Software with Automated Balance Optimization: The Matching package for R.''
```

```
## ## Journal of Statistical Software, 42(7): 1-52.  
## ##
```

```
library(ggplot2)  
library(Matching)
```

```
# dependent variable
```

```
y1 <- PD$MPP  
y2 <- SD$MPP
```

```
# treatment
```

```
tr1 <- PD$Treat  
tr2 <- SD$Treat
```

```
# Convert character variable to numeric
```

```
PD$Treat <- as.numeric(PD$Treat)  
PD$Age <- as.numeric(PD$Age)  
PD$Race.and.Ethnicity <- as.numeric(PD$Race.and.Ethnicity)  
PD$Gender <- as.numeric(PD$Gender)  
PD$Birthplace <- as.numeric(PD$Birthplace)  
PD$Education <- as.numeric(PD$Education)  
PD$Household.Income.Lev <- as.numeric(PD$Household.Income.Lev)  
PD$Discriminatory.Exper <- as.numeric(PD$Discriminatory.Exper)
```

```
SD$Treat <- as.numeric(SD$Treat)  
SD$Age <- as.numeric(SD$Age)  
SD$Race.and.Ethnicity <- as.numeric(SD$Race.and.Ethnicity)  
SD$Gender <- as.numeric(SD$Gender)  
SD$Birthplace <- as.numeric(SD$Birthplace)  
SD$Education <- as.numeric(SD$Education)  
SD$Household.Income.Lev <- as.numeric(SD$Household.Income.Lev)  
SD$Discriminatory.Exper <- as.numeric(SD$Discriminatory.Exper)
```

```
# create a propensity score model for the political discrimination treatment
```

```
glm1 <- glm(Treat~Age+Race.and.Ethnicity+Gender+Birthplace+Education+Residence.area.1+Household.Income.Lev,  
            family=binomial, data=PD)
```

```
#make sure the length of fitted value is the same with the treated ones
```

```
length(glm1$fitted)
```

```
## [1] 156
```

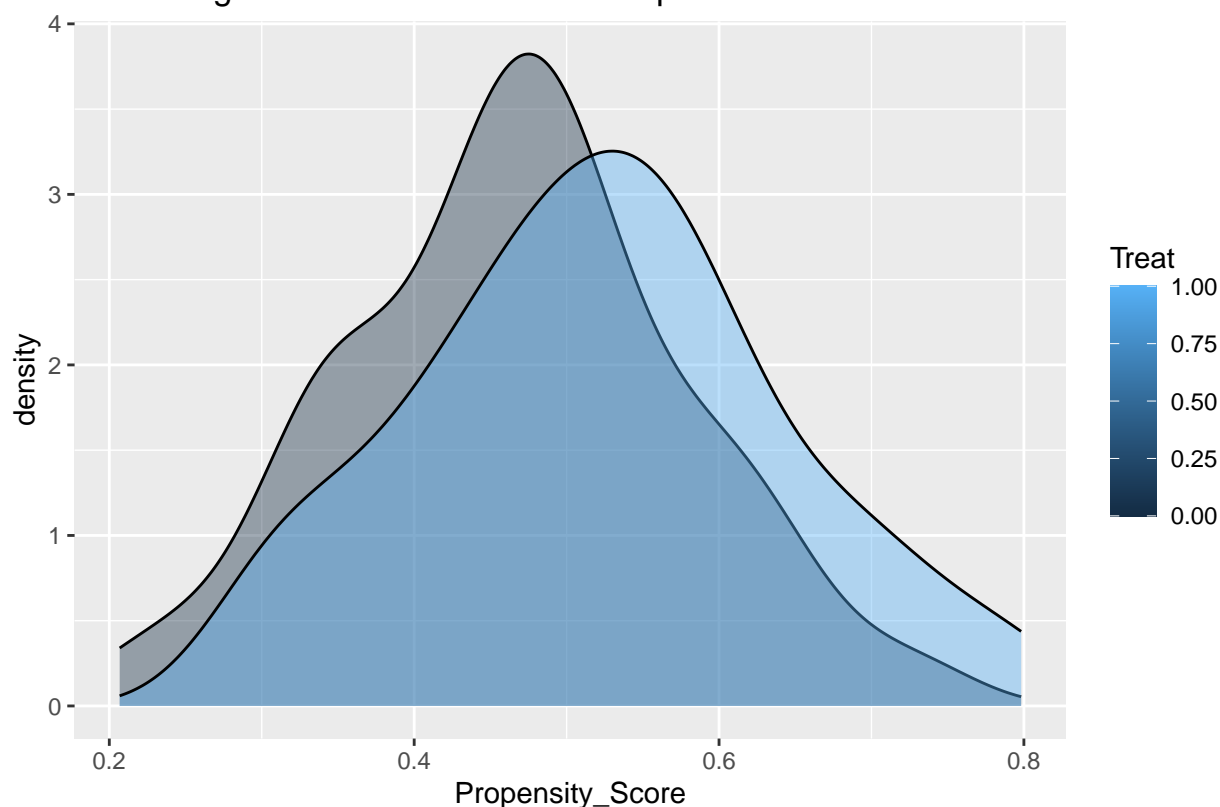
```
joinscore1 = cbind(PD, glm1$fitted)
```

