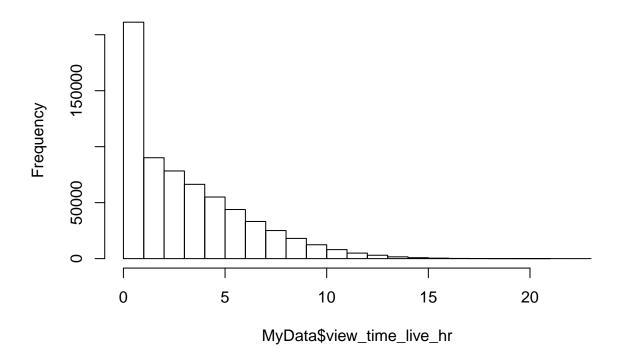
TSTV-Obs-Feb_26_DM.R

danny 2020-02-26

```
#*** MSBA 6440 ***#
#*** Gordon Burtch and Gautam Ray***#
#*** Updated Feb 2020 ***#
#*** Code for Lecture 4 ***#
#*** Propensity Score Matching ***#
library(stargazer)
##
## Please cite as:
## Hlavac, Marek (2018). stargazer: Well-Formatted Regression and Summary Statistics Tables.
## R package version 5.2.2. https://CRAN.R-project.org/package=stargazer
library(ggplot2)
## Warning: package 'ggplot2' was built under R version 3.6.2
library(MatchIt)
## Warning: package 'MatchIt' was built under R version 3.6.2
library(data.table)
library(tableone)
## Warning: package 'tableone' was built under R version 3.6.2
#**** Load the data ***#
MyData<-read.csv("TSTV-Obs-Dataset-2.csv")</pre>
hist(MyData$view_time_live_hr)
```

Histogram of MyData\$view_time_live_hr



```
#*** Let's get a sense of the data ***#

#how long is the period of observation?
max(MyData$week)-min(MyData$week)
```

[1] 13

```
#How many subjects got TSTV? (Treated)
length(unique(MyData$premium==TRUE]))
```

[1] 8348

```
#How many subjects did not get TSTV? (Control)
length(unique(MyData$id[MyData$premium==FALSE]))
```

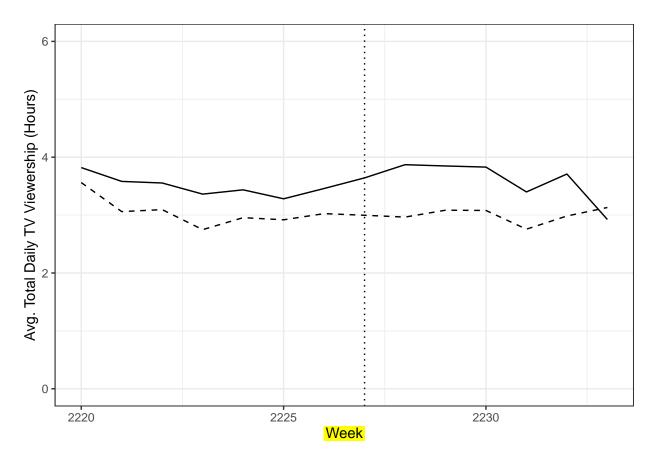
[1] 41686

```
#In what 'week' does the "treatment" begin?
min(unique(MyData$week[MyData$after==TRUE]))
```

