Annotated code for Violence and Discrimination Against Men Who Have Sex With Men in Lebanon: The Role of International Displacement and Migration

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Set up

Libraries use in this analysis are set to be installed if necessary, and loaded.

```
if (!require("dplyr")) {
  install.packages("dplyr", dependencies = TRUE)
  library(dplyr)
}

if (!require("oddsratio")) {
  install.packages("oddsratio", dependencies = TRUE)
  library(oddsratio)
}


if (!require("lme4")) {
  install.packages("lme4", dependencies = TRUE)
  library(lme4)
}

if (!require("igraph")) {
  install.packages("igraph", dependencies = TRUE)
  library(igraph)
}
```

The following data set is a pre-processed version of the interview responses in which potentially identifying, and extraneous information has been removed.

```
dat <- read.csv("lebanon_msm_trimed_cleaned.csv", as.is = TRUE)
```

Abstract

Several statistics are cited in the abstract. These include the number of interviews:

```
nrow(dat)
```

```
## [1] 292
```

Most foreign born participants are from Syria (72 out of 83). Note that 2 = *Syria*, 3 = *Iraq*, 5 = *Other*:

```
table(dat$country, useNA = "always")
```

```
##
##    1    2    3    5 <NA>
```

```
## 206 72 2 9 3
```

Proportion of foreign and native born participants who experienced discrimination or violence:

```r
prop.table(table(Discrim = dat$discrim, Foreign = dat$foreign_born), margin = 2)
```

```
##        Foreign
## Discrim         0         1
##       0 0.6813725 0.2926829
##       1 0.3186275 0.7073171
```

Results

Rates and co-occurrence of discrimination and violence

How many, and what proportion of respondents experienced any form of discrimination/violence in the past year?

```r
table(Discrim = dat$discrim, useNA = "always")
```

```
## Discrim
##    0    1 <NA>
##  163  123    6
```

```r
prop.table(table(Discrim = dat$discrim, useNA = "always"))
```

```
## Discrim
##          0          1       <NA>
## 0.55821918 0.42123288 0.02054795
```

How many respondents experienced discrimination/violence multiple domains? Most (64%) participants who experienced any discrimination experienced it in multiple domains. This group constitutes 27% of all participants.

```r
table(dat$levels, useNA = "always")
```

```
##
##    0    1    2    3    4    5    6    7 <NA>
##  163   44   29   23   14    7    4    2    6
```

```r
sum(dat$levels > 1, na.rm = TRUE) / sum(dat$discrim, na.rm = TRUE)
```

```
## [1] 0.6422764
```

```r
sum(dat$levels > 1, na.rm = TRUE) / 292
```

```
## [1] 0.2705479
```

How many, and what proportion of respondents experienced rape and/or beating in the past year?

```r
table(dat$violence, useNA = "always")
```

```
##
##    0    1 <NA>
##  220   66    6
```

```r
prop.table(table(dat$violence, useNA = "always"))
```

```
##
##          0          1       <NA>
```

```
## 0.75342466 0.22602740 0.02054795
```

```
prop.table(table(dat$d_beaten, useNA = "always"))
```

```
##
##          0          1       <NA>
## 0.82876712 0.14383562 0.02739726
```

```
prop.table(table(dat$d_rape, useNA = "always"))
```

```
##
##          0          1       <NA>
## 0.83904110 0.13013699 0.03082192
```

```
table(dat$d_rape, dat$d_beaten, useNA = "always")
```

```
##
##          0   1 <NA>
##   0    216  27    2
##   1     24  14    0
##   <NA>   2   1    6
```

```
prop.table(table(dat$d_rape, dat$d_beaten, useNA = "always"))
```

```
##
##                  0           1        <NA>
##   0    0.739726027 0.092465753 0.006849315
##   1    0.082191781 0.047945205 0.000000000
##   <NA> 0.006849315 0.003424658 0.020547945
```

```
sum(dat$d_rape & dat$d_beaten, na.rm = TRUE) / sum(dat$violence, na.rm = TRUE)
```

```
## [1] 0.2121212
```

Table 1: Rates and co-occurrence

```
msmdiscrim8 <- dat[ ,c("d_insult", "d_employment", "d_beaten", "d_rape",
                       "d_housing", "d_church", "d_service", "d_healthcare")]
msmcofrequ <- matrix(NA, 8, 8)
msmcofrequ_percent <- matrix(NA, 8, 8)
for(i in 1:8){
  for(j in 1:8){
    msmcofrequ[i,j] <- sum(msmdiscrim8[,i] == 1 & msmdiscrim8[,j] == 1, na.rm = T)
    msmcofrequ_percent[i,j] <-
      round(sum(msmdiscrim8[,i] == 1 & msmdiscrim8[,j] == 1, na.rm = T)/
              nrow(msmdiscrim8), 2)
  }
}
msmcofrequ_names <- c("Insult", "Employment", "Beat", "Rape",
                      "Housing", "Worship", "Service", "Healthcare")

msmcofrequ[lower.tri(msmcofrequ)] <- ''
msmcofrequ_percent[upper.tri(msmcofrequ_percent)] <- ''

frequ_percent <- trimws(matrix(paste(msmcofrequ, msmcofrequ_percent),
                               nrow = nrow(msmcofrequ),
```

```
                              dimnames = list(msmcofrequ_names, msmcofrequ_names)))
frequ_percent
```

```
##            Insult     Employment Beat      Rape      Housing   Worship
## Insult     "110 0.38" "36"       "40"      "32"      "33"      "15"
## Employment "0.12"     "43 0.15"  "21"      "19"      "19"      "11"
## Beat       "0.14"     "0.07"     "42 0.14" "14"      "22"      "7"
## Rape       "0.11"     "0.07"     "0.05"    "38 0.13" "14"      "7"
## Housing    "0.11"     "0.07"     "0.08"    "0.05"    "35 0.12" "8"
## Worship    "0.05"     "0.04"     "0.02"    "0.02"    "0.03"    "16 0.05"
## Service    "0.04"     "0.02"     "0.03"    "0.01"    "0.02"    "0.01"
## Healthcare "0.01"     "0.01"     "0.01"    "0.01"    "0.01"    "0.01"
##            Service   Healthcare
## Insult     "11"      "3"
## Employment "6"       "4"
## Beat       "8"       "3"
## Rape       "4"       "2"
## Housing    "6"       "3"
## Worship    "3"       "3"
## Service    "11 0.04" "0"
## Healthcare "0"       "5 0.02"
```

Figure 1 (reported in Supplementary Information C)

