A link to the online notebook is here: https://github.com/thetruejacob/CS112/blob/master/Assignment/Causal%20Inference%20Assignment/Causal%20Inference%20Assignment.ipynb (https://github.com/thetruejacob/CS112/blob/master/Assignment/Causal%20Inference%20Assignment/Causal%20Inference%20Assignment.ipynb)

Debugging

In the 3 cases below (a through c), identify the major coding error in each case and explain how to fix it, in 1-2 sentences. DO NOT actually copy/paste corrected code:

1. https://gist.github.com/diamonaj/2e5d5ba5226b7b9760f5d1bf1e7bf765 (https://gist.github.com/diamonaj/2e5d5ba5226b7b9760f5d1bf1e7bf765)
2. https://gist.github.com/diamonaj/3b6bc83d040098486634184d99fc4c55 (https://gist.github.com/diamonaj/3b6bc83d040098486634184d99fc4c55)
3. https://gist.github.com/diamonaj/a88cb40132ed8584e5182b585e1c84c8 (https://gist.github.com/diamonaj/a88cb40132ed8584e5182b585e1c84c8)

1. The problem is that Match was never run, and so instead of the Match object being fed into the the MatchBalance function, the GenMatch object was incorrectly used instead.
2. There is a mismatch between the 'ATE' specified in the GenMatch function and the default 'ATT' in the Match function. This can be fixed by specifying 'ATE' in the Match function.
3. There is a mistmatch between the M = 2 in the Match function and the default M = 1 in the GenMatch function. This can fixed by making both specifications of M equivalent. Secondly, Y should only be included as an argument in Match after covariate balance has been established. It is unclear if this was done prior, and so this may not necessarily be a mistake.

Replication

Replicate figure 8 in https://gking.harvard.edu/files/counterf.pdf (https://gking.harvard.edu/files/counterf.pdf).

A few suggestions:

- Read the class breakout instructions above to get the data and relevant columns,
- If you are not clear on the model, read the relevant sections of the paper and focus on understanding Table 2;
- To plot the figure, you should use a strategy similar to the one we used in the statistics scavenger hunt, which was also used in a previous assignment (e.g., holding predictors at their medians and looping through values of one variable to obtain treatment effects at different levels of the variable--you may want to review the answer key for that previous assignment, but please note that you WON'T have to simulate coefficients this time because there is no need to estimate uncertainty e.g., intervals).
  However, you don't need to simulate coefficients this time.

In [1]:
```
foo <- read.csv("https://course-resources.minerva.kgi.edu/uploaded_files/mke/00086677-3767/peace.csv")
foo <- foo[c(-19, -47), ]
head(foo)
```

X	dataset	ccode	cnumb	cluster	clust2	cname	yrbeg	yrend	decade	⋯	L13	Phat13	
1	8	AFG2	2	AFG	AFG	Afghanistan-Taliban	93	NA	5	⋯	-0.9587072	0.2771371	-2.8
2	1	AFG1	1	AFG	AFG	Afghanistan	78	92	4	⋯	-0.9591957	0.2770393	-3.2
3	9	MEX	88	MEX	MEX	Mexico	92	94	5	⋯	-0.1507243	0.4623901	1.4
4	1	RUS	109	RUS	FSU	Russia-Chechnya	94	96	5	⋯	0.2437635	0.5606409	-1.8
5	9	THA	123	THA	THA	Thailand-Commun.	67	85	3	⋯	-0.2880664	0.4284773	0.1
6	1	CHD1	24	CHD	CHD	Chad	65	79	3	⋯	-1.0295979	0.2631621	-1.7

In [2]:
```
glm1 <- glm(pbs2s3 ~  wartype + logcost + wardur + factnum + factnum2 + trnsfcap + untype4 + treaty + develop + exp + decade,  data = foo, family = binomial)
summary(glm1)
```

```
Call:
glm(formula = pbs2s3 ~ wartype + logcost + wardur + factnum +
    factnum2 + trnsfcap + untype4 + treaty + develop + exp +
    decade, family = binomial, data = foo)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.5438  -0.6184  -0.2655   0.4773   2.7049

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  8.6088620  2.1965592   3.919 8.88e-05 ***
wartype     -1.7420043  0.5966755  -2.920  0.00351 **
logcost     -0.4448499  0.1366487  -3.255  0.00113 **
wardur       0.0063857  0.0039946   1.599  0.10991
factnum     -1.2589333  0.8257914  -1.525  0.12738
factnum2     0.0616696  0.0930082   0.663  0.50730
trnsfcap     0.0040934  0.0020585   1.989  0.04675 *
untype4      3.1351843  1.4934804   2.099  0.03580 *
treaty       2.1243681  0.7785943   2.728  0.00636 **
develop      0.0007901  0.0004655   1.697  0.08967 .
exp         -6.0161789  3.5523605  -1.694  0.09035 .
decade      -0.2987758  0.1925220  -1.552  0.12068
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 158.345  on 121  degrees of freedom
Residual deviance:  91.297  on 110  degrees of freedom
AIC: 115.3

Number of Fisher Scoring iterations: 6
```