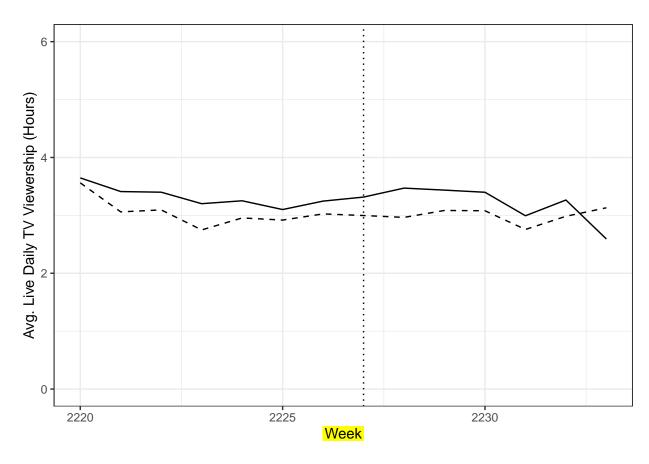
[1] 2227

```
#Let's just look at what is going on with average viewership behavior
#for treated vs. untreated, in the weeks around the treatment date.
MyDataAggregated <- aggregate(MyData,by=list(MyData$premium, MyData$week),FUN=mean)

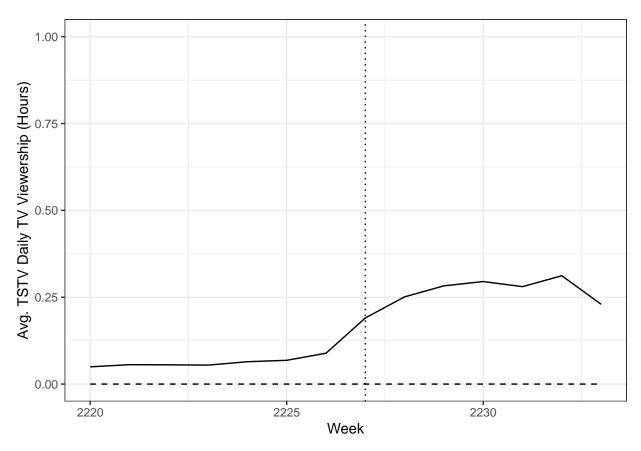
# plot for total TV time
p <- ggplot(MyDataAggregated)
p <- p + geom_line(data=MyDataAggregated[MyDataAggregated$premium==FALSE,], aes(week, view_time_total_h
p <- p + geom_line(data=MyDataAggregated[MyDataAggregated$premium==TRUE,], aes(week, view_time_total_hr
p <- p + geom_vline(xintercept=2227, linetype='dotted')
p <- p + xlab("Week") + ylab("Avg. Total Daily TV Viewership (Hours)")
p <- p + ylim(0, 6) + xlim(2220,2233) + theme_bw()</pre>
```



```
# plot for live TV time
p <- ggplot(MyDataAggregated)
p <- p + geom_line(data=MyDataAggregated[MyDataAggregated$premium==FALSE,], aes(week, view_time_live_hr
p <- p + geom_line(data=MyDataAggregated[MyDataAggregated$premium==TRUE,], aes(week, view_time_live_hr)
p <- p + geom_vline(xintercept=2227, linetype='dotted')
p <- p + xlab("Week") + ylab("Avg. Live Daily TV Viewership (Hours)")
p <- p + ylim(0, 6) + xlim(2220,2233) + theme_bw()
p</pre>
```



```
# plot for TSTV time
p <- ggplot(MyDataAggregated)
p <- p + geom_line(data=MyDataAggregated[MyDataAggregated$premium==FALSE,], aes(week, view_time_tstv_hr
p <- p + geom_line(data=MyDataAggregated[MyDataAggregated$premium==TRUE,], aes(week, view_time_tstv_hr)
p <- p + geom_vline(xintercept=2227, linetype='dotted')
p <- p + xlab("Week") + ylab("Avg. TSTV Daily TV Viewership (Hours)")
p <- p + ylim(0, 1) + xlim(2220,2233) + theme_bw()</pre>
```



```
#*** Propensity Score Matching ***#
#For this demonstration, we will use data from the pre-period for matching.
#We will then estimate the effect of TSTV gifting in the post period.
#*** CREATE A SUMMARY DATASET BEFORE us. AFTER TSTV IS AVAILABLE ***#
MyDataSummary <- aggregate(MyData,by=list(MyData$id,MyData$after),FUN=mean)</pre>
MyDataSummary$view_time_total_sq <- MyDataSummary$view_time_total_hr^2</pre>
# Okay, let's check out our covariate balance; we have one confounder here, view_time_total_hr.
# This is a dependent variable, but we are going to match on it in the pre-period.
# That is, we only want subjects who had similar viewership activity before TSTV showed up.
MyPreData <- MyDataSummary[MyDataSummary$after == FALSE,]</pre>
tabUnmatched <- CreateTableOne(vars=c("view_time_total_hr","view_time_total_sq"), strata="premium", tes
print(tabUnmatched, smd=TRUE)
##
                                    Stratified by premium
##
                                                   1
                                                                         test
##
                                     41686
                                                    8348
     view_time_total_hr (mean (SD)) 2.98 (2.42) 3.46 (2.69) <0.001</pre>
##
     view_time_total_sq (mean (SD)) 14.72 (22.20) 19.21 (28.21) <0.001
##
```