Figure 1 is shaded based on the following rates:

```
neighborhood_rates <- group_by(dat, neighborhood) %>%
  summarise(discrim = mean(discrim, na.rm = TRUE),
            violence = mean(violence, na.rm = TRUE),
            levels = mean(levels, na.rm = TRUE),
            N = n())

SItable <- neighborhood_rates[neighborhood_rates$N > 4,]
SItable[,2:4] <- round(SItable[,2:4], 2)

SItable
```

```
## # A tibble: 19 x 5
##    neighborhood    discrim violence levels     N
##    <chr>             <dbl>    <dbl>  <dbl> <int>
##  1 Achrafiyeh        0.28     0.2    0.64     25
##  2 Baabda            0.43     0.14   0.570     7
##  3 Borj Hammoud      0.62     0.38   1.25     24
##  4 Chiyah            0.580    0.25   0.83     12
##  5 Chouf             0.18     0.05   0.44     39
##  6 Dekwaneh          0.22     0      0.44      9
##  7 Hadath            1        0.4    1.6       5
##  8 Hamra             0.85     0.6    2.5      20
##  9 Jdaydeh           0.88     0.38   1.88      8
## 10 Kesserwan         0.7      0.1    1.2      10
## 11 Kfarchima         0.5      0.5    1.5       6
## 12 Khaldeh           0.31     0.19   1.12     16
## 13 Matn              0.47     0.4    1.87     16
## 14 Mazraa            0.62     0.5    1.88      8
```

```
## 15 Ras Beirut        0.44     0.11   0.89     11
## 16 Saida             0.08     0.04   0.23     26
## 17 Sin el Fil        0.33     0.27   0.87     15
## 18 Tarik El-Jdideh   0.570    0.290  1.14      7
## 19 <NA>              0.35     0.12   1.06     20
```

Regression Analysis

Sample characteristics

The covariates used in the regression analysis have the following distributions:

```
prop.table(table(dat$foreign_born, useNA = "always"))
```

```
##
##          0          1       <NA>
## 0.70547945 0.28424658 0.01027397
```

```
prop.table(table(dat$no_college[dat$foreign_born == 1], useNA = "always"))
```

```
##
##          0          1       <NA>
## 0.33720930 0.62790698 0.03488372
```

```
prop.table(table(dat$unemployed[dat$foreign_born == 1], useNA = "always"))
```

```
##
##          0          1       <NA>
## 0.33720930 0.61627907 0.04651163
```

```
prop.table(table(dat$sexexchange[dat$foreign_born == 1], useNA = "always"))
```

```
##
##          0          1       <NA>
## 0.51162791 0.45348837 0.03488372
```

```
prop.table(table(dat$groupsex[dat$foreign_born == 1], useNA = "always"))
```

```
##
##          0          1       <NA>
## 0.70930233 0.23255814 0.05813953
```

```
prop.table(table(dat$no_college[dat$foreign_born == 0], useNA = "always"))
```

```
##
##          0          1       <NA>
## 0.68421053 0.30143541 0.01435407
```

```
prop.table(table(dat$unemployed[dat$foreign_born == 0], useNA = "always"))
```

```
##
##          0          1       <NA>
## 0.71291866 0.27272727 0.01435407
```

```
prop.table(table(dat$sexexchange[dat$foreign_born == 0], useNA = "always"))
```

```
##
##          0          1       <NA>
## 0.69377990 0.28708134 0.01913876
```

```r
prop.table(table(dat$groupsex[dat$foreign_born == 0], useNA = "always"))
```

```
##
##          0          1       <NA>
## 0.77990431 0.19617225 0.02392344
```

```r
prop.table(table(dat$no_college, useNA = "always"))
```

```
##
##          0          1       <NA>
## 0.58904110 0.40068493 0.01027397
```

```r
prop.table(table(dat$unemployed, useNA = "always"))
```

```
##
##          0          1       <NA>
## 0.60958904 0.37671233 0.01369863
```

```r
prop.table(table(dat$sexexchange, useNA = "always"))
```

```
##
##          0          1       <NA>
## 0.64726027 0.33904110 0.01369863
```

```r
prop.table(table(dat$groupsex, useNA = "always"))
```

```
##
##         0         1      <NA>
## 0.7671233 0.2089041 0.0239726
```

Table 2: Risk and expectation of violence or discrimination

First we calculate the unadjusted risk ratios.

```r
country_model_risk <- glm(discrim ~ foreign_born, data = dat, family = poisson(link = "log"))
employ_model_risk <- glm(discrim ~ unemployed, data = dat, family = poisson(link = "log"))
edu_model_risk <- glm(discrim ~ no_college, data = dat, family = poisson(link = "log"))
sexex_model_risk <- glm(discrim ~ sexexchange, data = dat, family = poisson(link = "log"))
groupsex_model_risk <- glm(discrim ~ groupsex, data = dat, family = poisson(link = "log"))

country_rr <- exp(confint(country_model_risk, level = 0.95)[2,])
employ_rr <- exp(confint(employ_model_risk, level = 0.95)[2,])
edu_rr <- exp(confint(edu_model_risk, level = 0.95)[2,])
sexex_rr <- exp(confint(sexex_model_risk, level = 0.95)[2,])
groupsex_rr <- exp(confint(groupsex_model_risk, level = 0.95)[2,])
```

Next we calculate the adjusted risk ratios.

```r
dscrim_model_risk <- glm(discrim ~ foreign_born + unemployed + no_college +
                      sexexchange + groupsex, data = dat, family = poisson(link = "log"))

dicrim_rr <- exp(confint(dscrim_model_risk, level = 0.95)[-1,])
```

Finally we fit a linear model predicting the expected number of domains of discrimination and violence conditional on covariates.

```r
levels_model <- lm(levels ~ foreign_born + unemployed + no_college +
                      sexexchange + groupsex, data = dat)
```

These results are presented in Table 2:

```
table2_col1 <- cbind(unadjusted = exp(c(country_model_risk$coefficients[2],
                           employ_model_risk$coefficients[2],
                           edu_model_risk$coefficients[2],
                           sexex_model_risk$coefficients[2],
                           groupsex_model_risk$coefficients[2])),
                      rbind(country_rr, employ_rr, edu_rr, sexex_rr, groupsex_rr))
table2_col2 <- cbind(adjusted = exp(dscrim_model_risk$coefficients[-1]), dicrim_rr)
table2_col3 <- mutate(data.frame(summary(levels_model)$coefficients)[-1,],
                        CI_low = Estimate - 1.96*Std..Error,
                        CI_high = Estimate + 1.96*Std..Error)[, c(1, 5, 6)]
table2N <- sum(complete.cases(dat[, c("discrim", "foreign_born", "unemployed",
                                      "no_college", "sexexchange", "groupsex")]))
table2adjR2 <- summary(levels_model)$adj.r.squared

cbind(table2_col1, table2_col2, table2_col3)
```

```
##                unadjusted     2.5 %   97.5 %  adjusted     2.5 %   97.5 %
## foreign_born   2.219887 1.5547425 3.162030 1.8197512 1.2157495 2.715321
## unemployed     2.489297 1.7375085 3.600116 2.2280855 1.4951904 3.339607
## no_college     1.163705 0.8121768 1.658769 0.7066722 0.4573221 1.084898
## sexexchange    1.186359 0.8194997 1.699600 1.1764298 0.7780919 1.761643
## groupsex       1.145073 0.7420747 1.713791 0.9497388 0.6093377 1.438596
##                   Estimate      CI_low   CI_high
## foreign_born  1.30867459  0.93920298 1.6781462
## unemployed    0.78749612  0.44674869 1.1282435
## no_college   -0.18682202 -0.54076410 0.1671201
## sexexchange   0.32121259 -0.02992816 0.6723533
## groupsex      0.08332553 -0.29487384 0.4615249
```

```
table2N
```

```
## [1] 284
```

```
table2adjR2
```

```
## [1] 0.2732041
```