```
colnames(joinscore1)[12] = "Propensity_Score"
```

```
# With transparency
```

```
ggplot(data=joinscore1, aes(x=Propensity_Score, group=Treat, fill=Treat)) + geom_density(adjust=1, alpha=0.5)
```

Assessing Mainstream Political Participation W/ Political Discrimination



```
# default options: estimand="ATT", M=1, exact=NULL, caliper=NULL, replace=TRUE
```

```
#one-to-one matching for PD
```

```
rr1 <- Match(Y=y1, Tr=tr1, X=glm1$fitted)
summary(rr1)
```

```
##
## Estimate... -0.1513
## AI SE..... 0.1955
## T-stat..... -0.77392
## p.val..... 0.43898
##
## Original number of observations..... 156
## Original number of treated obs..... 77
## Matched number of observations..... 77
## Matched number of observations (unweighted). 80
```

```
atc <- Match(Y=y1, Tr=tr1, X=glm1$fitted, estimand = "ATC")
summary(atc)
```

```
##
## Estimate... 0.11709
## AI SE..... 0.18916
## T-stat..... 0.61898
## p.val..... 0.53593
##
## Original number of observations..... 156
```



```

## Original number of control obs..... 79
## Matched number of observations..... 79
## Matched number of observations (unweighted). 81

matched <- PD[c(rr1$index.treated,rr1$index.control),]

Matchdefinition <- function(Y=NULL,Tr,X,Z=X,V=rep(1,length(Y)), estimand="ATT", M=1, BiasAdjust=FALS

# Assess balance for one covariate
# Do we have balance on discrimination experience after matching?
qqout1 <- qqstats(PD$Discriminatory.Exper[rr1$index.treated], PD$Discriminatory.Exper[rr1$index.contr
print(qqout1)

## $meandiff
## [1] 0.04375
##
## $mediandiff
## [1] 0.04375
##
## $maxdiff
## [1] 0.0875

# check balance
postmatchbal1 = MatchBalance(Treat~Age+Gender+Race.and.Ethnicity+Birthplace+Education+Residence.area.

##
## ***** (V1) Age *****
##
## Before Matching After Matching
## mean treatment..... 2.3896 2.3896
## mean control..... 2.5443 2.2511
## std mean diff..... -10.718 9.5982
##
## mean raw eQQ diff..... 0.19481 0.1875
## med raw eQQ diff..... 0 0
## max raw eQQ diff..... 1 2
##
## mean eCDF diff..... 0.031317 0.03125
## med eCDF diff..... 0.023673 0.0375
## max eCDF diff..... 0.091731 0.075
##
## var ratio (Tr/Co)..... 1.0578 1.2786
## T-test p-value..... 0.49847 0.53096
## KS Bootstrap p-value.. 0.486 0.681
## KS Naive p-value..... 0.47666 0.66761
## KS Statistic..... 0.091731 0.075
##
##
## ***** (V2) Gender *****
##
## Before Matching After Matching
## mean treatment..... 1.7143 1.7143
## mean control..... 1.5823 1.7468
## std mean diff..... 25.919 -6.3748
##
## mean raw eQQ diff..... 0.14286 0.0875

```