SMD

Stratified by premium

##

##

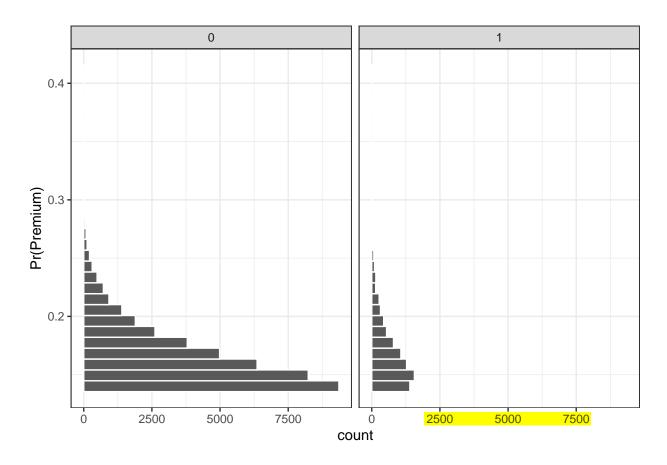
```
## view_time_total_hr (mean (SD)) 0.191
## view_time_total_sq (mean (SD)) 0.177

# Whoa, lots of imbalance here...

# Let's see what propensity scores look like...

MyPreData$PS<-glm(premium~view_time_total_hr+view_time_total_sq, data=MyPreData, family = "binomial")$f
ggplot(MyPreData, aes(x = PS)) +
    geom_histogram(color = "white") +
    facet_wrap(~premium) + xlab("Pr(Premium)") +theme_bw() + coord_flip()</pre>
```

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.



#*** Match treated and control households on propensity to receive premium based on pre-treatment time
Note: the matchit command may take a long time to run with large datasets

Matched_Output <- matchit(premium ~ view_time_total_hr + view_time_total_sq, data = MyPreData, method =</pre>

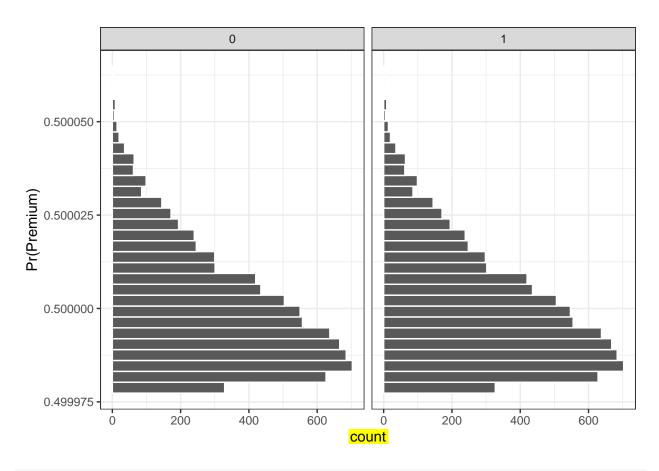
```
##
## Call:
```

summary(Matched_Output)