Table 3: Risk of violence

First we calculate the unadjusted risk ratios.

```
Vcountry_model_risk <- glm(violence ~ foreign_born, data = dat, family = poisson(link = "log"))
Vemploy_model_risk <- glm(violence ~ unemployed, data = dat, family = poisson(link = "log"))
Vedu_model_risk <- glm(violence ~ no_college, data = dat, family = poisson(link = "log"))
Vsexex_model_risk <- glm(violence ~ sexexchange, data = dat, family = poisson(link = "log"))
Vgroupsex_model_risk <- glm(violence ~ groupsex, data = dat, family = poisson(link = "log"))

Vcountry_rr <- exp(confint(Vcountry_model_risk, level = 0.95)[2,])
Vemploy_rr <- exp(confint(Vemploy_model_risk, level = 0.95)[2,])
Vedu_rr <- exp(confint(Vedu_model_risk, level = 0.95)[2,])
Vsexex_rr <- exp(confint(Vsexex_model_risk, level = 0.95)[2,])
Vgroupsex_rr <- exp(confint(Vgroupsex_model_risk, level = 0.95)[2,])
```

Next we calculate the adjusted risk ratios.

```r
violence_model_risk <- glm(violence ~ foreign_born + unemployed + no_college +
                      sexexchange + groupsex, data = dat, family = poisson(link = "log"))

violence_rr <- exp(confint(violence_model_risk, level = 0.95)[-1,])
```

These results are presented in Table 3:

```r
table3_col1 <- cbind(unadjusted = exp(c(Vcountry_model_risk$coefficients[2],
                           Vemploy_model_risk$coefficients[2],
                           Vedu_model_risk$coefficients[2],
                           Vsexex_model_risk$coefficients[2],
                           Vgroupsex_model_risk$coefficients[2])),
                     rbind(Vcountry_rr, Vemploy_rr, Vedu_rr,
                            Vsexex_rr, Vgroupsex_rr))
table3_col2 <- cbind(adjusted = exp(violence_model_risk$coefficients[-1]), violence_rr)

table3N <- sum(complete.cases(dat[, c("violence", "foreign_born", "unemployed",
                                       "no_college", "sexexchange", "groupsex")]))

cbind(table3_col1, table3_col2)
```

```
##              unadjusted     2.5 %   97.5 %  adjusted     2.5 %   97.5 %
## foreign_born   4.353659 2.6599493 7.291879 3.4339427 1.9705196 6.082130
## unemployed     3.633028 2.1772400 6.283399 2.5959190 1.4685737 4.716427
## no_college     1.399488 0.8605626 2.270526 0.6561755 0.3619607 1.185412
## sexexchange    1.328100 0.8050981 2.158882 1.1551390 0.6557952 2.005148
## groupsex       1.406348 0.7961599 2.376727 1.1223306 0.6251580 1.934755
```

```r
table3N
```

```
## [1] 284
```

Table 4: Risk of violence and discrimination by national origin

Here, adjusted risk is reported separately for native and foreign born participants.

```r
discrim_model_risk_nat <- glm(discrim ~ unemployed + no_college +
                                sexexchange + groupsex,
                              data = dat[dat$foreign_born == 0,],
                              family = poisson(link = "log"))

discrim_model_risk_for <- glm(discrim ~ unemployed + no_college +
                                sexexchange + groupsex,
                              data = dat[dat$foreign_born == 1,],
                              family = poisson(link = "log"))

violence_model_risk_nat <- glm(violence ~ unemployed + no_college +
                                 sexexchange + groupsex,
                               data = dat[dat$foreign_born == 0,],
                               family = poisson(link = "log"))

violence_model_risk_for <- glm(violence ~ unemployed + no_college +
                                 sexexchange + groupsex,
                               data = dat[dat$foreign_born == 1,],
                               family = poisson(link = "log"))
```

```
discrim_rr_nat <- exp(confint(discrim_model_risk_nat, level = 0.95)[-1,])
discrim_rr_for <- exp(confint(discrim_model_risk_for, level = 0.95)[-1,])
violence_rr_nat <- exp(confint(violence_model_risk_nat, level = 0.95)[-1,])
violence_rr_for <- exp(confint(violence_model_risk_for, level = 0.95)[-1,])
```

These results are presented in Table 4:

```
table4_col1 <- cbind(discrim_nat = exp(discrim_model_risk_nat$coefficients[-1]), discrim_rr_nat)
table4_col2 <- cbind(discrim_for = exp(discrim_model_risk_for$coefficients[-1]), discrim_rr_for)

table4_col3 <- cbind(violence_nat = exp(violence_model_risk_nat$coefficients[-1]), violence_rr_nat)
table4_col4 <- cbind(violence_for = exp(violence_model_risk_for$coefficients[-1]), violence_rr_for)

table4N_col1 <- sum(complete.cases(dat[dat$foreign_born == 0, c("discrim", "unemployed", "no_college",
table4N_col2 <- sum(complete.cases(dat[dat$foreign_born == 1, c("discrim", "unemployed", "no_college",
table4N_col3 <- sum(complete.cases(dat[dat$foreign_born == 0, c("violence", "unemployed", "no_college",
table4N_col4 <- sum(complete.cases(dat[dat$foreign_born == 1, c("violence", "unemployed", "no_college",

round(cbind(table4_col1, table4_col2, table4_col3, table4_col4), 2)
```

```
##              discrim_nat 2.5 % 97.5 % discrim_for 2.5 % 97.5 % violence_nat
## unemployed          2.89  1.75   4.77        1.43  0.78   2.73         3.30
## no_college          0.66  0.35   1.18        0.84  0.45   1.62         0.52
## sexexchange         1.28  0.71   2.24        1.05  0.59   1.88         1.04
## groupsex            0.92  0.50   1.63        0.96  0.49   1.76         1.01
##              2.5 % 97.5 % violence_for 2.5 % 97.5 %
## unemployed   1.44   7.68         2.02  0.95   4.70
## no_college   0.16   1.41         0.78  0.37   1.71
## sexexchange  0.35   2.69         1.19  0.60   2.36
## groupsex     0.36   2.49         1.20  0.57   2.37
```

```
table4N_col1
```

```
## [1] 204
```

```
table4N_col2
```

```
## [1] 80
```

```
table4N_col3
```

```
## [1] 204
```

```
table4N_col4
```

```
## [1] 80
```

Statistical significance of difference across these populations are assessed via interactive models, reported in the SI Table 5.

```
discrim_model_risk_int <- glm(discrim ~ unemployed*foreign_born +
                                no_college*foreign_born +
                                sexexchange*foreign_born +
                                groupsex*foreign_born,
                             data = dat, family = poisson(link = "log"))

violence_model_risk_int <- glm(violence ~ unemployed*foreign_born +
                                no_college*foreign_born +
```

```
                                  sexexchange*foreign_born +
                                  groupsex*foreign_born,
                               data = dat, family = poisson(link = "log"))

round(cbind(discrim_int = exp(discrim_model_risk_int$coefficients[-1]),
      exp(confint(discrim_model_risk_int, level = 0.95)[-1,])), 2)
```

```
##                            discrim_int 2.5 % 97.5 %
## unemployed                        2.89  1.75   4.77
## foreign_born                      2.70  1.29   5.40
## no_college                        0.66  0.35   1.18
## sexexchange                       1.28  0.71   2.24
## groupsex                          0.92  0.50   1.63
## unemployed:foreign_born           0.50  0.23   1.12
## foreign_born:no_college           1.28  0.53   3.15
## foreign_born:sexexchange          0.82  0.37   1.88
## foreign_born:groupsex             1.04  0.43   2.46
```

```
length(discrim_model_risk_int$residuals)
```

```
## [1] 284
```

```
round(cbind(violence_int = exp(violence_model_risk_int$coefficients[-1]),
      exp(confint(violence_model_risk_int, level = 0.95)[-1,])), 2)
```

```
##                            violence_int 2.5 % 97.5 %
## unemployed                         3.30  1.44   7.68
## foreign_born                       3.68  1.30  10.14
## no_college                         0.52  0.16   1.41
## sexexchange                        1.04  0.35   2.69
## groupsex                           1.01  0.36   2.49
## unemployed:foreign_born            0.61  0.20   1.98
## foreign_born:no_college            1.49  0.42   5.99
## foreign_born:sexexchange           1.14  0.35   4.06
## foreign_born:groupsex              1.18  0.37   4.03
```

```
length(violence_model_risk_int$residuals)
```

```
## [1] 284
```

