```r
#install.packages("Matching", dependencies=TRUE)
#install.packages("rgenoud")
setwd("C:/Users/Darin/Documents/sanctionsbackslide/Spectrum")
library(Matching)
library(rgenoud)
library(dplyr)
library(stargazer)
library(readr)

df <- read_csv("SanctionsFinal.csv") %>%
  mutate(pop1 = log(pop1)) %>%
  filter(!is.na(GDP_UN))

df$murban[df$murban < 0] <- 0

dsum <- as.data.frame(select(df, polity2, sanctions, GDP_UN, pop1, menergy, mindustry, murba

dt <-  df %>%
  group_by(sanctions) %>%
  summarise(polity2 = mean(polity2))
dt <- as.data.frame(dt)
```

```r
stargazer(dsum, title = "Summary Statistics")
```

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
polity2	4,043	0.153	7.555	−10	10
sanctions	4,043	0.197	0.398	0	1
GDP_UN	4,043	3,902.012	6,605.237	14	43,165
pop1	4,043	8.987	1.544	4.984	14.065
menergy	4,043	5.621	1.954	0.000	12.261
mindustry	4,043	37.808	10.452	2.000	85.000
murban	4,043	8,735.562	30,395.150	0.000	531,307.000
dpolityb	4,008	0.109	0.312	0	1

```r
stargazer(dt, summary = F, title = "Average Score of Democracy: Sanctioned vs Non-Sanctioned
```

Table 2: Average Score of Democracy: Sanctioned vs Non-Sanctioned

sanctions	polity2
0	0.518
1	-1.332

```
X <- select(df, GDP_UN, pop1, menergy, mindustry, murban)

BalanceMatrix <- cbind(df$GDP_UN, df$pop1, df$menergy, df$mindustry, df$murban, I(df$GDP_UN*
                       I(df$GDP_UN*df$mindustry), I(df$GDP_UN*df$murban), I(df$pop1*df$murb

gen1 <- GenMatch(Tr = df$sanctions, X = X, BalanceMatrix = BalanceMatrix, pop.size = 10)

##
##
## Mon Nov 02 15:00:09 2015
## Domains:
##  0.000000e+00   <=  X1   <=    1.000000e+03
##  0.000000e+00   <=  X2   <=    1.000000e+03
##  0.000000e+00   <=  X3   <=    1.000000e+03
##  0.000000e+00   <=  X4   <=    1.000000e+03
##  0.000000e+00   <=  X5   <=    1.000000e+03
##
## Data Type: Floating Point
## Operators (code number, name, population)
##  (1) Cloning..........................  0
##  (2) Uniform Mutation.................  1
##  (3) Boundary Mutation................  1
##  (4) Non-Uniform Mutation.............  1
##  (5) Polytope Crossover...............  1
##  (6) Simple Crossover.................  2
##  (7) Whole Non-Uniform Mutation........  1
##  (8) Heuristic Crossover..............  2
##  (9) Local-Minimum Crossover..........  0
##
## SOFT Maximum Number of Generations: 100
## Maximum Nonchanging Generations: 4
## Population size       : 10
## Convergence Tolerance: 1.000000e-03
##
## Not Using the BFGS Derivative Based Optimizer on the Best Individual Each Generation.
## Not Checking Gradients before Stopping.
## Using Out of Bounds Individuals.
```