##

```
## matchit(formula = premium ~ view_time_total_hr + view_time_total_sq,
##
       data = MyPreData, method = "nearest", distance = "logit",
##
       caliper = 0.001, replace = FALSE)
##
## Summary of balance for all data:
##
                      Means Treated Means Control SD Control Mean Diff
                                            0.1659
                                                       0.0267
## distance
                             0.1714
                                                                 0.0055
                                            2.9754
                                                       2.4220
## view_time_total_hr
                             3.4632
                                                                 0.4878
## view_time_total_sq
                            19.2077
                                           14.7191
                                                      22.1998
                                                                 4.4887
##
                      eQQ Med eQQ Mean eQQ Max
## distance
                       0.0042
                                0.0055 0.0288
## view_time_total_hr 0.4336
                                0.4873 1.6377
## view_time_total_sq 2.3247
                                4.4755 39.9870
##
##
## Summary of balance for matched data:
##
                      Means Treated Means Control SD Control Mean Diff
## distance
                             0.1686
                                            0.1686
                                                       0.0262
                                                                 0.0000
                             3.2484
                                            3.2483
                                                       2.3880
                                                                 0.0001
## view_time_total_hr
## view_time_total_sq
                            16.2544
                                           16.2533
                                                      21.4272
                                                                 0.0011
##
                      eQQ Med eQQ Mean eQQ Max
## distance
                       0.0000
                                0.0000 0.0000
## view_time_total_hr 0.0007
                                0.0008 0.0031
## view_time_total_sq 0.0031
                                0.0055 0.0369
##
## Percent Balance Improvement:
##
                      Mean Diff. eQQ Med eQQ Mean eQQ Max
                         99.9718 99.8336 99.8466 99.9042
## distance
## view_time_total_hr
                         99.9699 99.8347 99.8336 99.8121
## view_time_total_sq
                         99.9762 99.8665 99.8762 99.9076
##
## Sample sizes:
##
             Control Treated
## All
               41686
                        8348
## Matched
                8110
                        8110
## Unmatched
               33576
                         238
## Discarded
                   0
                           0
Matched.ids <- data.table(match.data(Matched_Output))$id</pre>
Matched_Data = match.data(Matched_Output)
Matched_Data$PS = glm(premium ~ view_time_total_hr, data = Matched_Data, family = "binomial")$fitted.va
ggplot(Matched_Data, aes(x = PS)) +
  geom histogram(color = "white") +
 facet_wrap(~premium) + xlab("Pr(Premium)") +theme_bw() + coord_flip()
```

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.



tabMatched <- CreateTableOne(vars=c("view_time_total_hr","view_time_total_sq"), strata="premium", test="
print(tabMatched, smd=TRUE)</pre>

```
Stratified by premium
##
                                      0
##
                                                     1
                                                                           test
##
                                       8110
                                                     8110
     view_time_total_hr (mean (SD)) 3.25 (2.39)
                                                     3.25 (2.39)
##
                                                                     0.997
     view_time_total_sq (mean (SD)) 16.25 (21.43) 16.25 (21.43) 0.997
##
##
                                    Stratified by premium
                                      SMD
##
##
##
     view_time_total_hr (mean (SD)) <0.001</pre>
     view_time_total_sq (mean (SD)) <0.001</pre>
##
#Now let's estimate the treatment effect with vs. without matching.
MyDataPost <- MyDataSummary[MyDataSummary$after==TRUE,]</pre>
unmatched_ate <- lm(data=MyDataPost, view_time_total_hr~premium)</pre>
matched_ate <- lm(data=MyDataPost[MyDataPost$id %in% Matched.ids,], view_time_total_hr ~ premium)</pre>
#Produce the output table.
stargazer(unmatched_ate,matched_ate,title="Matched vs. Unmatched Estimates",column.labels=c("Total View
##
## Matched vs. Unmatched Estimates
```

##		Dependent variable:		
##		view time total hr		
##		Total Viewership		
##		(1)	(2)	
##		 0.614***	0.199***	
##	premium	(0.031)	(0.040)	
##		(0.000)	(3.5-2)	
##	Constant	2.990***	3.238***	
##		(0.013)	(0.029)	
##				
##	Observations	48,483	15,914	
	R2	0.008	0.002	
##	Adjusted R2	0.008	0.001	
##	Residual Std. Error	2.586 (df = 48481)	2.549 (df = 15912)	
##	F Statistic	388.341*** (df = 1; 48481)	24.130*** (df = 1; 15912)	
##	Note:	*]	p<0.1; **p<0.05; ***p<0.01	