Table 5 and Figure 2

These results are based on a generalized linear mixed model of discrimination and violence.

```
glmm_model_risk <- glmer(discrim ~ foreign_born + unemployed + no_college +
                      sexexchange + groupsex + (1|neighborhood),
                    data = dat, family = poisson(link = "log"))
```

Individual level predictors, with region random effects, are presented in Table 5.

```
glmm_fe_risk <- exp(summary(glmm_model_risk)$coefficients[,1])
glmm_feCI_risk <- exp(confint(glmm_model_risk, level = 0.95))
table5N_risk <- length(summary(glmm_model_risk)$residuals)

cbind(adjusted = glmm_fe_risk[-1], glmm_feCI_risk[-c(1,2),])
```

```
##                adjusted     2.5 %   97.5 %
```

```
## foreign_born 1.6329351 1.0229067 2.556765
## unemployed   2.2512674 1.4758545 3.454353
## no_college   0.7294076 0.4593809 1.151490
## sexexchange  1.2145059 0.7775122 1.882219
## groupsex     0.8808360 0.5490096 1.370437
```

```
table5N_risk
```

```
## [1] 267
```

Region random effects are displayed in Figure 2.

```
glmm_re_risk <- exp(ranef(glmm_model_risk)$neighborhood)
glmm_re_risk <- data.frame(neighborhood = rownames(glmm_re_risk),
                           intercept = round(glmm_re_risk$`(Intercept)`, 2))

figure2N <- dat[complete.cases(dat[,c("discrim", "foreign_born", "unemployed",
                      "no_college", "sexexchange", "groupsex", "neighborhood")]),] %>%
            group_by(neighborhood) %>%
            summarise(neighborhoodN = n())

glmm_re_risk <- merge(glmm_re_risk, figure2N, by = "neighborhood")
glmm_re_risk <- glmm_re_risk[order(glmm_re_risk$intercept),]


figure2_risk <- glmm_re_risk[glmm_re_risk$neighborhoodN >= 5,]
figure2_risk
```

```
##       neighborhood intercept neighborhoodN
## 20           Saida      0.75            26
## 8            Chouf      0.80            39
## 16         Khaldeh      0.82            16
## 1       Achrafiyeh      0.88            25
## 21      Sin el Fil      0.89            15
## 9         Dekwaneh      0.96             9
## 17            Matn      0.98            14
## 19      Ras Beirut      0.98             9
## 2           Baabda      1.00             7
## 18          Mazraa      1.03             8
## 15       Kfarchima      1.05             6
## 23 Tarik El-Jdideh      1.05             7
## 13         Jdaydeh      1.11             8
## 5     Borj Hammoud      1.12            24
## 10          Hadath      1.15             5
## 7           Chiyah      1.17            12
## 14       Kesserwan      1.23            10
## 11           Hamra      1.40            20
```

Network Analysis

We estimate homophily of discrimination and violence using Newman's Assortativity/ Modularity. First we record all recruitment events, keep complete cases, and remove recruitment by study personnel (seeds).

```
recruits <- dat[,c("sid", "rid", "discrim", "violence", "levels")]
recruits <- recruits[complete.cases(recruits), ]
```

```
recruits <- recruits[!recruits$rid == 0, ]
recruits[,1:2] <- data.frame(lapply(recruits[,1:2], function(x) gsub("[^0-9]", "", x)))
```

Next we save an edge list and graph, and add individual attributes.

```
recruits_el <- as.matrix(recruits[,1:2])
recruits_G <- graph_from_edgelist(recruits_el, directed = FALSE)

V(recruits_G)$discrim <- dat$discrim[match(V(recruits_G)$name, gsub("[^0-9]", "", dat$sid))]
V(recruits_G)$violence <- dat$violence[match(V(recruits_G)$name, gsub("[^0-9]", "", dat$sid))]
V(recruits_G)$levels <- dat$levels[match(V(recruits_G)$name, gsub("[^0-9]", "", dat$sid))]

V(recruits_G)$foreign_born <- dat$foreign_born[match(V(recruits_G)$name, gsub("[^0-9]", "", dat$sid))]
```

Finally we calculate modularity based on any experience of discrimination or violence, just violence, and number of domains of discrimination and violence.

```
modD <- modularity(recruits_G, membership = V(recruits_G)$discrim + 1)
modD
```

```
## [1] 0.192892
```

```
modV <- modularity(recruits_G, membership = V(recruits_G)$violence + 1)
modV
```

```
## [1] 0.1384541
```

```
modL <- modularity(recruits_G, membership = V(recruits_G)$levels + 1)
modL
```

```
## [1] 0.1182618
```

We compare these results to a null distribution created by permuting experiences of discrimination and violence. Here we present results based on 1000 permutations, but results in the paper are based on a much larger simulation, 1000000 permutations.

```
sims <- 1000
modD_perm <- rep(NA, sims)
modV_perm <- rep(NA, sims)
modL_perm <- rep(NA, sims)

v_discrim  = V(recruits_G)$discrim + 1
v_violence = V(recruits_G)$violence + 1
v_levels   = V(recruits_G)$levels + 1

for (i in 1:sims) {
  # if(i%%1000 == 0) cat("i =", i, "/", sims,"\n")

  discrim_perm  = sample(v_discrim)
  violence_perm = sample(v_violence)
  levels_perm   = sample(v_levels)

  modD_perm[i] <- modularity(recruits_G, membership = discrim_perm)
  modV_perm[i] <- modularity(recruits_G, membership = violence_perm)
  modL_perm[i] <- modularity(recruits_G, membership = levels_perm)
}
```

We calculate p-values directly from the simulation, and based on normal approximations.

```r
mean(modD_perm > modD)
```

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

```r
mean(modV_perm > modV)
```

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

```r
mean(modL_perm > modL)
```

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

```r
1 - pnorm(q = modD, mean = mean(modD_perm), sd = sd(modD_perm))
```

```
## [1] 2.156453e-11
```

```r
1 - pnorm(q = modV, mean = mean(modV_perm), sd = sd(modV_perm))
```

```
## [1] 3.585076e-10
```

```r
1 - pnorm(q = modV, mean = mean(modL_perm), sd = sd(modL_perm))
```

```
## [1] 5.316203e-11
```