In [3]:
```
glm2 <- glm(pbs2s3 ~  wartype + logcost + wardur + factnum +
                              factnum2 + trnsfcap + untype4 +
treaty + develop + exp + decade + I(wardur*untype4),  data = foo, family = binomia
l)
summary(glm2)
```

```
Call:
glm(formula = pbs2s3 ~ wartype + logcost + wardur + factnum +
    factnum2 + trnsfcap + untype4 + treaty + develop + exp +
    decade + I(wardur * untype4), family = binomial, data = foo)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.4725  -0.6082  -0.2733   0.4336   2.6419

Coefficients:
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)          8.1892936  2.4675178   3.319 0.000904 ***
wartype             -1.6663860  0.5962554  -2.795 0.005194 **
logcost             -0.4371467  0.1361314  -3.211 0.001322 **
wardur               0.0055304  0.0041052   1.347 0.177922
factnum             -1.0453757  1.1122909  -0.940 0.347300
factnum2             0.0322828  0.1454713   0.222 0.824377
trnsfcap             0.0040839  0.0021462   1.903 0.057054 .
untype4              0.2616384  2.8207883   0.093 0.926099
treaty               2.1262049  0.7726535   2.752 0.005926 **
develop              0.0007643  0.0004609   1.658 0.097308 .
exp                 -6.2153385  3.5594910  -1.746 0.080788 .
decade              -0.2836770  0.1916737  -1.480 0.138873
I(wardur * untype4)  0.0372672  0.0498959   0.747 0.455125
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 158.345  on 121  degrees of freedom
Residual deviance:  89.804  on 109  degrees of freedom
AIC: 115.8

Number of Fisher Scoring iterations: 8
```

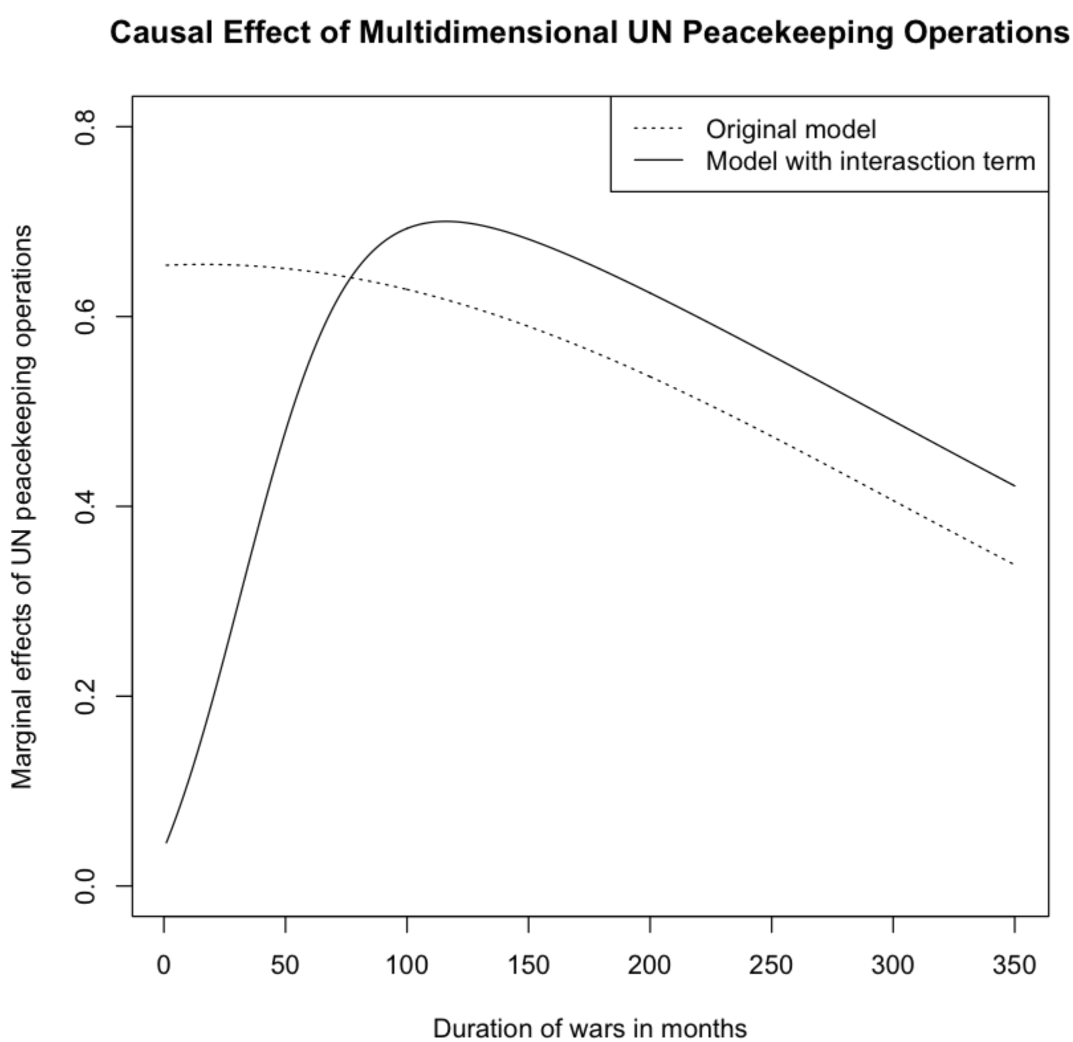
In [4]:
```
attach(foo)
treat = data.frame(wartype = mean(wartype),
                   logcost = mean(logcost),
                   wardur = 1:350,
                   untype4 = 1,
                    factnum = mean(factnum),
                    factnum2 = mean(factnum2),
                    trnsfcap = mean(trnsfcap),
                    treaty = mean(treaty),
                    develop = mean(develop),
                    exp = mean(exp),
                    decade = mean(decade)
                   )
control = treat; control$untype4 = 0
head(treat)
head(control)
```

```
The following object is masked from package:datasets:

    euro
```