```
##
## Maximization Problem.
## GENERATION: 0 (initializing the population)
## Lexical Fit..... 4.714527e-04  2.299518e-03  3.147996e-03  3.582045e-03  9.971920e-03  1.
## #unique......... 10, #Total UniqueCount: 10
## var 1:
## best............ 1.927923e+02
## mean............ 4.669902e+02
## variance........ 1.175986e+05
## var 2:
## best............ 6.908474e+02
## mean............ 4.813716e+02
## variance........ 1.173796e+05
## var 3:
## best............ 1.653877e+02
## mean............ 5.677351e+02
## variance........ 1.112741e+05
## var 4:
## best............ 2.184367e+01
## mean............ 4.405547e+02
## variance........ 1.320683e+05
## var 5:
## best............ 5.950875e+02
## mean............ 4.063405e+02
## variance........ 1.120444e+05
##
## GENERATION: 1
## Lexical Fit..... 9.678060e-04  2.168151e-03  5.089865e-03  7.056201e-03  7.117076e-03  8.
## #unique......... 9, #Total UniqueCount: 19
## var 1:
## best............ 5.068376e+01
## mean............ 1.999897e+02
## variance........ 1.040164e+04
## var 2:
## best............ 7.719775e+02
## mean............ 6.542473e+02
## variance........ 2.761785e+04
## var 3:
## best............ 1.195896e+02
## mean............ 3.118353e+02
## variance........ 5.574966e+04
## var 4:
## best............ 9.509240e+02
## mean............ 3.198305e+02
## variance........ 1.465488e+05
```

```
## var 5:
## best............ 9.587737e+02
## mean............ 8.138168e+02
## variance........ 2.977944e+04
##
## GENERATION: 2
## Lexical Fit..... 1.424364e-03  2.854093e-03  6.044482e-03  7.268840e-03  9.971920e-03  1.
## #unique......... 7, #Total UniqueCount: 26
## var 1:
## best............ 4.608889e+01
## mean............ 7.758797e+01
## variance........ 2.949482e+03
## var 2:
## best............ 7.746007e+02
## mean............ 7.098544e+02
## variance........ 1.835571e+04
## var 3:
## best............ 1.181088e+02
## mean............ 1.906628e+02
## variance........ 1.238775e+04
## var 4:
## best............ 9.809645e+02
## mean............ 7.724594e+02
## variance........ 1.191711e+05
## var 5:
## best............ 9.705330e+02
## mean............ 8.542124e+02
## variance........ 2.369435e+04
##
## GENERATION: 3
## Lexical Fit..... 1.424364e-03  2.854093e-03  6.044482e-03  7.268840e-03  9.971920e-03  1.
## #unique......... 7, #Total UniqueCount: 33
## var 1:
## best............ 4.608889e+01
## mean............ 1.057613e+02
## variance........ 1.883227e+04
## var 2:
## best............ 7.746007e+02
## mean............ 7.545992e+02
## variance........ 7.619782e+03
## var 3:
## best............ 1.181088e+02
## mean............ 1.417075e+02
## variance........ 1.445524e+04
## var 4:
```

```
## best........... 9.809645e+02
## mean........... 9.582721e+02
## variance....... 1.800560e+03
## var 5:
## best........... 9.705330e+02
## mean........... 9.611305e+02
## variance....... 3.557963e+02
##
## GENERATION: 4
## Lexical Fit..... 1.424364e-03  2.854093e-03  6.044482e-03  7.268840e-03  9.971920e-03  1.
## #unique......... 8, #Total UniqueCount: 41
## var 1:
## best........... 4.608889e+01
## mean........... 5.868395e+01
## variance....... 2.078953e+03
## var 2:
## best........... 7.746007e+02
## mean........... 7.735409e+02
## variance....... 1.066289e+01
## var 3:
## best........... 1.181088e+02
## mean........... 1.775666e+02
## variance....... 3.198792e+04
## var 4:
## best........... 9.809645e+02
## mean........... 9.215829e+02
## variance....... 1.478850e+04
## var 5:
## best........... 9.705330e+02
## mean........... 9.364306e+02
## variance....... 4.950395e+03
##
## GENERATION: 5
## Lexical Fit..... 1.424364e-03  2.854093e-03  6.044482e-03  7.268840e-03  9.971920e-03  1.
## #unique......... 5, #Total UniqueCount: 46
## var 1:
## best........... 4.608889e+01
## mean........... 4.826822e+01
## variance....... 5.156063e+01
## var 2:
## best........... 7.746007e+02
## mean........... 7.319363e+02
## variance....... 1.621537e+04
## var 3:
## best........... 1.181088e+02
```