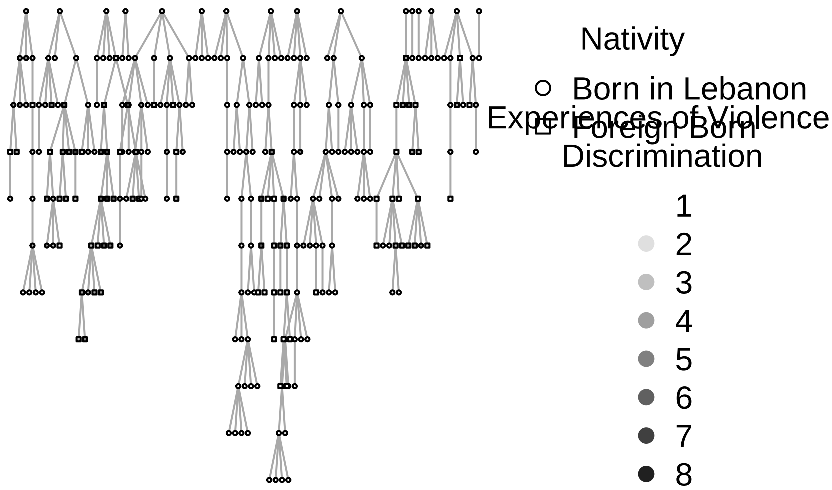
We display the recruitment graph with node shading to indicate level of discrimination or violence, and shape to indicate whether or not the individual was born in Lebanon.

```r
seeds <- unique(recruits$rid[!recruits$rid %in% recruits$sid])

plot.igraph(recruits_G,
            layout = layout_as_tree(recruits_G, root = which(V(recruits_G)$name %in% seeds)),
            vertex.size = 1.75,
            vertex.color = rgb((8:1)/8, (8:1)/8, (8:1)/8)[1 + V(recruits_G)$levels],
            vertex.shape = c("circle", "square")[1 + V(recruits_G)$foreign_born],
            main = "Recruitment Network",
            vertex.label.cex = 0.8,
            vertex.label = NA)

legend(x = 1, y = 0.5, title = "Experiences of Violence,\nDiscrimination",
       legend = c("1", "2", "3", "4", "5", "6", "7", "8"),
       pch = 19, col = rgb((8:1)/8, (8:1)/8, (8:1)/8), bty = "n")
legend(x = 1.15, y = 1, title = "Nativity        ",
       legend = c("Born in Lebanon", "Foreign Born"),
       pch = c(1, 0), bty = "n")
```

Recruitment Network



Supplementary Information

C

Note that section C results are reported above, as Figure 1 output.

D

In contrast to the main results reported as risk ratios, this section of the supplementary information reports odds ratios perfectly analogous to the main results.

Table 2

Table 2 presents individual level predictors of experiencing discrimination and violence. First we calculate unadjusted odds ratios.

```
country_model <- glm(discrim ~ foreign_born, data = dat, family = "binomial")
employ_model <- glm(discrim ~ unemployed, data = dat, family = "binomial")
edu_model <- glm(discrim ~ no_college, data = dat, family = "binomial")
sexex_model <- glm(discrim ~ sexexchange, data = dat, family = "binomial")
groupsex_model <- glm(discrim ~ groupsex, data = dat, family = "binomial")

country_or <- or_glm(data = dat, model = country_model, incr = list(foreign_born = 1))
```

```
employ_or <- or_glm(data = dat, model = employ_model, incr = list(unemployed = 1))
edu_or <- or_glm(data = dat, model = edu_model, incr = list(no_college = 1))
sexex_or <- or_glm(data = dat, model = sexex_model, incr = list(sexexchange = 1))
groupsex_or <- or_glm(data = dat, model = groupsex_model, incr = list(groupsex = 1))
```

Next we calculate adjusted odds ratios.

```
dscrim_model <- glm(discrim ~ foreign_born + unemployed + no_college +
                    sexexchange + groupsex, data = dat, family = "binomial")

dicrim_or <- or_glm(data = dat, model = dscrim_model,
                   incr = list(foreign_born = 1, unemployed = 1, no_college = 1,
                               sexexchange = 1, groupsex = 1))
```

Model 3, the expected number of domains of discrimination and violence experienced conditional on covariates, is identical to that reported in the main text as it does not rely on odds or risk. It is therefore omitted here, but can be seen above in the main text Table 2 replication.

These results are presented in SI Table 2:

```
SItable2_col1 <- rbind(country_or[-5], employ_or[-5], edu_or[-5],
                       sexex_or[-5], groupsex_or[-5])
SItable2_col2 <- dicrim_or[-5]

SItable2_col1
```

```
## # A tibble: 5 x 4
##   predictor    oddsratio `CI_low (2.5)` `CI_high (97.5)`
##   <chr>            <dbl>          <dbl>            <dbl>
## 1 foreign_born      5.17          2.99              9.18
## 2 unemployed        5.64          3.38              9.59
## 3 no_college        1.31          0.812             2.11
## 4 sexexchange       1.36          0.83              2.22
## 5 groupsex          1.28          0.721             2.26
```

```
SItable2_col2
```

```
## # A tibble: 5 x 4
##   predictor    oddsratio `CI_low (2.5)` `CI_high (97.5)`
##   <chr>            <dbl>          <dbl>            <dbl>
## 1 foreign_born     3.95            2.11            7.57
## 2 unemployed       4.94            2.77            8.98
## 3 no_college       0.492           0.25            0.937
## 4 sexexchange      1.42            0.76            2.65
## 5 groupsex         0.879           0.45            1.70
```

Table 3

Table 3 presents individual level predictors of experiencing violence. First we calculate unadjusted odds ratios.

```
Vcountry_model <- glm(violence ~ foreign_born, data = dat, family = "binomial")
Vemploy_model <- glm(violence ~ unemployed, data = dat, family = "binomial")
Vedu_model <- glm(violence ~ no_college, data = dat, family = "binomial")
Vsexex_model <- glm(violence ~ sexexchange, data = dat, family = "binomial")
Vgroupsex_model <- glm(violence ~ groupsex, data = dat, family = "binomial")
```

```
Vcountry_or <- or_glm(data = dat, model = Vcountry_model, incr = list(foreign_born = 1))
Vemploy_or <- or_glm(data = dat, model = Vemploy_model, incr = list(unemployed = 1))
Vedu_or <- or_glm(data = dat, model = Vedu_model, incr = list(no_college = 1))
Vsexex_or <- or_glm(data = dat, model = Vsexex_model, incr = list(sexexchange = 1))
Vgroupsex_or <- or_glm(data = dat, model = Vgroupsex_model, incr = list(groupsex = 1))
```

Next we calculate adjusted odds ratios.

```
violence_model <- glm(violence ~ foreign_born + unemployed + no_college +
                      sexexchange + groupsex, data = dat, family = "binomial")

violence_or <- or_glm(data = dat, model = violence_model,
                    incr = list(foreign_born = 1, unemployed = 1, no_college = 1,
                                sexexchange = 1, groupsex = 1))
```