```

## med raw eQQ diff..... 0 0
## max raw eQQ diff..... 1 1
##
## mean eCDF diff..... 0.044002 0.029167
## med eCDF diff..... 0.025974 0.025
## max eCDF diff..... 0.10603 0.0625
##
## var ratio (Tr/Co)..... 1.053 1.3538
## T-test p-value..... 0.10327 0.59904
## KS Bootstrap p-value.. 0.167 0.433
## KS Naive p-value..... 0.18646 0.48209
## KS Statistic..... 0.10603 0.0625
##
##
## ***** (V3) Race.and.Ethnicity *****
## Before Matching After Matching
## mean treatment..... 7.961 7.961
## mean control..... 8.0759 7.3506
## std mean diff..... -2.0758 11.027
##
## mean raw eQQ diff..... 0.49351 0.5125
## med raw eQQ diff..... 0 0
## max raw eQQ diff..... 4 3
##
## mean eCDF diff..... 0.02833 0.033929
## med eCDF diff..... 0.0217 0.025
## max eCDF diff..... 0.070689 0.075
##
## var ratio (Tr/Co)..... 0.96086 1.0882
## T-test p-value..... 0.89805 0.47383
## KS Bootstrap p-value.. 0.787 0.801
## KS Naive p-value..... 0.83278 0.81233
## KS Statistic..... 0.070689 0.075
##
##
## ***** (V4) Birthplace *****
## Before Matching After Matching
## mean treatment..... 1.3636 1.3636
## mean control..... 1.4051 1.3961
## std mean diff..... -8.5557 -6.7054
##
## mean raw eQQ diff..... 0.038961 0.025
## med raw eQQ diff..... 0 0
## max raw eQQ diff..... 1 1
##
## mean eCDF diff..... 0.020713 0.0125
## med eCDF diff..... 0.020713 0.0125
## max eCDF diff..... 0.041427 0.025
##
## var ratio (Tr/Co)..... 0.96056 0.96739
## T-test p-value..... 0.59762 0.66663
##
##
## ***** (V5) Education *****

```

	Before Matching	After Matching
##		
## mean treatment.....	3.7792	3.7792
## mean control.....	3.9367	3.7251
## std mean diff.....	-10.255	3.5235
##		
## mean raw eQQ diff.....	0.11688	0.15
## med raw eQQ diff.....	0	0
## max raw eQQ diff.....	1	1
##		
## mean eCDF diff.....	0.026248	0.025
## med eCDF diff.....	0.031317	0.01875
## max eCDF diff.....	0.04455	0.075
##		
## var ratio (Tr/Co).....	1.1171	1.2056
## T-test p-value.....	0.51179	0.81315
## KS Bootstrap p-value..	0.913	0.647
## KS Naive p-value.....	0.90096	0.66057
## KS Statistic.....	0.04455	0.075
##		
##		
## ***** (V6) Residence.area.12 *****		
##	Before Matching	After Matching
## mean treatment.....	0.68831	0.68831
## mean control.....	0.72152	0.7013
## std mean diff.....	-7.1227	-2.7856
##		
## mean raw eQQ diff.....	0.025974	0.05
## med raw eQQ diff.....	0	0
## max raw eQQ diff.....	1	1
##		
## mean eCDF diff.....	0.016604	0.025
## med eCDF diff.....	0.016604	0.025
## max eCDF diff.....	0.033207	0.05
##		
## var ratio (Tr/Co).....	1.0681	1.0242
## T-test p-value.....	0.65195	0.84197
##		
##		
## ***** (V7) Residence.area.13 *****		
##	Before Matching	After Matching
## mean treatment.....	0.064935	0.064935
## mean control.....	0.025316	0.051948
## std mean diff.....	15.974	5.2361
##		
## mean raw eQQ diff.....	0.051948	0.0125
## med raw eQQ diff.....	0	0
## max raw eQQ diff.....	1	1
##		
## mean eCDF diff.....	0.019809	0.00625
## med eCDF diff.....	0.019809	0.00625
## max eCDF diff.....	0.039619	0.0125
##		
## var ratio (Tr/Co).....	2.4615	1.2329
## T-test p-value.....	0.23768	0.56457