```
## mean........... 1.185059e+02
## variance........ 2.051905e+00
## var 4:
## best............ 9.809645e+02
## mean............ 9.182221e+02
## variance........ 1.748334e+04
## var 5:
## best............ 9.705330e+02
## mean............ 9.287696e+02
## variance........ 1.648753e+04
##
## GENERATION: 6
## Lexical Fit..... 1.424364e-03  2.854093e-03  6.044482e-03  7.268840e-03  9.971920e-03  1.
## #unique......... 8, #Total UniqueCount: 54
## var 1:
## best............ 4.608889e+01
## mean............ 1.071087e+02
## variance........ 2.551809e+04
## var 2:
## best............ 7.746007e+02
## mean............ 7.772103e+02
## variance........ 7.286933e+03
## var 3:
## best............ 1.181088e+02
## mean............ 1.175622e+02
## variance........ 2.107664e+02
## var 4:
## best............ 9.809645e+02
## mean............ 9.270602e+02
## variance........ 1.277711e+04
## var 5:
## best............ 9.705330e+02
## mean............ 9.720136e+02
## variance........ 9.212002e+00
##
## GENERATION: 7
## Lexical Fit..... 1.424364e-03  2.854093e-03  6.044482e-03  7.268840e-03  9.971920e-03  1.
## #unique......... 8, #Total UniqueCount: 62
## var 1:
## best............ 4.608889e+01
## mean............ 7.768395e+01
## variance........ 9.591236e+03
## var 2:
## best............ 7.746007e+02
## mean............ 7.740022e+02
```