These results are presented in SI Table 3:

```
SItable3_col1_or <- rbind(Vcountry_or[-5], Vemploy_or[-5], Vedu_or[-5],
                     Vsexex_or[-5], Vgroupsex_or[-5])
SItable3_col2_or <- violence_or[-5]

SItable3_col1_or
```

```
## # A tibble: 5 x 4
##   predictor    oddsratio `CI_low (2.5)` `CI_high (97.5)`
##   <chr>            <dbl>          <dbl>            <dbl>
## 1 foreign_born      7.88          4.33             14.7
## 2 unemployed        5.48          3.04             10.2
## 3 no_college        1.55          0.891             2.71
## 4 sexexchange       1.45          0.82              2.55
## 5 groupsex          1.58          0.82              2.95
```

```
SItable3_col2_or
```

```
## # A tibble: 5 x 4
##   predictor    oddsratio `CI_low (2.5)` `CI_high (97.5)`
##   <chr>            <dbl>          <dbl>            <dbl>
## 1 foreign_born     6.41           3.22             13.2
## 2 unemployed       4.01           2.03              8.13
## 3 no_college       0.503          0.22              1.10
## 4 sexexchange      1.27           0.606             2.62
## 5 groupsex         1.22           0.573             2.55
```

Table 4

SI Table 4 reports adjusted odds ratios separately for native and foreign born participants.

```
discrim_model_nat <- glm(discrim ~ unemployed + no_college +
                              sexexchange + groupsex,
                            data = dat[dat$foreign_born == 0,],
                            family = "binomial")

discrim_model_for <- glm(discrim ~ unemployed + no_college +
                              sexexchange + groupsex,
                            data = dat[dat$foreign_born == 1,],
```

```
                             family = "binomial")

violence_model_nat <- glm(violence ~ unemployed + no_college +
                                 sexexchange + groupsex,
                               data = dat[dat$foreign_born == 0,],
                               family = "binomial")

violence_model_for <- glm(violence ~ unemployed + no_college +
                                 sexexchange + groupsex,
                               data = dat[dat$foreign_born == 1,],
                               family = "binomial")

discrim_or_nat <- or_glm(data = dat, model = discrim_model_nat,
                         incr = list(unemployed = 1, no_college = 1,
                                     sexexchange = 1, groupsex = 1))
discrim_or_for <- or_glm(data = dat, model = discrim_model_for,
                         incr = list(unemployed = 1, no_college = 1,
                                     sexexchange = 1, groupsex = 1))
violence_or_nat <- or_glm(data = dat, model = violence_model_nat,
                         incr = list(unemployed = 1, no_college = 1,
                                     sexexchange = 1, groupsex = 1))
violence_or_for <- or_glm(data = dat, model = violence_model_for,
                         incr = list(unemployed = 1, no_college = 1,
                                     sexexchange = 1, groupsex = 1))
```

These results are presented in SI Table 4:

```
SItable4N_col1 <- sum(complete.cases(dat[dat$foreign_born == 0, c("discrim", "unemployed", "no_college"
SItable4N_col2 <- sum(complete.cases(dat[dat$foreign_born == 1, c("discrim", "unemployed", "no_college"
SItable4N_col3 <- sum(complete.cases(dat[dat$foreign_born == 0, c("violence", "unemployed", "no_college
SItable4N_col4 <- sum(complete.cases(dat[dat$foreign_born == 1, c("violence", "unemployed", "no_college

round(cbind(discrim_or_nat[,-c(1, 5)], discrim_or_for[,-c(1, 5)],
            violence_or_nat[,-c(1, 5)], violence_or_for[,-c(1, 5)]), 2)
```

```
##   oddsratio CI_low (2.5) CI_high (97.5) oddsratio CI_low (2.5)
## 1      5.94         2.99          12.20      3.15         1.06
## 2      0.50         0.22           1.07      0.53         0.14
## 3      1.49         0.70           3.19      1.23         0.41
## 4      0.86         0.37           1.88      0.86         0.27
##   CI_high (97.5) oddsratio CI_low (2.5) CI_high (97.5) oddsratio
## 1           9.93      4.08         1.64          10.36      3.93
## 2           1.83      0.46         0.13           1.38      0.57
## 3           3.77      1.04         0.33           2.99      1.47
## 4           2.95      1.02         0.33           2.82      1.53
##   CI_low (2.5) CI_high (97.5)
## 1         1.37          12.41
## 2         0.17           1.82
## 3         0.53           4.16
## 4         0.50           4.80
```

```
SItable4N_col1
```

```
## [1] 204
```

```
SItable4N_col2
```

```
## [1] 80
```

```
SItable4N_col3
```

```
## [1] 204
```

```
SItable4N_col4
```

```
## [1] 80
```

SI Table 5 reports results from the interacted model cited in the main text (above).

Table 6

These results are based on a generalized linear mixed model of discrimination and violence:

```
glmm_model <- glmer(discrim ~ foreign_born + unemployed + no_college +
                      sexexchange + groupsex + (1|neighborhood),
                    data = dat, family = binomial())
```

Individual level predictors are presented in Table 4:

```
SIglmm_fe <- exp(summary(glmm_model)$coefficients[,1])
SIglmm_feCI <- exp(confint(glmm_model, level = 0.95))
SItable5N <- length(summary(glmm_model)$residuals)

cbind(SIglmm_fe[-1], SIglmm_feCI[-c(1,2),])
```

```
##                             2.5 %    97.5 %
## foreign_born 3.0400340 1.3430432  7.086069
## unemployed   5.7172647 2.9222339 11.607646
## no_college   0.6231284 0.2785374  1.373599
## sexexchange  1.9277072 0.8822775  4.401572
## groupsex     0.6813608 0.3069481  1.473501
```

```
SItable5N
```

```
## [1] 267
```

The region random effects are displayed in SI Figure 2:

```
glmm_re <- exp(ranef(glmm_model)$neighborhood)
glmm_re <- data.frame(neighborhood = rownames(glmm_re), intercept = glmm_re$`(Intercept)`)
glmm_re <- merge(glmm_re, figure2N, by = "neighborhood")
glmm_re <- glmm_re[order(glmm_re$intercept),]

SIfigure2 <- glmm_re[glmm_re$neighborhoodN >= 5,]
SIfigure2
```