```
##
##
## ***** (V8) Household.Income.Lev *****
##           Before Matching           After Matching
## mean treatment.....      3.5584      3.5584
## mean control.....       3.8228      3.2468
## std mean diff.....      -14.32      16.885
##
## mean raw eQQ diff.....    0.2987      0.35
## med  raw eQQ diff.....     0      0
## max  raw eQQ diff.....     1      1
##
## mean eCDF diff.....    0.046312      0.05
## med  eCDF diff.....    0.029919      0.0375
## max  eCDF diff.....     0.1491      0.1375
##
## var ratio (Tr/Co).....    1.1286      1.1116
## T-test p-value.....     0.35879      0.20164
## KS Bootstrap p-value..     0.127      0.188
## KS Naive p-value.....    0.14538      0.19908
## KS Statistic.....       0.1491      0.1375
##
##
## ***** (V9) Discriminatory.Exper *****
##           Before Matching           After Matching
## mean treatment.....      1.5065      1.5065
## mean control.....       1.3924      1.4221
## std mean diff.....      22.671      16.775
##
## mean raw eQQ diff.....    0.11688      0.0875
## med  raw eQQ diff.....     0      0
## max  raw eQQ diff.....     1      1
##
## mean eCDF diff.....    0.057044      0.04375
## med  eCDF diff.....    0.057044      0.04375
## max  eCDF diff.....    0.11409      0.0875
##
## var ratio (Tr/Co).....    1.0487      1.0247
## T-test p-value.....     0.15412      0.22269
##
##
## Before Matching Minimum p.value: 0.10327
## Variable Name(s): Gender  Number(s): 2
##
## After Matching Minimum p.value: 0.188
## Variable Name(s): Household.Income.Lev  Number(s): 8
```

```
# Transform to a tabular format
```

```
SMDeepExtract <- function(PD, col = c("mean.Tr", "mean.Co", "var.Tr", "var.Co", "var.ratio", "p.value")) {
  cbind(
    t(sapply(PD[[ "BeforeMatching" ]], "[", col)),
    t(sapply(PD[[ "AfterMatching" ]], "[", col))
  )
}
```

```
}
```

```
# extract
```

```
res1 <- SMDeepExtract(postmatchball1)
```

```
rownames(res1) = c("Age", "Gender", "Race and Ethnicity", "Birthplace", "Education", "Suburban", "Rural")
```

```
colnames(res1) = c("mean.Tr", "mean.Co", "var.Tr", "var.Co", "var.ratio", "p.value", "sdiff", "A.mean.Tr", "A.mean.Co")
```

```
res1[] <- lapply(res1, round, 2)
```

```
kableExtra::kable(res1[])
```

	mean.Tr	mean.Co	var.Tr	var.Co	var.ratio	p.value	sdiff	A.mean.Tr	A.mean.Co
Age	2.39	2.54	2.08	1.97	1.06	0.5	-10.72	2.39	2.25
Gender	1.71	1.58	0.26	0.25	1.05	0.1	25.92	1.71	1.75
Race and Ethnicity	7.96	8.08	30.64	31.89	0.96	0.9	-2.08	7.96	7.35
Birthplace	1.36	1.41	0.23	0.24	0.96	0.6	-8.56	1.36	1.4
Education	3.78	3.94	2.36	2.11	1.12	0.51	-10.25	3.78	3.73
Suburban	0.69	0.72	0.22	0.2	1.07	0.65	-7.12	0.69	0.7
Rural	0.06	0.03	0.06	0.02	2.46	0.24	15.97	0.06	0.05
Household Income Level	3.56	3.82	3.41	3.02	1.13	0.36	-14.32	3.56	3.25
Discriminatory Experiences	1.51	1.39	0.25	0.24	1.05	0.15	22.67	1.51	1.42

```
# create a propensity score model for the second treatment
```

```
glm2 <- glm(Treat~Age+Gender+Race.and.Ethnicity+Birthplace+Education+Residence.area.1+Household.Income.Level,
            family=binomial, data=SD)
```