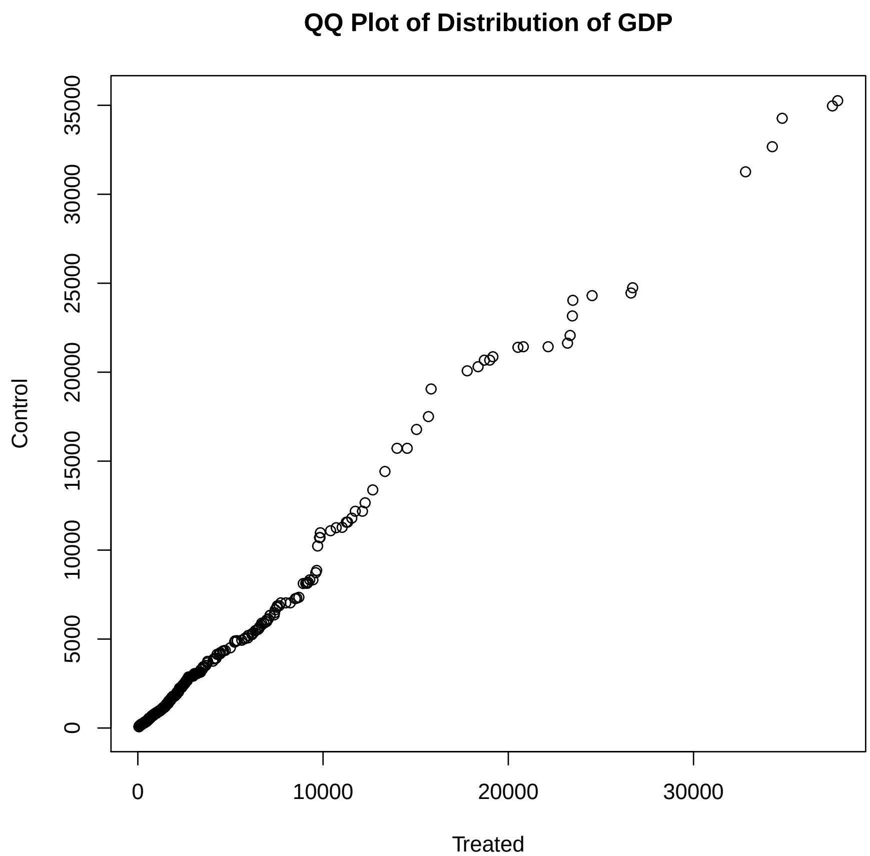
```
## variance........ 3.804271e+00
## var 3:
## best............ 1.181088e+02
## mean............ 1.723867e+02
## variance........ 2.693666e+04
## var 4:
## best............ 9.809645e+02
## mean............ 9.378040e+02
## variance........ 1.722392e+04
## var 5:
## best............ 9.705330e+02
## mean............ 9.574201e+02
## variance........ 1.602157e+03
##
## 'wait.generations' limit reached.
## No significant improvement in 4 generations.
##
## Solution Lexical Fitness Value:
## 1.424364e-03  2.854093e-03  6.044482e-03  7.268840e-03  9.971920e-03  1.374916e-02  2.162
##
## Parameters at the Solution:
##
##  X[ 1] : 4.608889e+01
##  X[ 2] : 7.746007e+02
##  X[ 3] : 1.181088e+02
##  X[ 4] : 9.809645e+02
##  X[ 5] : 9.705330e+02
##
## Solution Found Generation 2
## Number of Generations Run 7
##
## Mon Nov 02 15:00:37 2015
## Total run time : 0 hours 0 minutes and 28 seconds
```