wartype	logcost	wardur	untype4	factnum	factnum2	trnsfcap	treaty	develop	exp	decade
0.6393443	11.90362	1	1	3.336066	13.45082	58.66762	0.2868852	542.7804	0.1230395	3.47541
0.6393443	11.90362	2	1	3.336066	13.45082	58.66762	0.2868852	542.7804	0.1230395	3.47541
0.6393443	11.90362	3	1	3.336066	13.45082	58.66762	0.2868852	542.7804	0.1230395	3.47541
0.6393443	11.90362	4	1	3.336066	13.45082	58.66762	0.2868852	542.7804	0.1230395	3.47541
0.6393443	11.90362	5	1	3.336066	13.45082	58.66762	0.2868852	542.7804	0.1230395	3.47541
0.6393443	11.90362	6	1	3.336066	13.45082	58.66762	0.2868852	542.7804	0.1230395	3.47541

wartype	logcost	wardur	untype4	factnum	factnum2	trnsfcap	treaty	develop	exp	decade
0.6393443	11.90362	1	0	3.336066	13.45082	58.66762	0.2868852	542.7804	0.1230395	3.47541
0.6393443	11.90362	2	0	3.336066	13.45082	58.66762	0.2868852	542.7804	0.1230395	3.47541
0.6393443	11.90362	3	0	3.336066	13.45082	58.66762	0.2868852	542.7804	0.1230395	3.47541
0.6393443	11.90362	4	0	3.336066	13.45082	58.66762	0.2868852	542.7804	0.1230395	3.47541
0.6393443	11.90362	5	0	3.336066	13.45082	58.66762	0.2868852	542.7804	0.1230395	3.47541
0.6393443	11.90362	6	0	3.336066	13.45082	58.66762	0.2868852	542.7804	0.1230395	3.47541

In [5]:
```
glm1treatpreds = predict(glm1, treat, type = "response")
glm2treatpreds = predict(glm2, treat, type = "response")
glm1controlpreds = predict(glm1, control, type = "response")
glm2controlpreds = predict(glm2, control, type = "response")


plot(treat$wardur, glm1treatpreds - glm1controlpreds, type = 'l', lty = 3, ylim =
c(0,0.8),
    main = "Causal Effect of Multidimensional UN Peacekeeping Operations",
    xlab = "Duration of wars in months",
    ylab = "Marginal effects of UN peacekeeping operations")
lines(control$wardur, glm2treatpreds - glm2controlpreds)
legend('topright', legend = c("Original model", "Model with interasction term"), l
ty = c(3,1))
```



Treatment Specification

In [6]:
```
Tr <- rep(0, length(foo$untype))
Tr[which(foo$untype != "None")] <- 1
# What does this mean? What is "treatment"?
# Treatment means UN peacekeeping intervention
```

Table of ATTs

1. In no more than 1 sentence, articulate the causal question as best you can (being as clear as you can about treatment and control):
2. In no more than 1 sentence, explain how/why SUTVA might be violated here. In no more than 1 additional sentence, explain how you could in theory use the "restrict" argument (in Match()/GenMatch()) to help address this potential problem.
3. Use simple logistic regression, propensity score matching, and genetic matching to try to answer these questions.

1. By how much better or worse are countries who have recieved UN peacebuilding operations on the metric of lenient peacebuilding success 2 and 5 years into the future than if they not did not recieve peacebuilding operations?
2. In an increasingly globalist economy, the politics of any one country are rarely limited to the confines of a geographical border (for example, UN peacebuilding operations in one country can set a precedent making it easier for peacebuilding to be seen as the go-to solution for other similar cases). In theory, this could be mitigated by preventing two closely tied countries to be matched together, e.g. Austria and Germany.
3. See below.