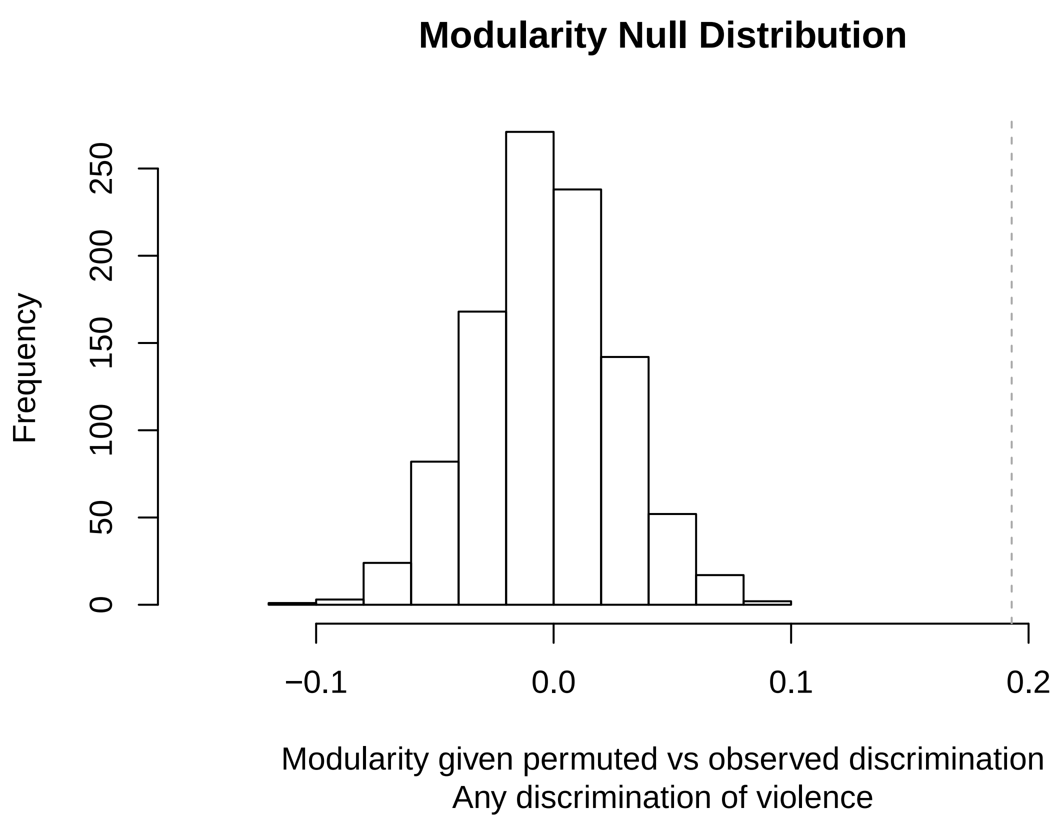
```
##      neighborhood intercept neighborhoodN
## 16        Khaldeh 0.2650538            16
## 20          Saida 0.3176627            26
## 8           Chouf 0.3758331            39
## 21     Sin el Fil 0.5307994            15
## 1      Achrafiyeh 0.6275587            25
## 9        Dekwaneh 0.7411283             9
## 19     Ras Beirut 0.7457053             9
```

```
## 17           Matn 0.7657736            14
## 2          Baabda 0.8543107             7
## 18         Mazraa 1.0991403             8
## 15      Kfarchima 1.2124521             6
## 23 Tarik El-Jdideh 1.2340528            7
## 5     Borj Hammoud 1.5419248           24
## 13        Jdaydeh 1.8194851             8
## 7          Chiyah 2.0063497            12
## 10         Hadath 2.6546865             5
## 14      Kesserwan 2.7498337            10
## 11          Hamra 3.9340166            20
```

E

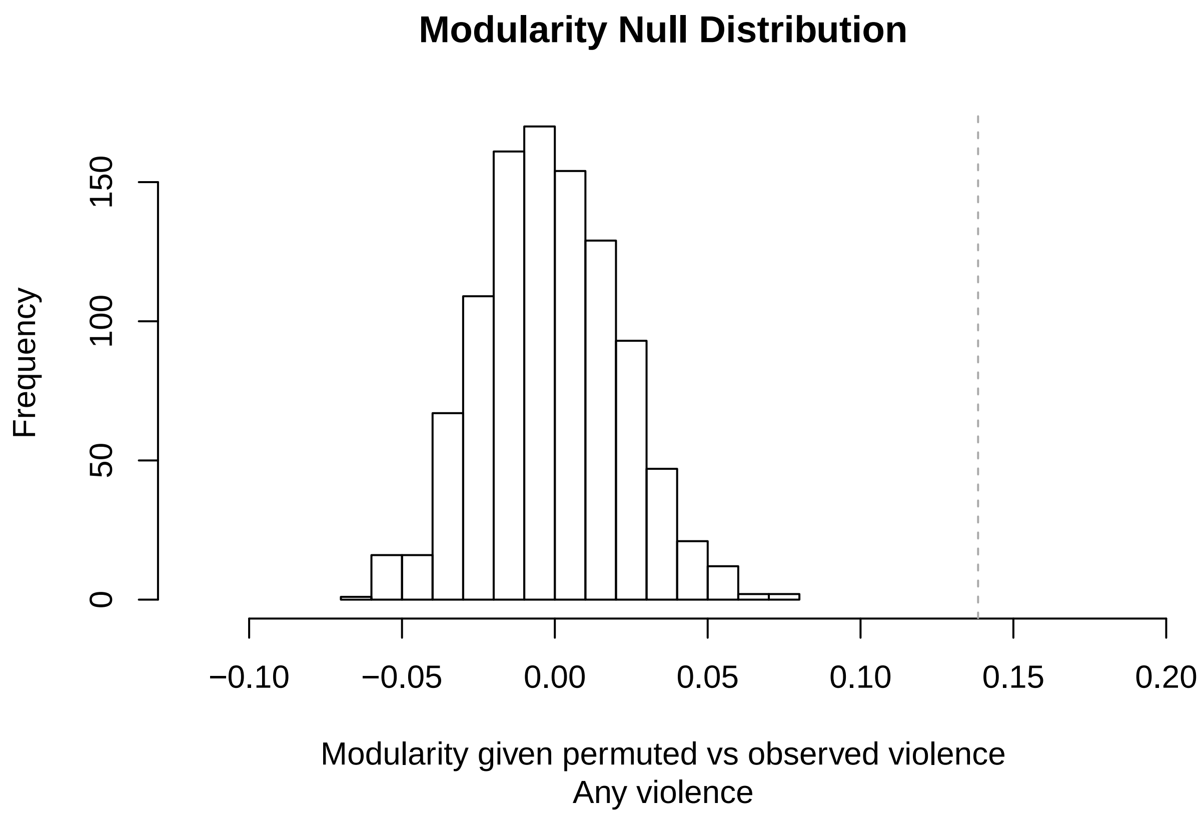
We plot null modularity distributions as histograms:

```r
hist(modD_perm, xlim = (c(min(modD_perm) - 0.05, modD + 0.05)),
     main = "Modularity Null Distribution",
     sub = "Any discrimination of violence",
     xlab = "Modularity given permuted vs observed discrimination")
abline(v = modD, col = "darkgrey", lty = 2)
```