```
#check the length
```

```
length(glm2$fitted)
```

```
## [1] 160
```

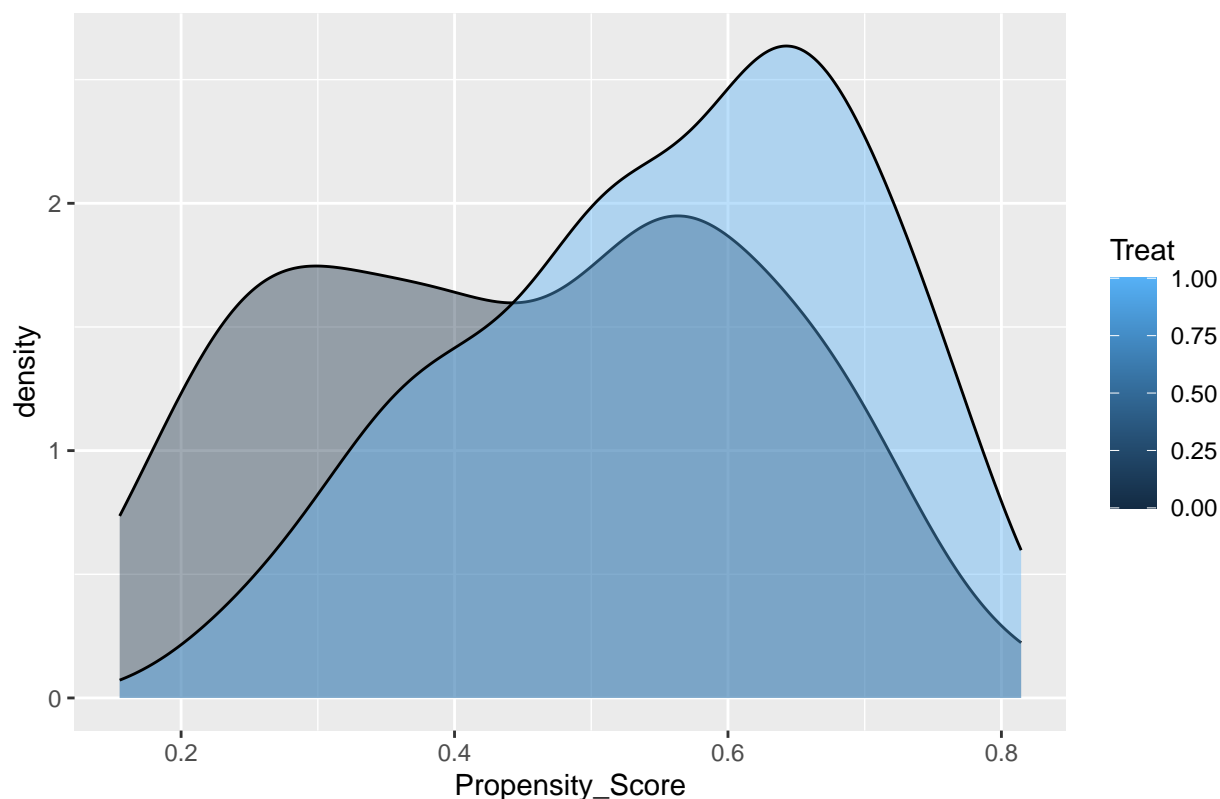
```
joinscore2 = cbind(SD, glm2$fitted)
```

```
colnames(joinscore2)[12] = "Propensity_Score"
```

```
# With transparency
```

```
ggplot(data=joinscore2, aes(x=Propensity_Score, group=Treat, fill=Treat)) + geom_density(adjust=1, alpha=0.5)
```

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#one-to-one matching for SD

```
rr2 <- Match(Y=y2, Tr=tr2, X=glm2$fitted)
summary(rr2)
```

```
##
## Estimate... 0.1037
## AI SE..... 0.19647
## T-stat..... 0.52784
## p.val..... 0.59761
##
## Original number of observations..... 160
## Original number of treated obs..... 81
## Matched number of observations..... 81
## Matched number of observations (unweighted). 85
```

```
atc <- Match(Y=y2, Tr=tr2, X=glm2$fitted, estimand = "ATC")
summary(atc)
```

```
##
## Estimate... 0.12722
## AI SE..... 0.18559
## T-stat..... 0.68545
## p.val..... 0.49306
##
## Original number of observations..... 160
## Original number of control obs..... 79
## Matched number of observations..... 79
## Matched number of observations (unweighted). 79
```

```

matched <- PD[c(rr2$index.treated,rr2$index.control),]

Matchdefinition <- function(Y=NULL,Tr,X,Z=X,V=rep(1,length(Y)), estimand="ATT", M=1, BiasAdjust=FALSE)

# Assess balance for one covariate
# Do we have balance on discrimination experience after matching?
qqout2 <- qqstats(SD$Race.and.Ethnicity[rr2$index.treated], SD$Race.and.Ethnicity[rr2$index.control])
print(qqout2)