In [107]:
```
## logistic regression - 2 years
library(Matching)

foo = cbind(foo, Tr)

glm2 = glm(pbs2l ~ Tr + wartype + logcost + wardur + factnum + factnum2 + trnsfcap
+
           treaty + develop + exp + decade, data = foo, subset = !is.na(pbs2l), fa
mily = binomial)
glm2
mb2 = MatchBalance(Tr ~ wartype + logcost + wardur + factnum + factnum2 + trnsfcap
+
           treaty + develop + exp + decade, data = foo, nboots = 500)
```

```
Call:  glm(formula = pbs2l ~ Tr + wartype + logcost + wardur + factnum +
    factnum2 + trnsfcap + treaty + develop + exp + decade, family = binomial,
    data = foo, subset = !is.na(pbs2l))

Coefficients:
(Intercept)           Tr      wartype      logcost       wardur      factnum
  7.3711369    0.7130543   -1.5672612   -0.3127275    0.0032791   -0.9587863
   factnum2     trnsfcap       treaty      develop          exp       decade
  0.0501228    0.0042836    1.5459400    0.0001873   -4.8553044   -0.3374430

Degrees of Freedom: 121 Total (i.e. Null);  110 Residual
Null Deviance:      167
Residual Deviance: 117.2        AIC: 141.2
```

```
***** (V1) wartype *****
before matching:
mean treatment........ 0.63889
mean control.......... 0.63953
std mean diff......... -0.13261

mean raw eQQ diff..... 0
med  raw eQQ diff..... 0
max  raw eQQ diff..... 0

mean eCDF diff........ 0.000323
med  eCDF diff........ 0.000323
max  eCDF diff........ 0.00064599

var ratio (Tr/Co)..... 1.0174
T-test p-value........ 0.99468


***** (V2) logcost *****
before matching:
mean treatment........ 12.904
mean control.......... 11.485
std mean diff......... 79.811

mean raw eQQ diff..... 1.4788
med  raw eQQ diff..... 1.1386
max  raw eQQ diff..... 3.3142

mean eCDF diff........ 0.16371
med  eCDF diff........ 0.16085
max  eCDF diff........ 0.30039

var ratio (Tr/Co)..... 0.49056
T-test p-value........ 0.00067727
KS Bootstrap p-value.. 0.014
KS Naive p-value...... 0.020516
KS Statistic.......... 0.30039


***** (V3) wardur *****
before matching:
mean treatment........ 78.083
mean control.......... 80.198
std mean diff......... -2.5968

mean raw eQQ diff..... 16.417
med  raw eQQ diff..... 6.5
max  raw eQQ diff..... 312

mean eCDF diff........ 0.035364
med  eCDF diff........ 0.028424
max  eCDF diff........ 0.11047

var ratio (Tr/Co)..... 0.68352
T-test p-value........ 0.90266
KS Bootstrap p-value.. 0.798
KS Naive p-value...... 0.91617
KS Statistic.......... 0.11047


***** (V4) factnum *****
before matching:
mean treatment........ 3.7778
mean control.......... 3.1512
std mean diff......... 41.389

mean raw eQQ diff..... 0.72222
```

In [84]:
```
## logistic regression - 5 years
glm5 = glm(pbs5l ~ Tr + wartype + logcost + wardur + factnum + factnum2 + trnsfcap
+
           treaty + develop + exp + decade, data = subset(foo, !is.na(pbs5l)), fam
ily = binomial)
glm5
mb5 = MatchBalance(Tr ~ wartype + logcost + wardur + factnum + factnum2 + trnsfcap
+
           treaty + develop + exp + decade, data = subset(foo, !is.na(pbs5l)), nbo
ots = 500)
```

```
Call:  glm(formula = pbs5l ~ Tr + wartype + logcost + wardur + factnum +
    factnum2 + trnsfcap + treaty + develop + exp + decade, family = binomial,
    data = subset(foo, !is.na(pbs5l)))

Coefficients:
(Intercept)           Tr      wartype      logcost       wardur      factnum
  7.0355574    0.8233143   -1.7061721   -0.2483537    0.0036864   -1.1098129
   factnum2     trnsfcap       treaty      develop          exp       decade
  0.0603537    0.0043292    1.3278703    0.0002431   -4.9364476   -0.3071584

Degrees of Freedom: 116 Total (i.e. Null);  105 Residual
Null Deviance:      160.7
Residual Deviance: 114  AIC: 138
```

```
***** (V1) wartype *****
before matching:
mean treatment........ 0.69697
mean control.......... 0.63095
std mean diff......... 14.146

mean raw eQQ diff..... 0.060606
med  raw eQQ diff..... 0
max  raw eQQ diff..... 1

mean eCDF diff........ 0.033009
med  eCDF diff........ 0.033009
max  eCDF diff........ 0.066017

var ratio (Tr/Co)..... 0.92424
T-test p-value........ 0.49864


***** (V2) logcost *****
before matching:
mean treatment........ 13.068
mean control.......... 11.448
std mean diff......... 98.484

mean raw eQQ diff..... 1.7034
med  raw eQQ diff..... 1.199
max  raw eQQ diff..... 3.912

mean eCDF diff........ 0.18876
med  eCDF diff........ 0.18398
max  eCDF diff........ 0.33658

var ratio (Tr/Co)..... 0.41403
T-test p-value........ 0.00010717
KS Bootstrap p-value.. 0.006
KS Naive p-value...... 0.0093267
KS Statistic.......... 0.33658


***** (V3) wardur *****
before matching:
mean treatment........ 83
mean control.......... 78.393
std mean diff......... 5.5292

mean raw eQQ diff..... 20.636
med  raw eQQ diff..... 12
max  raw eQQ diff..... 312

mean eCDF diff........ 0.047216
med  eCDF diff........ 0.040043
max  eCDF diff........ 0.12662

var ratio (Tr/Co)..... 0.74088
T-test p-value........ 0.79814
KS Bootstrap p-value.. 0.65
KS Naive p-value...... 0.84194
KS Statistic.......... 0.12662


***** (V4) factnum *****
before matching:
mean treatment........ 3.8485
mean control.......... 3.1786
std mean diff......... 43.401

mean raw eQQ diff..... 0.75758
```