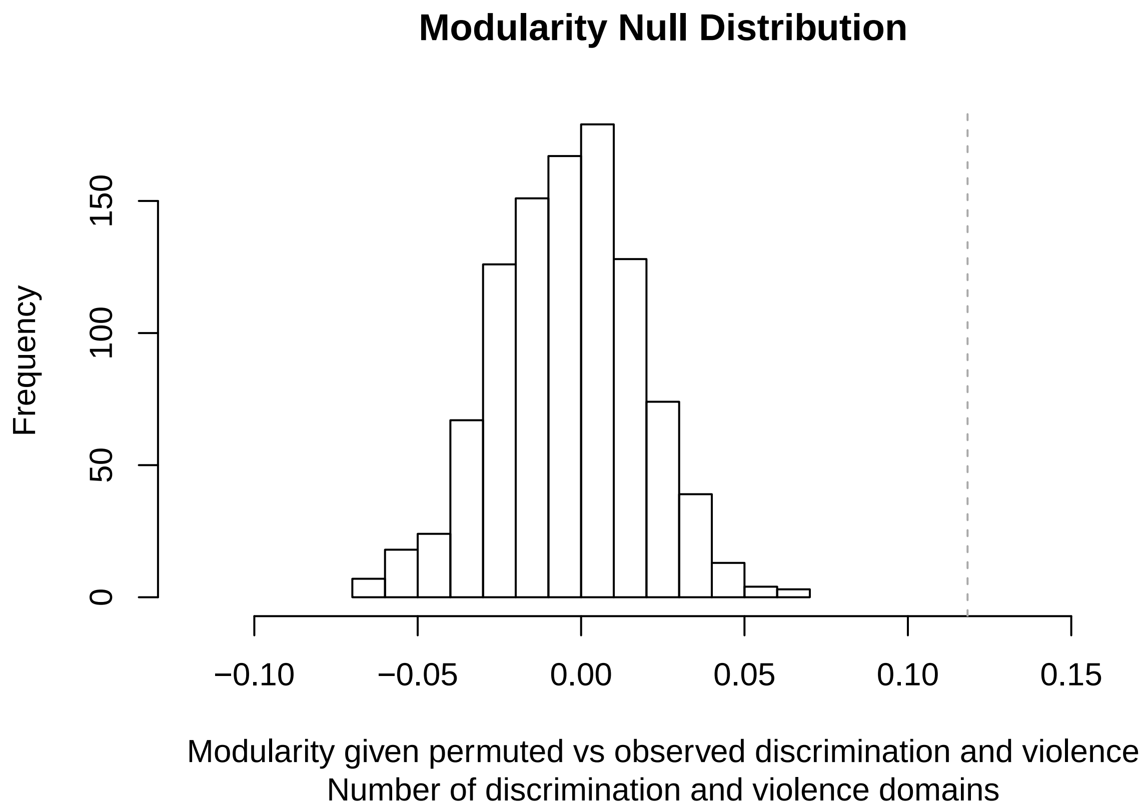



```r
hist(modV_perm, xlim = (c(min(modV_perm) - 0.05, modV + 0.05)),
     main = "Modularity Null Distribution",
     sub = "Any violence",
     xlab = "Modularity given permuted vs observed violence")
```

```r
abline(v = modV, col = "darkgrey", lty = 2)
```




```r
hist(modL_perm, xlim = (c(min(modL_perm) - 0.05, modL + 0.05)),
     main = "Modularity Null Distribution",
     sub = "Number of discrimination and violence domains",
     xlab = "Modularity given permuted vs observed discrimination and violence")
abline(v = modL, col = "darkgrey", lty = 2)
```



We display the observed recruitment trees, with outcomes colored:

```
png("Recruitment_nativity_discrim.png", width = 8, height = 6, res = 200, units = "in")
plot.igraph(recruits_G,
            layout = layout_as_tree(recruits_G, root = which(V(recruits_G)$name %in% seeds)),
            vertex.size = 1.75,
            vertex.color = c("white", "red")[1 + (V(recruits_G)$discrim == 1)],
            vertex.shape = c("circle", "square")[1 + V(recruits_G)$foreign_born],
            main = "Discrimination and Violence in the Recruitment Network",
            vertex.label = NA)
legend(x = 1, y = 0.5, title = "Experiences of Violence,\nDiscrimination",
       legend = c("Yes", "No"),
       pch = c(19, 1), col = c("red", "black"), box.col = "white")
legend(x = 1.15, y = 1, title = "Nativity        ",
       legend = c("Born in Lebanon", "Foreign Born"),
       pch = c(1, 0), bty = "n")
dev.off()
```

```
## pdf
##   2
```

```
png("Recruitment_nativity_violence.png", width = 8, height = 6, res = 200, units = "in")
plot.igraph(recruits_G,
            layout = layout_as_tree(recruits_G, root = which(V(recruits_G)$name %in% seeds)),
            vertex.size = 1.75,
            vertex.color = c("white", "red")[1 + (V(recruits_G)$violence == 1)],
            vertex.shape = c("circle", "square")[1 + V(recruits_G)$foreign_born],
```

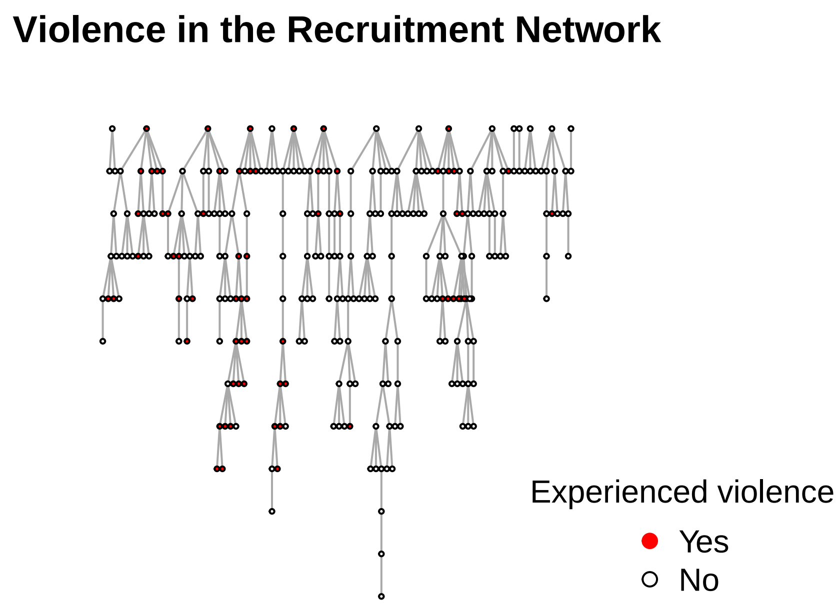
```r
            main = "Violence in the Recruitment Network",
            vertex.label = NA)
legend(x = 1, y = 0.5, title = "Experiences of Violence",
       legend = c("Yes", "No"),
       pch = c(19, 1), col = c("red", "black"), box.col = "white")
legend(x = 1.15, y = 1, title = "Nativity        ",
       legend = c("Born in Lebanon", "Foreign Born"),
       pch = c(1, 0), bty = "n")
dev.off()
```

```
## pdf
##   2
```

```r
plot.igraph(recruits_G, layout = layout_as_tree, vertex.size = 2,
            vertex.color = c("white", "red")[1 + (V(recruits_G)$discrim == 1)],
            main = "Discrimination and Violence in the Recruitment Network",
            vertex.label = NA)
legend(x = "bottomright", title = "Experienced violence or \ndiscrimination",
       legend = c("Yes", "No"),
       pch = c(19,1), col = c("red", "black"), box.col = "white")
```


```r
plot.igraph(recruits_G, layout = layout_as_tree, vertex.size = 2,
            vertex.color = c("white", "red")[1 + (V(recruits_G)$violence == 1)],
            main = "Violence in the Recruitment Network",
            vertex.label = NA)
legend(x = "bottomright", title = "Experienced violence",
       legend = c("Yes", "No"),
```

```
       pch = c(19,1), col = c("red", "black"), box.col = "white")
```




```
plot.igraph(recruits_G, layout = layout_as_tree, vertex.size = 2,
            vertex.color = rgb((8:1)/8, (8:1)/8, (8:1)/8)[1 + V(recruits_G)$levels],
            main = "Number of discrimination and violence
            \ndomains in the Recruitment Network",
            vertex.label = NA)
legend(x = "bottomright", title = "Experiences",
       legend = c("1", "2", "3", "4", "5", "6", "7", "8"),
       pch = 19, col = rgb((8:1)/8, (8:1)/8, (8:1)/8), bty = "n")
```

Number of discrimination and violence domains in the Recruitment Network