```
mgen1 <- Match(Y = df$polity2, Tr = df$sanctions, X = X, Weight.matrix = gen1)
print(summary(mgen1))
```

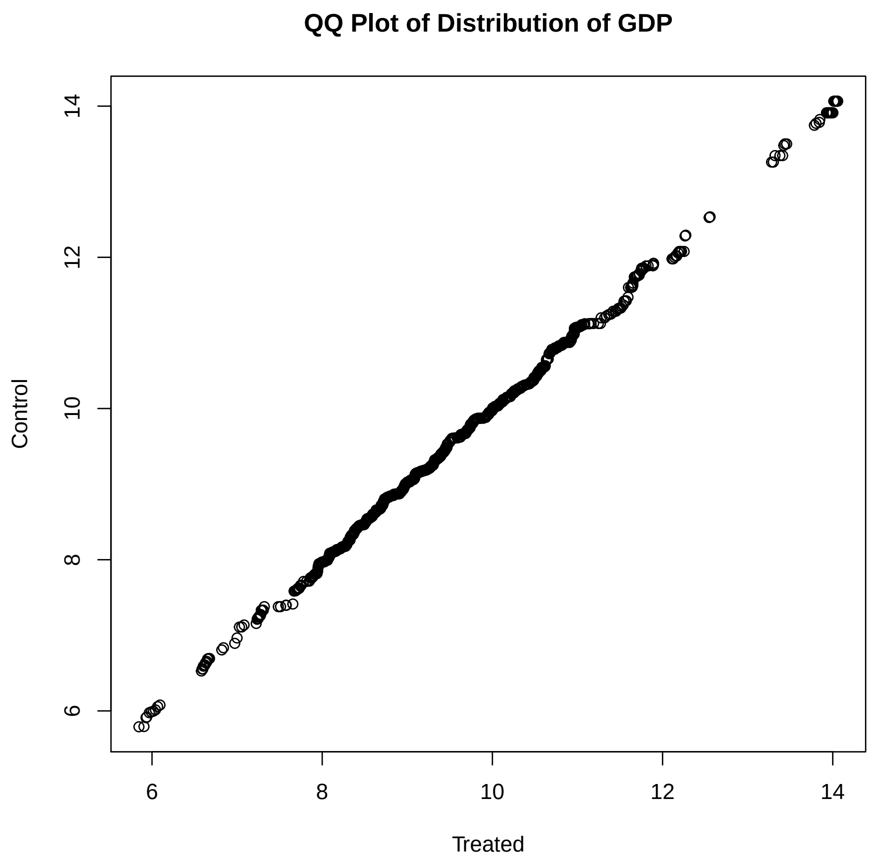
```
##
## Estimate...  -0.96738
## AI SE......  0.34803
## T-stat.....  -2.7795
## p.val......  0.0054434
##
## Original number of observations..............  4043
## Original number of treated obs...............  797
## Matched number of observations...............  797
```

```
## Matched number of observations  (unweighted).  797
```

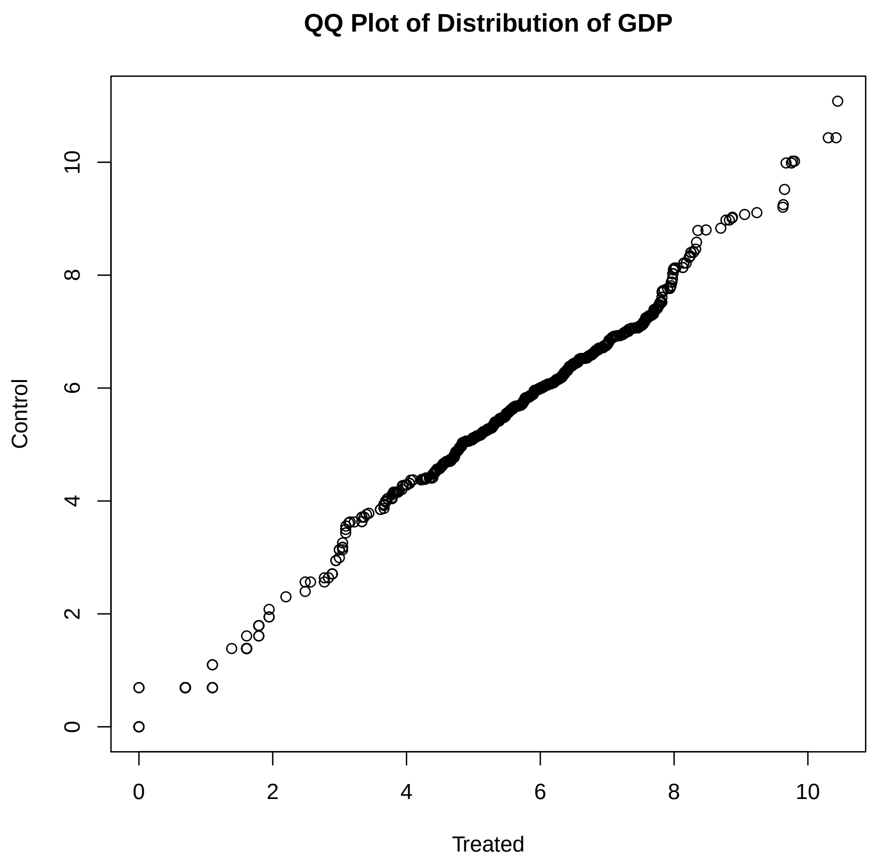
```
qqplot(df$GDP_UN[mgen1$index.treated], df$GDP_UN[mgen1$index.control],
                 xlab = "Treated", ylab = "Control", main = "QQ Plot of Distribution of GDP'
```



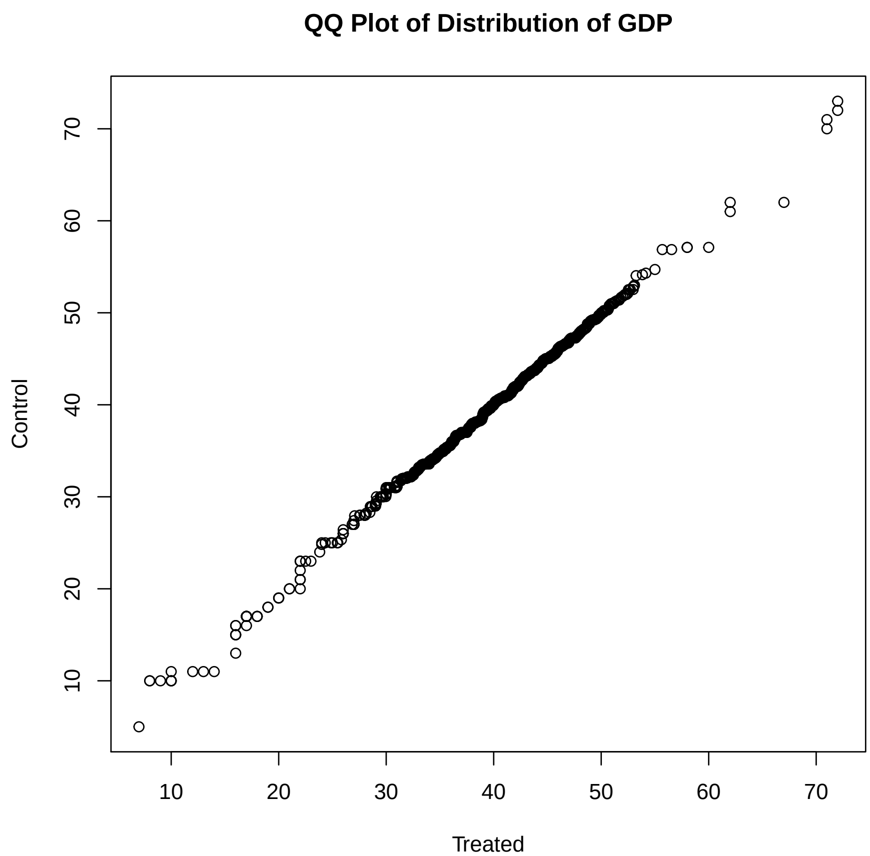

```
qqplot(df$pop1[mgen1$index.treated], df$pop1[mgen1$index.control],
                 xlab = "Treated", ylab = "Control", main = "QQ Plot of Distribution of GDP'
```