In [120]:
```
## propensity score matching - 2 years

glm.prop2 = glm(Tr ~ wartype + logcost + wardur + factnum + factnum2 + trnsfcap +
treaty + develop + exp + decade + I(wardur**2), data = foo, subset = !is.na(pbs2l)
, family = binomial)
mout.prop2 = Match(Tr = Tr[!is.na(foo$pbs2l)], X = glm.prop2$fitted.values, Y = fo
o$pbs2l, caliper = 0.2, M = 1)
mbprop2 = MatchBalance(Tr ~ wartype + logcost + wardur + factnum + factnum2 + trns
fcap + treaty + develop + exp + decade + I(wardur**2), data = foo, nboots = 500, m
atch.out = mout.prop2)
```

```
***** (V1) wartype *****
                       Before Matching          After Matching
mean treatment........     0.63889               0.66667
mean control..........     0.63953               0.89394
std mean diff.........    -0.13261               -47.476

mean raw eQQ diff.....           0               0.16216
med  raw eQQ diff.....           0                     0
max  raw eQQ diff.....           0                     1

mean eCDF diff........    0.000323              0.081081
med  eCDF diff........    0.000323              0.081081
max  eCDF diff........ 0.00064599                0.16216

var ratio (Tr/Co).....      1.0174                2.3438
T-test p-value........     0.99468              0.044013


***** (V2) logcost *****
                       Before Matching          After Matching
mean treatment........      12.904                12.747
mean control..........      11.485                12.375
std mean diff.........      79.811                 20.96

mean raw eQQ diff.....      1.4788               0.44013
med  raw eQQ diff.....      1.1386                0.3517
max  raw eQQ diff.....      3.3142                1.7813

mean eCDF diff........     0.16371              0.053563
med  eCDF diff........     0.16085              0.054054
max  eCDF diff........     0.30039               0.13514

var ratio (Tr/Co).....     0.49056               0.76697
T-test p-value........ 0.00067727                0.41714
KS Bootstrap p-value..       0.016                 0.822
KS Naive p-value......    0.020516               0.88811
KS Statistic..........     0.30039               0.13514


***** (V3) wardur *****
                       Before Matching          After Matching
mean treatment........      78.083                80.788
mean control..........      80.198                101.21
std mean diff.........     -2.5968               -24.235

mean raw eQQ diff.....      16.417                32.649
med  raw eQQ diff.....         6.5                    12
max  raw eQQ diff.....         312                   312

mean eCDF diff........    0.035364              0.072693
med  eCDF diff........    0.028424              0.081081
max  eCDF diff........     0.11047               0.13514

var ratio (Tr/Co).....     0.68352               0.66114
T-test p-value........     0.90266               0.30945
KS Bootstrap p-value..       0.738                 0.778
KS Naive p-value......     0.91617               0.88811
KS Statistic..........     0.11047               0.13514


***** (V4) factnum *****
                       Before Matching          After Matching
mean treatment........      3.7778                3.7879
mean control..........      3.1512                4.1465
std mean diff.........      41.389               -23.343

mean raw eQQ diff.....     0.72222               0.64865
```