## $meandiff
## [1] 0.05568627
##
## $mediandiff
## [1] 0.03529412
##
## $maxdiff
## [1] 0.2117647

# check balance
postmatchbal2 = MatchBalance(Treat~Age+Gender+Race.and.Ethnicity+Birthplace+Education+Residence.area.)

##
## ***** (V1) Age *****
##
##          Before Matching      After Matching
## mean treatment.....      2.5062      2.7273
## mean control.....      2.5443      2.1147
## std mean diff.....     -2.5837     38.612
##
## mean raw eQQ diff.....    0.12658      0.6875
## med  raw eQQ diff.....      0          0
## max  raw eQQ diff.....      1          3
##
## mean eCDF diff.....      0.02167      0.11458
## med  eCDF diff.....      0.020238      0.125
## max  eCDF diff.....      0.060947      0.1875
##
## var ratio (Tr/Co).....    1.1061      2.3569
## T-test p-value.....      0.86718     0.0043625
## KS Bootstrap p-value..      0.762      0.038
## KS Naive p-value.....      0.78988     0.026277
## KS Statistic.....      0.060947      0.1875
##
##
## ***** (V2) Gender *****
##
##          Before Matching      After Matching
## mean treatment.....      1.6914      1.6364
## mean control.....      1.5823      1.6883
## std mean diff.....      22.217     -10.173
##
## mean raw eQQ diff.....    0.10127      0.1
## med  raw eQQ diff.....      0          0
## max  raw eQQ diff.....      1          1
##

```

```

## mean eCDF diff..... 0.03636 0.03333
## med eCDF diff..... 0.012346 0.0125
## max eCDF diff..... 0.096734 0.0875
##
## var ratio (Tr/Co)..... 0.97849 1.1997
## T-test p-value..... 0.16429 0.48024
## KS Bootstrap p-value.. 0.208 0.286
## KS Naive p-value..... 0.25168 0.31796
## KS Statistic..... 0.096734 0.0875
##
##
## ***** (V3) Race.and.Ethnicity *****
## Before Matching After Matching
## mean treatment..... 7.0123 7.1299
## mean control..... 8.0759 7.5779
## std mean diff..... -20.745 -9.1391
##
## mean raw eQQ diff..... 1.2152 0.7625
## med raw eQQ diff..... 1 0
## max raw eQQ diff..... 6 6
##
## mean eCDF diff..... 0.056134 0.041346
## med eCDF diff..... 0.065479 0.0375
## max eCDF diff..... 0.11346 0.125
##
## var ratio (Tr/Co)..... 0.82427 0.84474
## T-test p-value..... 0.2145 0.594
## KS Bootstrap p-value.. 0.396 0.313
## KS Naive p-value..... 0.3867 0.30394
## KS Statistic..... 0.11346 0.125
##
##
## ***** (V4) Birthplace *****
## Before Matching After Matching
## mean treatment..... 1.5062 1.4545
## mean control..... 1.4051 1.4307
## std mean diff..... 20.098 4.7506
##
## mean raw eQQ diff..... 0.10127 0
## med raw eQQ diff..... 0 0
## max raw eQQ diff..... 1 0
##
## mean eCDF diff..... 0.050555 0
## med eCDF diff..... 0.050555 0
## max eCDF diff..... 0.10111 0
##
## var ratio (Tr/Co)..... 1.0369 1.0111
## T-test p-value..... 0.2015 0.7833
##
##
## ***** (V5) Education *****
## Before Matching After Matching
## mean treatment..... 3.9753 4.026
## mean control..... 3.9367 3.8506

```



```

## std mean diff.....      2.7298      12.652
##
## mean raw eQQ diff.....    0.11392      0.2
## med  raw eQQ diff.....      0      0
## max  raw eQQ diff.....      1      1
##
## mean eCDF diff.....      0.021279    0.033333
## med  eCDF diff.....      0.022582    0.03125
## max  eCDF diff.....      0.037975    0.0625
##
## var ratio (Tr/Co).....    0.94698    0.93888
## T-test p-value.....      0.86504    0.44251
## KS Bootstrap p-value..      0.937    0.784
## KS Naive p-value.....      0.93121    0.79246
## KS Statistic.....      0.037975    0.0625
##
##
## ***** (V6) Residence.area.12 *****
##                               Before Matching    After Matching
## mean treatment.....      0.64198    0.7013
## mean control.....      0.72152    0.65584
## std mean diff.....     -16.489    9.8666
##
## mean raw eQQ diff.....    0.088608    0.025
## med  raw eQQ diff.....      0      0
## max  raw eQQ diff.....      1      1
##
## mean eCDF diff.....      0.039772    0.0125
## med  eCDF diff.....      0.039772    0.0125
## max  eCDF diff.....      0.079544    0.025
##
## var ratio (Tr/Co).....      1.1435    0.92808
## T-test p-value.....      0.28287    0.50529
##
##
## ***** (V7) Residence.area.13 *****
##                               Before Matching    After Matching
## mean treatment.....      0.037037    0.051948
## mean control.....      0.025316      0
## std mean diff.....      6.1678    23.256
##
## mean raw eQQ diff.....      0      0.05
## med  raw eQQ diff.....      0      0
## max  raw eQQ diff.....      0      1
##
## mean eCDF diff.....      0.0058603    0.025
## med  eCDF diff.....      0.0058603    0.025
## max  eCDF diff.....      0.011721    0.05
##
## var ratio (Tr/Co).....      1.4449    Inf
## T-test p-value.....      0.67176    0.043409
##
##
## ***** (V8) Household.Income.Lev *****

```