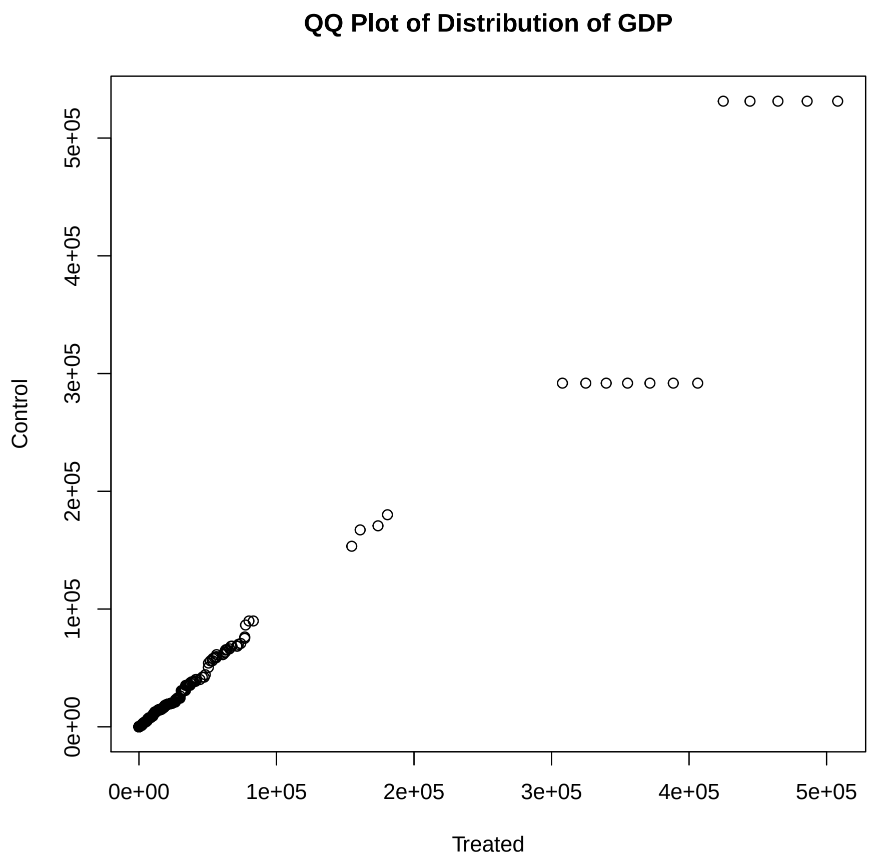

```
qqplot(df$menergy[mgen1$index.treated], df$menergy[mgen1$index.control],
                  xlab = "Treated", ylab = "Control", main = "QQ Plot of Distribution of GDP'
```




```
qqplot(df$mindustry[mgen1$index.treated], df$mindustry[mgen1$index.control],
       xlab = "Treated", ylab = "Control", main = "QQ Plot of Distribution of GDP'
```




```
qqplot(df$murban[mgen1$index.treated], df$murban[mgen1$index.control],
                 xlab = "Treated", ylab = "Control", main = "QQ Plot of Distribution of GDP'
```




```
stargazer(mgen1, title = "Summary Statistics")
```

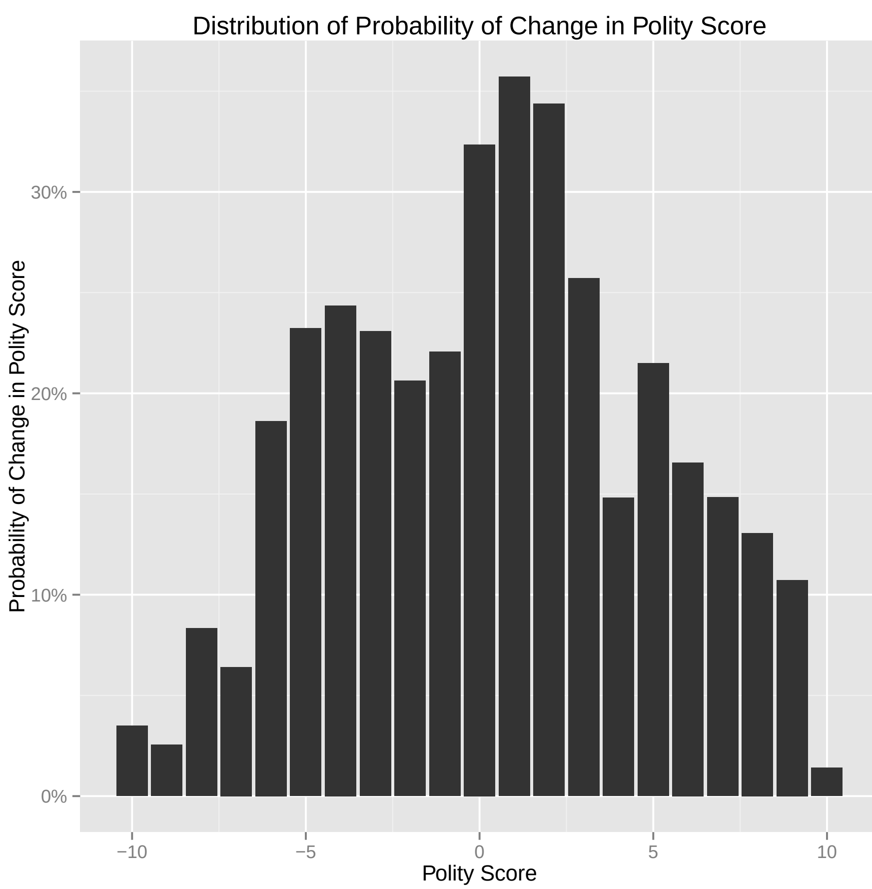
```
library(ggplot2)
library(scales)

##
## Attaching package:  'scales'
##
## The following objects are masked from 'package:readr':
##
##     col_factor, col_numeric

dp <- df %>%
  group_by(Year, polity2) %>%
  filter(!is.na(dpolityb)) %>%
```

```
  count(dpolityb, polity2) %>%