In [117]:
```
## propensity score matching - 5 years
glm.prop5 = glm(Tr ~ wartype + logcost + wardur + factnum + factnum2 + trnsfcap +
treaty + develop + exp + decade + I(wardur**2), data = foo, subset = !is.na(pbs5l)
, family = binomial)
mout.prop5 = Match(Tr = subset(foo, !is.na(pbs5l))$Tr, X = glm.prop5$fitted.values
, caliper = 0.2, M = 1)
mbprop5 = MatchBalance(Tr ~ wartype + logcost + wardur + factnum + factnum2 + trns
fcap + treaty + develop + exp + decade + I(wardur**2), data = subset(foo, !is.na(p
bs5l)), nboots = 500, match.out = mout.prop5)
```

```
***** (V1) wartype *****
                       Before Matching          After Matching
mean treatment........     0.69697                 0.69697
mean control..........     0.63095                 0.84848
std mean diff.........      14.146                 -32.466

mean raw eQQ diff.....    0.060606                 0.15152
med  raw eQQ diff.....           0                       0
max  raw eQQ diff.....           1                       1

mean eCDF diff........    0.033009                0.075758
med  eCDF diff........    0.033009                0.075758
max  eCDF diff........    0.066017                 0.15152

var ratio (Tr/Co).....     0.92424                  1.6429
T-test p-value........     0.49864                 0.12805


***** (V2) logcost *****
                       Before Matching          After Matching
mean treatment........      13.068                  13.068
mean control..........      11.448                  13.283
std mean diff.........      98.484                 -13.039

mean raw eQQ diff.....      1.7034                 0.40037
med  raw eQQ diff.....       1.199                 0.35417
max  raw eQQ diff.....       3.912                  1.2192

mean eCDF diff........     0.18876                0.072856
med  eCDF diff........     0.18398                0.060606
max  eCDF diff........     0.33658                 0.27273

var ratio (Tr/Co).....     0.41403                 0.75575
T-test p-value........ 0.00010717                  0.55159
KS Bootstrap p-value..       0.002                   0.136
KS Naive p-value......   0.0093267                  0.1717
KS Statistic..........     0.33658                 0.27273


***** (V3) wardur *****
                       Before Matching          After Matching
mean treatment........          83                      83
mean control..........      78.393                  76.061
std mean diff.........      5.5292                  8.3283

mean raw eQQ diff.....      20.636                  24.636
med  raw eQQ diff.....          12                      12
max  raw eQQ diff.....         312                      96

mean eCDF diff........    0.047216                0.092227
med  eCDF diff........    0.040043                0.060606
max  eCDF diff........     0.12662                 0.24242

var ratio (Tr/Co).....     0.74088                  2.2526
T-test p-value........     0.79814                 0.68689
KS Bootstrap p-value..       0.702                   0.188
KS Naive p-value......     0.84194                 0.28675
KS Statistic..........     0.12662                 0.24242


***** (V4) factnum *****
                       Before Matching          After Matching
mean treatment........      3.8485                  3.8485
mean control..........      3.1786                  4.5758
std mean diff.........      43.401                 -47.117

mean raw eQQ diff.....     0.75758                 0.90909
```

In [87]:

```
## genetic matching - 2 years
genout2 = GenMatch(Tr = Tr, X = foo[,c('wartype', 'logcost', 'wardur', 'factnum', 
'factnum2', 'trnsfcap', 'treaty', 'develop', 'exp', 'decade')], pop.size = 200, ma
x.generations = 30, wait.generations = 10)
mout.gen2 = Match(Tr = Tr, X = foo[,c('wartype', 'logcost', 'wardur', 'factnum', '
factnum2', 'trnsfcap', 'treaty', 'develop', 'exp', 'decade')], Weight.matrix = gen
out2)
summary(mout.gen2)
mbgen2 = MatchBalance(Tr ~ wartype + logcost + wardur + factnum + factnum2 + trnsf
cap + treaty + develop + exp + decade, data = foo, nboots = 500, match.out = mout.
gen2)
```

```
Sun Dec  2 19:28:51 2018
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
 0.000000e+00   <=  X6   <=    1.000000e+03
 0.000000e+00   <=  X7   <=    1.000000e+03
 0.000000e+00   <=  X8   <=    1.000000e+03
 0.000000e+00   <=  X9   <=    1.000000e+03
 0.000000e+00   <=  X10  <=    1.000000e+03

Data Type: Floating Point
Operators (code number, name, population)
        (1) Cloning..........................  22
        (2) Uniform Mutation.................  25
        (3) Boundary Mutation................  25
        (4) Non-Uniform Mutation.............  25
        (5) Polytope Crossover...............  25
        (6) Simple Crossover.................  26
        (7) Whole Non-Uniform Mutation........  25
        (8) Heuristic Crossover..............  26
        (9) Local-Minimum Crossover..........  0

SOFT Maximum Number of Generations: 30
Maximum Nonchanging Generations: 10
Population size       : 200
Convergence Tolerance: 1.000000e-03

Not Using the BFGS Derivative Based Optimizer on the Best Individual Each Genera
tion.
Not Checking Gradients before Stopping.
Using Out of Bounds Individuals.

Maximization Problem.
GENERATION: 0 (initializing the population)
Lexical Fit..... 3.619644e-02  3.663105e-02  4.443076e-02  5.993813e-02  1.36817
0e-01  1.463514e-01  3.364049e-01  4.608520e-01  5.023484e-01  5.041209e-01  5.0
41209e-01  6.135993e-01  6.993742e-01  6.993742e-01  8.781816e-01  1.000000e+00
1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
#unique......... 200, #Total UniqueCount: 200
var 1:
best............ 7.601709e+02
mean............ 5.088144e+02
variance........ 8.560847e+04
var 2:
best............ 8.134234e+02
mean............ 5.035996e+02
variance........ 7.879828e+04
var 3:
best............ 7.687076e+02
mean............ 5.129343e+02
variance........ 9.159326e+04
var 4:
best............ 2.865622e+02
mean............ 5.166789e+02
variance........ 7.636507e+04
var 5:
best............ 6.589374e+01
mean............ 4.720103e+02
variance........ 8.339195e+04
var 6:
best............ 6.291587e+01
mean............ 5.204777e+02
variance........ 8.980158e+04
```