```

##                               Before Matching      After Matching
## mean treatment.....         3.2099              3.4416
## mean control.....           3.8228              3.1061
## std mean diff.....          -41.627             19.855
##
## mean raw eQQ diff.....       0.68354            0.2375
## med  raw eQQ diff.....        1                  0
## max  raw eQQ diff.....        2                  1
##
## mean eCDF diff.....          0.091889           0.033929
## med  eCDF diff.....          0.077825           0.0375
## max  eCDF diff.....          0.19456            0.05
##
## var ratio (Tr/Co).....       0.71797            1.1585
## T-test p-value.....          0.017403           0.24645
## KS Bootstrap p-value..        0.018             0.937
## KS Naive p-value.....        0.027495           0.94356
## KS Statistic.....           0.19456            0.05
##
##
## ***** (V9) Discriminatory.Exper *****
##                               Before Matching      After Matching
## mean treatment.....         1.5432              1.5195
## mean control.....           1.3924              1.3961
## std mean diff.....          30.087             24.533
##
## mean raw eQQ diff.....       0.13924            0.1375
## med  raw eQQ diff.....        0                  0
## max  raw eQQ diff.....        1                  1
##
## mean eCDF diff.....          0.075402           0.06875
## med  eCDF diff.....          0.075402           0.06875
## max  eCDF diff.....          0.1508            0.1375
##
## var ratio (Tr/Co).....       1.0404            1.0435
## T-test p-value.....          0.056445           0.16231
##
##
## Before Matching Minimum p.value: 0.017403
## Variable Name(s): Household.Income.Lev  Number(s): 8
##
## After Matching Minimum p.value: 0.0043625
## Variable Name(s): Age  Number(s): 1

```

```
# Transform to a tabular format
```

```

SMDeepExtract <- function(SD, col = c("mean.Tr", "mean.Co", "var.Tr", "var.Co", "var.ratio", "p.value"),
  cbind(
    t(sapply(SD[[ "BeforeMatching" ]], "[", col)),
    t(sapply(SD[[ "AfterMatching" ]], "[", col))
  )
}

```

```
# extract
```

```
res2 <- SMDeepExtract(postmatchbal2)
```

```
rownames(res2) = c("Age", "Gender", "Race and Ethnicity", "Birthplace", "Education", "Suburban", "Rural")
colnames(res2) = c("mean.Tr", "mean.Co", "var.Tr", "var.Co", "var.ratio", "p.value", "sdiff", "A.mean.Tr", "A.mean.Co")
```

```
res2[] <- lapply(res2,round,2)
kableExtra::kable(res2[])
```

	mean.Tr	mean.Co	var.Tr	var.Co	var.ratio	p.value	sdiff	A.mean.Tr	A.mean.Co
Age	2.51	2.54	2.18	1.97	1.11	0.87	-2.58	2.73	2.11
Gender	1.69	1.58	0.24	0.25	0.98	0.16	22.22	1.64	1.69
Race and Ethnicity	7.01	8.08	26.29	31.89	0.82	0.21	-20.74	7.13	7.58
Birthplace	1.51	1.41	0.25	0.24	1.04	0.2	20.1	1.45	1.43
Education	3.98	3.94	2	2.11	0.95	0.87	2.73	4.03	3.85
Suburban	0.64	0.72	0.23	0.2	1.14	0.28	-16.49	0.7	0.66
Rural	0.04	0.03	0.04	0.02	1.44	0.67	6.17	0.05	0
Household Income Level	3.21	3.82	2.17	3.02	0.72	0.02	-41.63	3.44	3.11
Discriminatory Experiences	1.54	1.39	0.25	0.24	1.04	0.06	30.09	1.52	1.4