  group_by(polity2) %>%
  mutate(Pdpolity = n/sum(n)) %>%
  filter(dpolityb == 1) %>%
  select(polity2, Pdpolity)

ggplot(dp, aes(x = polity2, y = Pdpolity)) +
  geom_bar(stat="identity") +
  xlab("Polity Score") +
  ylab("Probability of Change in Polity Score") +
  ggtitle("Distribution of Probability of Change in Polity Score") +
  scale_y_continuous(labels=percent)
```




```
k1 <- select(df, polity2, Pdpolity)
set.seed(2)
fit1 <- kmeans(k1, 5)
```

```
aggregate(k1,by=list(fit1$cluster),FUN=mean) %>%
  arrange(-polity2)

##   Group.1    polity2   Pdpolity
## 1       3  9.3669951 0.05869939
## 2       1  5.6035714 0.17439929
## 3       4 -0.4593023 0.27545742
## 4       5 -4.9204301 0.21363801
## 5       2 -7.8866758 0.05593759

k1 <- data.frame(k1, fit1$cluster) %>%
  mutate(fit1.cluster = plyr::mapvalues(fit1.cluster, from = c(3, 1, 4, 5, 2), to = c(1, 2,
    select(cluster = fit1.cluster)

df <- cbind(df, k1)
```