In [122]:
```
## genetic matching - 5 years
genout5 = GenMatch(Tr = Tr[!is.na(foo$pbs5l)], X = foo[!is.na(foo$pbs5l), c('warty
pe', 'logcost', 'wardur', 'factnum', 'factnum2', 'trnsfcap', 'treaty', 'develop',
'exp', 'decade')], pop.size = 200, max.generations = 30, wait.generations = 10)
mout.gen5 = Match(Tr = Tr[!is.na(foo$pbs5l)], X = foo[!is.na(foo$pbs5l), c('wartyp
e', 'logcost', 'wardur', 'factnum', 'factnum2', 'trnsfcap', 'treaty', 'develop', '
exp', 'decade')], Weight.matrix = genout5)
summary(mout.gen5)
mbgen5 = MatchBalance(Tr ~ wartype + logcost + wardur + factnum + factnum2 + trnsf
cap + treaty + develop + exp + decade, data = subset(foo, !is.na(pbs5l)), nboots =
500, match.out = mout.gen5)
```

```
Sun Dec  2 19:48:53 2018
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
 0.000000e+00   <=  X6   <=    1.000000e+03
 0.000000e+00   <=  X7   <=    1.000000e+03
 0.000000e+00   <=  X8   <=    1.000000e+03
 0.000000e+00   <=  X9   <=    1.000000e+03
 0.000000e+00   <=  X10  <=    1.000000e+03

Data Type: Floating Point
Operators (code number, name, population)
        (1) Cloning..........................  22
        (2) Uniform Mutation.................  25
        (3) Boundary Mutation................  25
        (4) Non-Uniform Mutation.............  25
        (5) Polytope Crossover...............  25
        (6) Simple Crossover.................  26
        (7) Whole Non-Uniform Mutation.......  25
        (8) Heuristic Crossover..............  26
        (9) Local-Minimum Crossover..........  0

SOFT Maximum Number of Generations: 30
Maximum Nonchanging Generations: 10
Population size       : 200
Convergence Tolerance: 1.000000e-03

Not Using the BFGS Derivative Based Optimizer on the Best Individual Each Genera
tion.
Not Checking Gradients before Stopping.
Using Out of Bounds Individuals.

Maximization Problem.
GENERATION: 0 (initializing the population)
Lexical Fit..... 3.085053e-02  9.444451e-02  9.659111e-02  1.046843e-01  1.36969
3e-01  1.700211e-01  2.867543e-01  3.174823e-01  3.174823e-01  3.684836e-01  3.9
82818e-01  4.478101e-01  4.478101e-01  6.464668e-01  6.464668e-01  7.535576e-01
8.431776e-01  8.431776e-01  1.000000e+00  1.000000e+00
#unique......... 200, #Total UniqueCount: 200
var 1:
best............ 7.403834e+02
mean............ 4.754568e+02
variance........ 8.446285e+04
var 2:
best............ 9.381350e+01
mean............ 4.780446e+02
variance........ 8.425747e+04
var 3:
best............ 2.592302e+02
mean............ 4.909182e+02
variance........ 8.018370e+04
var 4:
best............ 3.268888e+02
mean............ 4.992295e+02
variance........ 8.639208e+04
var 5:
best............ 2.173523e+02
mean............ 5.016731e+02
variance........ 9.692432e+04
var 6:
best............ 6.529214e+02
mean............ 5.072512e+02
variance........ 8.031235e+04
```

In [152]:
```
table = matrix(nrow = 9, ncol = 3)
colnames(table) = c(" tmt effect (bias adj)", "tmt effect (no bias adj)", "p-value
(from MatchBalance)")
rownames(table) = c("logistic regression", "len success 2 years", "len success 5 y
ears",
                    "p- score matching", "len success 2 years", "len success 5 yea
rs",
                    "gen match", "len success 2 years", "len success 5 years")
table[2,] = c("NA", glm2$coef[2], mb2$BMsmallest.p.value)
table[3,] = c("NA", glm5$coef[2], mb5$BMsmallest.p.value)
table[5,] = c(Match(Tr = Tr[!is.na(foo$pbs2l)], X = glm.prop2$fitted.values, Y = p
bs2l[!is.na(foo$pbs2l)], caliper = 0.2, M = 1)$est,
              Match(Tr = Tr[!is.na(foo$pbs2l)], X = glm.prop2$fitted.values, Y = p
bs2l[!is.na(foo$pbs2l)], caliper = 0.2, M = 1)$est.noadj,
             mbprop2$AMsmallest.p.value)
table[6,] = c(Match(Tr = Tr[!is.na(foo$pbs5l)], X = glm.prop5$fitted.values, Y = s
ubset(foo, !is.na(pbs5l))$pbs5l, caliper = 0.2, M = 1)$est,
             Match(Tr = Tr[!is.na(foo$pbs5l)], X = glm.prop5$fitted.values, Y = su
bset(foo, !is.na(pbs5l))$pbs5l, caliper = 0.2, M = 1)$est.noadj,
             mbprop5$AMsmallest.p.value)
table[8,] = c(Match(Tr = Tr[!is.na(foo$pbs2l)], Y = pbs2l[!is.na(foo$pbs2l)], X =
foo[!is.na(foo$pbs2l), c('wartype', 'logcost', 'wardur', 'factnum', 'factnum2', 't
rnsfcap', 'treaty', 'develop', 'exp', 'decade')], Weight.matrix = genout2)$est,
             Match(Tr = Tr[!is.na(foo$pbs2l)], Y = pbs2l[!is.na(foo$pbs2l)], X = f
oo[!is.na(foo$pbs2l), c('wartype', 'logcost', 'wardur', 'factnum', 'factnum2', 'tr
nsfcap', 'treaty', 'develop', 'exp', 'decade')], Weight.matrix = genout2)$est.noad
j,
             mbgen2$AMsmallest.p.value)
table[9,] = c(Match(Tr = Tr[!is.na(foo$pbs5l)], Y = pbs5l[!is.na(foo$pbs5l)], X =
foo[!is.na(foo$pbs5l), c('wartype', 'logcost', 'wardur', 'factnum', 'factnum2', 't
rnsfcap', 'treaty', 'develop', 'exp', 'decade')], Weight.matrix = genout5)$est,
             Match(Tr = Tr[!is.na(foo$pbs5l)], Y = pbs5l[!is.na(foo$pbs5l)], X = f
oo[!is.na(foo$pbs5l), c('wartype', 'logcost', 'wardur', 'factnum', 'factnum2', 'tr
nsfcap', 'treaty', 'develop', 'exp', 'decade')], Weight.matrix = genout5)$est.noad
j,
             mbgen5$AMsmallest.p.value)
as.table(table)
```

```
                     tmt effect (bias adj) tmt effect (no bias adj)
logistic regression
len success 2 years NA                    0.713054334569193
len success 5 years NA                    0.823314327283805
p- score matching
len success 2 years 0.207070707070707     0.207070707070707
len success 5 years 0.393939393939394     0.393939393939394
gen match
len success 2 years 0.194444444444444     0.194444444444444
len success 5 years 0.151515151515152     0.151515151515152
                    p-value (from MatchBalance)
logistic regression
len success 2 years 3.27673510471804e-05
len success 5 years 0.000107165177905877
p- score matching
len success 2 years 0.0440132332461307
len success 5 years 0.0292387177729629
gen match
len success 2 years 0.30093349441952
len success 5 years 0.256
```

Decision Memo

(ii) Let's pretend you have to write a decision memo for policy purposes summarizing all your work (above). Your memo would begin with a a brief executive summary summarizing what you've done and your policy advice, and it would end with a brief concluding passage restating your analysis and what you want your reader to take away from it (including the policy advice). The executive summary and the conclusion would be very similar--to the extent the two are at all different, there is scope for the conclusion to be a bit more technical and/or nuanced, and the conclusion could also include some recommendations for relevant future analysis. DO NOT WRITE the ENTIRE decision memo. Instead, just provide a 3-5 sentence executive summary AND a separate 3-5 sentence conclusion. DO ADDRESS THE MEMO TO A SPECIFIC PERSON (USE YOUR IMAGINATION, BUT TAKE THE EXERCISE SERIOUSLY.)

To Alexis Diamond, IFC

Executive Summary

Under a naive analysis, we found UN peacebuilding efforts to be extremely successful, leading to a 71% increase in lenient peacebuilding success 2 years into the future, and a 82% increase 5 years into the future. By running a more sophisticated analysis, we found a more sensible estimated treatment effect of 19% increase 2 in success 2 years into the future, and 15% years into the future. As a rough rule of thumb, we suggest the UN evaluate decisions for further peacebuilding efforts by understanding that they would be increasing the probability of near future success by around 15-20%.

Conclusion

Using three different methods of estimating the effect of UN peacebuilding efforts (logistic regression, propensity score matching, and genetic matching), we found that the method that achieved the greatest covariate balance (and hence is likeliest to get to the true effect size) also gave the smallest estimate, while the most unbalanced method heavily overestimated the efficacy of peacebuilding operations. In future, it would be most interesting to perform quantile estimation to understand the characteristics of countries that benefited the most from peacebuilding efforts.